Equilibrium Matters for Market Power: A Case Study in French Gas Stations*

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Abstract

The rockets and feathers (RAF) gas station literature originates from a suspicion that firms exercise market power to keep prices high for artificially long periods of time. Because RAF studies aim to answer whether gas stations are setting prices unfairly, we argue it makes more sense to explicitly model firm reactions to changing profit margins using long-term equilibrium as a proxy rather than extrapolate market power from reactions to oil price increases and decreases as is done traditionally. To this end, we show asymmetric reactions towards equilibrium can exist in the absence of the more traditional market power indicator (i.e., asymmetry in response to positive and negative input price changes). Using a threshold vector error correction model (TVECM) where parameters change based on the sign of disequilibrium, we show that while French fuel prices respond with similar speed after oil price increases and decreases, prices adjust faster when margins are below equilibrium levels. Collectively, this indicates future RAF studies should include asymmetric adjustment towards equilibrium as a proxy for inflated profit margins.

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1 Introduction

The gas station market is often studied to understand how retail prices respond to fluctuations in input prices because the market is simplified by factors such as the presence of a single main input, product homogeneity, and widely available data. Within this field, the rockets and feathers (RAF) phenomenon, where fuel prices appear to go up faster than they fall (Tappata, 2009), has received great attention because it raises suspicion of anticompetitive behavior (i.e., firms using market power to maintain artificially high prices). Specifically, a leading explanation of the appearance and disappearance of asymmetric pricing is attributable to degrees of competition, with RAF occurring in the presence of market power (Borenstein et al., 1997; Hong and Lee, 2020; Zhang et al., 2023). For instance, while Borenstein et al. (1997) discuss the hypothesis of asymmetry coming from differences in inventory adjustment processes when costs rise compared to when they fall, the other two hypotheses involve gas stations seizing an opportunity to keep higher prices, with the first suggesting that gas stations act as oligopolies and lack incentive to lower prices following input cost decreases and the latter proposing that consumers may search among gas stations less when oil prices are volatile because they attribute observed gas price increases to input cost shocks which are common across stations rather than to individual stations attempting to raise their margins. Likewise, subsequent studies (Hong and Lee, 2020; Borenstein and Shepard, 2002; Tappata, 2009) have developed each of these hypotheses and indicated support for both inventory adjustment and market power as contributors to asymmetric prices. It is important to note however that RAF studies based in all above hypotheses maintain the overarching goal of answering whether gas stations are setting prices unfairly or rather if prices are being set as a result of competitive market activity.

To this end, one of the earliest papers with this goal is Borenstein et al. (1997) who used US data to lend support to the common assertion at the time that fuel prices react faster to crude oil price increases than decreases. Borenstein et al. (1997) inspired a large body of literature testing for quicker pass-through of positive oil price shocks than negative shocks to determine whether gas stations are exercising market power, with empirical findings of asymmetry being mixed across markets, data frequencies, sample periods, and estimation methods (Perdiguero-García, 2013; Ederington et al., 2019; Galeotti et al., 2003). Moreover, Frey and Manera (2007) categorize the many econometric models used within the RAF literature, with traditional models emphasizing different price reactions to positive and negative input price changes (e.g., Asymmetric ARDL used by Borenstein et al. (1997) or Asymmetric ECM from Bachmeier and Griffin (2003)) with Perdiguero-García (2013) adopting these classifications to distinguish between models in the empirical RAF literature, where all but one class involve differing responses to positive and negative input price changes.

However, asymmetry based on the sign of the input price change is not the only type of asymmetry observed. Another type of asymmetry occurs when the retail price adjusts with different speed when it is above or below its long-run equilibrium level with the input price. This type of asymmetry, though possibly correlated with asymmetry from the sign of the input cost change, is not identical (Frey and Manera, 2007; Ederington et al., 2019; Zhang et al., 2023). Therefore, it is possible to find one form of asymmetry (i.e., due to the sign of disequilibrium) in the absence of the other (i.e., due to the sign of input cost changes). To discuss the difference between these two general classes of asymmetry, we will use the terms disequilibrium asymmetry (DEA) for the former and input price asymmetry (IPA) for the latter. While previous papers have modeled both IPA and DEA, these asymmetry types have been largely treated as interchangeable and conflated in interpretation, with IPA being the more common measure (Perdiguero-García, 2013). Some work has been done to distinguish different types of asymmetry, with the review by Frey and Manera (2007) defining seven subclasses of asymmetry (four of which are IPA and three of which are DEA) but not explaining the economic distinction between IPA and DEA. In later works, both asymmetry types have been modeled at the same time, but once again interpretation of the difference between IPA and DEA has been limited. For instance, Zhang et al. (2023) use a threshold vector error correction model (TVECM) to examine the transmission of crude oil prices into diesel in the US market and find diesel reacts more quickly when underpriced versus oil. While they acknowledge that this is not identical to IPA, they do not explain say what this means for firm behavior. Likewise, Torrado and Escribano (2020) model both IPA and DEA but do not describe what each specific type of asymmetry says about firm market power. Moreover, Galeotti et al. (2003) uses an Asymmetric ECM to model both IPA and DEA, but mixes interpretation of DEA with other long-run asymmetry measures, such as reaction time and cumulated impact definitions from Frey and Manera (2007) which are both based on IPA.

To accurately assess whether gas stations exhibit anticompetitive behavior, it is essential to evaluate their actions based on profit margins. If they consistently maintain high margins above equilibrium levels for extended periods, this indicates anticompetitive behavior. Likewise, if they react quickly when operating below equilibrium margins, that behavior suggests the same. To this end, a disequilibrium or error correction term condenses information of past diesel and oil price changes and shows current price pressures in the diesel market, acting as a proxy to station profit margins and making DEA a potentially clearer indicator of market power than IPA. Many papers fail to include DEA (e.g., Borenstein et al. (1997) and Bachmeier and Griffin (2003) in the general RAF literature and Audenis et al. (2002), Lamotte et al. (2013), De Salles (2014), Boroumand et al. (2016) and Gautier et al. (2023) within the French market), and this oversight can lead to inconsistent findings regarding IPA as a form of omitted variable bias, thereby contributing to mixed asymmetry findings indicated in past literature (Frey and Manera, 2007; Perdiguero-García,

2013; Ederington et al., 2019).

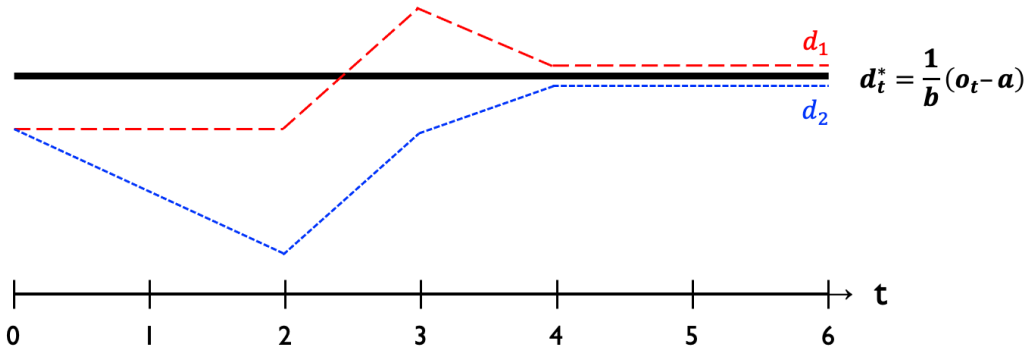


Figure 1: Illustration of diesel price increase from equilibrium to equilibrium. *Note:* Shown is a simple depiction of how adding an equilibrium relationship to price transmission models improves fit. Horizontal line shows the equilibrium diesel price d_t^* assuming a constant oil price o_t.

Additionally, there is possibly a broader economic misspecification in these models, as the incentives which gas stations face may not be accurately captured by oil price changes. Specifically, gas stations might not respond to changes in oil prices if their prices are significantly undervalued relative to those of crude oil. For instance, if the oil price decreases further while gasoline remains underpriced, stations may not adjust their pricing based on the direction of oil price changes but rather on their current margins. The reason adding equilibrium to a model matters can be explained visually with Figure 1. If looking at the two diesel price series d_1 and d_2 alone, what you observe is an identical increase from $t = 2$ to $t = 3$, but d_2 increases afterwards while d_1 decreases. This makes it hard to identify any patterns. Instead, when you take into account the equilibrium, the different behavior from $t = 3$ to $t = 4$ makes sense. Similarly, price behavior is clarified when the equilibrium is included in the model and when different speeds of adjustment depending on the sign of disequilibrium are incorporated.

Based on the above, the main goal of this paper is to test for DEA in a market where IPA methods failed to show asymmetry, and our results show a case where a DEA metric flags the presence of market power when IPA metrics fail to show market power. Specifically, we use a two-regime TVECM to analyze how quickly fuel prices respond when they are above and below equilibrium with crude oil. Note that besides our TVECM we estimate two models that have been used previously to study IPA including the panel method of Gautier et al. (2023) which regresses price changes across several days on a cost change together with other controls such as station fixed effects as well as price changes of neighboring stations, and the Asymmetric ECM of Bachmeier

and Griffin (2003). Importantly, neither Gautier et al. (2023) nor Bachmeier and Griffin (2003) test differences in pricing patterns based on positive and negative disequilibrium. We thereby implement all above models to distinguish between IPA and DEA using a French diesel price data set from Gautier et al. (2023).

We analyze the same data as Gautier et al. (2023) using DEA models because their findings in the French diesel market form a foundation for broader analysis in markets characterized by price stickiness. Specifically, Gautier et al. (2023) use a French government curated data set to investigate whether the kurtosis-to-frequency (KF) ratio of price changes of an individual firm summarize their particular retail price reaction to a common marginal cost change across firms, as indicated by the cumulative impulse response of prices (CIRP) which represents the cumulated effect of an input cost change on the retail price over a given time period. Gautier et al. (2023) derive the theoretical relationship between CIRP and the KF ratio from the work of Alvarez et al. (2016) concerning cumulative impulse responses of outputs to monetary policy changes. The resulting relationship tested empirically by Gautier et al. (2023) is given by

$$CIRP_{iH}(\delta) = \delta H - \frac{\delta}{6}\frac{Kur_i}{Freq_i} \tag{1}$$

where $CIRP_{iH}(\delta)$ is the cumulative impulse response of prices to variable cost shocks of size δ for station i over horizon H, Kur_i represents the kurtosis of price changes over time for station i and $Freq_i$ is the frequency of price changes for station i. The rationale behind the KF ratio is that higher kurtosis suggests less state dependence in pricing behavior, where retailers only adjust prices when variable cost changes are sufficiently large. Additionally, increased frequency denotes a quicker pass-through of variable cost shocks to retail prices. Following testing using a variety of regressions, Gautier et al. (2023) find a negative correlation between the KF ratio and CIRP values and estimated coefficients which align with theoretical predictions. Together, Gautier et al. (2023) take these results to mean that the KF ratio accurately captures how retail diesel prices respond to variable cost fluctuations within the French market context, thereby implying applicability across other industries characterized by sticky prices.

While Gautier's results may be useful for broad economic modeling, they hinge on lack of asymmetry, making this a compelling case study for trying to rule out unfair pricing before conducting more detailed interpretation of firm behavior. Notably, the relationship in equation (1) does not allow for the possibility of either IPA or DEA, such that if any asymmetric pricing behavior was found in France, the use of the KF ratio would be invalidated for that market. Throughout the process of robustness testing for their theoretical relationship, Gautier et al. (2023) do test for IPA. However, even if there is no IPA as their results would suggest, there could nonetheless be unaccounted for DEA.

Given the need for symmetry to use the KF ratio result detailed above, we investigated previous studies using data from French gas stations and find reports of asymmetric pricing diminish over time. Specifically, Audenis et al. (2002) focused on IPA and found evidence of such asymmetry. Later studies such as Lamotte et al. (2013) and Boroumand et al. (2016) similarly test IPA and confirm its presence using data from 1990-2011 and 1990-2012, respectively. In contrast, studies using more recent data like De Salles (2014; spanning 2006 – 2013) and Gautier et al. (2023; spanning 2007 – 2018) also examine possible IPA but do not find supporting evidence for it. Regarding the trend of disequilibrium response, Galeotti et al. (2003) addressed both aspects by analyzing data from 1985 to 2000 in the French market and found evidence for both IPA and DEA. Further analysis by Gautier and Le Saout (2015) focused on estimating positive and negative equilibrium adjustment thresholds at individual gas stations using data from 2007-2009, revealing that approximately 15% exhibited larger adjustment thresholds for positive than negative disequilibrium responses. A subsequent study by Torrado and Escribano (2020) employed a double threshold ECM to explore interactions between DEA and IPA but concluded that French stations showed no evidence of asymmetry from 2011 to 2017. Overall, there appears to be a declining trend in both the evidence of IPA and DEA over time. However, due to the limited number of studies reflecting the trend, further research is necessary to validate these findings. To this end, our study uses a similar timespan as Torrado and Escribano (2020); however, we provide new evidence through the TVECM, thereby allowing all coefficients and estimated variance to change based on the sign of the disequilibrium term. Furthermore, we expand studies from Torrado and Escribano (2020) by conducting impulse response analysis and associated statistical significance tests.

Our results show asymmetric speeds of adjustment towards equilibrium both nationally and in urban and rural groups. Furthermore, we do not find asymmetric adjustment to positive and negative oil price changes. Together, the main contribution of the paper is to show that asymmetric responses towards equilibrium can be a clearer indicator of market power among gas stations than the traditionally used response to positive and negative oil price changes.

2 Data

Table 1: Summary of number of gas stations in France based on population

	Urban	Rural	Unknown	Total
Number of Stations	7,088	2,682	1,001	10,771

The diesel price data is taken from the replication package of Gautier et al. (2023) and was cleaned using methods outlined by Gautier et al. (2023). The base dataset originates from the

Table 2: Regularity of diesel price changes in French gas stations

Frequency			Implied Duration
All	Increase	Decrease	
20.80%	10.72%	10.08%	4.81 days

Note: The frequency is the percentage of observed days where a gas station changes prices. The frequency values shown were calculated by computing the frequency for each gas station and averaging over the values. Implied duration of the price is the inverse of average frequency.

French government[1], covering gas station data from 2007 to 2018 for stations with retail sales exceeding a volume limit of 500 cubic meters per year. Since 2007, stations meeting this criterion for sales volume have been required to report their prices to the governmental authority whenever they change prices. Gautier et al. (2023) study diesel instead of gasoline for their main results first because diesel has the highest market share among consumer fuels in France across the sample (e.g., 48% of cars use diesel versus 40% which use gasoline according to recent figures; ACEA (2026)). Moreover, the composition of gasoline fuel used in France changed across the sample period, potentially introducing differences in the dynamics of how input costs are being passed onto consumers. For these reasons, we also adopt diesel instead of gasoline for our analysis.

Preliminary data mapping was conducted on a panel of daily pre-tax prices across 10,771 stations from 2007-18. This introductory step is not directly related to the research question; however, it is important because it will aid in verifying the suitability of the chosen model and should also help in interpreting results. The distribution of price changes across the whole sample is shown in Figure 2, and the sample composition of the 10771 stations is presented in Table 1. Note, however, that the number of stations with data each day changes due to failures in reporting procedures (Figure 3). Most of the variation comes from interrupting price series after 30 days with no price change. Specifically, if a station does not report a price change within 30 days of the previously reported price change, price observations are treated as missing until a new price change is reported. Some of the missing observations are also caused by replacing price changes greater than $\pm$ 20% with a missing value; specifically, we do this to clarify visuals of the data but refrain from this step in constructing the six-year analytical sample.

Regarding the stickiness of diesel prices, we show that although the oil price changes daily, on most of the days the majority of the stations keep price unchanged, as evidenced by an average duration of $\sim$five days for diesel prices (Table 2). Furthermore, we collect information on the

[1]This data is publicly available at http://www.prix-carburants.gouv.fr

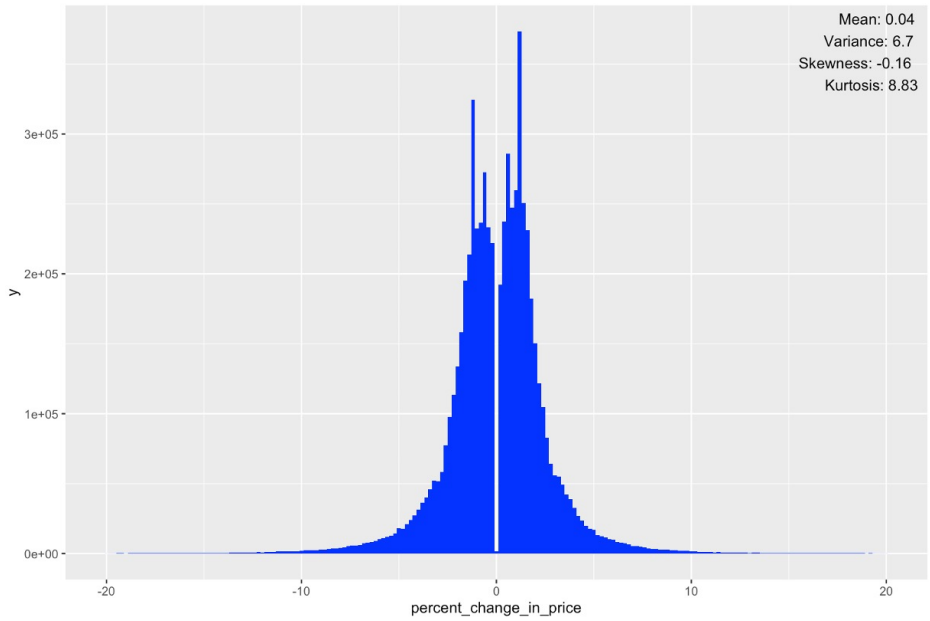


Figure 2: Pooled pre-tax nonzero diesel price changes in France. *Note:* Shown is the distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms. Data is pooled over the entire sample from 2007–2018.

distribution of final digits in prices (Appendix Figure A1), with results showing that psychological pricing appears to play a prominent role in the final digit of price, while it does not seem to have much relevance in the second-to-last digit. We also plot the distribution of nonzero price changes by day of the week in Appendix Figure A2 and find most days to have a significant share of price changes, with the exception of Sundays.

In Appendix Figures A3-6, we plot cross-sectional distributions for single days. Particularly, we choose a random pair of days (i.e., October 25th and 26th 2010), and examine non-zero diesel price changes. For the national data set on October 25th, the mean is near zero and it has a small negative skewness, but the distribution appears fairly symmetric with some weight to the positive side. However, when we break it up into urban and rural groups, they appear visually different, with the rural gas stations showing more mass to the positive side, as evidenced by a larger mean of 0.5 versus -0.16 in the urban group. Additionally, the variances are somewhat different, with a smaller variance of the rural group. Moving to the following day in the sample (i.e., October 26th, 2010), likewise, we see that the national distribution appears largely symmetric with more mass to the positive side. When data is broken into urban and rural groups, they are again visually different, with the rural group having larger spikes on both the negative and positive sides while the urban group contains a single large peak. Furthermore, in Appendix Figures A7-8 we pool the

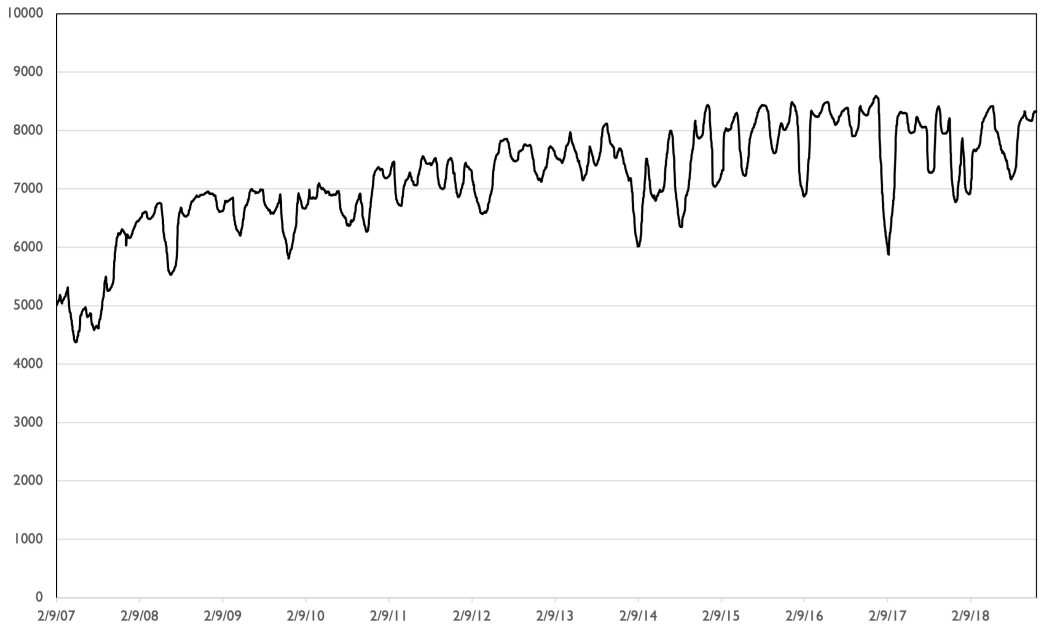


Figure 3: Number of French gas stations per day. *Note:* Shown are the number of stations with non-missing price observations each day, which fluctuates daily due to failures in reporting procedures. Price series are interrupted after 30 days with no price change and price changes greater than $\pm 20\%$ are also replaced with a missing value.

data from the randomly chosen week noted above and plot the resulting distribution. In doing this we observe similar patterns to the single day histograms, with differences between urban and rural groups noted with regard to mean and variance. Moreover, it is important to note that the oil price was increasing over all these time intervals, which explains the larger mass to the upside.

After establishing the basic properties of the data set and in preparation for our use of the TVECM model, we generated the six-year analytical sample used in Gautier et al. (2023) in which only stations with an uninterrupted price series over six years are included. This constraint is reportedly included by Gautier et al. (2023) to clarify pricing dynamics over time, and although it greatly reduces the available observations (i.e., by approximately 70%), we have done the same in an attempt to produce findings that can reasonably be compared to theirs.

A potential source of bias is the presence of measurement errors in the data due to missing reports of price changes. Even after conducting the data cleaning as outlined in Gautier et al. (2023), we observe irregularities in the cross-sectional distributions of price changes. Specifically, large price increases and decreases are both present in a single day, as shown in Appendix Figures A9-11. The reason this is irregular is because diesel prices are highly correlated with crude oil

prices (R^2 of cointegrating regression is 0.9), so very large diesel price changes in both directions is hard to explain given that this could not be caused by a large change in oil prices. In response to this irregularity, the presence of extreme positive and negative price changes in a single day could be explained by missing price reports. Specifically, data was observed only on days when stations report price changes, and a daily panel was created by assuming that prices remain constant when no adjustment is reported. If a station misses reporting a price change, the next observed adjustment will include both the missing and current price changes. This can create unusually large price changes or cause a change in the opposite direction as actually occurred that day. However, since aggregation occurs across numerous stations in our study, these errors are unlikely to significantly impact results unless this data missingness is associated with relevant station characteristics (e.g., urban stations have more missingness, especially on the same day, than rural stations).

Table 3: Summary statistics of data

	N Stations	$\bar{p_t}$	$Var(p_t)$	$\bar{\Delta p_t}$	$Var(\Delta p_t)$	$\bar{\Delta p_t^+}$	$Var(\Delta p_t^+)$	$\bar{\Delta p_t^-}$	$Var(\Delta p_t^-)$
National	3030	6.28	0.05	0.01	0.45	0.47	0.25	−0.45	0.23
Urban	2335	6.29	0.05	0.01	0.43	0.47	0.24	−0.44	0.22
Rural	695	6.28	0.05	0.01	0.52	0.49	0.27	−0.48	0.31
Oil		4.08	0.08	0.00	4.55	1.49	2.33	−1.53	2.21

Note: Number of stations shown are in the six-year analytical sample and stations with missing urbanicity information are omitted from analysis. Prices are in log terms. Δp_t^+ and Δp_t^- indicate positive and negative changes in the price series.

Regarding location, stations are divided based on a binary variable included in the replication package originally sourced from the French National Institute for Statistics and Economic Studies (INSEE), which designates the type of the municipality as either urban or rural. According to INSEE, an urban unit is a group of municipalities with continuously built-up areas having a minimum population of 2,000 people (INSEE, 2024) and all population densities that fall below this threshold are designated as rural. The number of stations included in our final sample for each group are shown in Table 3.

Regarding crude oil prices, we use the "Daily Europe Brent Spot Price FOB" data series sourced from the United States Energy Information Administration, which is measured in dollars per barrel. To convert the data series into euros per barrel, we use the exchange rate provided in the Gautier et al. (2023) replication package. Next, trends illustrating the oil and diesel price series are shown in Figure 4, which shows that the diesel price series follow a very similar path as the crude oil price, thereby indicating consistency with expected market behavior across numerous stations. The coming analysis uses prices in log terms, which are shown in Appendix Figure A14.

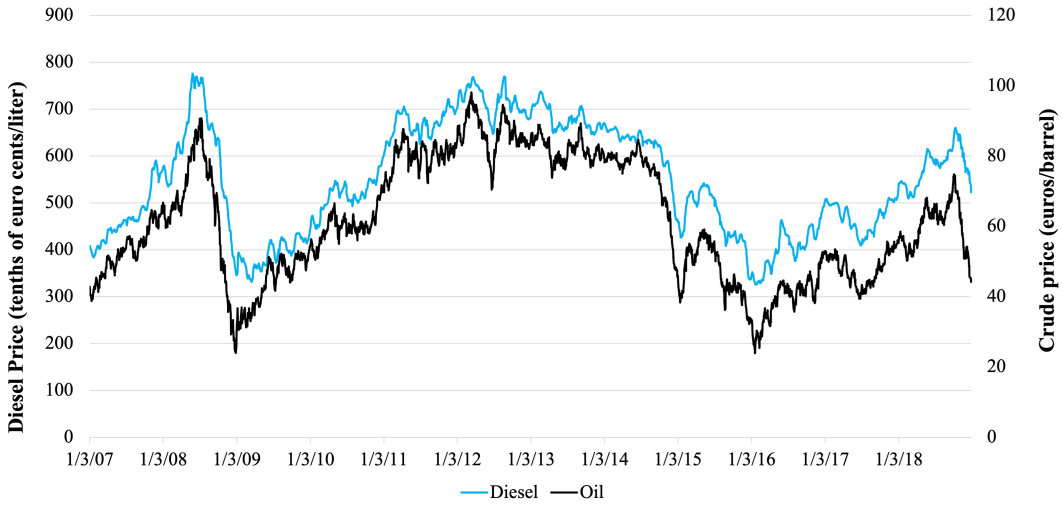


Figure 4: Daily retail diesel prices and brent crude oil prices.

3 Methods

Table 4: Phillips-Perron unit root test results

	Critical value	Crude oil price statistic	National diesel price statistic	Urban diesel price statistic	Rural diesel price statistic
Test for price levels	−21.8	−9.1	−6.4	−6.3	−6.6
Test for first-differenced prices	−14.1	−2949.8	−1319.1	−1256.6	−1651.7

H_0: Price series contains a unit root. H_1: Price series is stationary. Reject H_0 if test statistic < critical value. *Note:* Price series are in log terms and significance level $\alpha = 0.05$. Case 4 critical values are used for price levels and case 2 critical values are used for first-differenced prices.

3.1. Tests for unit roots

To investigate the stationarity of the crude oil and aggregated diesel price series, we use the Phillips-Perron unit root test (Phillips and Perron, 1988), where the null hypothesis is that the time series has a unit root. Specifically, the Phillips-Perron test is conducted on price series in log terms and on their differences with results shown in Table 4. For all price series in levels, we fail to reject the null hypothesis of a unit root. Furthermore, for all differenced price series we reject the null hypothesis of a unit root. Together, these tests indicate all log price series are integrated of order one (i.e., contain a unit root). It is also important to consider the possibility that the data series have a structural break rather than a unit root. To avoid the possibility of a spurious unit root finding, we also conduct Zivot-Andrews tests where the null hypothesis remains that the time series has a unit root, but the alternative is a stationary series with endogenous structural breaks

Table 5: Zivot-Andrews unit root test results

	Critical value	Crude oil price statistic	National diesel price statistic	Urban diesel price statistic	Rural diesel price statistic
Test for price levels	−5.1	−3.5	−2.8	−2.8	−2.7
Test for first-differenced prices	−4.8	−54.2	−27.2	−26.6	−30.5

H_0: Price series contains a unit root. H_1: Price series is stationary around broken trend and intercept for price levels, and broken intercept only for differenced series. Reject H_0 if test statistic < critical value.
Note: Price series are in log terms and significance level $\alpha = 0.05$.

Table 6: Phillips-Ouliaris cointegration test results and estimation of long-run relationships

	National diesel price	Urban diesel price	Rural diesel price
Cointegration test statistic	92.0	89.9	99.9
a_0	3.334 (0.016)	3.339 (0.016)	3.318 (0.016)
b_0	0.723 (0.004)	0.722 (0.004)	0.726 (0.004)

H_0: Price series is not cointegrated with the crude oil price. H_1: Price series is cointegrated with the crude oil price. Reject H_0 if test statistic > critical value = 33.7.
Note: Price series are in log terms and significance level $\alpha = 0.05$. Standard errors for coefficient estimates are shown in parentheses.

in deterministic components (Zivot and Andrews, 1992) in Table 5. As with the Phillips-Perron tests, all prices in levels fail to reject the null of a unit root while differenced series reject the null, thereby showing the finding of I(1) prices is robust to accounting for endogenous structural breaks.

3.2. Test for cointegration and identify initial long-run relationships

Following Zhang et al. (2023), the first step for analyzing how oil prices are passed through to retail diesel prices is to generate initial estimates for the long-run relationship between the crude oil and retail diesel prices. For the national, rural and urban samples, we estimate the OLS regression

$$d_t = a + bo_t + u_t \tag{2}$$

where o_t indicates the log crude oil price and d_t represents the log diesel price. Given that prices

Table 7: Selected lag lengths

	p_L	q_L	s_L	p_U	q_U	s_U
National	0	5	5	0	6	6
Urban	0	5	4	0	6	5
Rural	0	8	1	0	6	5

are in log terms, b indicates the long-run impact of a one percent change in the oil price on the diesel price. The constant a is included in the regression to account for the difference in levels of the price series due to units for the crude oil and diesel price series (i.e., euros per barrel and tenths of euro cents per liter). However, a linear trend is not included because this would mean the paths of the two series deterministically diverge across time, a trend that would be economically illogical as crude oil is an input for diesel production. Given the presence of unit roots in both o_t and d_t, this regression is estimated consistently only if the series are cointegrated, meaning they share a common stochastic trend. To test for the presence of cointegration, we use the Phillips-Ouliaris test (Phillips and Ouliaris, 1990), where the null hypothesis is that the series are not cointegrated. All of our tests reject the null hypothesis, thereby indicating the crude oil price is cointegrated with each of the diesel price series. Cointegration test results and estimated coefficients from equation (2) are shown in Table 6.

3.3. Estimation of TVECM

To determine adjustment patterns towards equilibrium, this study employs a two-regime TVECM conditional on the threshold of zero, based largely on the application of the three-regime TVECM by Zhang et al. (2023) to study asymmetric pricing from crude oil to jet fuel and diesel prices in the US market combined with the one-step estimation approach similar to Hansen and Seo (2002). A TVECM may incorporate multiple thresholds (e.g., Zhang et al. (2023) use two thresholds); however, in this analysis, we establish a single threshold at zero to clearly isolate speeds of adjustment corresponding to positive and negative disequilibrium, with the resulting model being

$$\begin{bmatrix} \Delta o_t \\ \Delta d_t \end{bmatrix} = \begin{cases} \sum_{i=1}^{p_R} \alpha_{Ri} \Delta o_{t-i} + \varepsilon_{Rt,1} \\ \sum_{i=1}^{q_R} \pi_{Ri}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_R} \pi_{Ri}^{d} \Delta d_{t-i} + \delta_R (d_{t-1} - a - b o_{t-1}) + \varepsilon_{Rt,2} \end{cases} \qquad \begin{cases} R = L & \text{if } (d_{t-1} - a - b o_{t-1}) \leqslant 0 \\ R = U & \text{if } (d_{t-1} - a - b o_{t-1}) > 0 \end{cases} \tag{3}$$

where R indicates the regime determined by the threshold variable, which is the lagged error correction term u_{t-1} from equation (2). L denotes the lower regime and U indicates the upper regime. The lower regime corresponds to a relative decrease in the diesel price, which can be shown by solving for

$$u_t = d_t - (a + b o_t) \tag{4}$$

in equation (2). Since d_t is the actual diesel price and $(a + b o_t)$ is the equilibrium diesel price, then a negative value of u_t means that the actual diesel price is below equilibrium. The lags of Δo_t in the oil equation and Δd_t in the diesel equation are included to control for serial correlation in the error

terms. δ_R indicates the speed of adjustment of the diesel price towards equilibrium within a single day. We restrict the model so that the lagged error correction term and diesel price changes are not included in the oil price equation. Together, these restrictions treat the oil price as exogenous in the system. The purpose of these restrictions is to create a more plausible causal model since it is reasonable to assume the global crude oil price is not significantly influenced by the diesel price in the relatively small French market. Finally, separating the error term into ε_{Lt} and ε_{Ut} based on the threshold variable allows us to model different variances for each regime.

To estimate the TVECM, we use a one-step procedure as in Hansen and Seo (2002) rather than a two-step Engle-Granger estimation used by Zhang et al. (2023) to minimize compounding of estimation error across steps. The two-step procedure involves estimating the cointegrating regression first using OLS and saving the lagged residuals $\hat{u}_{t-1}$. The second step estimates two VECMs with data separated based on the value of $\hat{u}_{t-1}$. Specifically, a threshold model with a known threshold and differing variances between regimes can be estimated using methods from Chapter 7 of Enders (2014), as follows. To start, lags are generated so each observation includes the set $(\Delta d_t, \Delta d_{t-p}, \Delta o_t, \Delta o_{t-p}, \hat{u}_{t-1})$. Then, these observations are divided into upper and lower regimes based on whether $\hat{u}_{t-1}$ is greater than zero. Once this occurs, a VECM is estimated for each of the two regimes using ordinary least squares (OLS).

In using a two-stage Engle-Granger estimation procedure as done by Zhang et al. (2023), we discovered evidence suggesting that final results were influenced by compounding estimation error across steps. In particular, two-stage asymmetry results were not robust to flipping oil and diesel in the cointegrating regression (Appendix Figure A15), when asymptotically, TVECM results from long-run equations $d_t = a + bo_t + u_t$ and $o_t = \alpha + \beta d_t + v_t$ are equivalent. This seems to be caused by estimation error in $\hat{u}_{t-1}$ affecting output at the second stage which depends on $\hat{u}_{t-1}$ to classify all observations into upper and lower regimes. In particular, 12% of observations changed regime based on whether oil or diesel was on the left-hand side. To address this, we conduct a one-step estimation thereby making the asymmetric IRFs robust to flipping the cointegrating regression (Appendix Figure A16).

To this end, Hansen and Seo (2002) create an algorithm which estimates long-run and short-run parameters jointly using a grid search around initial estimates of the long-run parameters and minimizing an objective function (e.g., log likelihood in Hansen and Seo (2002) or SSR as in Chan (1993)). Specifically, the OLS estimate of the cointegrating parameter b_0 from Table 6 is used as the initial guess of b. The short run and long run parameters are then estimated jointly using a grid search around the OLS estimate b_0. The grid is composed of b_0 with 400 points in the range $b_0 \pm 0.05$. In order to maintain the interpretation of diesel being above or below equilibrium, we set $a = \bar{d}–b\bar{o}$ for each iteration of the grid search where $\bar{d}$ and $\bar{o}$ are sample averages. Next, the a and b values are used to partition data into upper and lower regimes and estimate short-run parameters

akin to the earlier described two-step approach. For every iteration, the sum of squared residuals $\sum_{t=1}^{n} \hat{\varepsilon_{Rt}}^2$ is calculated and then minimized to identify the final parameter $\hat{b}$. Finally, the TVECM model parameters are estimated holding b equal to $\hat{b}$.

Lag lengths p_R, q_R and s_R are selected using the Bayesian Information Criterion (BIC) run separately by regime and between oil and diesel equations holding a and b fixed to their initial OLS estimates in Table 6. The selected lag lengths for the national, rural and urban diesel price series are shown in Table 7. The TVECM simplifies to

$$\begin{bmatrix} \Delta o_t \\ \Delta d_t \end{bmatrix} = \begin{cases} \varepsilon_{Rt,1} \\ \sum_{i=1}^{q_R} \pi_{Ri}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_R} \pi_{Ri}^{d} \Delta d_{t-i} + \delta_R (d_{t-1} - a - b o_{t-1}) + \varepsilon_{Rt,2} \end{cases} \quad \begin{cases} R = L & \text{if } (d_{t-1} - a - b o_{t-1}) \leqslant 0 \\ R = U & \text{if } (d_{t-1} - a - b o_{t-1}) > 0 \end{cases} \tag{5}$$

because p_R was chosen to be zero for all urbanicity groups. Results for the national series where lag lengths are restricted to be the same across regimes (i.e., $q_L = q_U$ and $s_L = s_U$) are presented in Appendix Table A5 and Appendix Figure A12.

To analyze the effects of oil price increases and decreases on the diesel price within the TVECM, we conduct impulse response analysis following Goodwin and Piggott (2001). Impulse response functions for threshold models depend on the history of past observations given the presence of a regime change. Goodwin and Piggott (2001) approach this issue by choosing a single history and calculating the impulse response at time $t + k$ defined on the basis of observed data $(z_t, z_{t-1}, \dots)$ and a shock v given by

$$I_{t+k}(v, z_t, z_{t-1}, ...) = E[Z_{t+k} | Z_t = z_t + v, Z_{t-1} = z_{t-1}, ...] - E[Z_{t+k} | Z_t = z_t, Z_{t-1} = z_{t-1}, ...]. \tag{6}$$

We choose the starting history as equilibrium where $u_{t-1} = 0$ by initializing d_t at the sample average diesel price $\bar{d}$ and setting $o_t = -\frac{a}{b} + \frac{1}{b}\bar{d}$. Equation (6) compares diesel prices generated from $\Delta o_t^s = \pm 0.01$ and $\Delta o_t^n = 0$ where superscript s denotes the shocked oil price series and superscript n denotes the series without the shock. This shows the effect of a one-time one percent change in the oil price on diesel prices assuming no other changes occur (i.e., errors are set to zero). First, to show comparability with Gautier et al. (2023), we conduct impulse response analysis using a symmetric VECM equivalent to equation (5) without the threshold. Then, we run impulse response analysis using the estimated coefficients from equation (5). Finally, pointwise confidence intervals for the impulse response functions are generated using a residual-based bootstrap. See Appendix B for details.

3.5. Local projection model from Gautier et al. (2023)

We estimate two models which test for IPA instead of DEA, the first of which is the local projection model from Gautier et al. (2023). Specifically, for each horizon $h = 0, ..., 40$, Gautier et al. (2023) estimates the OLS regression given by

$$\Delta p_{i_{t-1,t+h}} = \alpha_h + \theta_h \Delta R_{t-1,t} + \eta_{t_h} + \chi_{hi} + \varepsilon_{i,t_h} \tag{7}$$

where $\Delta p_{i_{t-1,t+h}}$ is the percentage change in diesel price for station i from time $t-1$ to $t+h$, $\Delta R_{t-1,t}$ is the percentage change in oil price from $t-1$ to t, η_{t_h} are time (horizon-specific) controls consisting of five lagged differences of oil prices and average prices of local area competitors and χ_{hi} are gas-station-specific and horizon-specific fixed effects. The authors plot coefficients θ_h to generate a symmetric impulse response function, and the 95% confidence intervals for the θ_h coefficients are connected to form the confidence interval for the impulse response function.

A January 2022 working paper version of Gautier et al. (2023) (Gautier et al., 2022) plots asymmetric impulse response functions and finds no evidence of asymmetry. We adapt the model in equation (7) following the working paper version with the resulting model given by

$$\Delta p_{i_{t-1,t+h}} = \alpha_h + \theta_h^+ \Delta R_{t-1,t}^+ + \theta_h^- \Delta R_{t-1,t}^- + \sum_{j=1}^{5} k_{hj}^+ \Delta R_{t-j-1,t-j}^+ + \sum_{j=1}^{5} k_{hj}^- \Delta R_{t-j-1,t-j}^- + l_{t_h} + \chi_{hi} + \varepsilon_{i,t_h} \tag{8}$$

where $\Delta R_{t-i,t}^+ = \max\{\Delta R_{t-i,t}, 0\}$ and $\Delta R_{t-i,t}^- = \min\{\Delta R_{t-i,t}, 0\}$. Note that l_{t_h} consists of five lagged differences of average local area competitor prices. The positive and negative impulse response functions are generated by plotting θ_h^+ and θ_h^- and the 95% confidence intervals of θ_h^- for each $h = 0, ..., 40$ are connected to form a confidence interval for the negative impulse response function.

3.6. Asymmetric ECM from Bachmeier and Griffin (2003)

The second IPA model comes from Bachmeier and Griffin (2003) where an Asymmetric ECM is estimated using a two-stage Engle-Granger approach. First, the long-run relationship between log diesel price d_t and log oil price o_t is estimated by running the OLS regression

$$d_t = \gamma_0 + \gamma_1 o_t + z_t. \tag{9}$$

The residuals $\hat{z}_t$ from equation (9) are then used in the second stage OLS regression

$$\Delta d_t = \sum_{i=0}^{l_o} \beta_{oi}^{+} \Delta o_{t-i}^{+} + \sum_{i=0}^{l_o} \beta_{oi}^{-} \Delta o_{t-i}^{-} + \sum_{i=1}^{l_d} \beta_{di} \Delta d_{t-i} + \mathbf{1}\{\Delta o_t > 0\}\theta^{+}\hat{z}_{t-1} + \mathbf{1}\{\Delta o_t \leqslant 0\}\theta^{-}\hat{z}_{t-1} + \varepsilon_t \quad (10)$$

where $\Delta o_{t-i}^{+} = \max\{\Delta o_{t-i}, 0\}$ and $\Delta o_{t-i}^{-} = \min\{\Delta o_{t-i}, 0\}$. The lag lengths l_o and l_d are selected using the Bayesian Information Criterion on a symmetric version of equation (10). As was done by Bachmeier and Griffin (2003), impulse response functions are generated using the earlier method of Borenstein et al. (1997) given by

$$B_k = B_{k-1} + \beta_{ok} + \theta(B_{k-1} - \gamma_1) + \sum_{i=1}^{k} \beta_{di}(B_{k-i} - B_{k-i-1}) \quad (11)$$

where B_k is the cumulative adjustment of the diesel price to a one-time, one percent change in the oil price after k periods starting in equilibrium. For a one-percent oil price increase, β_{ok} is replaced with β_{ok}^{+}. Also θ is replaced with θ^{-} because Δo_t equals zero in all periods after the initial shock. For a one-percent oil price decrease, β_{ok} is replaced with β_{ok}^{-} and likewise we replace θ with θ^{-}. To generate the final impulse response function, B_k is plotted for $k = 0, \ldots, 40$.

3.7. Nested TVECM

To determine the mechanism driving observed asymmetry (IPA vs. DEA) in the TVECM impulse response functions, we modify the TVECM to allow asymmetry based on the sign of the oil price change. Specifically, we nest a model similar to Bachmeier and Griffin (2003) within each regime resulting in

$$\Delta d_t = \sum_{i=1}^{q_R} (\pi_{Ri}^{o+} \Delta o_{t-i}^{+} + \pi_{Ri}^{o-} \Delta o_{t-i}^{-}) + \sum_{i=1}^{s_R} \pi_{Ri}^{d} \Delta d_{t-i} + \delta_R(d_{t-1} - a - bo_{t-1}) + \varepsilon_{Rt}$$
$$\begin{cases} R = L & \text{if } (d_{t-1} - a - bo_{t-1}) \leqslant 0 \\ R = U & \text{if } (d_{t-1} - a - bo_{t-1}) > 0 \end{cases} \begin{cases} \Delta o_{t-i}^{+} = \max\{\Delta o_{t-i}, 0\} \\ \Delta o_{t-i}^{-} = \min\{\Delta o_{t-i}, 0\} \end{cases} \quad (12)$$

and use an F test to compare this model with the model given by equation (5). This test indicates if allowing for IPA significantly improves model fit. Results using the same lags across regimes are shown in Appendix A.

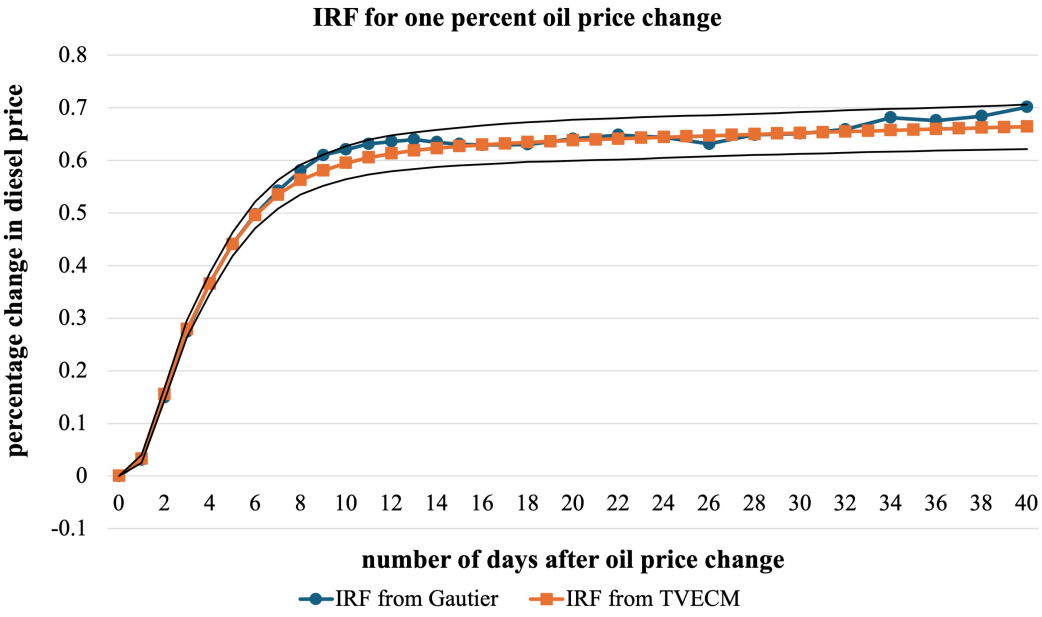


Figure 5: Impulse response function for one percent oil price increase. *Note:* Shown is a replication of Gautier et al. (2023) Figure 4 using the crude oil price and daily data alongside an impulse response function from a symmetric version of the TVECM in equation (5).

4 Results

The initial phase of our analysis involves testing for comparability between a symmetric version of the TVECM in equation (5) and a cumulative impulse response function from the panel approach of Gautier et al. (2023) in equation (7). To this end, Figure 5 presents an impulse response function generated from a symmetric VECM next to a replicated cumulative impulse response function from Gautier et al. (2023). The final pass through from symmetric impulse response functions in Figure 5 is approximately 70%, which is less than the 80% pass through from wholesale prices to retail

Table 8: F test results

	Lower regime	Upper regime
Numerator degrees of freedom	5	6
Denominator degrees of freedom	1602	1362
F	0.9871181	0.2175547
Critical value for $\alpha = 0.05$	2.21	2.10

H_0: Equation (12) fits data as well as equation (5). H_1: Equation (12) fits data better than equation (5). Reject H_0 if $F >$ critical value.

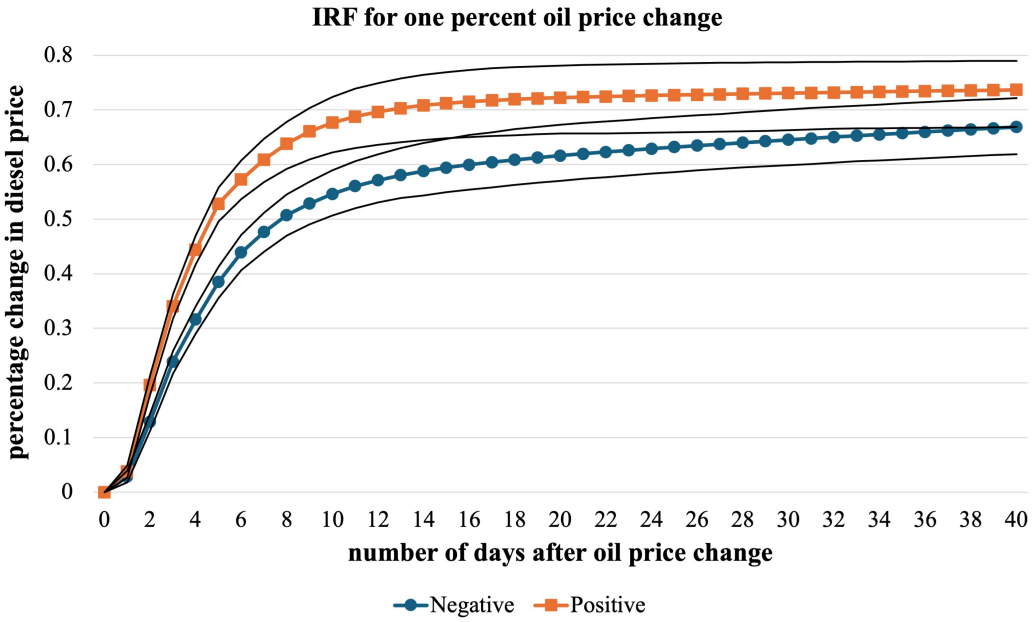


Figure 6: Impulse response function for one percent oil price change. *Note:* impulse response functions generated for national data set with equation (5) estimates beginning at equilibrium.

prices displayed in Gautier et al. (2023). This is sensible because the refining process from oil to wholesale introduces additional costs that are reflected in the smaller fraction of the retail diesel price determined by oil prices than wholesale prices. The purpose of Figure 5 is to show that in finding DEA with the TVECM, that does cast doubt on the KF ratio results from Gautier et al. (2023). Specifically, Figure 5 shows that the basic symmetric versions of our TVECM and Gautier's local projection method are equivalent which proves that outputs from the two approaches are comparable. While Gautier et al. (2023) do test for IPA, their local projection model cannot handle DEA as the TVECM does. Therefore, we use the TVECM to answer whether firms change prices faster when margins are below equilibrium, which would invalidate the symmetry assumption of Gautier et al. (2023).

Note that the symmetric version of equation (5) is not history-dependent and thus shows the effect of an oil price change at any starting point. In contrast, the impulse responses for the asymmetric TVECM are forced to start at equilibrium, meaning that when the oil price deviates from that baseline it shows the effect of the diesel price being put out of equilibrium (i.e., either over or under priced relative to oil according to our estimated long run relationship depicted in equation 2). Given the similarity in Figure 5, we analyze asymmetric impulse response functions generated from equation (5) in Figure 6 and find that the impulse response for a positive oil price change goes up faster than for a negative one, thereby suggesting DEA in this data set. Coefficients used to

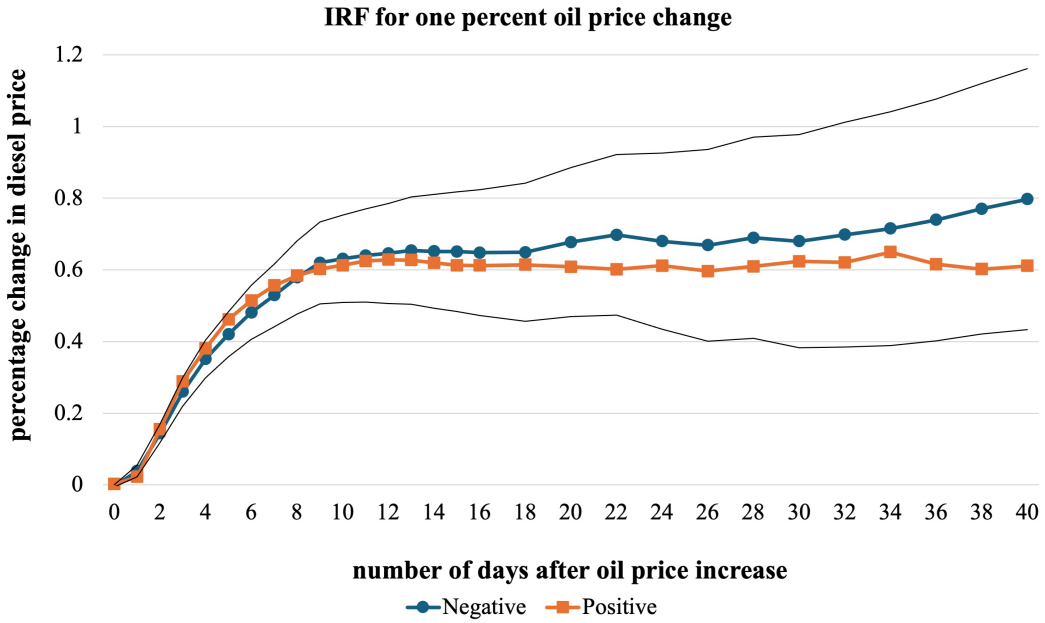


Figure 7: Impulse response function for one percent oil price change. *Note:* Shown is a replication of Gautier et al. (2022) Figure B4 using the crude oil price and updated methods described in Section 3.5.

generate the impulse response functions are shown in Appendix Table A1. The confidence intervals indicate that this difference is statistically significant at the 95% level of confidence. Specifically, the lower bound for the positive curve separates from the upper bound of the negative curve two days after impact and only crosses again after 15 days, which is three weeks given the five-day week length in the sample. These results indicate strong evidence of DEA for the first three weeks after an oil price change. Beyond statistical significance, the faster response to diesel being underpriced is economically meaningful to consumers and sellers. The reaction rate one week (5 days) out is $\sim 15\%$ more for negative disequilibrium rather than positive disequilibrium, while at three weeks out the gap remains at $\sim 10\%$. Considering the sales price difference is cumulative, this accounts for a large change in revenues and costs on the consumer side. Moreover, these results are robust to using the same lag specification across regimes (Appendix Figure A12). To this end, we see faster reactions to negative disequilibrium when compared to positive disequilibrium and the results are significant for more than two weeks. Together, these results indicate that diesel price responds faster when it is relatively underpriced versus oil and are consistent with the previous RAF literature where again gas stations are believed to have an incentive to maintain high margins (Borenstein et al., 1997).

Building on the findings at the national level, we conduct similar impulse response analysis for both urban and rural data sets in Appendix Figures A17-18 to see if the overall asymmetry

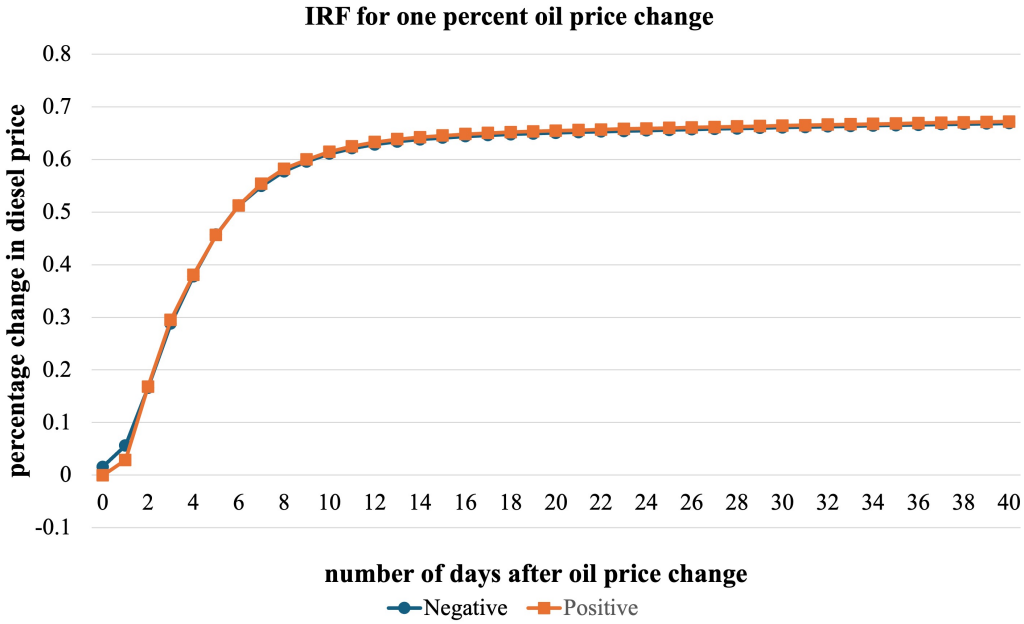


Figure 8: Impulse response function for one percent oil price change. *Note:* Shown are impulse response functions generated from the Bachmeier and Griffin (2003) model beginning at equilibrium.

can be explained mostly by a single urbanicity group, with corresponding coefficient estimates presented in Appendix Tables A2-3. Results show that the urban group elicits similar reactions as the national level because the positive curve increases faster than the negative curve in both cases. As for statistical significance, we likewise see that the confidence bands diverge after two days and intersect after two weeks, thereby indicating that diesel prices react significantly faster to being underpriced than overpriced relative to oil. To determine if the asymmetry is only present in the urban subset, we analyze the rural impulse response functions which also show statistically significant DEA. Together, these findings indicate that DEA is not affected by population density because the impulse responses are very similar in both urban and rural populations. Moreover, following the data cleaning steps of Gautier et al. (2023), we drop all diesel price observations appearing on days when the crude oil price is not available (i.e., weekends and holidays). However, this potentially introduces heteroskedasticity given that the diesel price changes from Friday to Monday include multiple days worth of price changes. To see if this substantially affects results, in Appendix Figure 13 we keep only Wednesday price observations to have uniform time segments between observations and replicate the TVECM and impulse response analysis. The core findings in this figure are the same, with diesel prices reacting faster when underpriced. The statistical significance is weaker as the intervals for the two curves overlap when both are included. However, we only present intervals for the positive IRF to show that there is still a statistically significant

difference during the first two weeks.

In addition, we examine variation in DEA across time by estimating the TVECM and associated IRFs across three subsample periods (2007-2010, 2011-2014 and 2015-2018; Appendix Figures A19-A21). The first subsample covers the Great Financial Crisis (GFC) and the early US shale revolution, the second subsample covers the middle of the US shale revolution and the Arab Spring revolutions, and finally the third subsample covers an oil supply glut and reorganization of OPEC. The GFC occurring from 2008-2009 (Livingston, 2014) was preceded by an increase in the oil price given a high demand for consumer goods and growing oil consumption by China. After the onset of the GFC, the oil price declined due the global recession suppressing demand for oil (Hamilton, 2009). At the same time, the shale revolution, where producers were able to drill from previously inaccessible areas, began to have significant effects on oil supply from the US around 2009. Moreover, from 2011-2014 US shale oil production quadrupled from one to four million barrels per day (Sieminski, 2014). This increase in global oil supply placed downward pressure on prices and increased competition in the petroleum market. In response, OPEC attempted to push out the higher-cost US producers from the market by maintaining elevated production (Behar and Ritz, 2016) which created an oil supply glut in 2015. In late 2016, OPEC reorganized to increase prices in the wake of the supply glut and formed OPEC+ which includes more countries (EIA, 2023). Beyond the above supply shifters, the Arab Spring revolutions in 2011 across Middle Eastern and North African states led to oil supply cuts from the region, most substantially from Libya (Fattouh and Darbouche, 2011).

Due to the potential for economic and oil related events to change how prices are set, we analyze DEA across the three subsamples. Appendix Figure A19 shows statistically significant DEA for the first subsample across the period of the GFC and initial oil supply increases from the US. In the second and third subsamples (Appendix Figures A20-21), asymmetry is statistically insignificant which we attribute to fewer data points given that the confidence bands for the subsample analyses are much wider than the confidence bands of full sample results. Future studies will address this by increasing the number of data points across time. However, this does suggest that asymmetry is stronger in the first subsample than in the latter two, which may occur because oil market volatility was highest across the early sample (see the realized volatility chart in Appendix Figure A22). Specifically, Borenstein et al. (1997) and later Tappata (2009) provide evidence supporting oil market volatility as an opportunity for gas stations to keep large margins because consumers attribute high prices to underlying cost shocks common across firms rather than to individual gas stations attempting to make more profit and thus search less among gas stations. In the latter two subsamples, although there was significant volatility at times (e.g., during 2015 supply glut), the volatility was generally lower supporting that reduced oil market volatility does create less DEA.

After the above robustness experiments showing that gas stations react faster when they are

in negative disequilibrium, the next step is to determine if this result is caused by gas stations reacting quickly following oil price increases. In the event that negative disequilibrium is correlated with increases in the crude oil price, we could falsely conclude that gas stations set prices based on the sign of disequilibrium when in fact they set prices based on the sign of the oil price change. To determine if the observed asymmetry is actually due to disequilibrium, we run the modified TVECM in equation (12), which allows for distinct coefficients for positive and negative oil price changes (i.e., π^{o}_{Ri} is separated into π^{o+}_{Ri} and π^{o-}_{Ri}; coefficient estimates shown in Appendix Table A4. Based on the above, the coefficients π^{o+}_{Ri} and π^{o-}_{Ri} should be identical if gas stations are reacting based on the sign of disequilibrium and not on the sign of oil price changes. We conduct an F test in Table 8 to determine if the coefficients for positive and negative oil price changes are jointly different across all lags. The null hypothesis states that the models in equations (5) and (12) fit the data equally well. The alternative hypothesis suggests that the model accounting for IPA provides a better fit. Ultimately, we failed to reject the null hypothesis, which serves as our initial piece of evidence. Additionally, we apply this method using consistent lags across regimes and also fail to reject the null hypothesis, thereby reinforcing our earlier finding of asymmetry due to disequilibrium (Appendix Tables A6 and A7). Moving on to further testing, we run two models which only permit IPA without allowing DEA. The first model is the local projection approach adapted from Gautier et al. (2023) where no statistically significant asymmetry is detected (Figure 7). Similarly, the asymmetric ECM model based on Bachmeier and Griffin (2003) found no signs of asymmetry (Figure 8). Collectively, these results suggest that the observed asymmetry originates from disequilibrium responses rather than varying responses to increases and decreases in the crude oil price.

5 Discussion

In this paper, we test for multiple asymmetry types in a market where pricing is thought to be competitive. Specifically, we distinguish between faster fuel price responses when fuel is above and below equilibrium with its input price (disequilibrium asymmetry or DEA) and asymmetry based on reactions to positive and negative input price changes (input price asymmetry or IPA). While IPA is traditionally measured to study market power in RAF papers, we argue DEA is a clearer signal of market power because deviations from long-term equilibrium approximate profit margins. Supporting this, we find that asymmetric responses to disequilibrium exist in the absence of more traditional market power metrics based on differential responses to oil price increases and decreases. This finding holds in the French market across a variety of population densities and model specifications. The evidence provided indicates that future RAF studies should include asymmetric adjustment towards equilibrium as a proxy for inflating margins. DEA should at least

be considered in conjunction with IPA to avoid omitted variable bias, if not taken as the initial standard for testing market power since current price levels are a closer approximation to the motivating factor for firms (i.e., keeping high profit margins) than observing responses to positive and negative input price changes, which may or may not affect margins.

Regarding the results of Gautier et al. (2023), their KF ratio result indicates that the cumulative impulse response of prices to a cost shock can be expressed as the ratio of the kurtosis of price changes over time for a single station divided by the frequency of that station's price changes. The KF ratio used by Gautier et al. (2023) and originally by Alvarez et al. (2016) is potentially useful for analysis of firm responses to input price changes because macroeconomic theory models indicate that this ratio is an effective summary of how firms will respond to a common cost shock, and as an extension, how consumer prices in general would respond to inflation (Alvarez et al., 2016). This is of interest to central banks considering inflationary measures, such as printing currency or lowering rates. However, our concern with use of the KF ratio is oversimplification of firm pricing decisions and failure to account for empirically documented patterns that may run counter to the assumptions of theory (e.g., asymmetric price responses by gas stations). Using the same database of this study, Gautier et al. (2023) demonstrated that IPA does not exist from wholesale diesel prices to retail prices which is a result we were able to confirm using Brent crude oil prices (Figure 7). However, Gautier et al. (2023) did not test for DEA, which appears to be present based on our TVECM results where IRFs for positive and negative disequilibrium are not equivalent. The CIRP implied by the positive and negative IRFs in Figure 6 can be calculated as the area under the IRF and divided by the overall pass-through. Given that there are differences in the Figure 6 IRFs, this leads to variations in the CIRP implied by positive and negative disequilibrium. Since equation (1) does not permit varying CIRP based on the sign of disequilibrium between the input and retail prices, TVECM results show the symmetry assumption required for use of the KF ratio does not hold. Together, the results of the current study indicate that the KF ratio should be used with caution in the French market because the symmetry assumption imposed by the preceding theory does not hold up when DEA is considered in addition to IPA. Moreover, because the purpose of the study by Gautier et al. (2023) is to empirically test the KF ratio result from Alvarez et al. (2016), the upshot of our study is that caution should be exercised in summarizing firm price responses to inflation using the KF statistic of Alvarez et al. (2016).

Our work contrasts with previous findings of competitive pricing in the French market. Regarding IPA in the French market, a substantial number of studies found that asymmetric transmission of crude oil prices into retail fuel indeed occurs in France. For instance, Audenis et al. (2002), Galeotti et al. (2003), Lamotte et al. (2013) and Boroumand et al. (2016) all found that fuel prices react faster to increases in oil prices than decreases. While these studies above show a persistent pattern of IPA in France, notably they all contain data from before 2012, while Torrado and Escribano

(2020) as well as Gautier et al. (2023) who do not find IPA extend to 2017 and 2018, respectively, with our study likewise extending to 2018. Figures 7-8 show no evidence for IPA, which lends support to the earlier described trend suggesting decreased IPA across time in France. However, our finding of DEA contrasts with results of Torrado and Escribano (2020), who found minimal DEA in France. The contradictory results could be due to a difference in data frequency as they use weekly data, which has been shown by past studies to impact results (Bachmeier and Griffin, 2003; Perdiguero-García, 2013).

More generally, previous RAF studies which do not include DEA are brought into question due to possible omitted variable bias and unclear modeling of station incentives. Many papers fail to include DEA (e.g., Audenis et al. (2002); Lamotte et al. (2013); De Salles (2014); Boroumand et al. (2016); Gautier et al. (2023) for the French market) which could contribute to mixed results when testing for IPA. Specifically, because positive and negative oil price changes could be correlated with positive and negative disequilibrium, IPA tests may suffer from omitted variable bias if gas stations are in fact reacting to positive and negative disequilibrium. Perhaps more important though is clarity of station incentives in IPA models because gas stations do not necessarily care about oil price changes, but rather what those changes do to their profit margins. Therefore, if the goal of RAF studies is to understand whether stations are keeping unreasonably high margins, explicit modeling of margins using long-run equilibrium makes more sense than modeling reactions to oil price increases and decreases.

A limitation of our study stems from selecting stations with at least six years of data to avoid sample composition changes and in so doing remain consistent with the selection criteria employed by Gautier et al. (2023), in which approximately 70% of the stations were removed due to requiring that only those stations continuously reporting data for six years or more be considered. It is important to note that using this six-year analytical sample may limit our analysis to stations with relatively greater market power, as it is reasonable to expect that stations with enhanced market power would remain operational for a longer time. Consequently, our results could be biased toward increased market power. The use of this sample restriction also comes with the tradeoff that insights into overall market responses may be limited by the sample size. Therefore, future studies should incorporate stations with shorter lengths of time within the sample by conducting analysis with the supporting two- and four-year analytical samples generated in Gautier et al. (2023) for the purpose of robustness, and to the extent that conclusions are drawn using the primary six-year sample, they should be interpreted with caution in light of the unusually restrictive selection criteria. Another limitation is that our current model does not account for differing responses of the diesel price based on the magnitude of the disequilibrium with the oil price. Therefore, a future methodological addition would involve implementing a three-regime TVECM model capable of amplifying effects related to significant disequilibrium by allowing for a middle regime where stations

rarely change prices (Zhang et al., 2023). This is a relevant consideration for our data set given the extensive documentation of price stickiness (Gautier and Le Saout, 2015; Gautier et al., 2023). Our results also highlight the need for an equilibrium concept in the KF ratio relationship which may be developed by later work. Finally, it is worth noting that we assume the long-run relationship between oil and diesel in equation (2) does not change over time, a point that was practical for this analysis but that would nonetheless be advisable to test in future studies.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author used Claude for drafting code. The author reviewed and edited the output as needed and takes full responsibility for the content of the published article.

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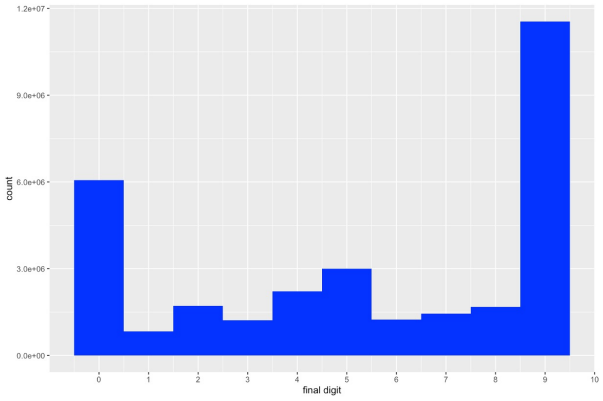
A ADDITIONAL RESULTS

Table A.1: TVECM Coefficients, National

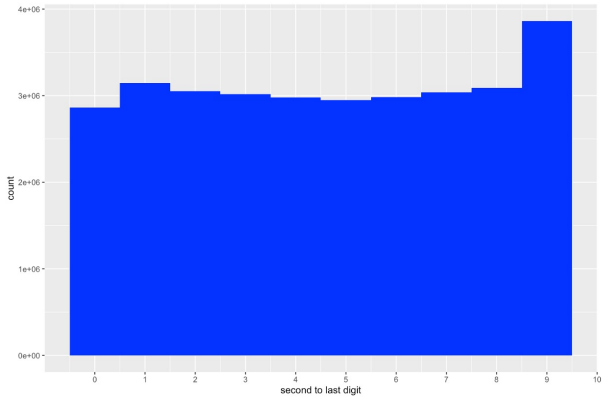
	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0042	0.0017	−2.4336	0.0151
Δo_{t-1}	0.0345	0.0057	6.0995	0.0000
Δo_{t-2}	0.1437	0.0056	25.8650	0.0000
Δo_{t-3}	0.0938	0.0062	15.1778	0.0000
Δo_{t-4}	0.0584	0.0068	8.5822	0.0000
Δo_{t-5}	0.0459	0.0065	7.0178	0.0000
Δd_{t-1}	0.3047	0.0251	12.1595	0.0000
Δd_{t-2}	−0.0121	0.0271	−0.4479	0.6543
Δd_{t-3}	0.0225	0.0266	0.8465	0.3974
Δd_{t-4}	0.0880	0.0249	3.5331	0.0004
Δd_{t-5}	0.0482	0.0211	2.2872	0.0223
Upper Regime				
$\hat{u}_{t-1}$	−0.0080	0.0020	−3.9241	0.0001
Δo_{t-1}	0.0217	0.0054	4.0130	0.0001
Δo_{t-2}	0.0882	0.0055	15.9220	0.0000
Δo_{t-3}	0.0792	0.0062	12.8319	0.0000
Δo_{t-4}	0.0365	0.0063	5.7971	0.0000
Δo_{t-5}	0.0332	0.0063	5.2329	0.0000
Δo_{t-6}	0.0216	0.0062	3.4995	0.0005
Δd_{t-1}	0.2224	0.0261	8.5066	0.0000
Δd_{t-2}	0.1052	0.0258	4.0739	0.0000
Δd_{t-3}	0.0393	0.0258	1.5236	0.1278
Δd_{t-4}	−0.0338	0.0252	−1.3414	0.1800
Δd_{t-5}	0.1698	0.0245	6.9340	0.0000
Δd_{t-6}	−0.0457	0.0225	−2.0367	0.0419

Table A.2: TVECM Coefficients, Urban

	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0039	0.0017	−2.3414	0.0193
Δo_{t-1}	0.0350	0.0055	6.3851	0.0000
Δo_{t-2}	0.1465	0.0054	27.1294	0.0000
Δo_{t-3}	0.0910	0.0061	14.9245	0.0000
Δo_{t-4}	0.0543	0.0067	8.1363	0.0000
Δo_{t-5}	0.0416	0.0063	6.5670	0.0000
Δd_{t-1}	0.3089	0.0250	12.3506	0.0000
Δd_{t-2}	0.0077	0.0271	0.2838	0.7766
Δd_{t-3}	0.0189	0.0268	0.7049	0.4810
Δd_{t-4}	0.1161	0.0220	5.2824	0.0000
Upper Regime				
$\hat{u}_{t-1}$	−0.0077	0.0019	−3.9647	0.0001
Δo_{t-1}	0.0212	0.0052	4.0811	0.0000
Δo_{t-2}	0.0882	0.0053	16.5913	0.0000
Δo_{t-3}	0.0746	0.0059	12.5647	0.0000
Δo_{t-4}	0.0333	0.0061	5.4939	0.0000
Δo_{t-5}	0.0319	0.0061	5.2479	0.0000
Δo_{t-6}	0.0221	0.0058	3.7780	0.0002
Δd_{t-1}	0.2431	0.0259	9.3932	0.0000
Δd_{t-2}	0.1004	0.0259	3.8693	0.0001
Δd_{t-3}	0.0333	0.0258	1.2943	0.1958
Δd_{t-4}	−0.0377	0.0251	−1.4982	0.1343
Δd_{t-5}	0.1450	0.0226	6.4094	0.0000



(a) Distribution of final digit of diesel price



(b) Distribution of second to last digit of diesel prices

Figure A.1: Distribution of final and second-to-last digits of diesel prices.

Table A.3: TVECM Coefficients, Rural

	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0058	0.0022	−2.5911	0.0097
Δo_{t-1}	0.0334	0.0070	4.7954	0.0000
Δo_{t-2}	0.1353	0.0068	19.9753	0.0000
Δo_{t-3}	0.1241	0.0072	17.1959	0.0000
Δo_{t-4}	0.0750	0.0076	9.9092	0.0000
Δo_{t-5}	0.0697	0.0071	9.8603	0.0000
Δo_{t-6}	0.0427	0.0069	6.1482	0.0000
Δo_{t-7}	0.0417	0.0068	6.1256	0.0000
Δo_{t-8}	0.0278	0.0066	4.2240	0.0000
Δd_{t-1}	0.1453	0.0245	5.9227	0.0000
Upper Regime				
$\hat{u}_{t-1}$	−0.0091	0.0024	−3.7284	0.0002
Δo_{t-1}	0.0227	0.0061	3.7150	0.0002
Δo_{t-2}	0.0872	0.0063	13.9383	0.0000
Δo_{t-3}	0.0892	0.0068	13.1118	0.0000
Δo_{t-4}	0.0499	0.0070	7.1418	0.0000
Δo_{t-5}	0.0402	0.0070	5.7549	0.0000
Δo_{t-6}	0.0251	0.0068	3.7009	0.0002
Δd_{t-1}	0.1871	0.0257	7.2952	0.0000
Δd_{t-2}	0.1037	0.0243	4.2587	0.0000
Δd_{t-3}	0.0347	0.0241	1.4368	0.1510
Δd_{t-4}	−0.0421	0.0230	−1.8304	0.0674
Δd_{t-5}	0.1454	0.0219	6.6531	0.0000

Table A.4: TVECM Coefficients, National - Nested Model, Different Lags Across Regimes

	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0037	0.0025	−1.4861	0.1374
Δo^{+}_{t-1}	0.0355	0.0088	4.0240	0.0001
Δo^{+}_{t-2}	0.1554	0.0084	18.4691	0.0000
Δo^{+}_{t-3}	0.0856	0.0089	9.5729	0.0000
Δo^{+}_{t-4}	0.0512	0.0099	5.1512	0.0000
Δo^{+}_{t-5}	0.0505	0.0097	5.2026	0.0000
Δo^{-}_{t-1}	0.0341	0.0121	2.8298	0.0047
Δo^{-}_{t-2}	0.1252	0.0119	10.5191	0.0000
Δo^{-}_{t-3}	0.1045	0.0113	9.2413	0.0000
Δo^{-}_{t-4}	0.0668	0.0113	5.9020	0.0000
Δo^{-}_{t-5}	0.0406	0.0109	3.7191	0.0002
Δd_{t-1}	0.3078	0.0251	12.2443	0.0000
Δd_{t-2}	−0.0125	0.0272	−0.4581	0.6470
Δd_{t-3}	0.0225	0.0267	0.8413	0.4003
Δd_{t-4}	0.0864	0.0250	3.4548	0.0006
Δd_{t-5}	0.0488	0.0211	2.3102	0.0210
Upper Regime				
$\hat{u}_{t-1}$	−0.0070	0.0035	−1.9678	0.0493
Δo^{+}_{t-1}	0.0165	0.0097	1.7015	0.0891
Δo^{+}_{t-2}	0.0933	0.0102	9.1832	0.0000
Δo^{+}_{t-3}	0.0772	0.0107	7.2359	0.0000
Δo^{+}_{t-4}	0.0347	0.0100	3.4602	0.0006
Δo^{+}_{t-5}	0.0305	0.0101	3.0209	0.0026
Δo^{+}_{t-6}	0.0261	0.0099	2.6433	0.0083
Δo^{-}_{t-1}	0.0270	0.0091	2.9582	0.0031
Δo^{-}_{t-2}	0.0851	0.0092	9.2313	0.0000
Δo^{-}_{t-3}	0.0815	0.0098	8.3391	0.0000
Δo^{-}_{t-4}	0.0385	0.0099	3.8842	0.0001
Δo^{-}_{t-5}	0.0366	0.0101	3.6293	0.0003
Δo^{-}_{t-6}	0.0176	0.0098	1.7882	0.0740
Δd_{t-1}	0.2220	0.0262	8.4710	0.0000
Δd_{t-2}	0.1061	0.0259	4.0983	0.0000
Δd_{t-3}	0.0381	0.0259	1.4718	0.1413
Δd_{t-4}	−0.0339	0.0253	−1.3390	0.1808
Δd_{t-5}	0.1690	0.0246	6.8720	0.0000
Δd_{t-6}	−0.0450	0.0226	−1.9929	0.0465

Table A.5: TVECM Coefficients, National - Same Lags Across Regimes

	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0041	0.0017	−2.3531	0.0187
Δo_{t-1}	0.0345	0.0056	6.1263	0.0000
Δo_{t-2}	0.1436	0.0055	25.9424	0.0000
Δo_{t-3}	0.0938	0.0063	15.0119	0.0000
Δo_{t-4}	0.0602	0.0069	8.6972	0.0000
Δo_{t-5}	0.0493	0.0068	7.2147	0.0000
Δo_{t-6}	0.0168	0.0067	2.5204	0.0118
Δd_{t-1}	0.3026	0.0253	11.9543	0.0000
Δd_{t-2}	−0.0163	0.0271	−0.6022	0.5471
Δd_{t-3}	0.0080	0.0272	0.2933	0.7693
Δd_{t-4}	0.0690	0.0259	2.6607	0.0079
Δd_{t-5}	0.0979	0.0247	3.9636	0.0001
Δd_{t-6}	−0.0554	0.0207	−2.6723	0.0076
Upper Regime				
$\hat{u}_{t-1}$	−0.0080	0.0020	−3.9241	0.0001
Δo_{t-1}	0.0217	0.0054	4.0130	0.0001
Δo_{t-2}	0.0882	0.0055	15.9220	0.0000
Δo_{t-3}	0.0792	0.0062	12.8319	0.0000
Δo_{t-4}	0.0365	0.0063	5.7971	0.0000
Δo_{t-5}	0.0332	0.0063	5.2329	0.0000
Δo_{t-6}	0.0216	0.0062	3.4995	0.0005
Δd_{t-1}	0.2224	0.0261	8.5066	0.0000
Δd_{t-2}	0.1052	0.0258	4.0739	0.0000
Δd_{t-3}	0.0393	0.0258	1.5236	0.1278
Δd_{t-4}	−0.0338	0.0252	−1.3414	0.1800
Δd_{t-5}	0.1698	0.0245	6.9340	0.0000
Δd_{t-6}	−0.0457	0.0225	−2.0367	0.0419

Table A.6: TVECM Coefficients, National - Nested Model, Same Lags Across Regimes

	Estimate	Std. Error	t value	p value
Lower Regime				
$\hat{u}_{t-1}$	−0.0037	0.0025	−1.4963	0.1348
Δo^{+}_{t-1}	0.0353	0.0089	3.9845	0.0001
Δo^{+}_{t-2}	0.1549	0.0085	18.2876	0.0000
Δo^{+}_{t-3}	0.0863	0.0091	9.5403	0.0000
Δo^{+}_{t-4}	0.0545	0.0102	5.3622	0.0000
Δo^{+}_{t-5}	0.0538	0.0100	5.3964	0.0000
Δo^{+}_{t-6}	0.0144	0.0101	1.4299	0.1529
Δo^{-}_{t-1}	0.0342	0.0123	2.7938	0.0053
Δo^{-}_{t-2}	0.1261	0.0119	10.5851	0.0000
Δo^{-}_{t-3}	0.1039	0.0113	9.1775	0.0000
Δo^{-}_{t-4}	0.0671	0.0115	5.8517	0.0000
Δo^{-}_{t-5}	0.0441	0.0111	3.9896	0.0001
Δo^{-}_{t-6}	0.0193	0.0110	1.7528	0.0798
Δd_{t-1}	0.3052	0.0254	12.0084	0.0000
Δd_{t-2}	−0.0169	0.0272	−0.6209	0.5347
Δd_{t-3}	0.0079	0.0273	0.2908	0.7713
Δd_{t-4}	0.0681	0.0261	2.6148	0.0090
Δd_{t-5}	0.0967	0.0248	3.8953	0.0001
Δd_{t-6}	−0.0535	0.0208	−2.5680	0.0103
Upper Regime				
$\hat{u}_{t-1}$	−0.0070	0.0035	−1.9678	0.0493
Δo^{+}_{t-1}	0.0165	0.0097	1.7015	0.0891
Δo^{+}_{t-2}	0.0933	0.0102	9.1832	0.0000
Δo^{+}_{t-3}	0.0772	0.0107	7.2359	0.0000
Δo^{+}_{t-4}	0.0347	0.0100	3.4602	0.0006
Δo^{+}_{t-5}	0.0305	0.0101	3.0209	0.0026
Δo^{+}_{t-6}	0.0261	0.0099	2.6433	0.0083
Δo^{-}_{t-1}	0.0270	0.0091	2.9582	0.0031
Δo^{-}_{t-2}	0.0851	0.0092	9.2313	0.0000
Δo^{-}_{t-3}	0.0815	0.0098	8.3391	0.0000
Δo^{-}_{t-4}	0.0385	0.0099	3.8842	0.0001
Δo^{-}_{t-5}	0.0366	0.0101	3.6293	0.0003
Δo^{-}_{t-6}	0.0176	0.0098	1.7882	0.0740
Δd_{t-1}	0.2220	0.0262	8.4710	0.0000
Δd_{t-2}	0.1061	0.0259	4.0983	0.0000
Δd_{t-3}	0.0381	0.0259	1.4718	0.1413
Δd_{t-4}	−0.0339	0.0253	−1.3390	0.1808
Δd_{t-5}	0.1690	0.0246	6.8720	0.0000
Δd_{t-6}	−0.0450	0.0226	−1.9929	0.0465

Table A.7: F test results using same lags across regimes

	Lower regime	Upper regime
Numerator degrees of freedom	6	6
Denominator degrees of freedom	1599	1362
F	0.7261603	0.2175547
Critical value	2.10	2.10

H_0: Equation (12) fits data as well as equation (5). H_1: Equation (12) fits data better than equation (5). Reject H_0 if $F >$ critical value.

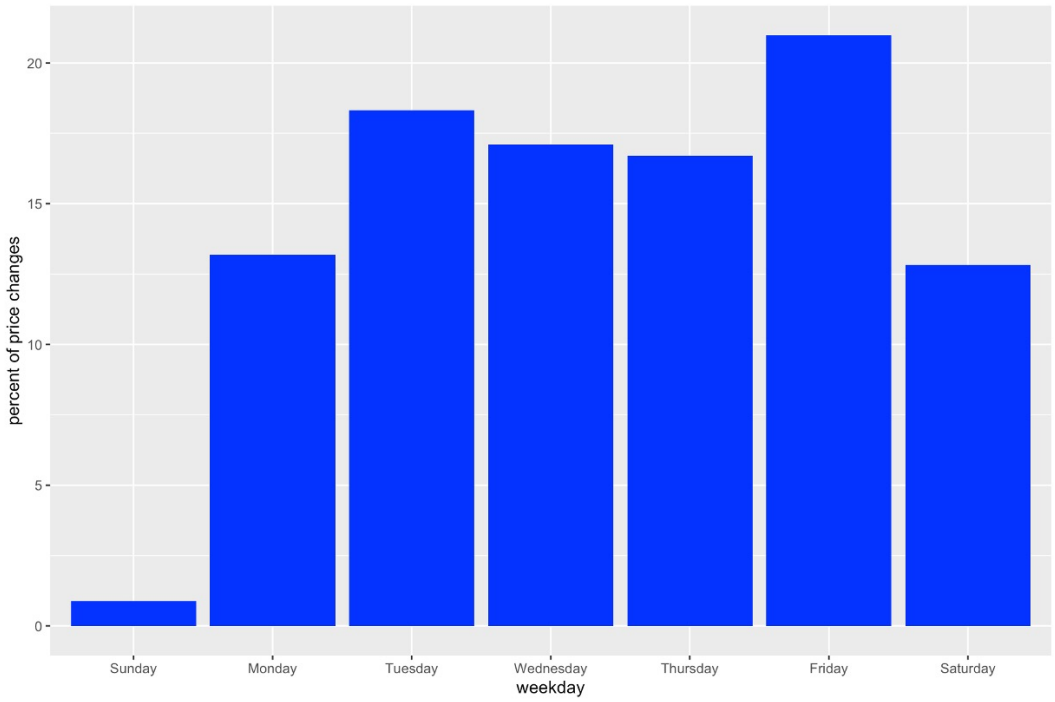


Figure A.2: Distribution of nonzero price changes by weekday.

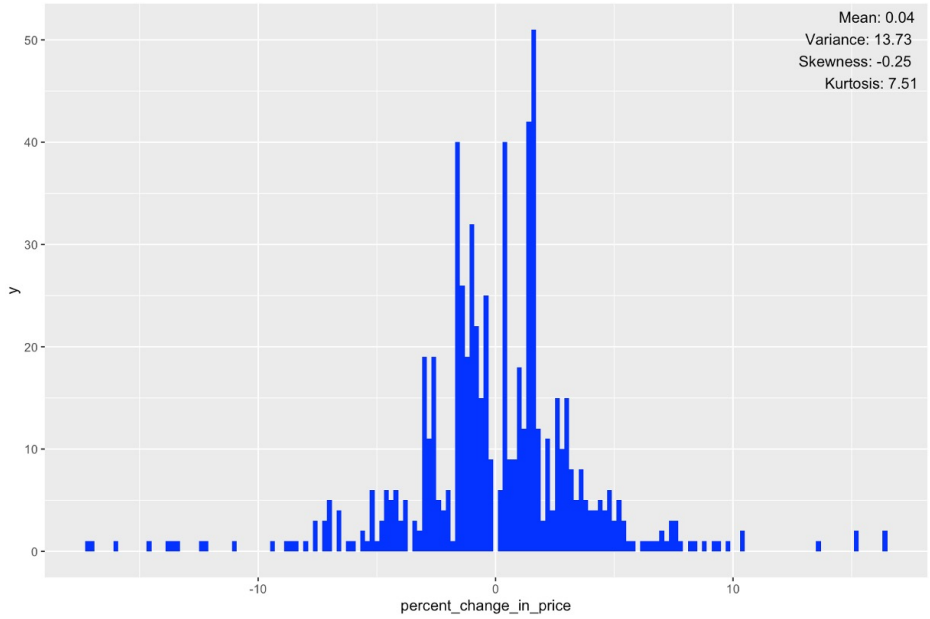
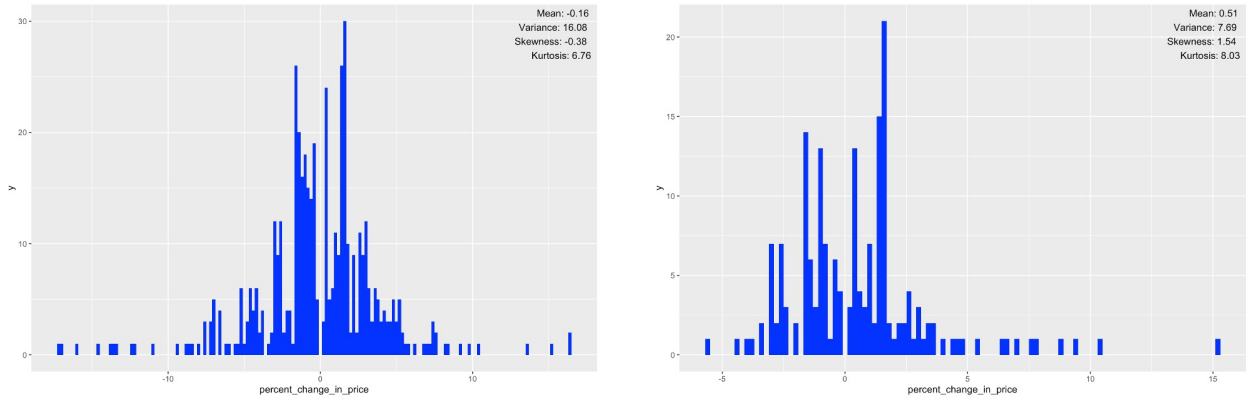


Figure A.3: Diesel price changes October 25, 2010. *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms. The oil price change on this day is 1.43%.



(a) Urban (b) Rural

Figure A.4: Diesel price changes October 25, 2010, urban vs. rural French populations. *Note:* Shown are the cross-sectional distributions of non-zero pre-tax price changes in diesel prices across urban and rural gas stations in France, in percentage terms. The oil price change on this day is 1.43%.

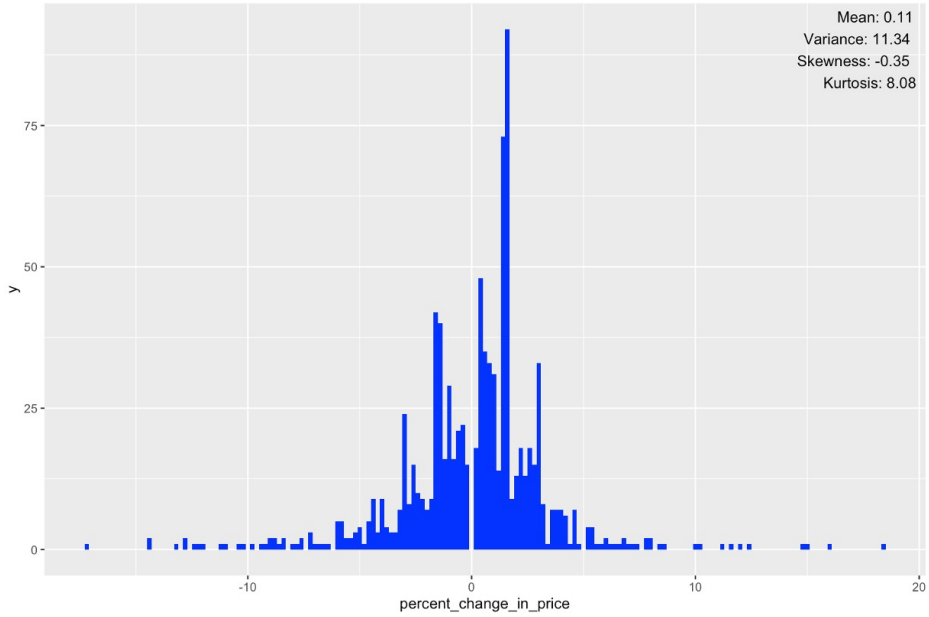
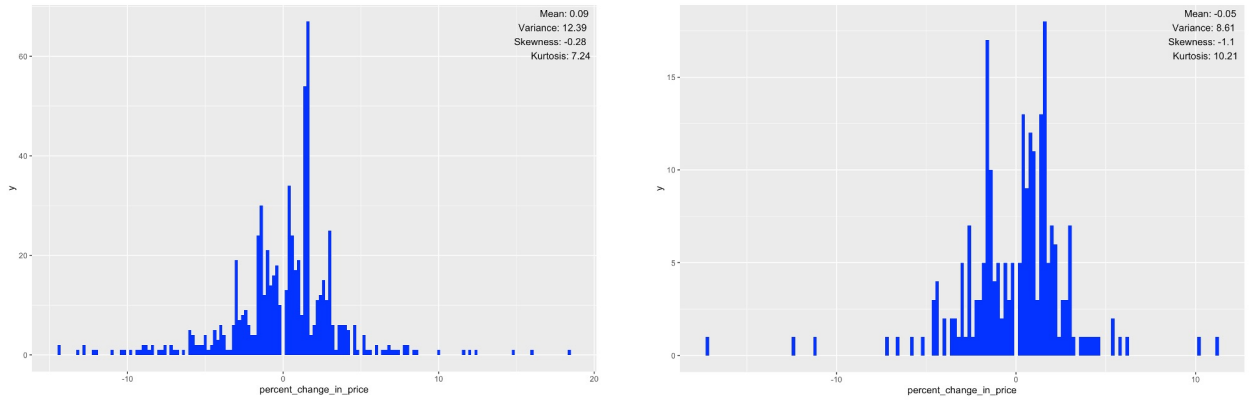


Figure A.5: Diesel price changes October 26, 2010. *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms. The oil price change on this day is 0.86%.



(a) Urban (b) Rural

Figure A.6: Diesel price changes October 26, 2010, urban vs. rural populations in France. *Note:* Shown are the cross-sectional distributions of non-zero pre-tax price changes in diesel prices across urban and rural gas stations in France, in percentage terms. The oil price change on this day is 0.86%.

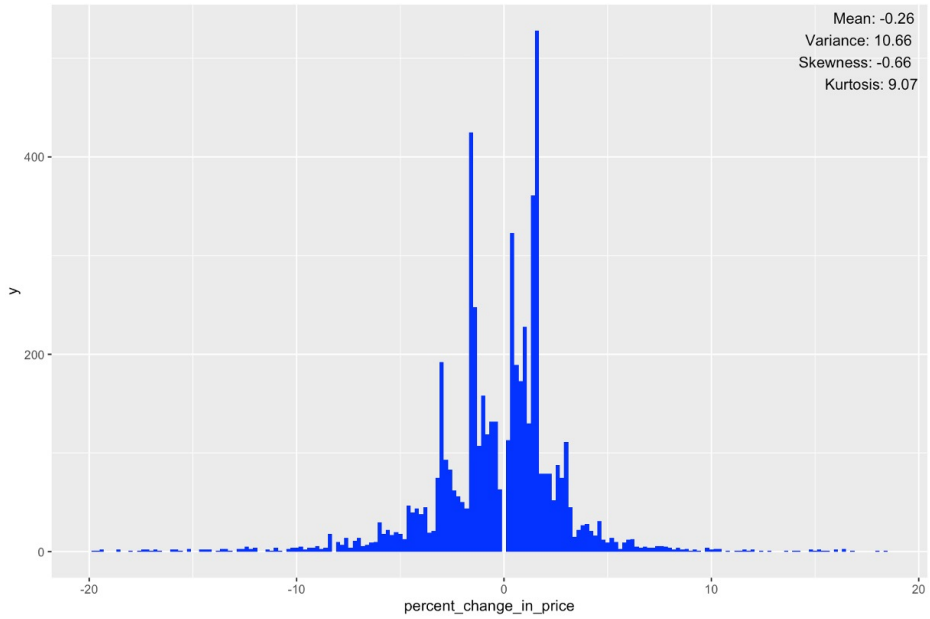
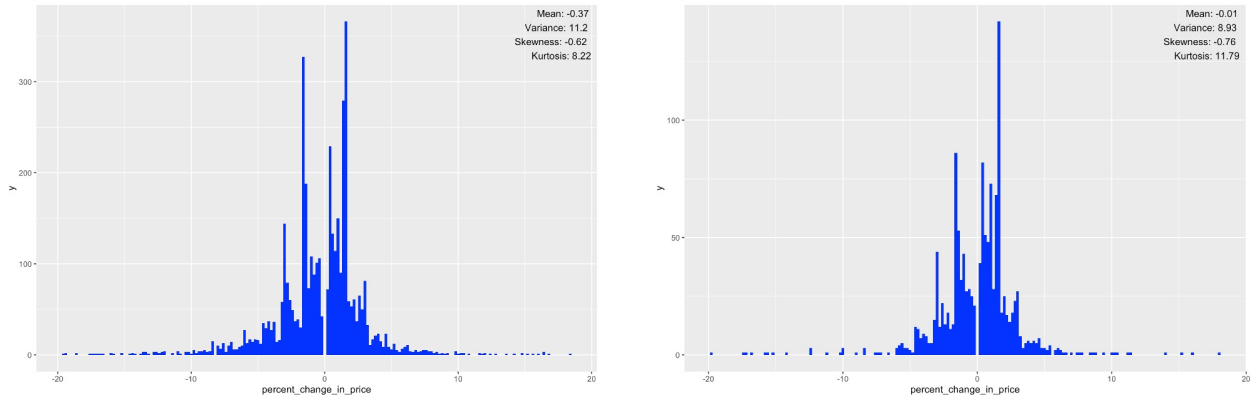


Figure A.7: Diesel price changes in week of October 25, 2010. *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms this week. The oil price change on this week is 2.11%.



(a) Urban (b) Rural

Figure A.8: Diesel price changes in week of October 25, 2010, urban vs. rural populations in France. *Note:* Shown are the cross-sectional distributions of non-zero pre-tax price changes in diesel prices across urban and rural gas stations in France, in percentage terms. The oil price change on this week is 2.11%.

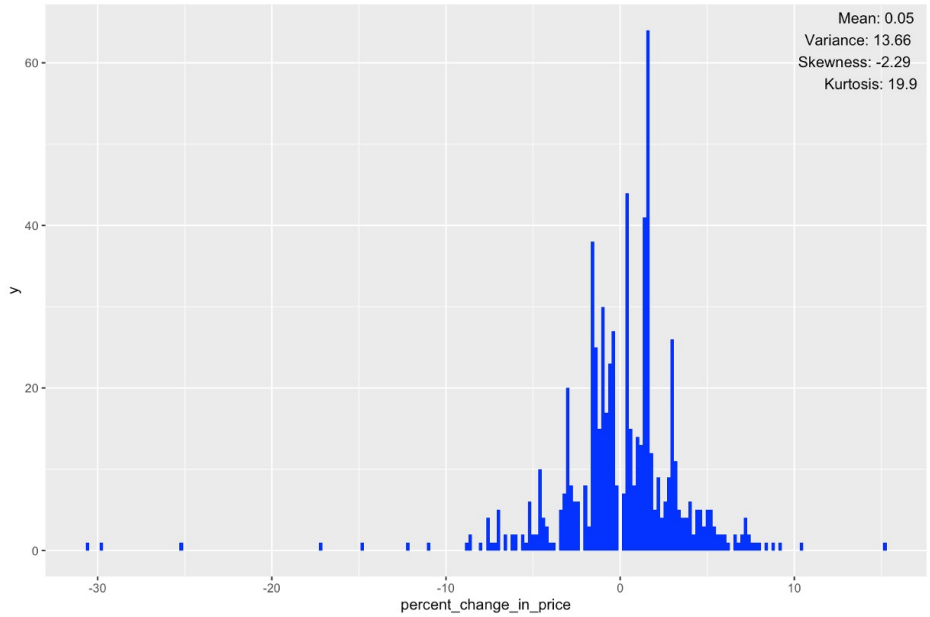


Figure A.9: Diesel price changes October 25, 2010 (Monday). *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms, for the six-year analytical sample on this day.

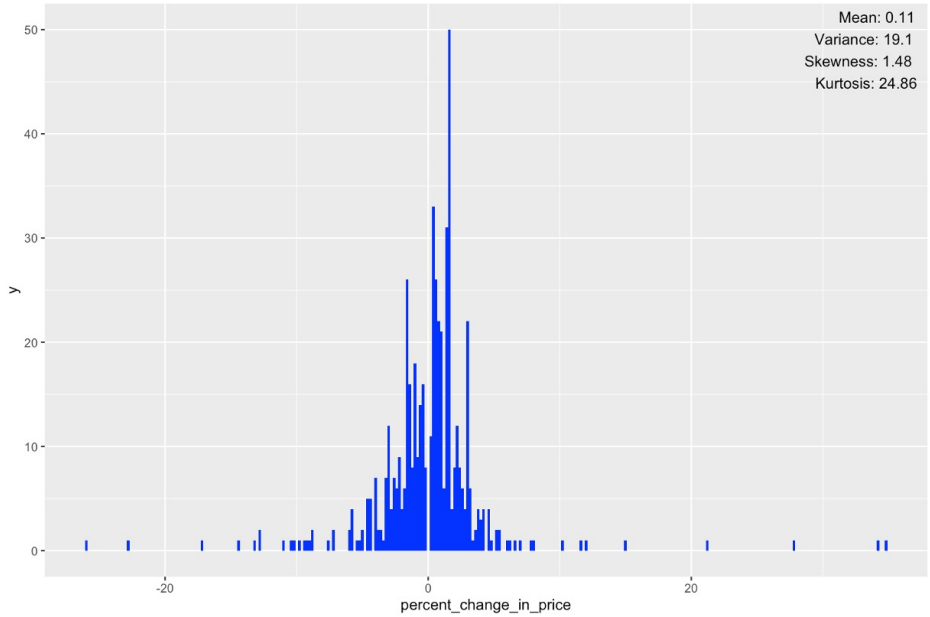


Figure A.10: Diesel price changes October 26, 2010 (Tuesday). *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms, for the six-year analytical sample for this day.

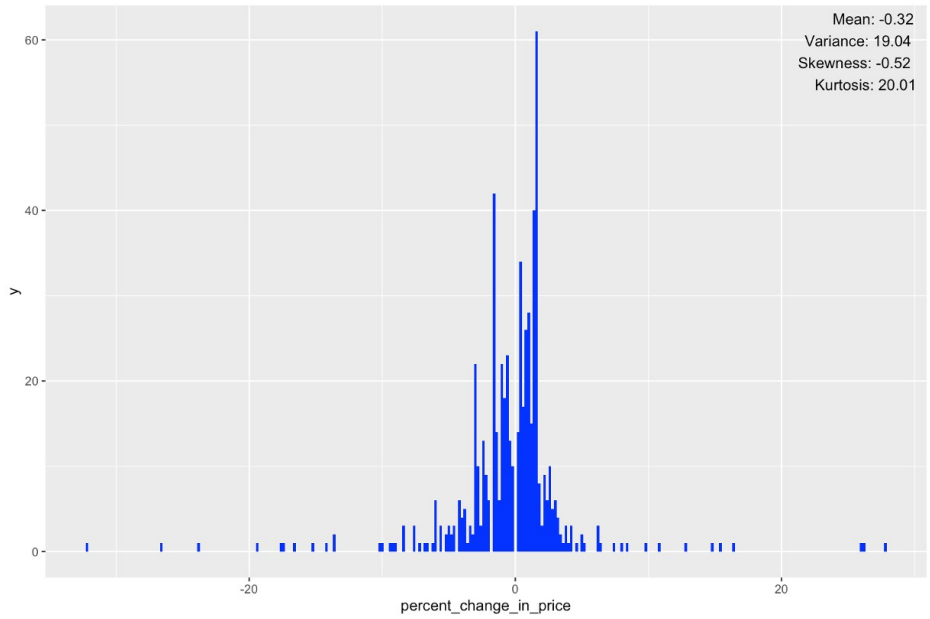


Figure A.11: Diesel price changes October 27, 2010 (Wednesday). *Note:* Shown is the cross-sectional distribution of non-zero pre-tax price changes in diesel prices across France, in percentage terms, for the six-year analytical sample on this day.

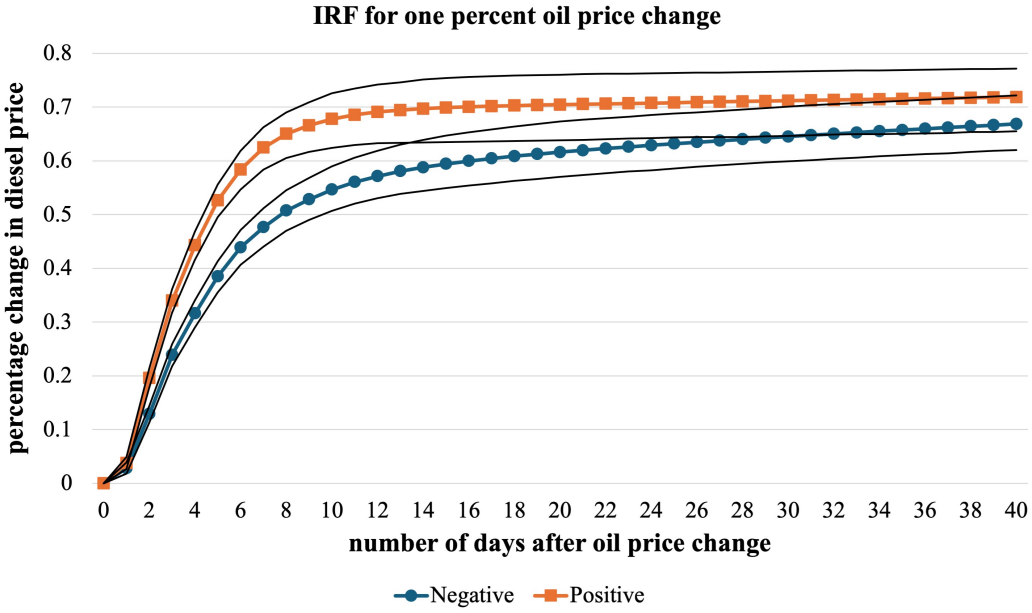


Figure A.12: Impulse response function for one percent oil price change. *Note:* impulse response functions generated for national data set with equation (5) estimates, where lags are forced to be the same across regimes and beginning at equilibrium.

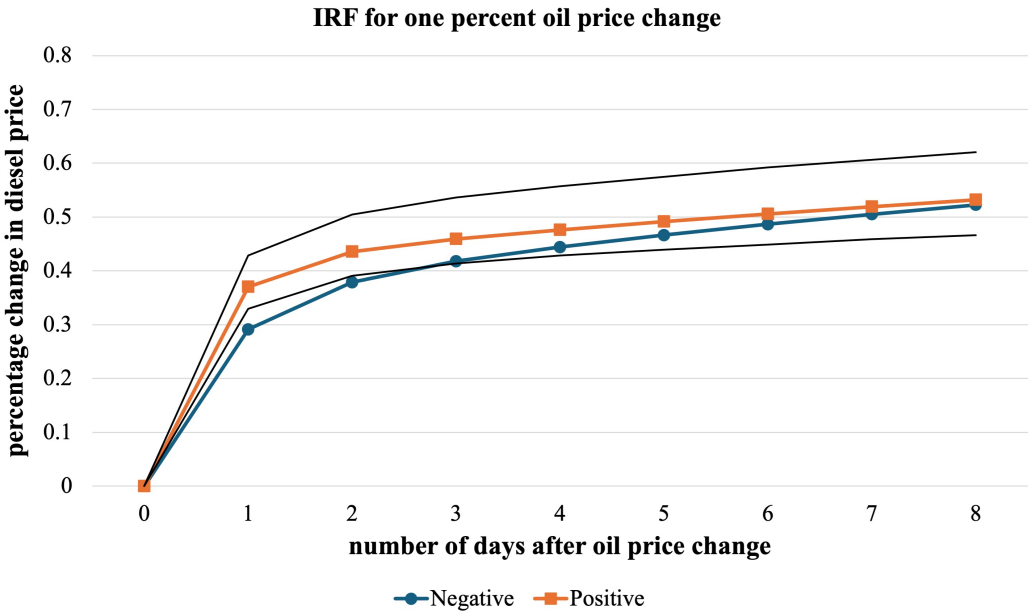


Figure A.13: Impulse response function for one percent oil price change. *Note:* impulse response functions generated for national data set with equation (5) estimates beginning at equilibrium using data for Wednesdays only.

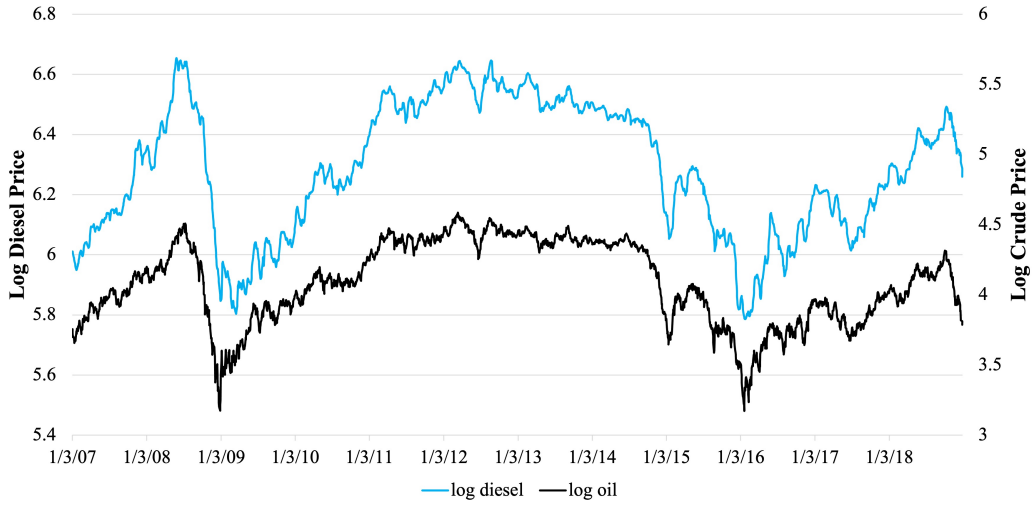


Figure A.14: Log daily retail diesel prices and brent crude oil prices.

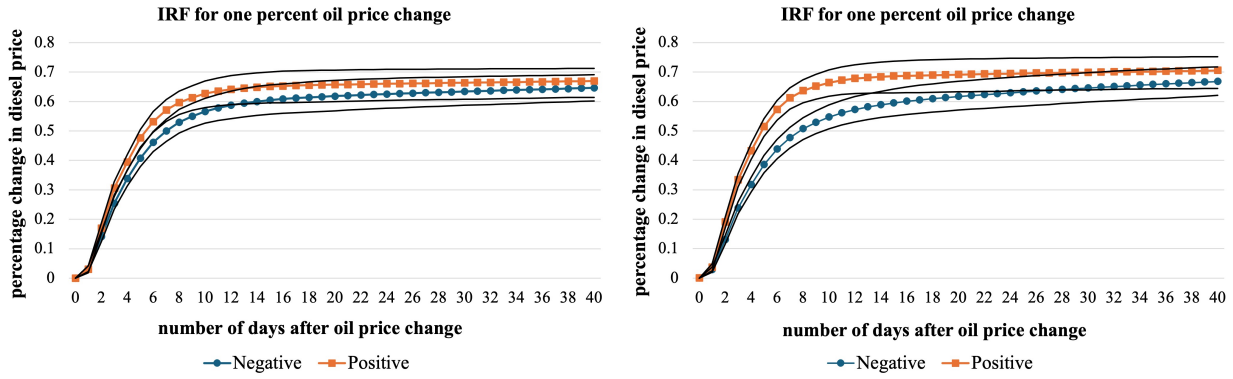


Figure A.15: Impulse response functions for one percent oil price change. *Note:* impulse response functions generated for national data set with two-stage estimation of equation (5) using the same lags across regimes. Left panel estimates the cointegrating regression $d_t = a + bo_t + u_t$ and right panel estimates $o_t = \alpha + \beta d_t + v_t$.

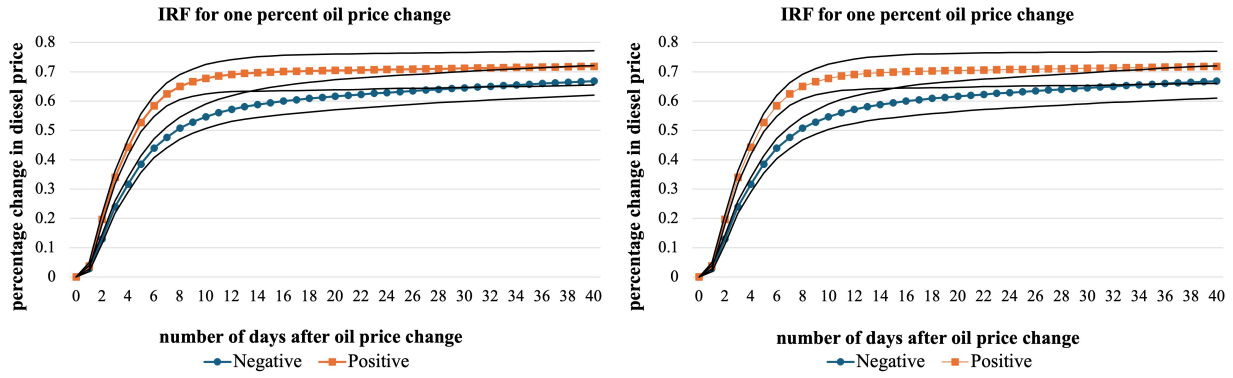


Figure A.16: Impulse response functions for one percent oil price change. *Note:* impulse response functions generated for national data set with one-stage estimation of equation (5) using the same lags across regimes. Left panel estimates the cointegrating regression $d_t = a + bo_t + u_t$ and right panel estimates $o_t = \alpha + \beta d_t + v_t$.

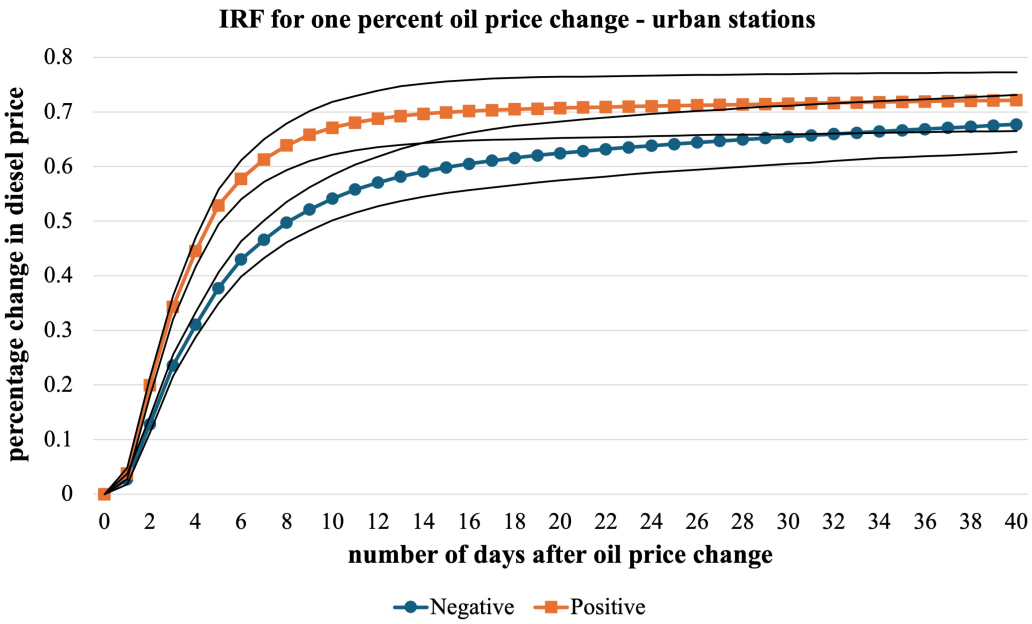


Figure A.17: Impulse response function for one percent oil price change. *Note:* Impulse response functions generated for urban data set with equation (5) estimates beginning at equilibrium.

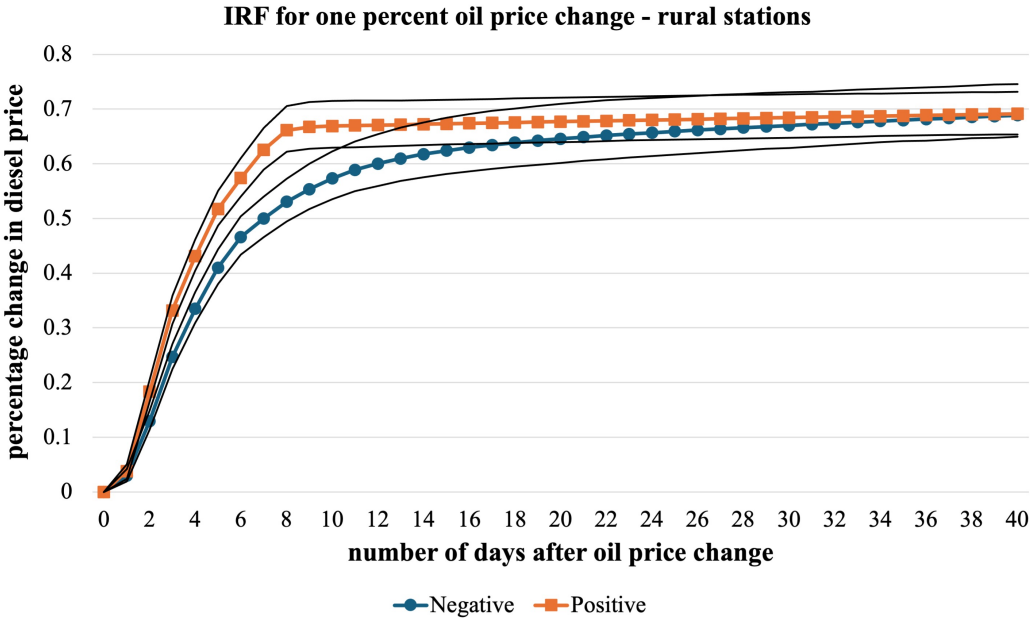


Figure A.18: Impulse response function for one percent oil price change. *Note:* Impulse response functions generated for rural data set with equation (5) estimates beginning at equilibrium.

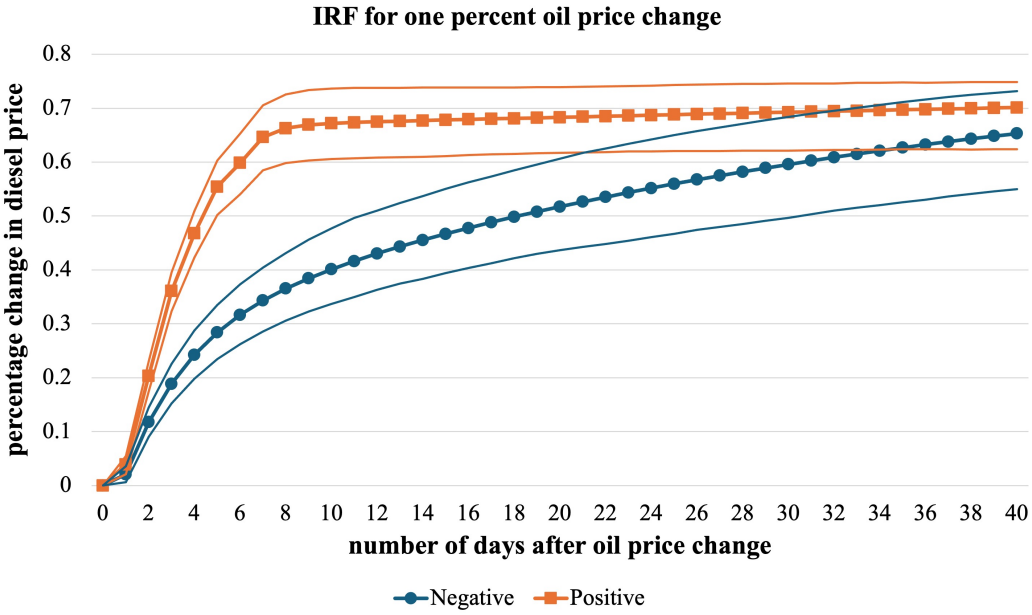


Figure A.19: Impulse response function for one percent oil price change. *Note:* Impulse response functions generated for national data set during subsample from 2007-2010 with equation (5) estimates beginning at equilibrium. Confidence bands are color coded to their associated impulse response function.

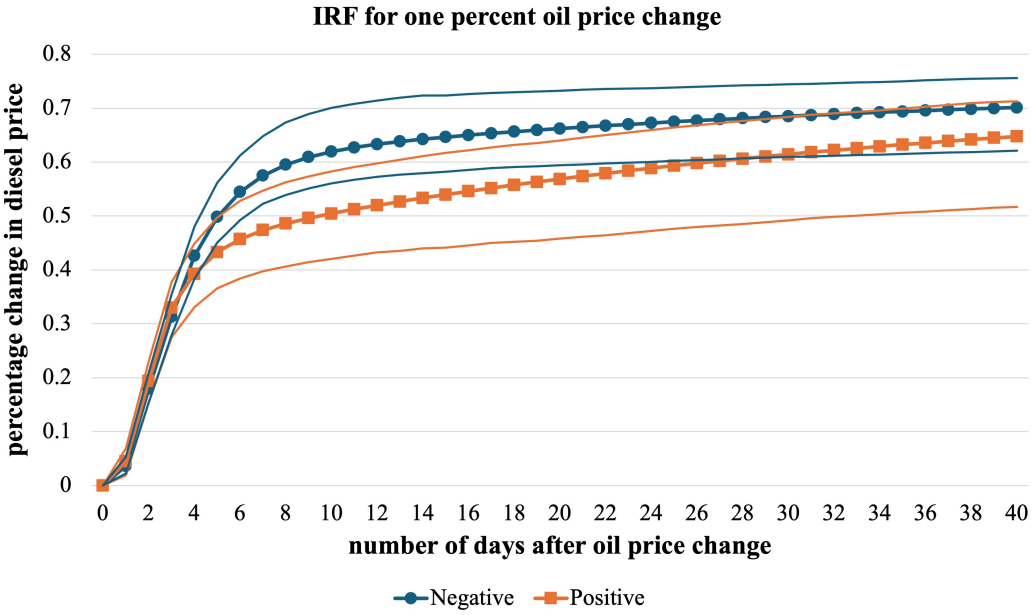


Figure A.20: Impulse response function for one percent oil price change. *Note:* Impulse response functions generated for national data set during subsample from 2011-2014 with equation (5) estimates beginning at equilibrium. Confidence bands are color coded to their associated impulse response function.

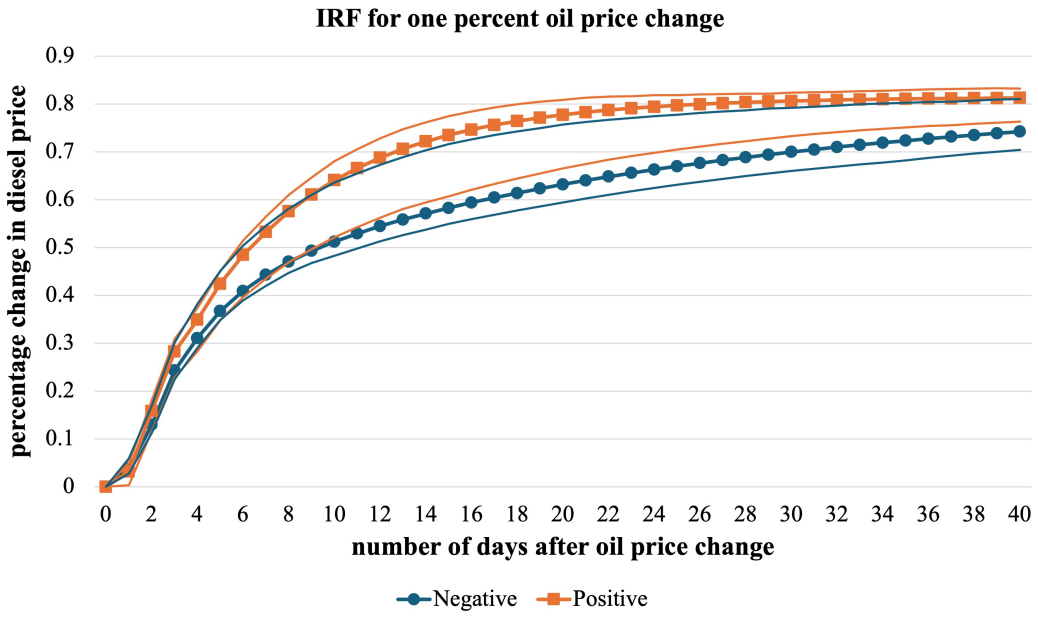


Figure A.21: Impulse response function for one percent oil price change. *Note:* Impulse response functions generated for national data set during subsample from 2015-2018 with equation (5) estimates beginning at equilibrium. Confidence bands are color coded to their associated impulse response function.



Figure A.22: 20-day rolling window realized volatility of Brent crude oil price.

B BOOTSTRAP CONFIDENCE INTERVAL PROCEDURE

A) Estimate the TVECM and the associated IRF in equations (5) and (6). This gives estimates $(\hat{a}, \hat{b}, \hat{\pi}, \hat{\delta})$ and $I\hat{R}F = \hat{I}_{t+k}$ for $k = 0, ..., 40$.

B) Resample residuals $\tilde{\varepsilon}_{Lt}^{(r)}$ from $\hat{\varepsilon}_{Lt}$ and $\tilde{\varepsilon}_{Ut}^{(r)}$ from $\hat{\varepsilon}_{Ut}$ with replacement.

C) Get $\Delta\tilde{d}_t^{(r)} =$

$$\begin{cases} \sum_{i=1}^{q_L} \hat{\pi}_{Li}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_L} \hat{\pi}_{Li}^{d} \Delta d_{t-i} + \hat{\delta}_L (d_{t-1} - \hat{a} - \hat{b} o_{t-1}) + \tilde{\varepsilon}_{Lt}^{(r)} & \text{if } (d_{t-1} - \hat{a} - \hat{b} o_{t-1} \leqslant 0) \\ \sum_{i=1}^{q_U} \hat{\pi}_{Ui}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_U} \hat{\pi}_{Ui}^{d} \Delta d_{t-i} + \hat{\delta}_U (d_{t-1} - \hat{a} - \hat{b} o_{t-1}) + \tilde{\varepsilon}_{Ut}^{(r)} & \text{if } (d_{t-1} - \hat{a} - \hat{b} o_{t-1} > 0) \end{cases}$$

D) Regress $\Delta\tilde{d}_t^{(r)}$ onto $\Delta o_{t-i}, \Delta d_{t-i}, o_{t-1}$ and d_{t-1} to get $(\tilde{a}, \tilde{b}, \tilde{\pi}^{(r)}, \tilde{\delta}^{(r)})$ with the model

$\Delta\tilde{d}_t^{(r)} =$

$$\begin{cases} \sum_{i=1}^{q_L} \pi_{Li}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_L} \pi_{Li}^{d} \Delta d_{t-i} + \delta_L (d_{t-1} - a - b o_{t-1}) + \varepsilon_{Lt} & \text{if } (d_{t-1} - a - b o_{t-1} \leqslant 0) \\ \sum_{i=1}^{q_U} \pi_{Ui}^{o} \Delta o_{t-i} + \sum_{i=1}^{s_U} \pi_{Ui}^{d} \Delta d_{t-i} + \delta_U (d_{t-1} - a - b o_{t-1}) + \varepsilon_{Ut} & \text{if } (d_{t-1} - a - b o_{t-1} > 0). \end{cases}$$

E) Use $(\tilde{a}^{(r)}, \tilde{b}^{(r)}, \tilde{\pi}^{(r)}, \tilde{\delta}^{(r)})$ to get $I\tilde{R}F^{(r)}$.

F) Do steps B-E a total of 999 times. Then combine $I\hat{R}F$ with $I\tilde{R}F^{(r)}$ for $r = 1, ..., 999$. For each point $k = 0, ..., 40$, calculate the 2.5 and 97.5 quantiles of the 1000 estimated IRFs. Connect the quantiles for each point to get the 95% confidence interval.