WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

How do Gasoline Prices Respond to a Cost Shock ?[1]

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January 2022, WP #861

ABSTRACT

Using several millions of daily prices collected over the period 2007-2018 in France, we investigate how gasoline retail prices respond to a common shock on marginal cost (i.e. the wholesale gasoline price quoted on the Rotterdam market). We find that the pass-through is complete: a 1% change in Rotterdam price translates to a change in retail price of 0.8%, in line with the share of the wholesale gasoline in total costs. The adjustment is gradual: the full pass through takes about 3 weeks. In a broad class of sticky price models, the ratio of the kurtosis over the frequency of price changes is shown to be a sufficient statistic for the cumulative impulse response of prices (CIRP) to a nominal shock. We provide evidence that the sufficient statistic prediction holds when we look at how gasoline prices respond to a common cost shock. Relating, at the gas station level, the CIRP to moments of the price change distribution, we find that the CIRP correlates with the ratio of kurtosis over frequency, but also with both frequency and kurtosis taken separately. The sign and the magnitude of the correlations are fully in line with theoretical predictions. We also show that other moments do not correlate with CIRP as robustly as the frequency and the kurtosis.

Keywords: Price Rigidity, Gasoline, Sufficient Statistic.

JEL classification: E31, D43, L11

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[1] We thank Sarah Lein and also Fernando Alvarez, Hervé Le Bihan and Francesco Lippi for their detailed comments and suggestions. We are grateful to Luca Dedola, Riemer Faber, Yuriy Gorodnichenko, Peter Karadi, Franck Portier, Daniele Siena and participants of the Cardiff University Workshop on Micro Prices and Inflation (Cardiff, 2019), the ECB NIPE workshop (Frankfurt, 2019), virtual PRISMA meeting (2021), Banque de France research seminar (2021), Inflation Workshop (2021) for their useful comments and suggestions. All remaining errors are our own. The views expressed in this paper are those of the authors and do not necessarily represent those of the Banque de France or the Eurosystem.

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NON-TECHNICAL SUMMARY

Price rigidity is a key ingredient in standard macro models to generate short term real effects of monetary policy. A recent theoretical literature has shown that in a very broad class of sticky-price models, the cumulated responses of output to a monetary shock is proportional to the ratio of two moments of the observed price change distribution: the kurtosis of non-zero price changes (i.e. a measure of "fat tails" of the distribution) and the frequency of price changes. This ratio is what we call a sufficient statistic for real effects of a monetary shock. The intuition behind this result is the following: when prices adjust very frequently, prices will respond quickly to the cost shock and the cumulative response of output will be smaller. For a given frequency of price changes, the size of price changes also matters: if firms adjusting their prices are the ones whose prices are the furthest away from the price that would have prevailed under price flexibility, the price response will be quicker and the cumulative real effects smaller. The kurtosis of price changes is shown to capture this "price selection effect" accelerating the price response to a shock. However, empirical evidence testing this sufficient statistic proposition is quite scarce. In this paper, we provide new empirical evidence supporting this prediction, focusing on the cumulated response of prices (CIRP). To do so, we use a dataset covering daily gasoline prices collected in about 10,000 gas stations in France between 2007 and 2018.

Gasoline offers a clean case study for testing the sufficient statistic prediction for at least two reasons: first, we can relate individual prices to observed variations in one of the main component of their costs (i.e. the wholesale gasoline traded on the Rotterdam market) and we are able to derive precise estimates of the price response to a cost shock at the gas station level; second, kurtosis often raises measurement issues because this statistic is quite sensitive to outliers and product heteregoneity. In our dataset, for each gas station, we observe several hundreds of price changes for a homogenous good, which helps us to obtain quite precise measures of kurtosis at the gas station level. We then rely on variation of kurtosis and frequency of price changes across gas stations to test the sufficient statistic prediction.

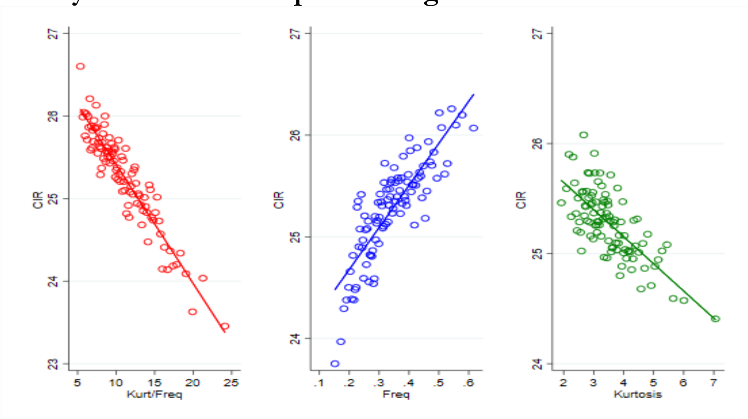
First, we document that gasoline prices are sticky (relative to the high frequency of shocks): (i) while oil prices vary every day, the typical duration between two gasoline price changes is 4 opening days, (ii) the distribution of gasoline price changes does not mirror the distribution of wholesale price changes: the former displays a two-peak distribution with few small price changes whereas the latter is close to a normal distribution centered around 0; (iii) relating prices to observed cost, we find persistent gaps between actual prices and prices that gas stations would charge if they passed changes in marginal cost into their prices every day; moreover, the probability of changing prices is an increasing function of this gap.

We then estimate the reaction of gasoline prices to a marginal cost shock at both the aggregate and gas station levels. A 1% change in Rotterdam wholesale diesel price translates into a change in retail price of 0.8%, in line with the share of the wholesale gasoline in total costs and a full pass-through of costs to prices. The adjustment is gradual: the pass through takes about 3 weeks. We also find that shocks on the markup (proxied by the average local price changes) are transmitted immediately, with a much smaller pass-through (20%) that gradually fades out to become insignificant after 20 days. We do not find any evidence of asymmetric price reactions to negative or positive shocks.

To test the sufficient statistic prediction, we relate the cumulative impulse response function of prices to marginal cost to the ratio of kurtosis over frequency calculated at the gas station level using two different empirical exercises. The first one is conducted pooling all price observations together, while the second exercise uses the cross sectional dispersion of both the cumulated price response and the ratio of the kurtosis to the frequency of price changes at the gas station level. Both empirical exercises provide robust and consistent evidence that

this ratio correlates negatively with CIRP as predicted by the sufficient statistic theory (Figure – left panel). The estimated coefficient relating CIRP and the ratio is also close to -0.167, the value predicted by the theory. Besides, both the frequency and the kurtosis of price changes taken separately correlate equally and significantly with CIRP and with the expected sign (Figure center and right panels). Other moments of the price change distribution do not show the same robust and significant relationship with CIRP as the one obtained for the ratio kurtosis over frequency.

Figure: Correlation between the cumulative impuse response of gasoline prices to a cost shock (CIRP) and key moments of the price change distribution



Note: correlations are calculated across gas stations; statistics are measured for every gas station in France based on a dataset of daily gasoline prices in France between 2007 and 2018 collected by the Ministry of Economy.

Comment les prix à la pompe réagissent-ils à un choc sur le prix du pétrole ?

RÉSUMÉ

À partir de plusieurs millions de prix collectés quotidiennementsur la période 2007-2018 en France, nous étudions comment les prix de détail de l'essence réagissent à un choc commun sur le coût marginal (i.e. le prix de gros coté sur le marché de Rotterdam). La transmission est complète : une variation de 1 % du prix de gros se traduit par une variation du prix de détail de 0,8%, en ligne avec la part de l'essence vendue en gros dans les coûts totaux. L'ajustement est progressif : la transmission complète prend environ 3 semaines. Dans une large classe de modèles à prix rigides, il a été démontré que le ratio de la kurtosis sur la fréquence des changements des prix est une statistique suffisante de la réponse cumulée des prix à un choc nominal. En estimant, pour chaque station, la réaction des prix à un choc sur le prix de gros, et en liant le cumul de leur fonction de réponse aux moments de leur distribution de changements de prix, nous montrons que la prédiction théorique est vérifiée : le cumul de la fonction de réponse est corrélé au ratio kurtosis sur fréquence, mais également à la fréquence et à la kurtosis considérées séparément. Nous montrons que les autres moments de la distribution ne sont pas aussi fortement corrélés au cumul de la fonction de réponse que la fréquence et la kurtosis.

Mots-clés : rigidité des prix, prix à la pompe, statistique suffisante.

Price Micro Setting Analysis Network (PRISMA)

This paper contains research conducted within the Price Micro Setting Analysis Network (PRISMA). PRISMA consists of economists from the ECB and the national central banks (NCBs) of the European System of Central Banks (ESCB).

PRISMA is coordinated by a team chaired by Luca Dedola (ECB), and consisting of Chiara Osbat (ECB), Peter Karadi (ECB) and Georg Strasser (ECB). Fernando Alvarez (University of Chicago), Yuriy Gorodnichenko (University of California Berkeley), Raphael Schoenle (Federal Reserve Bank of Cleveland and Brandeis University) and Michael Weber (University of Chicago) act as external consultants.

PRISMA collects and studies various kinds of price microdata, including data underlying official price indices such as the Consumer Price Index (CPI) and the Producer Price Index (PPI), scanner data and online prices to deepen the understanding of price-setting behaviour and inflation dynamics in the euro area and EU, with a view to gaining new insights into a key aspect of monetary policy transmission (for further information see https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_prisma.en.html)

The refereeing process of this paper has been co-ordinated by a team composed of Luca Dedola (ECB), Anton Nakov (ECB), Chiara Osbat (ECB), Elvira Prades (Banco d'Espana), Sergio Santoro (ECB), Henning Weber (Bundesbank).

1. Introduction

How do prices respond to a marginal cost shock? Recently, Alvarez et al. (2016) and Alvarez et al. (2021a) have theoretically shown that in a general class of sticky price models (nesting in particular the standard menu cost and the Calvo models), the cumulated output response to an aggregate nominal shock can be summarized by a sufficient statistic which is the ratio of kurtosis of non-zero price changes over the frequency of price changes. The intuition behind the result is quite simple. If prices are sticky, they respond slowly to a given shock (leading to real effects) and the frequency of price changes will capture the speed of price adjustment. For a given frequency, the size of price adjustment also matters. If firms adjusting their prices are the ones whose prices are the furthest from the price that would have prevailed under price flexibility, the price response will be larger and quicker and the cumulated output response will be smaller. The kurtosis of price changes captures this price selection effect accelerating the price response and reducing the real effects of a nominal shock.

In this paper, we provide new empirical evidence testing this sufficient statistic property using a unique dataset containing several millions of gasoline retail prices collected daily by the Ministry of Economy and covering the universe of French gas stations over the period 2007-2018.

Gasoline prices offer a very clean case study for testing the sufficient statistic property for at least two reasons. First, the kurtosis of the price changes distribution is generally measured quite imprecisely because it is highly sensitive to outliers and to product heterogeneity. Our gasoline price data help us to overcome these measurement difficulties. First, gasoline is a very homogenous product and second, prices contain almost no measurement error since they are reported by stations themselves under the control of the Ministry of Economy. Besides, each gas station has a long time series with several years of daily prices, which allows us to compute a precise measure of kurtosis at the gas station level, using several hundreds of price changes for every gas station. We then rely on the variation of this statistic across gas stations to test the sufficient statistic property. A second reason why gasoline prices are a clean case study for testing the sufficient statistic is that we can measure quite precisely how gasoline prices respond to an observed marginal cost shock. To do this, we link daily gasoline price trajectories with the price change of wholesale diesel quoted daily on the Rotterdam wholesale market, which is a large cost component for gas stations. This shock is arguably exogenous and displays high-frequency variation. Since each gas station has a relatively long time series, we can estimate for every gas station an accurate measure of the cumulative impulse response function of gasoline prices to a marginal cost shock. We can then test the sufficient statistic prediction exploiting the variability of this measure across gas stations.

In this paper, we first document that if gasoline prices are updated much more frequently than other consumption goods, they are still sticky in comparison with the high frequency of shocks. On average, gas stations change their prices once a week, while the marginal cost changes every day. Second, the distribution of price changes displays some specific patterns. In particular, there are very few small price changes and the distribution of price changes is M-shaped, while the distribution of marginal cost shock is close to a normal distribution centered around 0. For most gas stations, we find that the kurtosis of price changes ranges between 1 and 6, which corresponds to the two "extreme" values predicted by the theoretical model of Alvarez et al. (2021a) (1 in a standard menu cost model and 6 in a Calvo model). We also find that the average kurtosis across gas stations is about 3, suggesting some moderate degree of price selection. Since we observe quite precisely a large component of the marginal cost of gasoline at a daily frequency, we can also compute the generalized adjustment hazard function relating the probability of price changes to the gap between the actual price and the price that would have been observed under perfect flexibility. We find that this function is monotonically increasing in the absolute value of the price gap. This result is quite consistent with predictions of random menu-cost models of price rigidity and Alvarez et al. (2021a) show that the sufficient statistic holds when we observe such patterns in the generalized hazard function.

We then show that gasoline prices do not respond immediately to a marginal cost shock. To do this, we estimate the average reaction of gasoline retail prices to a change in the wholesale price of diesel quoted in the international market, using a flexible local projection methodology (Jordà, 2005). This estimation method is particularly useful in our case since it imposes a minimal structure on the dynamics of the response, it does not require assuming any constraint on the long-run pass-through and allows us to estimate the impulse response function of prices to the cost shock for quite long horizons. We find that a 1%-variation in the Rotterdam wholesale price of diesel is gradually transmitted to gasoline prices within 3 weeks, and that the long-run pass-through is of 80%, in line with the share of marginal cost in the total cost of a gas station. The protracted adjustment of prices to the shock confirms the presence of significant price stickiness. We also document strong heterogeneity depending on station characteristics: stations with lower prices (which are also more likely to be supermarkets) show a larger pass-through; conversely, stations using more often psychological prices (ending with a 0 or a 9) have a lower pass-through. Finally, we do not find any evidence of asymmetric reactions between positive and negative shocks.

Using this empirical model to derive the cumulative impulse response of prices to a cost shock, we can investigate the sufficient statistic prediction. Here we follow closely the empirical strategy developed by Alvarez et al. (2021b): using sectoral French data, they relate the cumulative impulse response of prices (CIRP) to the ratio kurtosis over frequency. In our case, the identifying variability will come from variations across several thousands of gas stations. We rely on two different empirical exercises. First, pooling all gas stations together, we can include in our baseline local projection empirical model an interaction term between the common cost shock and the ratio kurtosis over frequency at the gas station level. In a second exercise, we estimate for each gas station of our sample the impulse response function of prices to a marginal cost shock. We then normalize the long-run pass-through across gas stations so that we calculate the CIRP at different horizons for an equivalent nominal shock of 1%. We finally investigate the relationship across gas stations between CIRP and moments of the price distribution under the restrictions implied by the theory and as developed in Alvarez et al. (2021b).

In both empirical approaches, our results provide evidence strongly supporting the sufficient statistic property. As predicted by the theory, the CIRP to a positive marginal cost shock is negatively related to the ratio of kurtosis over frequency. This result is robust to a variety of robustness checks and to considering different measures of the cost shock. We find that the magnitude of the coefficient associated with the ratio is in line with predictions of the model. The estimated coefficients vary between -0.1 and -0.15 according to specifications, whereas the standard predicted value is -0.167. Another finding is that both frequency and kurtosis are correlated with the CIRP with the expected sign, and the magnitude of the coefficients is also fully in line with the theoretical predictions. Interestingly, we also obtain that for both frequency and kurtosis, T-statistics associated with estimated coefficients are quite high and similar, suggesting that both moments contribute as much to the cross-sectional dispersion of CIRP. Besides, we find that other moments of the price distribution do not correlate as robustly as the frequency and the kurtosis of price changes. We obtain that T-statistics associated with these moments are much lower and that depending on the specification or the sample we consider the magnitude and even the sign of the regression coefficients associated with other moments can vary. In the empirical exercise where we pool all gas stations together, interaction terms corresponding to other moments of the price change distribution are not statistically significant for long-term horizons (at which the theoretical prediction is supposed to hold).

We run several robustness exercises using different measures of shocks, different horizons for the calculation of long-term pass-through and the CIRP, different samples of gas stations, or alternative measure of kurtosis taking into account possible heterogeneity. They all confirm that the sufficient statistic prediction holds: the ratio of kurtosis over frequency correlates significantly with CIRP and both moments taken separately are also correlated with equal importance and significance with CIRP.

Our paper is a contribution to the very recent but growing literature testing the sufficient statistic prediction of Alvarez et al. (2016, 2021a). Using French sectoral data, Alvarez et al. (2021b) propose to investigate empirically this prediction and provide an empirical framework for these tests. We here build on this first contribution and follow closely their empirical framework to document new empirical evidence focusing on a specific product for which we have more precise information both on the marginal cost and on moments of the price change distribution. Contrary to Alvarez et al. (2021b), we do not look at monetary policy shock but to an observed marginal cost shock common to all gas stations. As underlined in Alvarez et al. (2021b), the theory applies to any common shock shifting the marginal costs of all firms the same way; the wholesale price of diesel here affects all gas stations at the same time. We can then use the heterogeneity of CIRP across gas stations to test the sufficient statistic predictions. Since gasoline is a quite homogenous product and we have daily observations, we are able to compute higher moments of price changes with less serious measurement issues than in other empirical settings. In a related contribution to this literature testing the sufficient statistic, Hong et al. (2021) on US producer price data find that frequency is the only moment which is robustly related to the price response to a monetary shock whereas Henkel (2020) documents that sectoral heterogeneity in the response to a monetary shock can be related to cross-sectoral dispersion in the frequency of price changes. We here emphasize that the frequency is not the only moment which can be related to the cumulated price response to a marginal cost shock, the kurtosis also matters as predicted by the theoretical result of Alvarez et al. (2016, 2021a).

Our work is also related to a very large literature focusing on how gasoline prices respond to an oil price shock (see Hosken et al. 2008 for instance). In particular, Davis and Hamilton (2004) or Douglas and Herrera (2010) both investigate price stickiness of gasoline prices in the

United States looking at the determinants of the probability of price changes.[1] Gautier and Le Saout (2015) have used similar micro data as the ones we use in this paper on a much shorter period of time and have investigated how the probability but also the size of price changes are related to marginal cost shocks. They have estimated station-specific models of price rigidity to derive aggregate implications for the price dynamics. They conclude that individual price responses to a cost shock are consistent with a model of random menu cost and that the response to a shock is gradual.[2] Our contribution to this empirical literature is to provide estimates of the impulse response function of gasoline prices to a cost shock using a very flexible empirical model with a minimal structure (see also Balleer and Zorn (2019) and Dedola et al. (2020) for a similar empirical approach on producer price data or Karadi et al. (2019) on consumer scanner data). In particular, we do not impose any constraint on the long run response or on the shape of the price dynamics.[3] Moreover, this method and the long-time dimension of the data allow us to estimate the impulse response function at every day after the shock and over a long horizon (relative to the half-life of the impulse response).

The remainder of the paper is as follows. In section 2, we describe the main characteristics of our dataset and we document that gasoline prices are sticky at daily frequency. In section 3, we present the empirical model we use to estimate the price response to a marginal cost shock and we describe the results. In Section 4, we test the sufficient statistic theory by relating the cumulative impulse response of prices to the moments of the price change distribution and we document the main empirical results of this test. In Section 5, we present results of robustness exercises. Section 6 concludes.

2. Micro dataset and stylized facts on price stickiness

In this section, we present our micro dataset and we document the main stylized facts on the relative stickiness of retail gasoline prices.

2.1 Daily micro-data

Our dataset consists of individual prices reported by all gas stations selling gasoline in France. Since January 1st 2007, all gas stations selling more than 500 m^3 in a year have to report the

[1] Carlsson (2017), using Swedish PPI, relates marginal cost to the probability of PPI price changes on annual data for a very large number of manufacturing sectors.
[2] See also Cardenas et al. (2017) for another empirical study using these data to investigate price convergence.
[3] Eckert (2013) has pointed the importance of high-frequency station-level data whereas Deltas and Polemis (2020) report a large set of methods and data to review the strengths and weaknesses of usual estimates.

prices of their fuels to the Ministry of Economy every time they update these prices. All prices collected are then made available for free to consumers on a governmental web site http://www.prix-carburants.gouv.fr.[4] We use daily historical data extracted between January 1st 2007 and December 31st 2018. Overall, our dataset contains about 30 million price quotes. These data cover more than 10,000 stations.[5] Price quotes contained in this dataset have also been used by Insee (French National Statistical Institute) since 2017 to calculate the official monthly consumer price index for gasoline, which supports that price information contained in this dataset can be considered as highly reliable.

The main variables contained in the dataset are as follows: (i) an identification number for each retailer, with detailed information on location, brand name, type of available services (shop,…); (ii) the price of a liter of diesel including all taxes, and expressed in euros with three decimals (as posted publicly outside the station); (iii) the exact date (DD/MM/YYYY) of the price update (see also Appendix A for more details on data cleaning). Prices are directly collected at the gas station since they are reported by the gas station owner under the administrative control of the Ministry of Economy. Prices are displayed on a public web site and the accuracy of the information can be easily checked (by customers and the Ministry of Economy). However, some prices might be subject to measurement errors, mainly related to the dates at which gas stations are closed, sometimes very temporarily. We focus on gas stations opening more than 500 days (2 years of opening days) with continuous price observations. We also drop price observations on the weekends because there is no Rotterdam price change during the weekends and because there is almost no gas station changing its prices on Sunday. Overall, our data sample contains about 15 millions of prices.

Every gas station reports prices for a maximum of four types of gasoline: diesel, super unleaded petrol SP95, super unleaded petrol SP95-E10 and super unleaded petrol SP98. In this paper, we focus on diesel prices for two reasons. First, over our sample period, diesel has the highest market share among gasoline products, representing about 60% of the value of household consumption of road fuels (according to the HICP weights). Second, diesel prices are available

[4] This obligation is legally binding. A ministerial decree dated December 12, 2006 provides details on this obligation and states that any failure to comply with this obligation is punishable by a fine. Price updates are reported by gas station managers through a specific and secured IT platform with a restricted access. The French competition authority (DGCCRF) is in charge of controlling the accuracy of the information provided by gas stations and run on-site controls. Consumers are also invited to report to the control authority any inaccurate information reported on the web site where prices are publicly available.

[5] The data set is not exhaustive in terms of gas stations since there is a threshold requirement for participation, but still covers a large majority of gas stations operating in France.

over the whole sample period, which is not the case for other types of gasoline products sold in France over the same period.[6]

Our dataset contains prices as they are publicly displayed by gas stations, i.e. in euros with three decimals and including consumption taxes. Two taxes are paid on gasoline prices: TICPE (*Taxe Intérieure de Consommation sur les Produits Énergétiques*, i.e. carbon tax) is a lump sum tax that can vary over years and possibly across regions (in 2018, this tax was about 0.6 euros in most regions); Value Added Tax (VAT) whose standard rate was 19.6% until January 2014, and 20% afterwards. VAT applies on the sum of pre-tax price and carbon tax. In the rest of the paper, we will use pre-tax prices that can be recovered following the formula:

$$P_{BT} = \frac{P_{AT}}{(1+TVA)} - TICPE \qquad (1)$$

where P_{BT} represents the price before taxes, and P_{AT} represents the price all taxes included (as displayed by gas stations). In our sample, the average price after all taxes is about 1.25 euros whereas the average price before taxes is about 0.56 euros. Overall, taxes represent about 55% of the price after taxes (Table A.1 in the Appendix for a complete decomposition of gasoline prices).

Figure A.2 in the Appendix plots the average daily price of gasoline in our dataset and compares it with the "official" gasoline price series (computed and released by the Ministry of Economy, using the same data source), as well as with the price of crude oil (Brent, in euros) and of the wholesale diesel price quoted on the Rotterdam market (in euros). As expected, our average price series and the "official" price series are highly similar and the average retail price co-moves very closely with crude oil or wholesale gasoline prices quoted on international markets.

2.2Are gasoline prices sticky?

We provide two sets of stylized facts consistent with some price stickiness of retail gasoline prices at a daily frequency.

Frequency and size of and price changes

First, retail gasoline prices do not change every day contrary to oil prices or wholesale diesel prices quoted on international markets. For each gas station of our sample, we have calculated the frequency of price changes. Table 1 reports the results. The frequency of price change of

[6] Unleaded petrol SP98 is only available since 2013; the number of stations selling unleaded petrol SP95 has been sharply decreasing over the last 10 years since unleaded petrol SP95-E10 has been progressively replacing SP95 in many stations (and these two types of gasoline have different prices).

the median gas station is 27%, implying a price duration of a little less than 4 opening days. There is some heterogeneity across gas stations: one quarter of gas stations have frequencies lower than 21% (i.e. price durations longer than 5 days) while for one quarter of stations this frequency is larger than 36% (i.e. price durations shorter than 3 days) (Figure 1a and Table 1).

[Table 1]

[Figure 1]

Second, the distribution of price changes displays a two-peak distribution with fewer small price changes while the distribution of daily changes in the wholesale gasoline prices is close to a normal distribution centered around 0 (Figure 2). This M-shaped distribution of price changes is quite in line with the prediction of a menu-cost model where small price changes are quite rare. In a typical menu cost model, this relative low proportion of small price changes can be explained by the fact that prices are more likely to be updated when they are far from the price that would have prevailed under price flexibility. This leads to a selection of prices that will adjust, and price changes are more likely to be large. According to Alvarez et al. (2021a), kurtosis of non-zero price changes can capture this selection effect (a very high selection effect corresponds to a small kurtosis equal to 1 while the absence of selection effect as in the Calvo setting corresponds to the largest kurtosis of 6). However, in practice, this statistic is usually hard to measure accurately and empirical measures of kurtosis are often very far from typical values predicted by theory and so, hard to relate to standard theoretical model predictions. Interestingly, we find that for a large majority of gas stations of our sample, kurtosis ranges between 1 and 6, which supports that our gasoline price data are reliable to investigate the sufficient statistic prediction. We find that the average kurtosis across gas stations is about 3 but as for the frequency, it is also quite heterogeneous across gas stations (Table 1 and Figure 1 – panel b).

[Figure 2]

Overall, price changes are quite infrequent and kurtosis values at the gas-station level suggest that there is some selection in price changes.

Adjustment hazards

If prices are not perfectly flexible, the price p_{it-1} (set at the date of the last price adjustment) differs from the current frictionless price p_{it}^{*} and there is a price gap $x_{it} = p_{it-1} - p_{it}^{*}$, the markup deviating from the one that would exist when a firm maximizes its profits. The gap will be closed only if firms can adjust their prices, so that $\Delta p_{it} = \Delta p^*_{it}$. Following Alvarez et al. (2021a), in a general class of sticky-price models, the optimal decision to change prices can be summarized by the general hazard function which relates the price gap to the probability of price adjustment. In a pure time-dependent model, this probability of price adjustment is the same whatever the value of x_{it} can be. In a random menu-cost model, the probability of price adjustment is expected to increase monotonically with x_{it} in absolute values (Caballero and Engel, 1999, 2007).

[Figure 3]

In practice, the price gap is often hard to measure since p^*_{it} cannot be directly observed and the literature often use the average price of competitors as a proxy for this frictionless price (see for instance Gagnon et al. 2012 or Karadi et al.2019) whereas Eichenbaum et al. (2011) construct a measure of costs relying on data on profits and sales in different stores. In our case, we can use a proxy of a large component of marginal cost of gas station to approximate more direclty p^*_{it} and the price gap. We have computed x_{it} for all gas stations of our sample, as the difference between the observed price p at time *(t-1)* and wholesale price observed at Rotterdam market R_t at time *t*.[7] We have then calculated the probability of price change at date *t* as a function of this difference. First, on the distribution of x_{it}, the first and third quartiles of x_{it} are respectively -2.7% and 2.6% whereas more than 90% of observations are between -7.1% and 7.3%. Figure 3 plots the probability of price changes depending on the value of x_{it}. We find that for low values of *x* in absolute value terms (between -2% and 2%), the probability of price changes is quite flat around 20%. When *x* increases, the probability of price changes is higher: for *x* equal to 5% in absolute value terms, the probability of price changes is close to 0.25. On the bottom panel of Figure 3, we plot separately the probability of price increases and decreases depending on the value of *x*. We find that the relation between the price gap and the probability of price increases is quite linear whereas the probability of price decreases is a little less responsive to negative price gaps than to positive price gaps. Overall, the main patterns of the adjustment hazard function are quite typical of a random menu cost model and are very in

[7] For each gas station, we estimate a simple linear regression between actual retail price and wholesale Rotterdam price. We use the estimated coefficient to calculate for each gas stations the difference between the actual price and the Rotterdam price multiplied by the estimated coefficient of the linear regression. We have then demeaned this difference.

line with the theoretical setting of Alvarez et al. (2021a) where the sufficient statistic prediction is shown to hold.

3. Assessing the impact of a shock on retail gasoline prices

In this section, we investigate how marginal cost shocks are transmitted to retail gasoline prices. We present our empirical model based on a standard local projection method, we then estimate the model on all prices and then for each gas station of our sample. Using these results obtained at the gas station level, we can compute for every gas station an accurate measure of the cumulated impulse response of prices (CIRP) to a cost shock.

3.1 Empirical model

Our empirical model derives from a standard theoretical model of price setting. Under imperfect monopolistic competition and if prices were flexible, at every date, firms would set their price p_{it}^* as a markup (μ_{it}) over their marginal cost (mc_{it}). In log terms, we can write:

$$p_{it}^* = mc_{it} + \mu_{it} \quad (2)$$

One key determinant of marginal cost is here easily observable since a large share of the production cost of gas stations consists of the wholesale price of diesel bought by gas companies either on international markets or to local refineries in France. We here use the price of the wholesale diesel sold on the Rotterdam market as a proxy for this wholesale price and so as a proxy for the marginal cost of diesel retail prices (Figure A.2 in Appendix).[8] We can write the marginal cost as:

$$mc_{it} = \varphi R_t + \omega_{it} \quad (3)$$

where φ is the share of wholesale diesel R_t in overall marginal cost and ω_{it} corresponds other components of the marginal cost which can include labour costs or rents for instance.

In a similar set-up, Amiti et al. (2019) show that we can then express price changes as a combination of a change in the marginal cost and a change in the price of competitors:

$$\Delta p_{it}^* = \alpha \Delta mc_{it} + \beta \Delta p_t^{-i} + \varepsilon_{it} \quad (4)$$

[8] There are several arguments supporting this point: the Rotterdam price is the opportunity cost for a refinery of an integrated oil company; production and sales are often different divisions within oil companies, and the Rotterdam price can be used as an internal transfer price; finally, a little less than 50% of diesel is directly imported from abroad, traded on this international market and not refined in France (see also Asplund et al. (2000) or Faber and Janssen (2019) for a more detailed discussion).

where Δp_{t}^{-i} is the average price change of competitors and capture markup changes, α is the average cost pass-through of the firm whereas β measures the importance of strategic complementarities in price setting (since it represents the elasticity of prices of firm *i* to its own competitors). In our case, we observe all gas stations with their exact geographical position. This means that we can define competitors as the closest gas stations using distance in kilometers and compute average price changes of closest neighbors as a proxy for competitors' price changes.[9] We can then decompose more explicitly the marginal cost (combining equations (3) and (4)):

$$\Delta p_{it}^{*} = \alpha\left(\varphi\Delta R_t + \Delta\omega_{it}\right) + \beta\Delta p_t^{-i} + \varepsilon_{it} \qquad (5)$$

This leads us to the following relation that could be estimated using our observable variables (retail gasoline price changes, wholesale price changes and local competitors' price changes):

$$\Delta p_{it}^{*} = \gamma\Delta R_t + \beta\Delta p_t^{-i} + \upsilon_{it} \qquad (6)$$

where γ will be equal to the share of wholesale diesel in overall costs times the degree of cost pass-through (i.e. the share of wholesale diesel in total costs).

If prices are sticky, prices charged by gas stations are not always equal to p_{it}^{*} (i.e. the price maximizing profits in a flexible price model) and it will take some time for a shock to be fully transmitted to retail prices. In that case, we need to take into account for a possible delay in the price response to shocks.

Our baseline empirical exercise will consist in estimating the previous equation using the local projection methodology described by Jordà (2005). Using this methodology, we can compute the full impulse response function of retail diesel prices to shocks in the Rotterdam wholesale price (see also Balleer and Zorn (2019) and Dedola et al. (2020) for a similar empirical approach using producer price data or Karadi et al. (2019) on scanner data). Our baseline regression for a given horizon *h* days after the shock is as follows:

$$\Delta p_{i_{t-1,t+h}} = \mu_h + \theta_h\Delta R_{t-1,t} + \delta_h\Delta p_{t-1,t}^{-i} + \eta_{t_h} + \chi_{hi} + \epsilon_{i,t_h} \qquad (7)$$

where $\Delta p_{i_{t-1,t+h}}$ is the before-tax log price difference for diesel between days *t-1* and day *t+h* in station *i*, $\Delta R_{t-1,t}$ is the log price difference of Rotterdam wholesale gasoline price between

[9] One difference here is that we cannot weight prices by market shares as suggested by Amiti et al. (2019) since we do not have any information on the sales of gas stations.

day *t-1* and day *t*, $\Delta p_{t-1,t}^{-i}$ is the average price change of local competitors of the gas station *i* (we consider here an average of the 10 closest gas stations of station *i*), η_{t_h} are time (horizon specific) controls including the lags of Rotterdam price changes, average diesel price changes in France and average local price changes at date *t* (we here use controls for five lags to control for all other common shocks at date *t* other than Rotterdam price shock). More precisely, the term η_{t_h} is specified as $\eta_{t_h} = l_h(\Delta R_{t-j-1,t-j}, \Delta p_{t-j-1,t-j}, \Delta p_{t-j-1,t-j}^{-i})|_{j=1,..,4}$ where l_h is a linear function whose parameters will be estimated jointly with all other parameters of the regression. Finally, χ_{ih} are gas-station- and horizon-specific fixed effects.

We run one OLS regression for each time horizon *h*, and at each period *t+h*, our parameters of interest are θ_h, which yields the overall variation of diesel prices in reaction to the shock and δ_h which captures the reaction of prices to a markup shock. Given that Rotterdam prices are listed only from Monday to Friday, Saturdays and Sundays are *de facto* excluded from our analysis (the shock variable being not defined on these days). On Mondays, the shock variable is then defined as the log variation between the price of wholesale gasoline observed on Monday and the one observed on Friday the week before.

As robustness, we also report results considering a different measure for Rotterdam price shocks using daily deviations from a 3-week moving-average of log Rotterdam prices calculated as $\Delta\widetilde{R_t} = R_t - \sum_{h=0}^{21} \frac{R_{t-h}}{22}$. This measure can help us to define the shock as a price deviation from a recent trend observed by gas stations.[10]

3.2 Aggregate Results

We look at aggregate results obtained by pooling all gas stations together. We first describe the average response of retail prices to a cost shock, then we document some heterogeneity of the price response across gas stations and according to the sign of the shock.

3.2.1 – Baseline results

Figure 4 plots the impulse response functions to a shock on Rotterdam wholesale price and to a shock on the average local price change in our baseline case.

Cost shock. We first present results associated with the response to the cost shock (red solid line, Figure 4). We find a delayed response of retail diesel prices to variation in the Rotterdam

[10] Other measures of exogenous oil shocks are available in the literature, at a monthly frequency as in Baumeister and Hamilton (2019) or Känzig (2021); to our knowledge yet, there is no variable of exogenous oil shock available at a daily frequency, which is the relevant frequency in our study.

wholesale price. It takes approximately 10 open days (i.e. excluding Saturdays and Sundays) for a cost shock to be transmitted at 90% into retail prices and a little more than 20 days for a full transmission. More specifically, there is almost no response at dates 0 and 1 and then the impulse response function increases pretty quickly. The long-term (40 open days after the shock, i.e. about 8 weeks) value of the elasticity of retail prices to the Rotterdam wholesale price is close to 0.8. This estimated value is consistent with the share of raw materials over total production in the sector of retail gasoline, which is estimated to be 81% using average price values of our sample (Table A.1 in the Appendix). This result implies a full pass through of the cost shock to retail prices: in the long term, stations pass on the entire increase in the commodity cost in proportion to its share in total costs. If we reason in price level terms, a 1% increase in the price of imported diesel (for an initial price of EUR 0.45 in early 2018 – see Figure A.2 in Appendix) is equivalent to EUR 0.45 cent and results in an identical increase over time for the diesel price excluding taxes (i.e. 0.8% of the initial price of diesel, equal to EUR 0.55 in early 2018, this latter price including other costs like transportation costs, labour costs…).

[Figure 4]

We run a robustness exercise where we use a different measure for the Rotterdam price shock. Instead of using the log difference in wholesale Rotterdam prices, we define the shock as the deviation from a 3-week moving average. In this case, the impulse response function is very close to our baseline estimate and a similar long run pass through of Rotterdam prices to retail prices. Finally, using the price of crude oil (Brent) instead of Rotterdam wholesale price leads to very similar results (Figure B.5 in Appendix). The impulse response function to the oil price shows similar patterns: a delayed response to the shock and a full pass-through after about 3 weeks. The long-term effect is smaller than the long-term response of prices to Rotterdam (0.7 versus 0.8), and the ratio of the two elasticities (about 0.9) should give the elasticity of wholesale price to Brent oil prices.

Competitors' prices and strategic complementarities. Our second main finding concerns how gasoline prices react to an exogenous change in prices of the closest neighbor gas stations (blue line - Figure 4). We obtain that retail gasoline prices do respond to the average price change of local competitors. This response decreases over time: a 1% change in local price changes increases retail prices by 0.2% but the impact is close to 0 and non-significant after 3 weeks. This would suggest that in the short run, markups of gas stations move in response to competitors' prices but these movements are quite limited and in the long run, the pass-through is full. This result provides evidence in favor of some limited strategic complementarities among gas stations. Alvarez et al (2021a) sufficient statistic result holds in a model with no strategic complementarities. Our results show that there are some strategic complementarities in our case-study, but that this is a quite limited issue. Controlling for shocks on crude oil (Brent) rather than Rotterdam wholesale price, the response of prices to local price changes is almost unchanged (Figure B.5 in Appendix).

3.2.2 – Heterogeneity and asymmetry

Heterogeneity. We document some heterogeneity across gas stations in the transmission of the cost shock. We first investigate whether responses of prices depend on their relative position of the gas station in the price distribution. We have classified all gas stations according to their most frequent position in the price distribution into four groups (defined using quartiles of the price change distribution (calculated day by day)): “very low price”, “low price”, “high price” and “very high price”. Using our baseline specification, we run separate regressions on stations belonging to the four different categories. Figure B.1 in Appendix plots the impulse response function for Rotterdam price changes and local average price changes for the 4 groups of gas stations. We find that the main difference in the pass-through of Rotterdam price changes to retail prices is between stations charging very high prices and all other stations. In stations with very high prices, the long-run pass-through is close to 0.70 whereas for the other 3 groups of gas stations, this long-term pass-through is about 0.8. These differences in long run pass through of Rotterdam prices to retail prices should mainly reflect differences in the share of Rotterdam prices in their marginal costs and to a lesser extent in their average markups.
In terms of speed of adjustment to the long-run pass-through, differences seem quite limited among the four groups of gas stations (Table B.1 in Appendix). Gas stations in lower prices categories respond only a little more quickly than gas stations in higher prices categories. In all groups, more than 90% of the long run response is observed between 10 and 15 days after the shock. In the very-low-price category, this threshold is reached after a little less than 10 days whereas for very high price stations after 15 days.

In Figure B.2 in Appendix, we plot the impulse response function for the baseline specification on two different subgroups of gas stations depending on their frequency of prices ending in 0 or 9. In particular, we find that gas stations using very frequently psychological prices (i.e. more than 98% of the time, corresponding to the top decile of stations with the highest share of psychological prices) are less reactive to Rotterdam price changes than others. The long-term pass-through of shocks on marginal costs is of 75% for these stations, against 80% for gas stations with a share of psychological prices lower than average (equal to 51%). This result might be related to the fact that gas stations with prices ending in 0 or 9 tend to have higher price variations on average (Figure B.3).

Concerning the reaction of gas stations to local prices, there is some heterogeneity across gas stations as for the cost shock. Looking at differences between high- and low-price stations, we find that very-high-price gas stations respond little and slowly to local price changes whereas very-low-price gas stations respond much more strongly and more quickly to changes in local prices. The elasticity of retail prices in very low price gas stations with respect to local price changes is 0.27 whereas it is less than 0.10 in very-high-price gas stations. These differences are consistent with the fact that markups in very-low-price gas stations are quite small and these gas stations have to respond quickly to changes in competitors' prices. However, in the long run, the markup elasticity is about the same in all four groups converging 20 days after the shock to a value close to 0.07. Looking at differences in the frequency of price endings, we find that gas stations using psychological prices less often also tend to be more reactive to the prices of local competitors in the short run. This would be consistent with the fact that the use of psychological prices is related to the markup level of gas stations.

Asymmetry. Finally, we test whether the price response to cost shock is asymmetric. Compared with our baseline specification, we interact systematically the shock (and its lags) with a dummy variable indicating whether the shock is positive or negative.

$$\Delta p_{i_{t-1,t+h}} = \theta_h^+ \Delta R_{t-1,t} 1_{\Delta R_{t-1,t}>0} + \theta_h^- \Delta R_{t-1,t} 1_{\Delta R_{t-1,t}<0} + \delta_h^+ \Delta p_{t-1,t}^{-i} 1_{\Delta p_{t-1,t}^{-i}>0} + \delta_h^- \Delta p_{t-1,t}^{-i} 1_{\Delta p_{t-1,t}^{-i}<0} + \mu_h + \eta_{t_h} + \chi_{hi} + \epsilon_{i,t_h} \quad (8)$$

where θ_h^+ (resp. θ_h^-) is the estimated impulse response function at date *h* in response to a positive (resp. negative) Rotterdam wholesale gasoline price change between dates *t-1* and *t* and δ_h^+ (resp. δ_h^-) is the estimated impulse response function at date *h* in response to a positive (resp. negative) average local price change between dates *t-1* and *t*.

We find that in response to changes in Rotterdam prices, gasoline retail prices react almost exactly the same to a negative or a positive shock (Figure B.4 in Appendix). The patterns of the impulse response functions are highly similar in both cases: same speed of adjustment and same long-term pass-through. Overall, we do not find any evidence in favor of asymmetric responses of gasoline price changes to Rotterdam price changes. On the contrary, we find that the responses to local price shocks are somewhat asymmetric, at least during the first two weeks. Retail gasoline prices respond more to negative local price changes than to positive ones. This would suggest that gas stations are more likely to decrease their prices when other local stations do so than when local stations increase their prices. This asymmetry would be consistent with a quick reduction in markups when gas stations around decrease their price in order not to lose market shares.

3.3 Gas-Station Level Results

We then run the same empirical exercise at the gas station level. Here, we take advantage of tracking prices at a very high frequency and for a long period of time to estimate the impulse response function (θ_h in equation (7)) for every gas station in our sample (θ_{ih}). We report some moments of the distribution of the long-run effects in Table 2. We find some heterogeneity across gas stations in the long-run effects. The average pass through is 0.8 and most gas stations have a long-run pass-through between 0.7 and 0.9. This heterogeneity reflects differences in the share of raw material in the cost function (see also Gautier and Le Saout (2015) for more details on the determinants of these differences).

[Table 2]

In order to test the sufficient statistic property, we calculate for each gas station the cumulated impulse response to the cost shock. However, contrary to a typical monetary shock which is expected to have the same long-term effect on prices and to have no relative price effect (under monetary neutrality), the oil price shock will lead to different reactions of gas prices in the long run reflecting the slight differences in the cost structure across gas stations. Thus, we first normalize all firm-level IRF so that for each gas station a shock corresponds to a 1%-increase in prices in the long run. To do this, we calculate the maximum value for θ_{ih} over the horizon 31 to 36 days after the shock to estimate the long-term response (θ_{iLT}) and then we divide all θ_{ih} for *h=1* to *30* days by θ_{iLT}. This normalization will assume that all gas stations are hit by a shock (which might be different from one gas station to another) but leading to the same long term effect on prices (1%) for all gas stations.[11] Finally, we calculate the cumulated impulse response of prices (CIRP) over the period from day 1 to day 30 after the shock. If prices adjust immediately to the long-run price level and are fully flexible, the CIRP should be equal to 30.

[11] Another interpretation would be to read the long-term response in terms of price levels: if there is a full pass-through of cost to prices in all gas stations (and regardless of the share of inputs in the price), an increase of EUR 1 cent of the marginal cost will lead to an increase of EUR 1 cent in all gas stations.

We compute alternative measures for the CIRP at the gas station level. The first one defines long-term pass-through as the maximum value for θ_{ih} over the horizon 25 to 31 days after the shock to estimate the long-term response (θ_{iLT}) and then calculate the CIRP over a period of 24 days. We compute these CIRP estimates for our baseline shock (Rotterdam price changes) but also the alternative measure of shock (gap between the current Rotterdam price and the average of Rotterdam price over the last 3 weeks).

Table 2 provides moments of the distribution of CIRP for the different horizons and measures of shocks. We find that the average CIRP is closer to 25 for the horizon 30 months and about 20 for the horizon 24 months. We also find that there is some heterogeneity across gas stations: the first quartiles of the CIRP are respectively 18.5 and 24 and the third quartiles of the CIRP are equal to 20 and 26.

4. Testing the Sufficient Statistic Property

In this section, we test the sufficient statistic property using two empirical strategies: first, we use the same empirical framework as the one estimated to derive the aggregate IRF but we add an interaction term between the common marginal cost shock and the ratio kurtosis over frequency at the gas station level; in a second empirical exercise, we will use the CIRP estimated at the gas station level and correlate them with the ratio kurtosis over frequency of price changes also calculated at the gas station level (as in Alvarez et al. 2021b with sectoral data).

In both empirical approaches, we follow the same strategy as the one described in Alvarez et al. (2021b). In a general class of price rigidity models nesting both Calvo and fixed menu cost models, the theoretical prediction of Alvarez et al (2021a) can be written as:

$$CIRP_{iT}(\delta) = \delta T - \frac{\delta}{6}\frac{Kur_i}{Freq_i} \qquad (9)$$

where $CIRP_{iT}(\delta)$ is the cumulated impulse response function of prices in sector *i* to a shock of size (δ) calculated at the horizon T, Kur_i is the kurtosis of the non-zero price change distribution in sector *i* and $Freq_i$ is the frequency of price changes. The relationship is quite intuitive. If prices are fully flexible (i.e. frequency equal to 1 and no selection effect $Kur_i = 6$), then prices will adjust to the long-term price level immediately and the cumulated effect will be equal to the time horizon over which the CIRP has been calculated (*T*) times the magnitude of the shock δ. For a given level of price selection, a longer price adjustment will lower the CIRP since prices will take more time to converge to their new level. If prices are more rigid, the price response is longer and the CIRP will be smaller. For a given frequency of price adjustment, if the degree of price selection is high (i.e. a low kurtosis), it means that prices that will adjust are the ones for which the price gap x_{it} is the largest, price changes will be large and a shock will be transmitted more quickly to prices (like in a standard Golosov and Lucas (2007) model). The CIRP will therefore be larger than in the case with weaker price selection and higher kurtosis.

An "unconstrained" version of the test could also be derived from equation (9) (using a first-order Taylor expansion around the sample means of K and F) to investigate separately the correlation with frequency and kurtosis (Alvarez et al., 2021b):

$$CIRP_{iT}(\delta) = \overline{CIRP}_T(\delta) - \frac{\delta}{6}\frac{\overline{K}}{\overline{F}}\frac{Kur_i}{\overline{K}} + \frac{\delta}{6}\frac{\overline{K}}{\overline{F}}\frac{Freq_i}{\overline{F}} \quad (10)$$

where $\overline{CIRP}_T$, $\overline{K}$ and $\overline{F}$ are the sample means of CIRP, kurtosis and frequency of price changes.

These relations are established for the aggregate price level of a group of firms facing the same marginal cost shock (here the wholesale price shock). We then run the test of sufficient statistic following two separate empirical approaches relying on the heterogeneity across gas stations: one looking at all data pooled together and interacting the response to the shock with the ratio kurtosis over frequency calculated at the gas station level and another one relating CIRP and the ratio kurtosis over frequency both estimated at the gas station level. As baseline regressions, we report results restricting our dataset to gas stations for which we have more than 6 years of continuous price observations, this covers a large majority of observations of our dataset and more than 3,000 gas stations. This allows us to estimate more precisely both the kurtosis of price changes and the CIRP at the gas station level. Section 5 will provide robustness analysis for gas stations with shorter uninterrupted price trajectories.

4.1 Testing the sufficient statistic property at the aggregate level

Empirical model. We start our empirical investigation by using the same baseline empirical framework as the one used for estimating the aggregate IRF and described in equation (7). We add to this empirical model an interaction term of the cost shock ($\Delta R_{t-1,t}$) with the ratio kurtosis over frequency ($\frac{K_i}{F_i}$) defined at the gas station *i*.

$$\Delta p_{i_{t-1,t+h}} = a_h \Delta R_{t-1,t} + b_h \left(\Delta R_{t-1,t} \times \frac{K_i}{F_i}\right) + l_h \Delta p_{t-1,t}^{-i} + u_h + v_{t_h} + w_{hi} + \epsilon_{i,t_h} \quad (11)$$

This additional term will capture how the ratio alters the IRF of prices to a given shock over the horizon h. Summing this expression over horizons, we are able to relate the cumulated sum of price changes between time horizons $h=1$ and H and the interaction term with the ratio kurtosis over frequency:

$$\sum_{h=1}^{H} \Delta p_{i_{t-1,t+h}} = \Delta R_{t-1,t} \sum_{h=1}^{H} a_h + \left(\Delta R_{t-1,t} \times \frac{K_i}{F_i}\right) \sum_{h=1}^{H} b_h + z_{it_h} \quad (12)$$

where $z_{it_h} = \sum_{h=1}^{H} \left(l_h \Delta p_{t-1,t}^{-i} + u_h + v_{t_h} + w_{hi} + \epsilon_{i,t_h}\ \right)$.[12]

Overall, we can estimate the following equation:

$$Cum\Delta p_{iH} = A_H \Delta R_{t-1,t} + B_H \left(\Delta R_{t-1,t} \times \frac{K_i}{F_i}\right) + z_{it_h} \quad (13)$$

where $Cum\Delta p_{iH} = \sum_{h=1}^{H} \Delta p_{i_{t-1,t+h}}$

According to the predictions of the model, if prices are fully flexible at each horizon h, the price change (a_h) in response to a 1%-shock ($\Delta R_{t-1,t} = 1$) should be equal to 1 and so, when cumulating price changes over H periods, A_H should be equal to H.[13] Another prediction is that $B_H = -1/6$, which is the core prediction of the sufficient statistic theory.

This first equation is a test of the constrained version of the model, as described in Alvarez et al (2021b) and we can extend this estimation to test an unconstrained version of the model:

$$Cum\Delta p_{iH} = A_H \Delta R_{t-1,t} + C_H \left(\Delta R_{t-1,t} \times \frac{K_i}{\overline{\overline{K}}}\right) + D_H \left(\Delta R_{t-1,t} \times \frac{F_i}{\overline{\overline{F}}}\right) + z_{it_h} \quad (14)$$

In this setting, following Alvarez et al (2021b) the prediction is that C_H=-D_H, and that C_H is equal to $-\frac{\bar{K}}{6\bar{F}}$. In our case, this term is equal to -1.7.

Results. Table 3 reports the main results of our analysis, for both the constrained and the unconstrained versions of the model. Moreover, we report results using two different definitions of shocks, either the observed change in Rotterdam prices or the gap between the current Rotterdam prices and the moving average over the last 3 weeks. Finally, we consider two

[12] The control variables are identical to those described in equation (7), and we interact the ratio kurtosis over frequency (constrained version) or kurtosis and frequency (unconstrained version) with all the control variables.

[13] We here normalize the shock to be equal to 1 for all gas stations by dividing the cumulating price change by the station-specific estimated long-term reaction of prices to a Rotterdam price change.

horizons H for the calculations of the $Cum\Delta p_{iH}$: 24 days and 30 days. Results for all horizons between 1 and 30 days (for the baseline shock) are plotted on Figures C.1 to C.14 in Appendix C.

[Table 3]

The upper panel of Table 3 reports results for the constrained version of the regression. First, we find that the coefficient related to the Rotterdam shock is very close to the horizon considered (21 for a regression cumulating price changes over 24 days after the shock, 27 for a regression cumulating price changes over 30 days after the shock). Second, we find that the coefficient of the shock interacted with the ratio kurtosis over frequency is between -0.14 and -0.15, a value which is very close to the theoretical prediction of $-\frac{1}{6} \approx -0.167$. Moreover, we cannot reject the hypothesis that our estimated coefficients are statistically (at a 5% level) different of the theoretical value of – 0.167. Interestingly, the values of the coefficient are very stable over the horizons and according to the type of shock considered. Figure C.2 (Appendix C) plots the coefficients estimated for all time horizons between 1 and 30 days after the shock and highlights that the coefficient of the parameter of interest reaches is minimum value after about 20 days (i.e. the time needed for the shock to be fully transmitted to prices) and remains then quite the same for longer horizons.

The lower panel of Table 3 reports results for the unconstrained version of the regression. We find that the coefficient related to the Rotterdam shock is close but slightly lower to those of the constrained regression (19 for the 24-day horizon, 25 for the 30-day horizon) as expected.[14] The coefficient of the shock interacted with frequency is found to be between 1.6 and 1.7, while the coefficient of the shock interacted with kurtosis varies between -1.2 and -1.3. The sign of these estimated coefficients are in line with the theory: for a given frequency of price changes, a larger kurtosis is associated with less price selection and a smaller CIRP. For a given kurtosis, a higher frequency is associated with a quicker response of prices and so a higher CIRP. Moreover, in absolute value terms, both coefficients are quite close and we cannot reject the hypothesis that they are equal to 1.7 (i.e. the value implied by theory). The coefficient corresponding to frequency is even exactly equal to the theoretical prediction of 1.7. The lower value of coefficients for kurtosis is likely to be explained by the fact that kurtosis is more sensitive to even small measurement errors than the frequency. Finally, as in the constrained

[14] In the unconstrained version of the model, the constant of the model is not predicted to be equal to δT any more but to $\overline{CIRP}_T(\delta) = \delta T - \frac{\bar{K}}{6\bar{F}}$ where in our case $-\frac{\bar{K}}{6\bar{F}}$ is about -1.7.

version, the coefficients are stable across horizons and specifications. As highlighted by the full evolution of coefficients over the time horizons (Figure C.4 in Appendix C), they are quite stable after about 20 days after the shock.

Placebo test. The sufficient statistic property also predicts that other moments of the non-zero price change distribution should not have an effect on the CIRP. To test this prediction, we run placebo regressions where we add in interaction with the common shock, the average of (non-zero) price changes, the standard deviation of price changes and the skewness of price changes. In this setting, as we do for the ratio kurtosis over frequency (constrained case) or frequency and kurtosis taken separately (unconstrained case), we interact the other moments with all the controls variables included in the regression. The placebo model could be written as:

$$\begin{aligned} Cum\Delta p_{iH}(\Delta R_{t-1,t}) \\ &= A_H \Delta R_{t-1,t} + B_H\left(\Delta R_{t-1,t} \times \frac{K_i}{F_i}\right) + E_H\left(\Delta R_{t-1,t} \times m_i\right) + F_H\left(\Delta R_{t-1,t} \times std_i\right) \\ &+ G_H\left(\Delta R_{t-1,t} \times skew_i\right) + \omega_{it} \quad (15) \end{aligned}$$

where m_i is the average price change over the sample period in gas station *i*, std_i is the standard deviation of price changes over the sample period in gas station *i* and $skew_i$ is the skewness of price changes over the sample period in gas station *i*.

Table 4 reports results for these placebo regressions. In the constrained regression, we find that the interaction between the shock and the ratio kurtosis over frequency is the only coefficient to be significant at any considered horizons, with coefficients very much in line with the theory (between -0.17 and -0.18). The mean and skewness of price changes are not significant at horizons 24 or 30 days, while standard deviation is significant only at the 24-day horizon but not at 30-day horizon. Figures C.6 to C.9 in the Appendix plot coefficients for all horizons between 1 and 30 days. They confirm that coefficients associated with the interaction terms between the shock and the mean and between the shock and the skewness of price changes are not statistically significant for most of the horizons over which we cumulate price changes. The interaction term between the shock and the standard deviation of price changes becomes insignificant at the 5% level for horizons longer than 28 days.

[Table 4]

In the unconstrained regression, the results are similar (see also Figures C.11 to C.14 for the complete set of coefficients for all time horizons *H* (from 1 to 30 days)): frequency and kurtosis are the only coefficients that are statistically significant, while other moments do not have a statistically significant effect. The significance of the standard deviation becomes even smaller than in the constrained placebo test (as it is not significant any more at the 5% level for the 24-day horizon). The respective coefficients of the shock interacted with frequency and kurtosis are slightly larger in absolute values than in the non-placebo regressions (between 2.1 and 2.2 for the shock interacted with frequency, and -1.5 for the shock interacted with kurtosis), and they remain very close to values predicted by the theory.

4.2 Testing the sufficient property at a disaggregated level

Empirical model. Our second empirical approach consists of using CIRP estimated at the gas station level (as in section 3.3) and relating them to the sufficient statistic also calculated at the gas station level:

$$CIRP_{iH} = \alpha + \beta \left(\frac{Kur}{Freq}\right)_i + \varepsilon_i \qquad (16)$$

where $CIRP_{iH}$ are the estimated cumulated price response to a marginal cost at the gas station over the long run horizon H (as described in section 3.3). The main predictions derived from the theory for a positive 1%-shock are as follows: β should be equal to $\left(-\frac{1}{6}\right)$ whereas the constant should be equal to H, the horizon over which the CIRP is calculated.

We can also test the unconstrained version of this model estimating the following equation:

$$CIRP_{iH} = \gamma + \beta_k \left(\frac{Kur}{\overline{K}}\right)_i + \beta_f \left(\frac{Freq}{\overline{F}}\right)_i + \varepsilon_i \quad (17)$$

Compared with the previous expression, the main prediction is now that $\beta_k = -\beta_f$. Following Alvarez et al (2021b), the estimated coefficients (in absolute values) should be equal to $\beta_k = -\frac{\overline{K}}{6\overline{F}}$. In our case, this term is equal to -1.7.[15]

Figure 5 represents the scatterplot of CIRP and of the ratio of kurtosis over frequency. As predicted by the theory, we find a clear negative slope relating CIRP and the ratio $\frac{Kur}{Freq}$. When looking at the correlation using separately frequency or kurtosis (Figure 6), we find as expected a positive relationship between frequency and CIRP whereas we find a strong negative relationship between kurtosis and CIRP.

[15] A last prediction is that $\gamma = \overline{CIRP}_T(\delta) = \delta T - \frac{\overline{K}}{6\overline{F}}$. In our case, it would imply $\gamma = \alpha - 1.7$.

[Figure 5]

[Figure 6]

Results. As for the aggregate test, we report results restricting our dataset to gas stations for which we have more than 6 years of continuous price observations, for two different definitions of shocks depending on how we measure it, and we consider two horizons for the calculations of CIRP (24 days and 30 days) (see Section 5 for robustness results using gas stations for which we observe continuously prices for more than 2 years without interruption).

Table 5 reports the results of constrained and unconstrained versions of the empirical exercise. In terms of presentation of the results, almost all coefficients are significant at 1%-level since we use a very large sample of individual gas stations (around 3,000 in our baseline regression), this can be partly explained by the small degree of dispersion of the left-hand side variable across gas stations. We here report T-statistics associated with estimated coefficients to provide more information on the relative precision of the estimates and on how much each variable contributes to explain the cross section differences in CIRP.

[Table 5]

In the constrained version of the model, we find a negative coefficient between CIRP and the ratio of kurtosis over frequency. This coefficient is between -0.14 to -0.15 and quite robust over the specifications of the shock or over the different horizons we consider. This estimated coefficient is statistically different from -0.167 but the size of the coefficient is still quite in line with the one predicted by the theory. We might expect to have still some mismeasurement in our variables of interest, which would bias downwards estimated coefficients.

Looking at the unconstrained version of the model, we find a positive correlation between CIRP and frequency whereas we find a negative correlation between kurtosis and CIRP (lower panel of Table 5), which is in line with theoretical predictions. Looking at the magnitude of the coefficients, we expect both coefficients to be equal in absolute values to 1.7. For the parameters associated with frequency, estimated coefficients are very close to this value (between 1.67 and 1.78). For kurtosis, we find slightly lower values than 1.7, but the estimated coefficients are still quite high (between 1.32 and 1.44) and the high values of T-stats provide strong evidence in favor of the relevance of kurtosis to explain the cross section dispersion of CIRP across gas stations.

Placebo test. As in the aggregate test, we run placebo regressions where we add the average of non-zero price changes, the standard deviation of price changes and the skewness of price changes. The regression model in the constrained version could be written as:

$$CIRP_{iH} = \alpha + \beta \left(\frac{Kur}{Freq}\right)_i + \gamma m_i + \theta std_i + \mu skew_i + \varepsilon_i \quad (18)$$

Results are reported in Table 6. In the constrained version of the model, we find that the coefficient associated with the ratio of kurtosis over frequency has a similar value as in the baseline regressions, the value is even closer to its predicted value of -0.167. The T-statistic is also very close to the one obtained in the baseline regressions. Other moments have all a significant effect but the T-statistics associated to these estimates are much smaller than the ones obtained for the ratio. For skewness, the estimates are not significantly different from 0 in all specifications. This suggests that the relationship between CIRP and the ratio is much more robust than the one with other moments. This also suggests that in relative terms, the ratio is much more relevant to explain the cross section of the CIRP than other moments of the price change distribution.

[Table 6]

When looking at the unconstrained version of the model, we find very similar evidence: the coefficients associated with kurtosis and frequency are in line with the ones obtained in the baseline regressions and the T-statistics are also quite the same. For other moments, the coefficients are significant but the T-stats are much lower than the ones associated with frequency or kurtosis. Interestingly, the T-stats associated with the coefficient associated with the kurtosis is also much higher than the ones associated with other moments.

5. Robustness analysis at the gas station level

In the robustness analysis, we perform different empirical exercises using our second empirical exercise which rely on the cross section variations at the gas station level of both CIRP and ratio kurtosis over frequency. The first robustness exercise looks at the full sample of gas stations and investigate to which extent our baseline results are robust to the inclusion of gas stations with fewer observations and a shorter time dimension. We also test whether our conclusions are sensitive to the definition of the horizon. We provide results using an alternative measure of kurtosis taking into account for product heterogeneity. We also perform regressions using the change in the price of Brent (crude oil price) as a measure of shock instead of the

Rotterdam price change. Finally, we include results of misspecified versions of the unconstrained of the model, to investigate to which extent not including the frequency (or the kurtosis) in the regression leads to a significant omitted variable bias.

5.1 Number of observations by gas station

In Tables 7 and 8, we report baseline and placebo regressions for different definitions of our sample of gas stations. When we consider all gas stations with more than 2 years of prices (over the 11 years of our sample), we find a somewhat smaller effect of the ratio. The coefficient is still equal to -0.13. This smaller estimated coefficient might be due to a slightly larger measurement issue for both estimated IRF at the gas station level but also for the kurtosis of price changes. We find that when we restrict the sample to gas stations with more observations, the coefficient is larger with a maximum at around -0.14 to -0.15 in absolute values. When considering the unconstrained model, we find similar conclusions. In particular, we find that coefficients associated with both frequency and kurtosis are lower than in the case considering gas stations with very long trajectories.

[Table 7]

In the placebo test, we obtain similar conclusions for the coefficients associated with the ratio of kurtosis over frequency. For all the samples, the coefficients are in line with theoretical predictions, the magnitude of the coefficients are not far from the baseline exercise and we find relatively larger T-stat for the ratio, frequency but also for kurtosis. More interestingly, in these robustness exercises, we find that kurtosis and frequency are the only moments for which coefficients keep the same sign and the same level of significance (here measured by T-stats). For mean, standard deviation and skewness of price changes, the coefficients do not have the same sign depending on the restrictions we impose on the length of station trajectories. Moreover, the T-statistics decrease when we consider gas stations with more observations, which suggest some issues regarding the robustness of the measure of CIRP or price change statistics. This evidence confirms that kurtosis and frequency are the only moments for which the sign and the relevance of the correlation are robust.

[Table 8]

5.2 Long-term horizon

In the baseline cross-section regressions, we have considered two definitions for the measure of the long-term pass through and the CIRP. In the first one, we measure the long-run pass through as the maximum effect over the horizon 25 to 30 days after the shock and calculate the CIRP as the sum of IRF over the period 1 to 24 days after the shock. In the second one, we use a window between 31 and 36 days for the long run horizon and the CIRP is calculated over the period 1 to 30 days. We consider these two cases since the estimation of the long-run pass through might depend on the horizon we consider. At the same time, the precision of the estimation might be smaller at longer horizons.

As a robustness exercise, we here use two other definitions. The first one defines the maximum looking at the pass through over the period 19 to 24 days and calculate CIRP over the period 1 to 18 days. The second uses a window 37 to 40 days to define the maximum pass through and the CIRP is calculated over the period 1 to 36 days. Results are reported in Tables 9 and 10.

[Table 9]

We find smaller estimated coefficients for the shortest and longest horizons but the coefficients have still the expected sign in the constrained and unconstrained models and show similar values for T-statistics. Moreover, in the placebo exercise, we also obtain that the sign of coefficients associated to other moments is not robust (in particular the mean of price changes), the T-statistics are quite lower than the ones associated with frequency and kurtosis and for skewness, the coefficient is even not significant in some cases.

[Table 10]

5.3 Kurtosis measurement

In this robustness exercise, we use an alternative measure of kurtosis introduced by Alvarez et al. (2021a) to control for mismeasurement of kurtosis due to the presence of unobserved heterogeneity. This issue should be arguably quite limited in our case since we observe the price of a very homogenous product for a given gas station over time. However, the correction for unobserved heterogeneity may help to deal with other potential price measurement issues. We find that kurtosis including this correction for heterogeneity is somewhat lower than our baseline measure of kurtosis but the correlation is very high (see Table D.1 and Figure D.2 in Appendix).

[Table 11]

In Table 11, we report the results of our baseline regressions, we find that in the constrained version of the model the coefficient on the ratio of kurtosis over frequency is somewhat larger and closer to the expected value of -0.167, in some cases we cannot even reject the equality of the estimated coefficients with the value predicted by the model. In the unconstrained version, results are also in line with the baseline results. The placebo estimation results are reported in Table D.3 in Appendix and show the robustness of our initial findings when we correct for unobserved heterogeneity in the measurement of the kurtosis.

5.4 Brent price

We also test the sufficient statistic predictions using the change in the price of Brent as a marginal cost shock instead of the Rotterdam price (see Table B.2 for descriptive statistics on this alternative shock). Oil prices should affect wholesale prices listed at Rotterdam and then retail prices. We here use oil prices converted in euros. The IRF are quite similar as the ones reported for Rotterdam prices except that the long run effects are on average smaller (see Figure B.5). This reflects the fact that the share of oil in the total cost of retail gas station is lower than the share of Rotterdam prices.

[Table 12]

Table 12 reports the results of OLS regressions. We find that baseline results are robust to the use of Brent as a cost shock. Estimated coefficients are smaller than in the baseline cases using Rotterdam prices but they are still in line with the theory in both the constrained and unconstrained version of the model. Placebo regressions (Table D.4 in Appendix) also confirm the baseline results: the ratio of kurtosis over frequency, frequency and also kurtosis have the expected sign, and they contribute more than other moments to explain the dispersion of CIRP across gas stations.

5.5 Misspecified unconstrained model

To investigate the role of kurtosis and frequency taken separately in explaining CIRP dispersion, we run two regressions where we exclude either frequency of kurtosis. Results are reported in Table 13.

[Table 13]

We find that running the model using only frequency or kurtosis leads to bias the estimated coefficient of the moment we include in the regression. For instance, if we include only frequency in the regression, the estimated coefficient is lower than in the case where we include both moments. This suggests an omitted variable bias: since there is a positive correlation between frequency and kurtosis and the regression coefficient of kurtosis on CIRP is negative, we expect a negative bias. A similar finding is obtained for the regression where we include only the kurtosis. In both cases, the R^2 of the regressions are much lower than in the case where we include both moments. A similar conclusion appears when we use the placebo regression, suggesting that the omitted variable in our first set of results (Table D.5 in Appendix) is not the mean, the standard deviation or the skewness of the price change distribution.

6. Conclusion

In this paper, we propose to test the sufficient statistic theoretical result of Alvarez et al. (2016, 2021a) in the clean case study of gasoline prices, where we can rely on the high frequency of price collection for a very homogenous good and where we can relate price changes to an observed marginal cost measure. We document several findings.

First, gasoline prices are sticky (relative to the high frequency of shocks) and we document several patterns of price rigidity. First, retail gasoline price changes are infrequent (the median gas station adjusts prices on average every 4 opening days) while the main cost of the gas station changes every day. Second, the distribution of price changes differs a lot from the cost shock distribution. Third, the probability of a price change monotonically increases with the price gap (i.e. the gap between the actual price and the price that would have been observed under flexible prices). This last pattern of the data is fully consistent with the theoretical set-up of Alvarez et al. (2021a) in which the sufficient statistic result is shown to hold. Then, we document that it takes some time (about 3 weeks) for gasoline prices to incorporate a marginal cost shock. We show that the long term pass through is consistent with the share of the cost of the material input into the total cost (about 0.8), which suggests a full pass through of cost to prices over a long-run horizon.

Second, we relate the cumulative impulse response function of prices to marginal cost to the ratio of kurtosis over frequency using two different empirical exercises. The first one is conducted pooling all price observations together while the second exercise uses the cross sectional dispersion of both the cumulated price response and the ratio kurtosis over frequency at the gas station level. In both empirical exercises, we provide robust and consistent evidence that this ratio correlates negatively with CIRP as predicted by the sufficient statistic theory. The estimated coefficient relating CIRP and the ratio is also very close to -0.167 which is the value predicted by the theory. Besides, we show that both the frequency and the kurtosis of price changes taken separately correlate equally and significantly with CIRP and with the expected sign. We also provide evidence that other moments of the price change distribution do not show the same robust and significant relationship with CIRP as the one obtained for the frequency or the kurtosis of price changes. Finally, we run several robustness exercises using different measures of shocks, different samples of gas stations, different definitions of the long run horizon or for the period over which we calculate the CIRP. In all specifications, the sufficient statistic prediction holds and the magnitudes of the estimated coefficients are robustly consistent with the values predicted by the theory.

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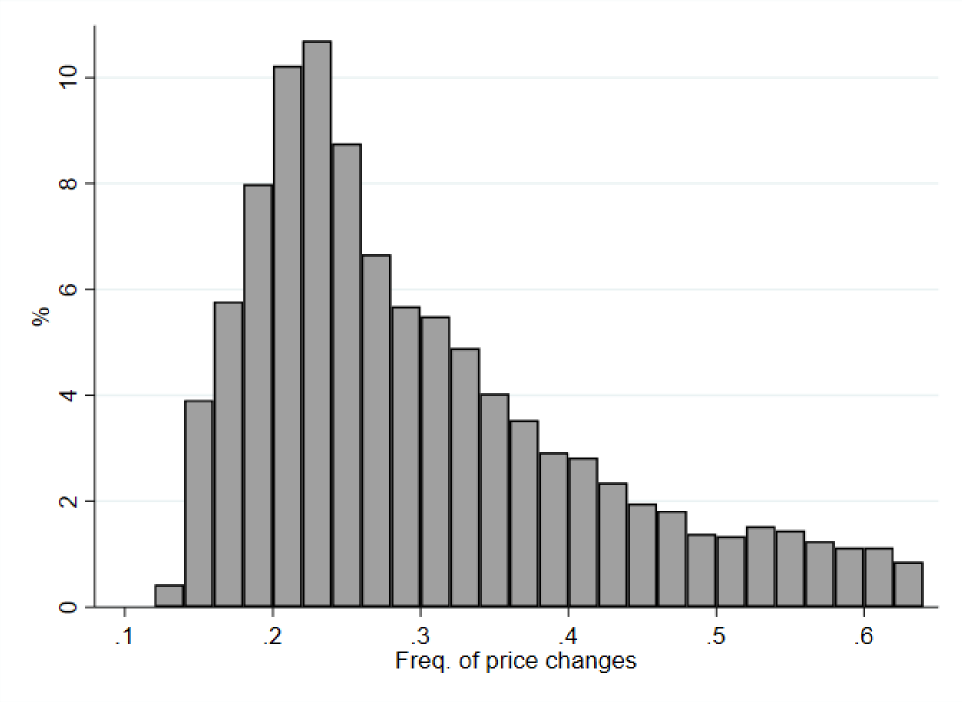
Figures and Tables

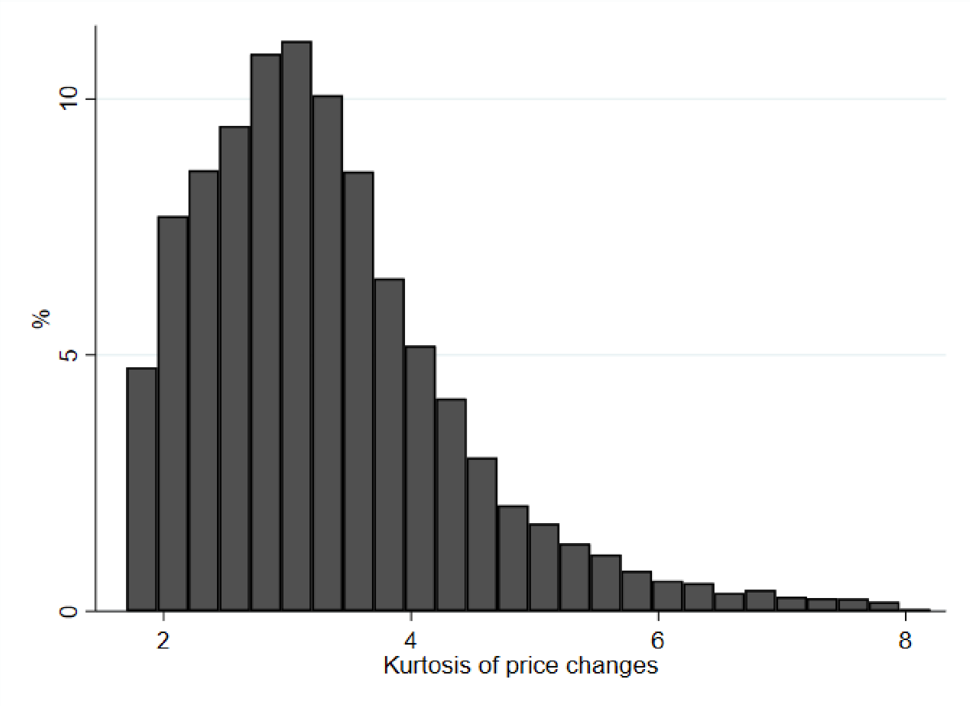
Figures

Figure 1: Distribution of Frequency and Kurtosis across Gas stations

a) Frequency

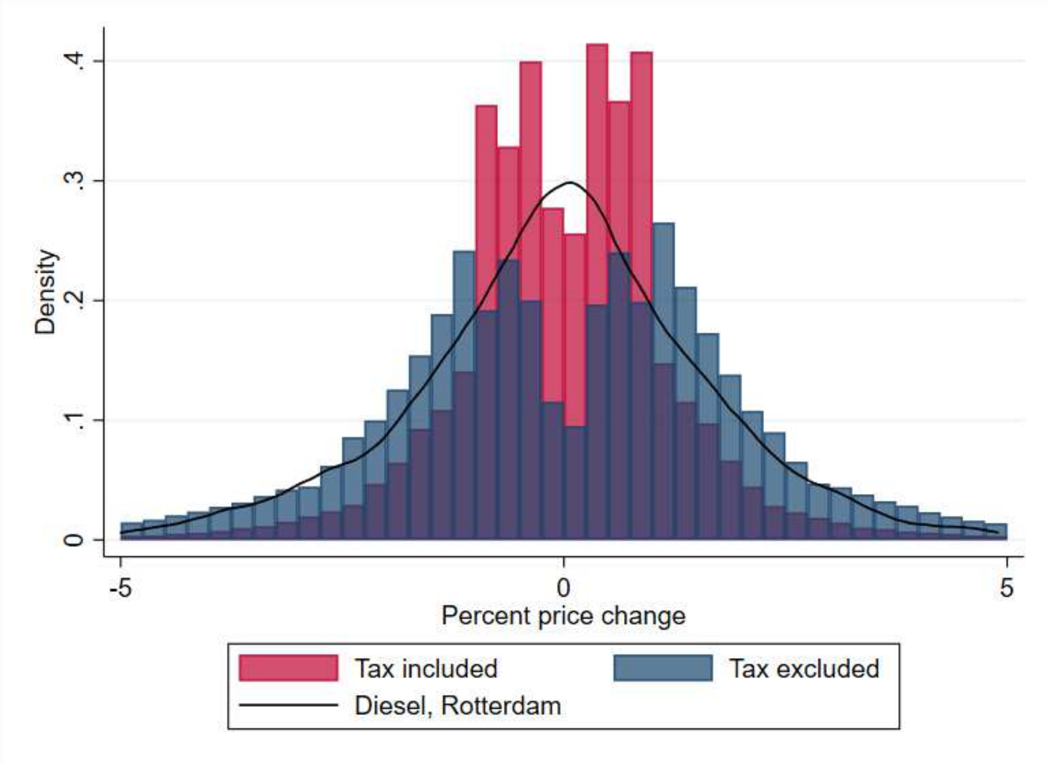


b) Kurtosis



Note: these figures represent the distribution of the frequency of price changes (top panel) and the kurtosis of price changes (bottom panel) calculated at the gas station level. Gas stations opening more than 500 days (2 years of opening days)

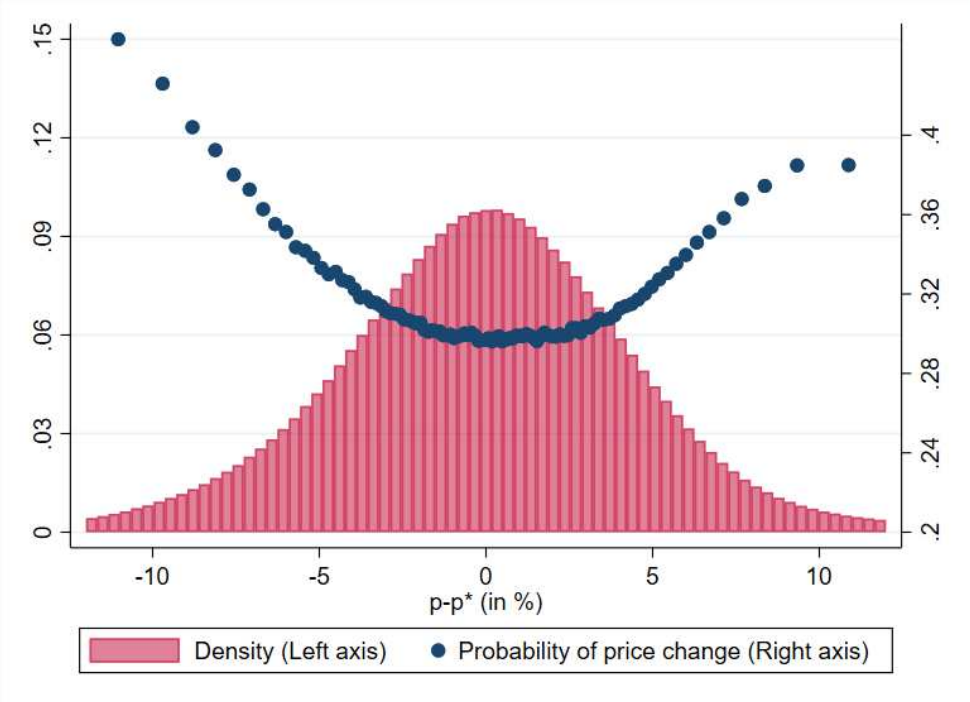
Figure 2: Price change distribution of diesel (before- and after- tax)



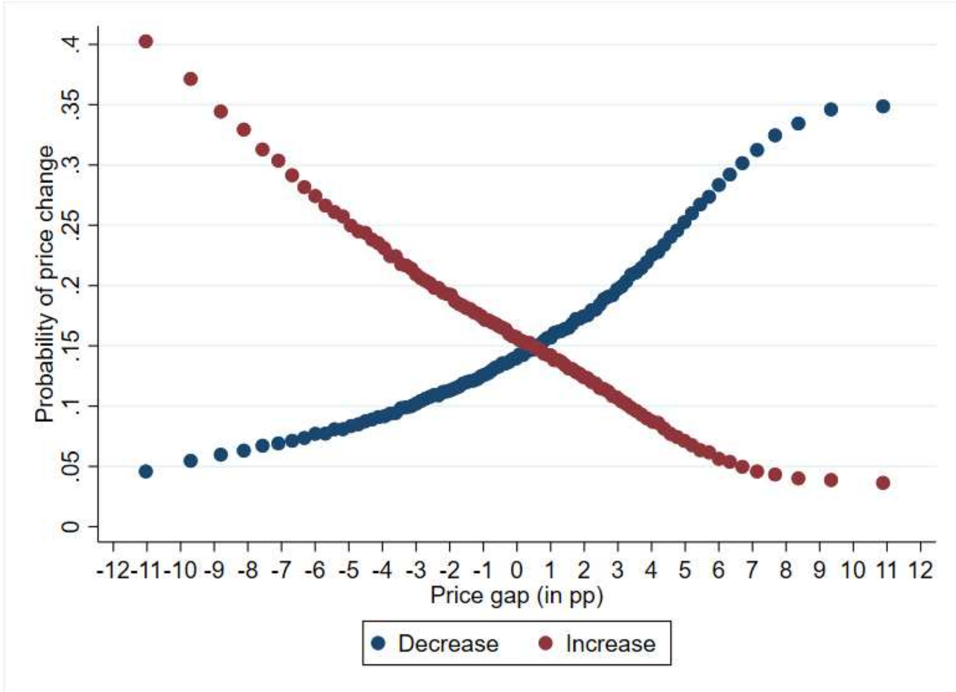
Note: this figure plots the distribution of diesel (non-zero) price changes (included taxes in red histogram and excluded taxes in blue histogram) (gas stations opening more than 500 days (2 years of opening days)). The black solid line plots the distribution of changes in the price of the wholesale diesel price at Rotterdam over the period 2007-2018.

Figure 3: Adjustment hazard rates

a) Probability of price changes

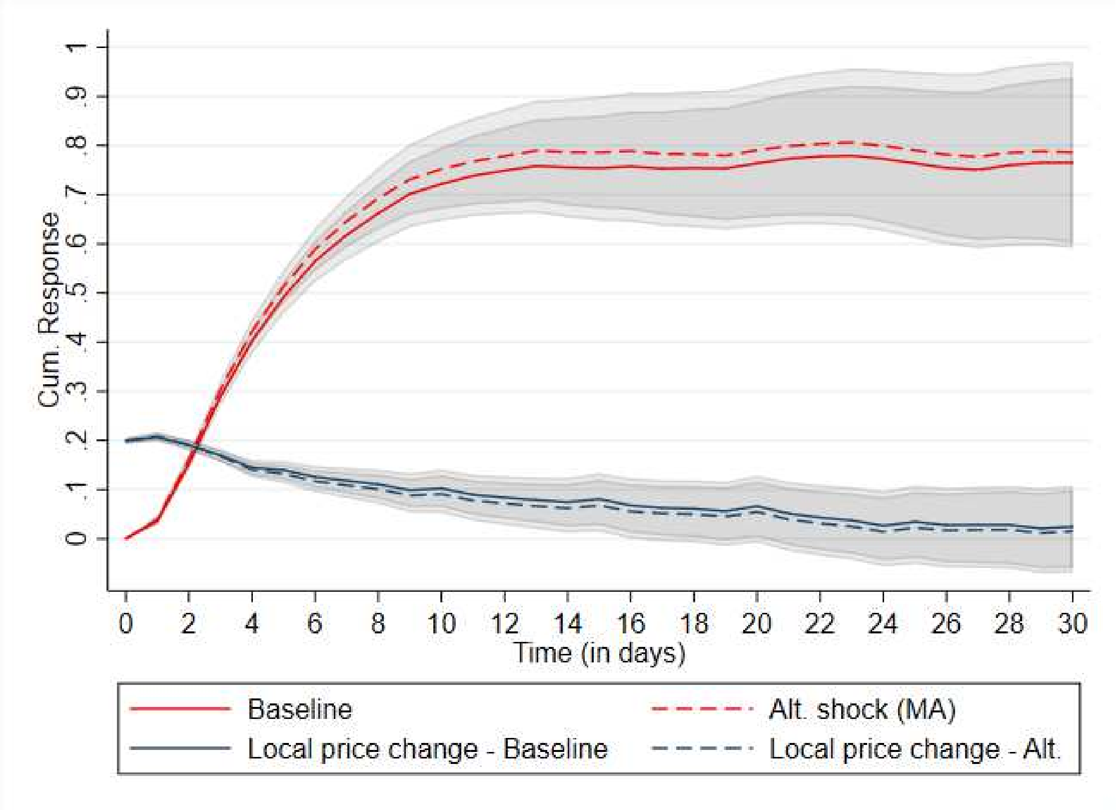


b) Probabilities of price increases/decreases



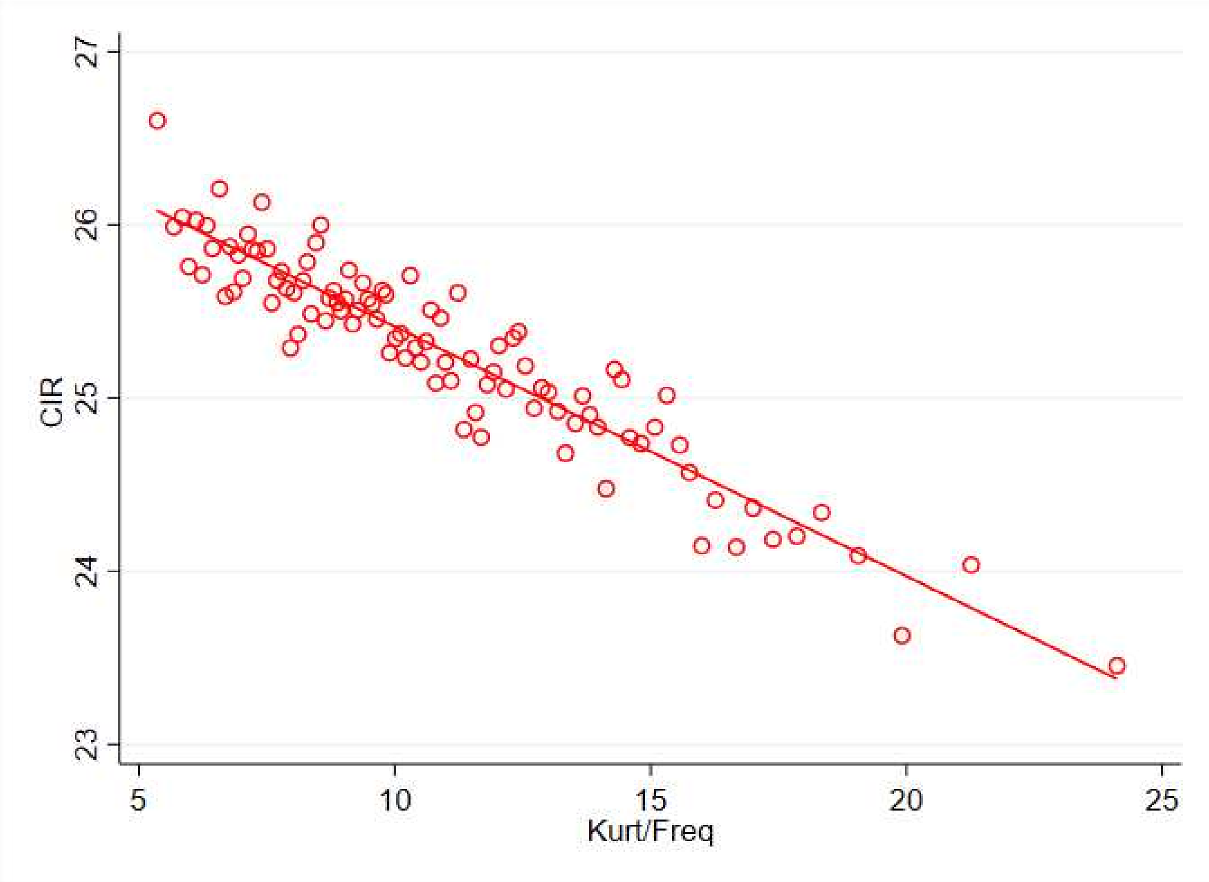
Note: these figures are binscatter plots representing adjustment hazards calculated as the probability of a price change conditional on the value of the difference between p and p*, for gas stations opening more than 500 days (2 years of opening days). p is the actual pre-tax price for a given station on a given day, and p* is the optimal price for that station and for that day, estimated by linear regressions of price levels on Rotterdam wholesale prices on the day of a price change at the station level. Left panel plots the adjustment hazard for all price changes whereas the bottom panel plots the adjustment hazard for price increases and decreases separately.

Figure 4: Impulse Reaction Function of Prices to a Cost Shock – Baseline Estimation



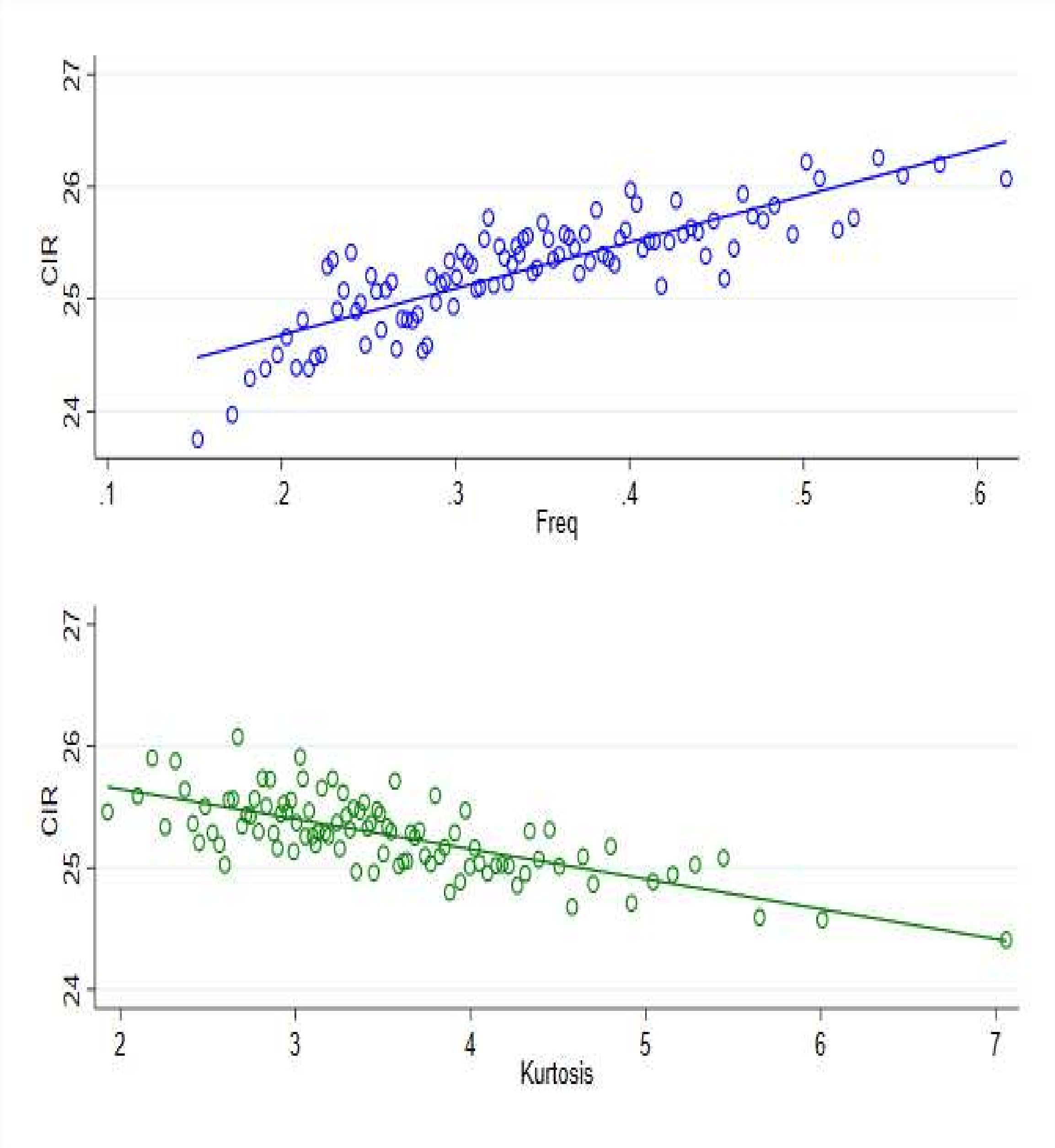
Note: this figure plots the impulse response function of diesel retail prices to a 1% shock in Rotterdam wholesale price (red line), a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue line), for gas stations opening more than 500 days (2 years of opening days). Grey areas correspond to the 95% confidence intervals. Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, as well as up to 5 lags of the average diesel retail price change and include station fixed effects. Standard errors are clustered by date.

Figure 5: Cumulative Impulse Response of Prices to a Cost Shock vs Ratio Kur/Freq (gas station level)



Note: this figure represents the binned scatterplot of the CIRP with respect to the ratio kurtosis over frequency both calculated at the gas station level (the sample is restricted to gas stations with more than 6 years of opening days).

Figure 6: Cumulative Impulse Response of Prices to a Cost Shock vs Kurtosis and Frequency of Price Changes (gas station level)



Note: these figures represent the binned scatterplots of the CIRP with respect to the frequency of price changes (in blue, top panel) both calculated at the gas station level, and of the CIRP with respect to the kurtosis of price changes (in green, bottom panel) both calculated at the gas station level (the sample is restricted to gas stations with more than 6 years of opening days).

Tables

Table 1: Descriptive Statistics on Diesel Price Changes

	Average	P10	P25	P50	P75	P90
Frequency of price changes	0.30	0.18	0.21	0.27	0.36	0.48
Distribution of non-zero price changes						
Average of price changes (in %)	0.01	-0.15	-0.05	0.01	0.09	0.18
Average of price increases (in %)	1.85	1.02	1.40	1.76	2.21	2.75
Average of price decreases (in %)	-1.95	-2.97	-2.36	-1.84	-1.40	-0.99
Standard Deviation (in %)	2.32	1.26	1.67	2.16	2.79	3.53
Skewness	-0.12	-0.45	-0.28	-0.11	0.05	0.21
Kurtosis	3.31	2.12	2.56	3.14	3.83	4.70

Note: in this table, statistics (frequency of price changes and moments of the (non-zero) price change distribution) are first calculated at the gas station level using the available time dimension for each gas station. Then, we calculate average and percentiles of the distribution of gas-station frequencies and moments of the price change distribution (we keep all gas stations opening more than 500 days (2 years of opening days)).

Table 2: Descriptive Statistics on Long term Pass through and Cumulated Impulse Response of Prices (CIRP)

	Average	P10	P25	P50	P75	P90
Long term pass through						
Horizon 25-30 days						
Baseline	0.79	0.67	0.75	0.80	0.84	0.88
Moving Average Shock	0.82	0.73	0.79	0.83	0.87	0.90
Horizon 31-36 days						
Baseline	0.80	0.68	0.76	0.81	0.85	0.88
Moving Average Shock	0.82	0.72	0.79	0.83	0.87	0.90
Cumulative Impulse Response						
Horizon 24 days						
Baseline	19.45	17.54	18.49	19.46	20.38	21.24
Moving Average Shock	19.64	17.76	18.69	19.67	20.60	21.40
Horizon 30 days						
Baseline	24.85	22.64	23.81	24.94	25.93	26.84
Moving Average Shock	25.35	23.17	24.30	25.49	26.47	27.31

Note: we first calculate the long term pass through and cumulative impulse response of prices by estimating the local projection regression at the gas station level, for gas stations opening more than 500 days (2 years of opening days). Then, we report the average and the percentiles of the distribution of estimated pass through and CIRP across gas stations. Long-term pass-through is evaluated as the maximum of long term effects over the horizon period between t+25 and t+30 or over the horizon period between t+31 and t+36.

Table 3: Pooled regressions linking cumulated price changes to the interaction variable "shock x ratio Kur/Freq"

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Shock x Ratio (Kur./Freq.)	-0.139	-0.144	-0.143	-0.147
	(-4.72)	(-4.61)	(-3.42)	(-3.36)
Shock	21.00	21.43	26.69	27.19
	(15.57)	(14.92)	(13.52)	(12.93)
R2	0.339	0.337	0.291	0.287
Unconstrained regression				
Shock x Frequency	1.664	1.701	1.693	1.730
	(5.72)	(5.61)	(4.27)	(4.20)
Shock x Kurtosis	-1.217	-1.273	-1.272	-1.325
	(-2.83)	(-2.79)	(-2.06)	(-2.03)
Shock	19.03	19.43	24.71	25.17
	(15.95)	(15.24)	(13.80)	(13.19)
R2	0.340	0.338	0.291	0.288

Note: in this table, we report the results of the regression of the cumulative price change on the ratio kurtosis over frequency interacted with the cost shock (equation 13) (top panel) and of the regression of the cumulative price change on the rescaled kurtosis and frequency both interacted with the cost shock (equation 14) (bottom panel). We consider two horizons for the calculation of the cumulative price change (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. Each regression controls for up to 5 lags of the shock, shocks on markup (with up to 5 lags of this variable) and the average price change over the sample of stations (with up to 5 lags of this variable). Each control variable is interacted with either the ratio kurtosis over frequency, or the rescaled kurtosis and frequency. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 4: PLACEBO – Pooled regressions linking cumulated price changes to the interaction variable "shock x ratio Kur/Freq"

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Shock x Ratio (Kur./Freq.)	-0.176	-0.183	-0.173	-0.180
	(-5.72)	(-5.62)	(-3.95)	(-3.91)
Shock x Mean	121.7	266.7	209.7	370.1
	(0.24)	(0.45)	(0.25)	(0.43)
Shock x Standard Deviation	35.40	35.80	27.68	28.54
	(2.39)	(2.44)	(1.41)	(1.47)
Shock x Skewness	-0.176	-0.220	-0.159	-0.203
	(-0.79)	(-0.95)	(-0.53)	(-0.64)
Shock	20.60	21.03	26.38	26.86
	(15.44)	(14.70)	(13.40)	(12.74)
R2	0.340	0.338	0.292	0.288
Unconstrained regression				
Shock x Frequency	2.153	2.222	2.093	2.171
	(6.00)	(6.05)	(4.30)	(4.36)
Shock x Kurtosis	-1.463	-1.518	-1.467	-1.52
	(-3.90)	(-3.77)	(-2.71)	(-2.64)
Shock x Mean	164.39	309.08	251.76	412.28
	(0.29)	(0.53)	(0.31)	(0.59)
Shock x Standard Deviation	33.78	33.99	25.54	26.30
	(1.79)	(0.53)	(1.00)	(1.02)
Shock x Skewness	-0.176	-0.219	-0.174	-0.214
	(-0.73)	(-0.87)	(-0.52)	(-0.61)
Shock	18.01	18.34	23.89	24.27
	(14.45)	(13.68)	(12.73)	(12.07)
R2	0.343	0.341	0.294	0.290

Note: in this table, we report the results of the regression of the cumulative price change over horizon *H* on the ratio kurtosis over frequency interacted with the cost shock and other moments interacted with the cost shock (mean, standard deviation, skewness) (equation 15) in the top panel and of the regression of the cumulative price change on the rescaled kurtosis and frequency and other moments (all moments interacted with the cost shock) in the bottom panel. We consider two horizons for the calculation of the cumulative price change (24 days for the first 2 columns, and 30 days for the last 2 columns) and two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. Each regression controls for up to 5 lags of the shock, shocks on markup (with up to 5 lags of this variable) and the average price change over the sample of stations (with up to 5 lags of this variable). Each control variable is interacted with either the ratio kurtosis over frequency, or the rescaled kurtosis and frequency and each of the other moments. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 5: OLS cross-section regressions linking CIRP and ratio

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Ratio (Kur./Freq.)	-0.141	-0.144	-0.146	-0.152
	(-25.7)	(-25.9)	(-23.4)	(-23.1)
Intercept	21.31	21.52	26.87	27.38
	(352.0)	(344.2)	(379.3)	(366.0)
R2	0.205	0.203	0.168	0.165
Unconstrained regression				
Frequency	1.670	1.704	1.753	1.782
	(24.2)	(23.7)	(21.1)	(20.3)
Kurtosis	-1.322	-1.347	-1.351	-1.442
	(-16.0)	(-16.2)	(-14.3)	(-14.6)
Intercept	19.42	19.57	24.87	25.37
	(199.5)	(198.1)	(219.2)	(212.2)
R2	0.190	0.186	0.158	0.152

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency (equation (16)) (top panel) and of the regression of the CIRP on the rescaled kurtosis and frequency (equation (17)) (bottom panel). We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 6: PLACEBO - OLS cross-section regressions linking CIRP and ratio

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Ratio (Kur./Freq.)	-0.184	-0.190	-0.175	-0.183
	(-24.8)	(-25.0)	(-20.6)	(-20.53)
Mean	274.10	377.4	142.2	327.8
	(6.60)	(8.79)	(2.95)	(6.48)
Standard Deviation	43.13	44.46	24.67	24.82
	(9.33)	(9.13)	(4.30)	(4.10)
Skewness	0.014	-0.024	-0.294	-0.347
	(0.12)	(-0.27)	(-2.14)	(-2.43)
Intercept	20.8	21.00	26.60	27.10
	(260.7)	(252.8)	(265.9)	(257.8)
R2	0.247	0.256	0.180	0.188
Unconstrained regression				
Frequency	2.279	2.359	2.137	2.206
	(23.68)	(23.6)	(19.05)	(18.46)
Kurtosis	-1.539	-1.572	-1.538	-1.624
	(-17.25)	(-17.51)	(-14.57)	(-14.9)
Mean	311.1	416.8	171.7	356.0
	(7.17)	(9.30)	(3.47)	(6.85)
Standard Deviation	41.63	42.92	22.62	21.67
	(8.54)	(8.33)	(3.81)	(3.43)
Skewness	0.029	-0.002	-0.300	-0.354
	(0.25)	(-0.02)	(-2.10)	(-2.38)
Intercept	18.08	18.15	24.12	24.56
	(102.1)	(98.17)	(115.2)	(108.9)
R2	0.231	0.239	0.170	0.175

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency and other moments (mean, standard deviation, skewness) in the top panel (equation (18)) and of the regression of the CIRP on the rescaled kurtosis and frequency and other moments (mean, standard deviation, skewness) in the bottom panel. We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 7: OLS cross-section regressions - robustness by duration of price trajectories

	>2years	>4years	>6years	>8years
Constrained regression				
Ratio (Kur./Freq.)	-0.127	-0.139	-0.146	-0.148
	(-22.7)	(-19.9)	(-23.4)	(-20.51)
Intercept	26.28	26.64	26.87	26.83
	(374.7.0)	(332.3)	(379.3)	(342.3)
R2	0.051	0.099	0.168	0.205
Number of gas stations	10,106	4,893	3,116	1,931
Unconstrained regression				
Frequency	1.415	1.601	1.544	1.637
	(18.24)	(19.54)	(21.09)	(21.15)
Kurtosis	-1.273	-1.399	-1.268	-1.005
	(-14.62)	(-13.93)	(-14.26)	(-9.85)
Intercept	24.61	24.79	24.87	24.40
	(227.8)	(203.9)	(219.2)	(182.8)
R2	0.044	0.100	0.158	0.206
Number of gas stations	10,106	4,893	3,116	1,931

Note: in this table, we report the results of the regression of the CIRP (for the baseline shock and after 30 days) on the ratio kurtosis over frequency (top panel) (equation (16)) and of the regression of the CIRP on the rescaled kurtosis and frequency (equation (17)) (bottom panel). We consider different definitions of the sample of gas stations: gas stations with more than 2 years of price observations (first column), 4 years (second column), 6 years (third column) and 8 years (fourth column). T-statistics of the estimates are reported in parentheses.

Table 8: PLACEBO - OLS cross section regressions linking CIRP and ratio

	>2years	>4years	>6years	>8years
Constrained regression				
Ratio (Kur./Freq.)	-0.089	-0.127	-0.175	-0.173
	(-13.44)	(-14.58)	(-20.60)	(-16.91)
Mean	423.8	524.6	142.2	-510.2
	(18.57)	(11.86)	(2.95)	(-5.79)
Standard Deviation	-48.59	-22.48	24.67	31.24
	(-13.07)	(-4.67)	(4.30)	(4.32)
Skewness	-0.830	-0.543	-0.294	-0.076
	(-7.59)	(-3.82)	(-2.14)	(-0.52)
Intercept	26.78	26.86	26.60	26.45
	(317.8)	(285.3)	(265.9)	(229.8)
R2	0.125	0.160	0.180	0.237
Unconstrained regression				
Frequency	0.736	1.530	1.881	1.947
	(7.42)	(14.63)	(19.05)	(18.08)
Kurtosis	-1.041	-1.282	-1.443	-1.134
	(-11.89)	(-12.02)	(-14.57)	(-10.67)
Mean	421.2	533.9	171.7	-528.6
	(18.37)	(12.04)	(3.47)	(-5.65)
Standard Deviation	-56.23	-20.76	22.62	33.40
	(-14.02)	(-4.20)	(3.81)	(4.43)
Skewness	-0.847	-0.591	-0.300	0.008
	(-7.69)	(-4.13)	(-2.10)	(0.051)
Intercept	26.19	25.06	24.12	23.49
	(147.6)	(128.4)	(115.2)	(92.40)
R2	0.122	0.162	0.170	0.240

Note: in this table, we report the results of the regression of the CIRP (for the baseline shock and after 30 days) on the ratio kurtosis over frequency and other moments (mean, standard deviation, skewness) in the top panel (equation (18)) and of the regression of the CIRP on the rescaled kurtosis and frequency and other moments (mean, standard deviation, skewness) in the bottom panel. We consider different definitions of the sample of gas stations: gas stations with more than 2 years of price observations (first column), 4 years (second column), 6 years (third column) and 8 years (fourth column). T-statistics of the estimates are reported in parentheses.

Table 9: OLS cross section regressions linking CIRP and ratio – Long term horizon and CIRP

CIRP horizon	18 days	24 days	30 days	36 days
Long term definition	19-24 days	25-30 days	31-36 days	37-40 days
Constrained regression				
Ratio (Kur./Freq.)	-0.114	-0.141	-0.146	-0.102
	(-24.1)	(-25.7)	(-23.41)	(-15.08)
Intercept	14.85	21.31	26.87	30.57
	(290.3)	(352.0)	(379.3)	(396.4)
R2	0.195	0.205	0.168	0.068
Unconstrained regression				
Frequency	1.425	1.670	1.753	1.339
	(24.12)	(24.20)	(21.09)	(14.74)
Kurtosis	-0.881	-1.322	-1.351	-0.684
	(-12.66)	(-15.97)	(-14.26)	(-6.25)
Intercept	13.06	19.42	24.87	28.79
	(159.1)	(199.5)	(219.2)	(211.7)
R2	0.182	0.186	0.158	0.066

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency (equation (16)) (top panel) and of the regression of the CIRP on the rescaled kurtosis and frequency (equation (17)) (bottom panel). We consider four horizons for the calculation of the CIRP and the long-term pass through 18 days (first column), 24 days (second column), 30 days (third column), 36 days (fourth column); the long-term horizon then corresponds to the maximum on the five following days. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 10: Placebo OLS cross section regressions linking CIRP and ratio – Long term horizon and CIRP

CIRP horizon	18 days	24 days	30 days	36 days
Long term definition	19-24 days	25-30 days	31-36 days	37-40 days
Constrained regression				
Ratio (Kur./Freq.)	-0.154	-0.184	-0.175	-0.135
	(-24.62)	(-24.78)	(-20.60)	(-15.66)
Mean	-181.4	274.1	142.2	-678.8
	(-5.122)	(6.60)	(2.95)	(-10.10)
Standard Deviation	46.60	43.13	24.67	44.72
	(12.45)	(9.33)	(4.30)	(7.67)
Skewness	0.106	0.014	-0.294	0.116
	(1.154)	(0.121)	(-2.14)	(0.761)
Intercept	14.33	20.81	26.60	30.09
	(224.3)	(260.7)	(265.9)	(286.4)
R2	0.251	0.247	0.180	0.133
Unconstrained regression				
Frequency	1.971	2.279	2.137	1.737
	(24.28)	(23.68)	(19.05)	(14.57)
Kurtosis	-1.125	-1.539	-1.538	-0.942
	(-15.37)	(-17.25)	(-14.57)	(-8.32)
Mean	-137.8	311.1	171.7	-637.9
	(-3.72)	(-7.17)	(3.47)	(-9.25)
Standard Deviation	46.79	41.63	22.62	44.83
	(11.57)	(8.54)	(3.81)	(7.30)
Skewness	0.164	0.029	-0.300	0.183
	(1.711)	(0.251)	(-2.103)	(1.151)
Intercept	11.78	18.08	24.12	27.81
	(79.35)	(102.1)	(115.2)	(118.9)
R2	0.235	0.231	0.170	0.127

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency and other moments (mean, standard deviation, skewness) in the top panel (equation (18)) and of the regression of the CIRP on the rescaled kurtosis and frequency and other moments (mean, standard deviation, skewness) in the bottom panel. We consider four horizons for the calculation of the CIRP and the long-term pass through 18 days (first column), 24 days (second column), 30 days (third column), 36 days (fourth column); the long-term horizon then corresponds to the maximum on the five following days. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 11: OLS cross section regressions linking CIRP and ratio – kurtosis corrected for heterogeneity

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Ratio (Kur./Freq.)	-0.152	-0.156	-0.159	-0.167
	(-23.4)	(-23.7)	(-21.10)	(-21.38)
Intercept	21.10	21.31	26.67	27.19
	(362.9)	(355.9)	(385.5)	(375.7)
R2	0.171	0.170	0.144	0.145
Unconstrained regression				
Frequency	1.514	1.545	1.599	1.623
	(22.06)	(21.70)	(19.45)	(18.79)
Kurtosis	-1.031	-1.059	-1.099	-1.224
	(-12.33)	(-12.65)	(-11.42)	(-12.31)
Intercept	19.28	19.44	24.77	25.31
	(183.3)	(181.8)	(202.4)	(197.3)
R2	0.161	0.159	0.138	0.135

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency (equation (16)) (top panel) and of the regression of the CIRP on the rescaled kurtosis and frequency (equation (17)) (bottom panel). We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The measure of the kurtosis that we use here is the alternative introduced in Alvarez et al. (2021a) to control for unobserved heterogeneity (we use 15 lags for the covariance term). The sample is restricted to gas stations with more than 6 years of opening days.

Table 12: OLS cross section regressions linking CIRP and ratio – Brent oil price

CIRP horizon	14 days	18 days	24 days	30 days
Long term definition	15-19 days	19-24 days	25-30 days	31-36 days
Constrained regression				
Ratio (Kur./Freq.)	-0.084	-0.092	-0.118	-0.073
	(-20.23)	(-19.87)	(-22.46)	(-12.09)
Intercept	14.51	14.11	20.19	24.04
	(317.5)	(276.9)	(348.7)	(360.3)
R2	0.145	0.142	0.165	0.053
Unconstrained regression				
Frequency	1.043	1.126	1.285	0.879
	(19.69)	(19.25)	(19.27)	(11.50)
Kurtosis	-0.614	-0.751	-1.224	-0.689
	(-10.38)	(-11.31)	(-16.17)	(-7.98)
Intercept	13.16	12.73	18.85	23.05
	(185.4)	(158.9)	(208.0)	(216.7)
R2	0.130	0.129	0.147	0.051

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency (equation (16)) (top panel) and of the regression of the CIRP on the rescaled kurtosis and frequency (equation (17)) (bottom panel). We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The CIRP is computed with respect to a cost shock measured by the Brent oil price. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table 13: OLS cross section regressions linking CIRP and Kurtosis, Frequency – Misspecified models

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Frequency	1.390	1.418	1.467	1.476
	(19.63)	(19.35)	(17.40)	(16.64)
Intercept	18.38	18.51	23.80	24.23
	(240.0)	(234.7)	(265.4)	(255.3)
R2	0.115	0.112	0.098	0.090
Kurtosis	-0.864	-0.880	-0.870	-0.953
	(-10.48)	(-10.64)	(-9.13)	(-9.61)
Intercept	20.63	20.81	26.14	26.66
	(243.0)	(242.4)	(264.9)	(257.7)
R2	0.034	0.033	0.027	0.029

Note: in this table, we report the results of the regression of the CIRP on the rescaled frequency (top panel) and of the regression of the CIRP on the rescaled kurtosis (equation 17). We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Online Appendix – Not Intended to Be Published

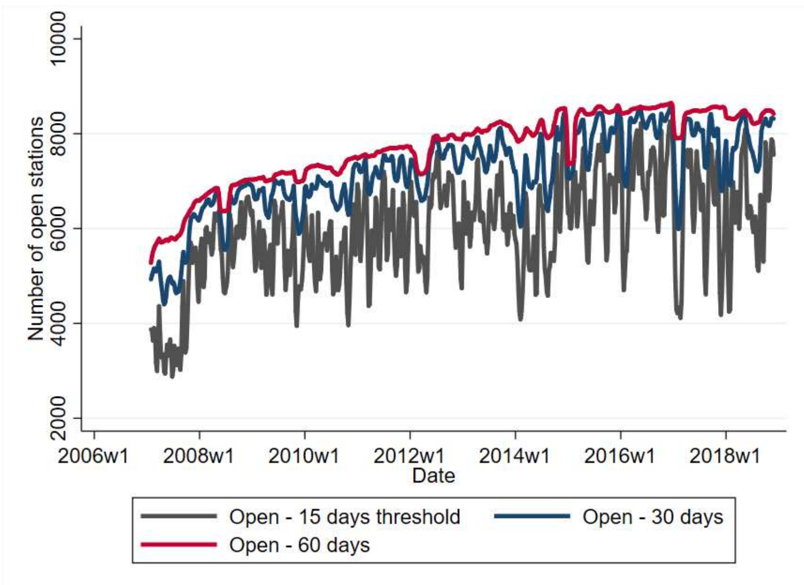
Appendix A - Gasoline micro price data

The dataset we used is provided in a systematic way (through XML files). on a website hosted by the French Government.[16] In this section, we describe the data transformation we operated.

First of all, the data have been put into a panel dataset. The dataset contain only the date of price changes and the new price at the price change date. To get panel series, we assume that a price tag remains similar until the next price change is recorded. When several changes are observed within a single day, we have kept the latest observation.

Another issue is that we do not observe whether a gas station is closed or not in a given day and no price change for a very long period of time could indicate that the gas station is closed. Since the dataset does not contain any information on quantities sold by a gas station, the identification of a closed gas station is inferred from price changes. We adopt the following approach: we consider a station as closed after observing that a price tag lasts for more than a given number of days. Our baseline threshold is 30 days. Therefore, after a period of 30 days with the same price, the price series for that gas station is interrupted. If another price change occurs after 30 days, we assign another identifier to the station and start a new station trajectory.

Figure A.1: Number of estimated open retailers of diesel

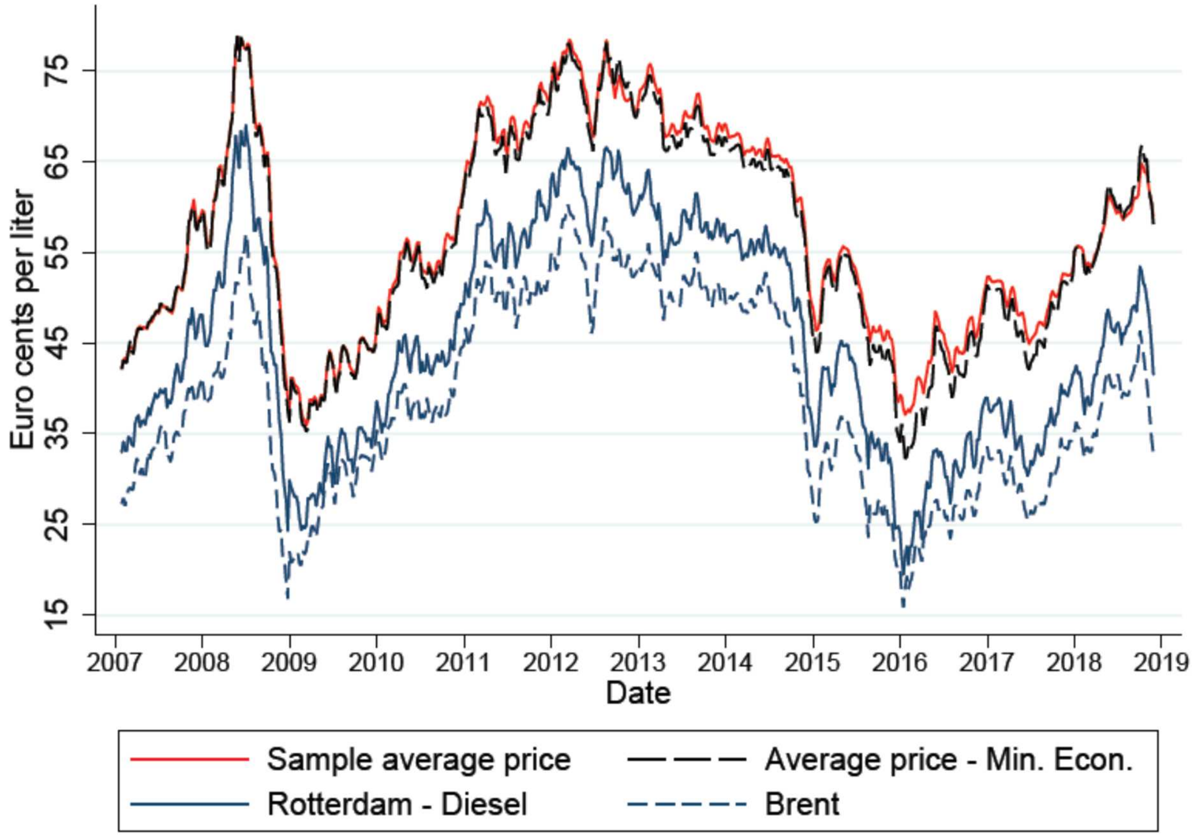


[16] https://www.prix-carburants.gouv.fr/rubrique/opendata/

We have tested three different thresholds: 15, 30 and 45 days. As indicated in Figure A1: the shorter the time span, the more fluctuations we observe in the number of open stations, and the lower the estimated number of open stations. However, using one or the other threshold does not change substantially the patterns of the aggregate price series.

We also exclude top high or low price levels or variations (the latter often corresponding to measurement issues in the reporting. which is subsequently corrected, thus leading to outliers in the price variations). We have dropped 1% of outlier observations.

Figure A.2: Diesel, Brent and Rotterdam wholesale gasoline, weekly level (2007-2018)



Note: the figure plots the weekly average of all diesel prices of our sample (unweighted and excluding taxes, red solid line), the average diesel price released by the Ministry of Economy (excluding taxes, black dashed line), the wholesale diesel price on Rotterdam markets (Reuters, blue sold line) and the price of crude oil (Brent, euros, Bloomberg, blue dashed line).

Table A.1: Diesel price decomposition

	Price incl. taxes	VAT	Other taxes	Price excl. taxes	Rotterdam price	Other costs
In euros	1.25	0.21	0.48	0.56	0.46	0.10
% of price incl. taxes	-	17.1	39.4	46.1	37.5	8.5
% of price excl. taxes	-	-	-	-	81.3	18.5

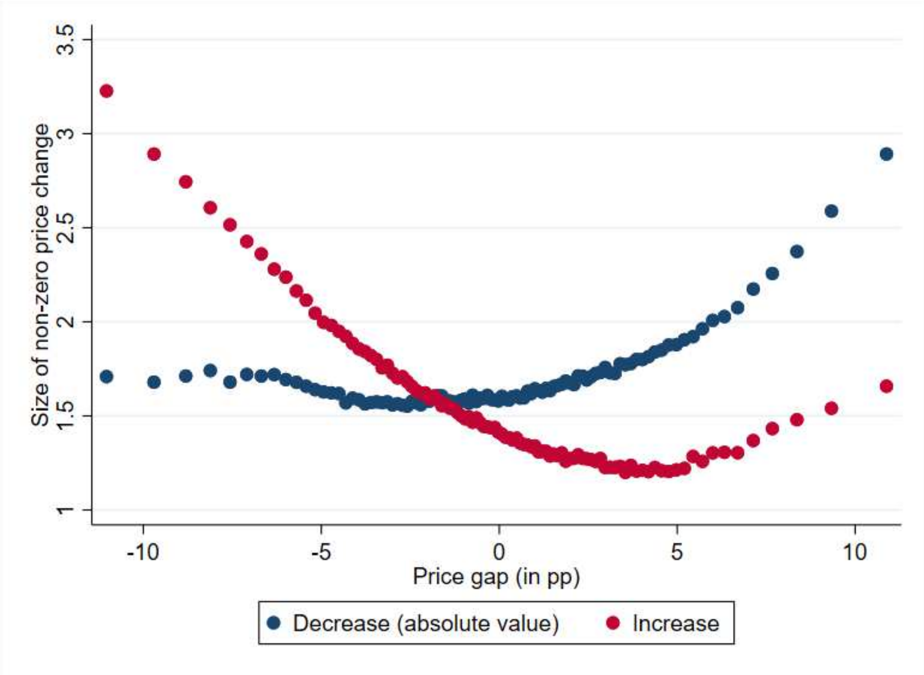
Note: calculations based on average values over the full sample. The first row reports average values of price levels, taxes, wholesale prices as observed over our sample period. "Other costs" is calculated as the difference between "price excluding taxes" and the wholesale Rotterdam price. The second row is calculated as the ratio of the average price including taxes (1.25 euros) and VAT, other taxes… The third row is calculated as the ratio between the average price excluding taxes and wholesale Rotterdam price and the ratio between price excluding taxes and "other costs".

Table A.2: Distribution of the marginal cost shock

In %	Average	P25	P50	P75	SD.	Kurtosis
Rotterdam price change	0.00	-0.99	0.00	1.00	0.19	6.30
Rotterdam price gap with its moving average	-0.02	-2.31	0.08	2.52	0.43	4.82
Brent price changes	-0.15	-1.09	-0.22	1.12	0.21	5.84

Note: in this table, we report descriptive statistics over the full sample on the different shocks we consider.

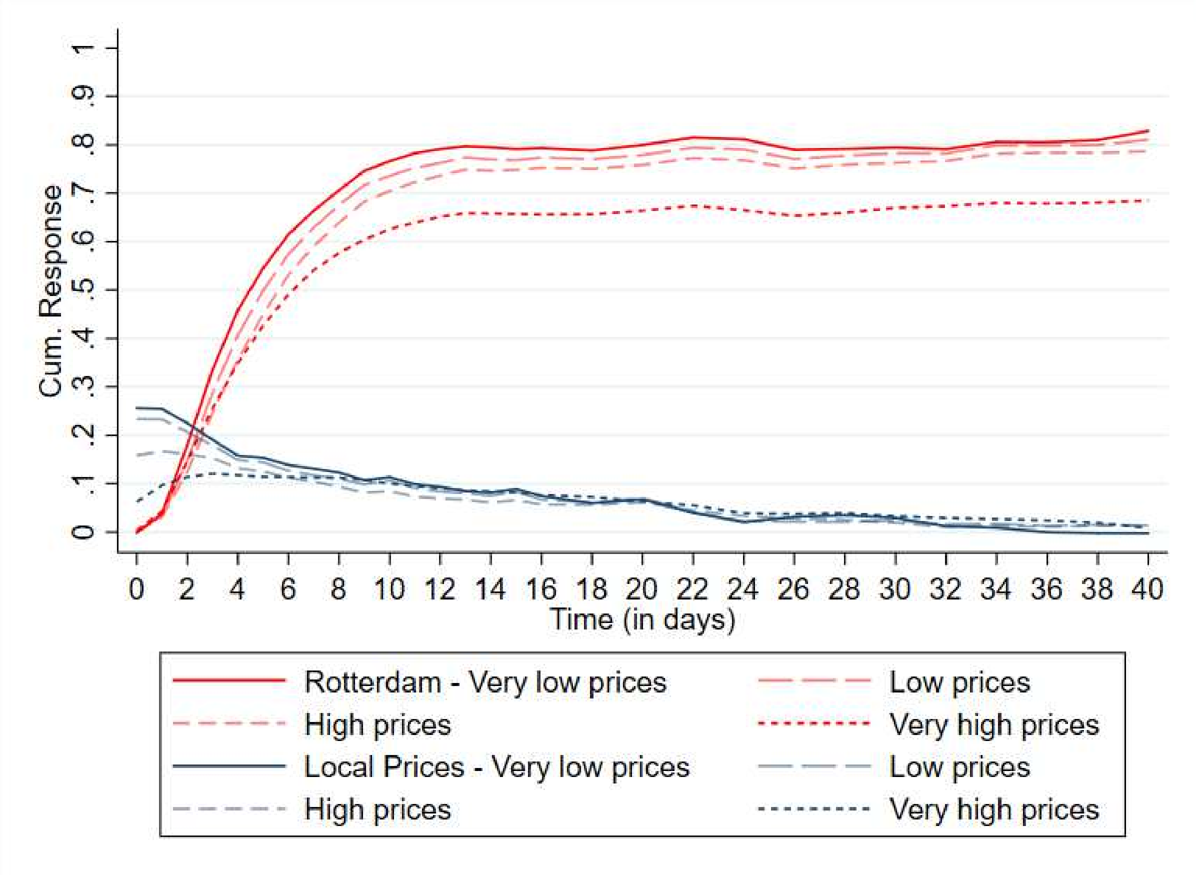
Figure A.3 Size of price changes depending on the price gap



Note: this figure is a binscatter plot representing the size of non-zero price changes conditional on the value of the difference between p and p*, for gas stations opening more than 500 days (2 years of opening days). p is the actual pre-tax price for a given station on a given day, and p* is the optimal price for that station and for that day, estimated by linear regressions of price levels on Rotterdam wholesale prices on the day of a price change at the station level.

Appendix B - Heterogeneity and asymmetry

Figure B.1: Impulse Reaction Function of Prices to a Cost Shock– Position in the Price Distribution



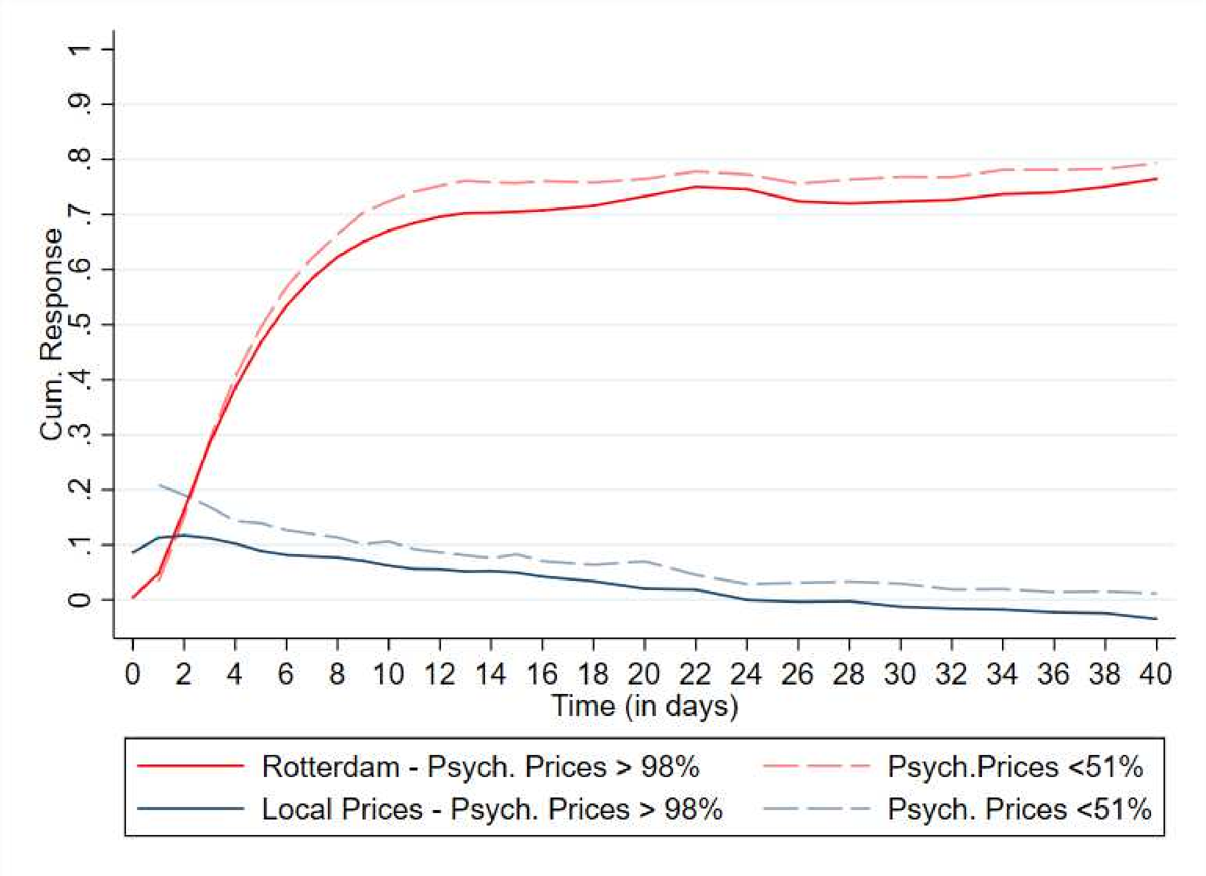
Note: this figure plots the impulse response functions of diesel retail prices to a 1% shock in Rotterdam wholesale price (red lines), and to a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue lines), estimated separately for stations with very low prices (solid), low prices (large dash), high prices (small dash) and very high prices (dotted), for gas stations opening more than 500 days (2 years of opening days). Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, as well as up to 5 lags of the average diesel retail price change and include station fixed effects. Standard errors are clustered by date.

Table B.1: Duration (in open days) before a full transmission of a marginal cost and markup shock

	Very low prices	Low prices	High prices	Very high prices
		Marginal cost		
t	0.00	0.00	0.00	0.00
t+3	0.34	0.29	0.25	0.26
t+5	0.55	0.50	0.45	0.43
t+10	0.77	0.74	0.70	0.63
t+15	0.79	0.77	0.75	0.66
t+20	0.80	0.78	0.76	0.66
Max. value	*0.82*	*0.80*	*0.78*	*0.68*
		Markups		
t	0.26	0.24	0.16	0.06
t+3	0.19	0.18	0.15	0.12
t+5	0.15	0.14	0.13	0.11
t+10	0.11	0.11	0.08	0.10
t+15	0.09	0.08	0.07	0.08
t+20	0.07	0.07	0.06	0.06
Max. value	*0.26*	*0.22*	*0.17*	*0.12*

Note : this table represents the values of the IRF of pre-tax diesel price change, for shocks on marginal costs and on markups, on the day of the shock (t), 3 days after (t+3), 5 days after (t+5), 10 days after (t+10), 15 days after (t+15) the shock, for gas stations opening more than 500 days (2 years of opening days). It also highlights the maximum value attained up until 40 days after the shock. Markup shocks are defined as the average price variation in the 10 closest stations. The marginal cost shock is defined as day-to-day log price variation of Rotterdam wholesale prices. Regressions are estimated separately for each group of price levels, and control simultaneously for marginal cost and markup shocks, as well as up to 5 lags of such shocks, as well as up to 5 lags of the average diesel retail price change over the sample and include station fixed effects.

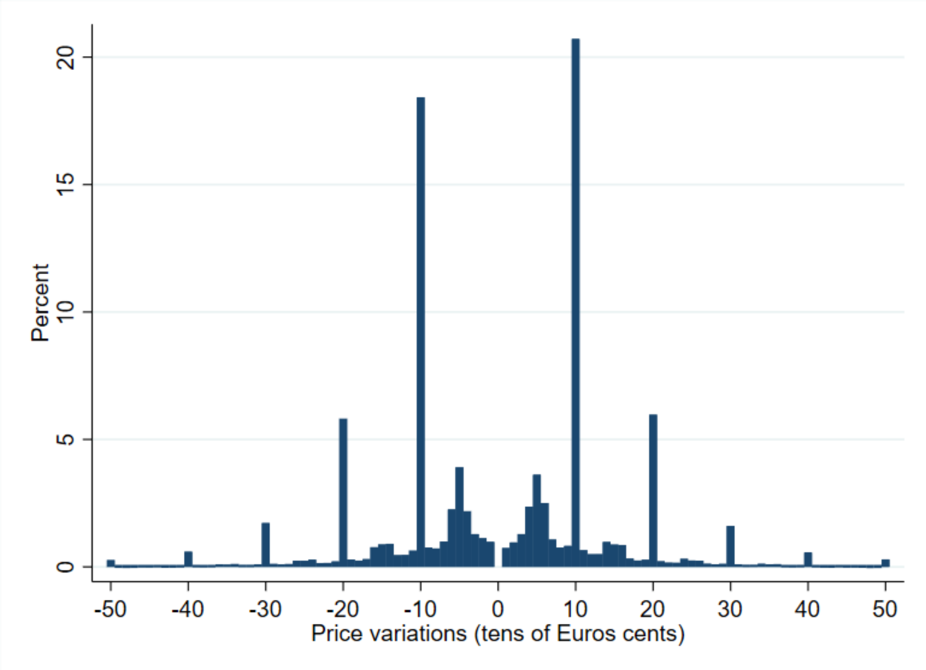
Figure B.2: Impulse Reaction Function of Prices to a Cost Shock – Role of the Frequency of Psychological Prices



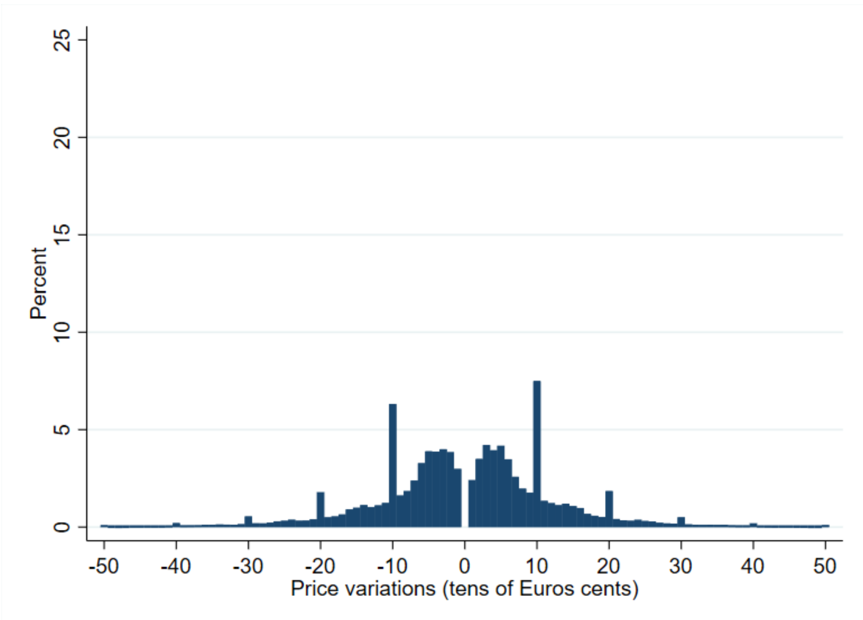
Note: this figure plots the impulse response functions of diesel retail prices to a 1% shock in Rotterdam wholesale price (red lines), and to a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue lines), estimated separately for stations using less psychological prices than average, equal to 51% (dashed) and more psychological prices than the top decile, equal to 98% (solid), for gas stations opening more than 500 days (2 years of opening days). Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, as well as up to 5 lags of the average diesel retail price change and include station fixed effects. Standard errors are clustered by date.

Figure B.3: Price variations (in tens of Euros cents), for stations with more or less psychological price changes than the average

a) Share of psychological price changes above average (>51%)

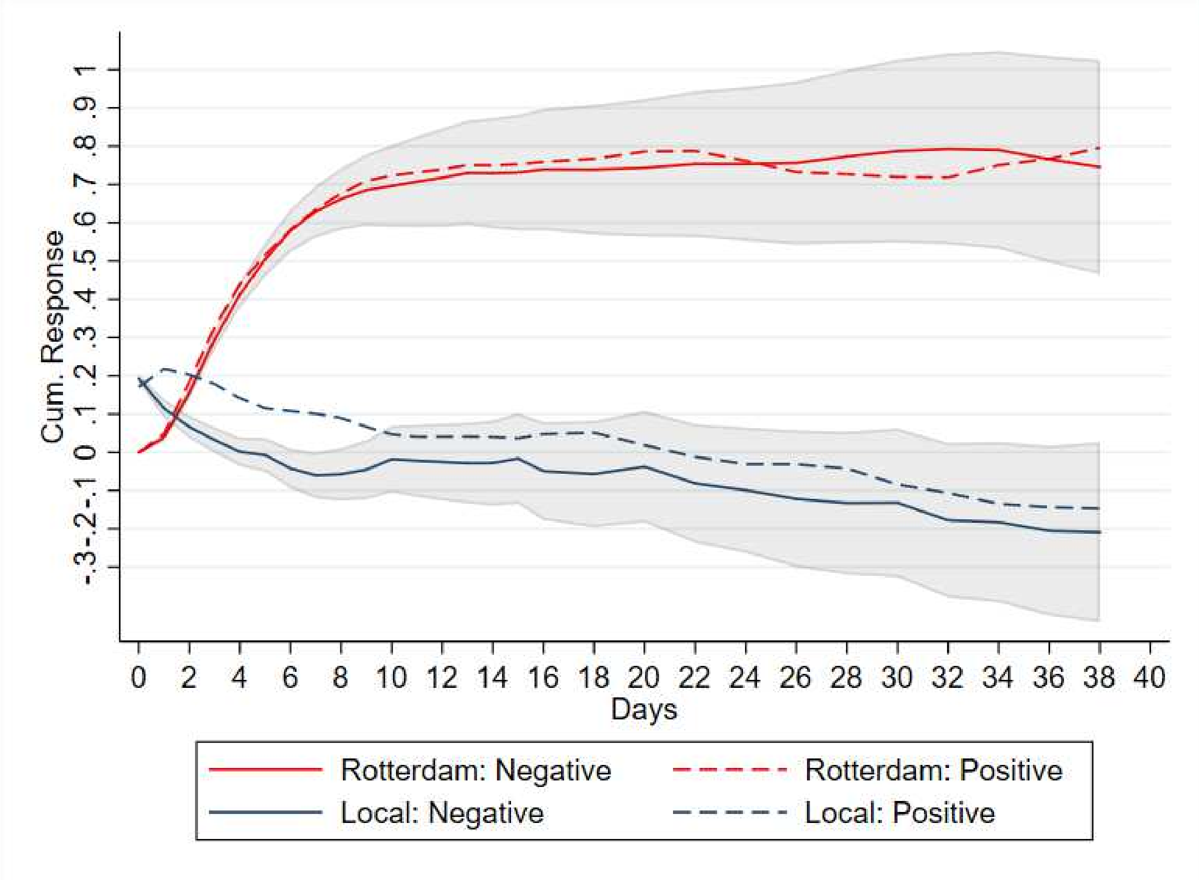


b) Share of psychological price changes below average (<=51%)



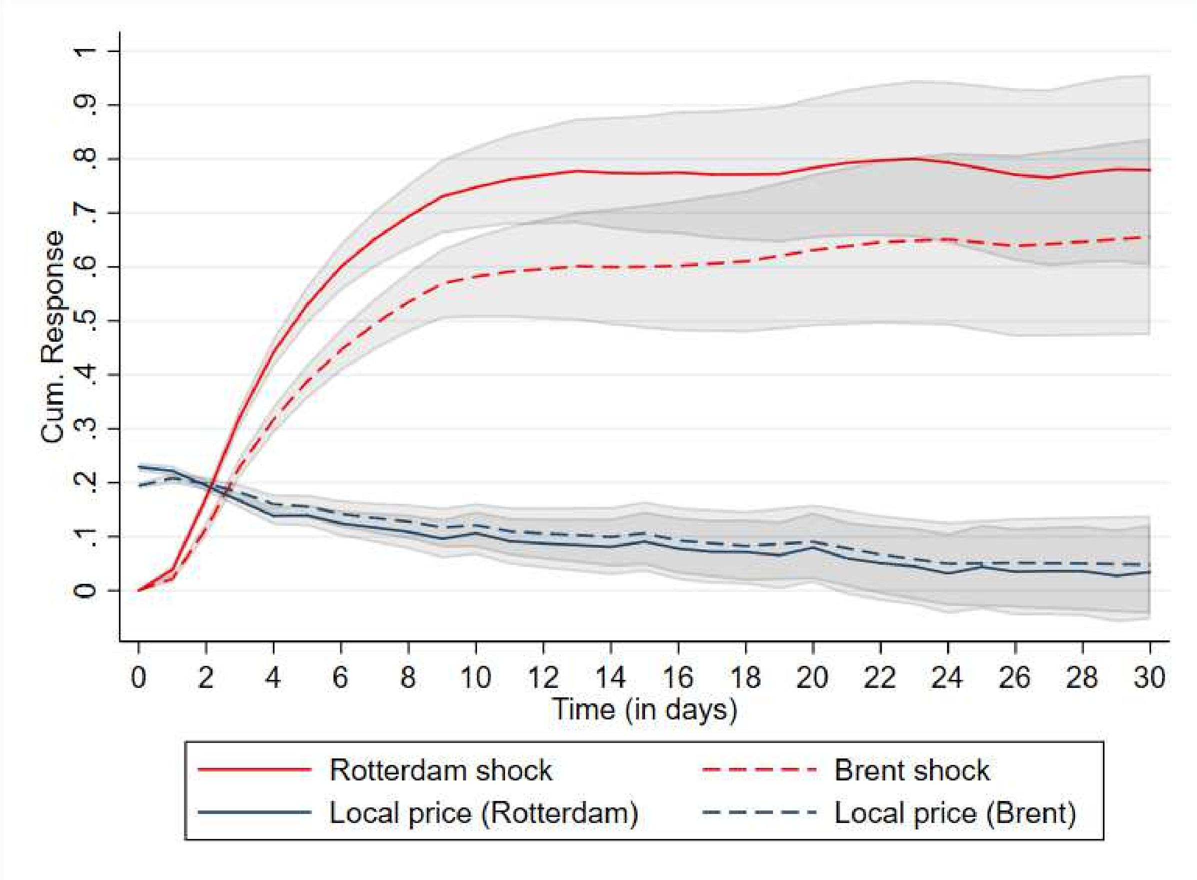
Note: this figure represents the distribution of absolute price variations on the estimating sample, distinguishing stations with above-average share of psychological prices and stations with below-average share of psychological prices (defined as tax-included price-trajectories with a third digit in 0 or 9), for gas stations opening more than 500 days (2 years of opening days).

Figure B.4: Impulse Reaction Function of diesel retail prices to positive and negative shocks on wholesale gasoline prices



Note: this figure plots the impulse response function of diesel retail prices to a 1% shock in Rotterdam wholesale price (red line), and to a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue lines), differentiating between positive and negative shocks (both for Rotterdam wholesale prices and average local prices), for gas stations opening more than 500 days (2 years of opening days). Shocks on Rotterdam wholesale prices are defined as deviation from a 3-weeks moving average of log-Rotterdam wholesale prices. Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, and include station fixed effects. Grey areas correspond to the 95% confidence intervals.

Figure B.5: Impulse Reaction Function of Diesel Retail Prices to Shocks on Wholesale Gasoline Prices and Brent Prices



Note: this figure plots the impulse response function of diesel retail prices to a 1% shock in Rotterdam wholesale price (solid red line) or in Brent crude oil price (dashed red line), and to a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue lines), for gas stations opening more than 500 days (2 years of opening days). Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, as well as up to 5 lags of the average diesel retail price change and include station fixed effects. Grey areas correspond to the 95% confidence intervals, with standard errors are clustered by date.

Appendix C – Estimated Coefficients over the Horizon - Pooled regressions linking cumulated price changes to the interaction variable "shock x ratio Kur/Freq"

"Baseline" shock – Coefficients of the constrained model

Figure C.1 – Shock (A_H)

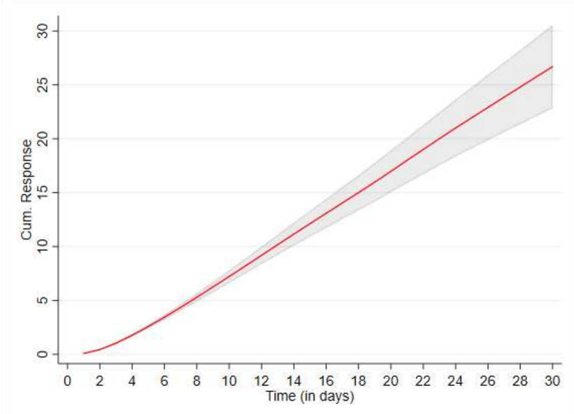
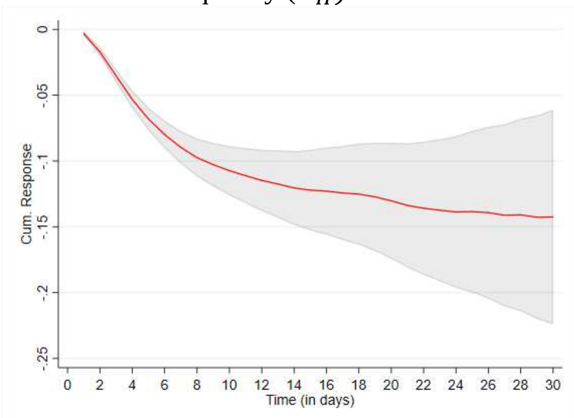


Figure C.2 – Shock interacted with the ratio kurtosis over frequency (B_H)



Note: these figures plot the estimated coefficients of equation (13) where we relate the cumulated price changes over horizon H to the shock (coefficient A_H – left panel) and to the shock interacted with K/F (coefficient B_H – right panel). The x axis gives the horizon H at which we estimate the coefficients. Gray shaded areas give the 95% confidence intervals. The sample is restricted to gas stations with more than 6 years of opening days.

Baseline shock – Coefficients of the unconstrained model

Figure C.3 – Shock (A_H)

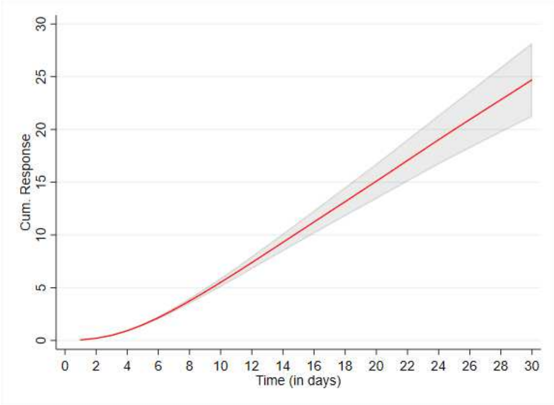
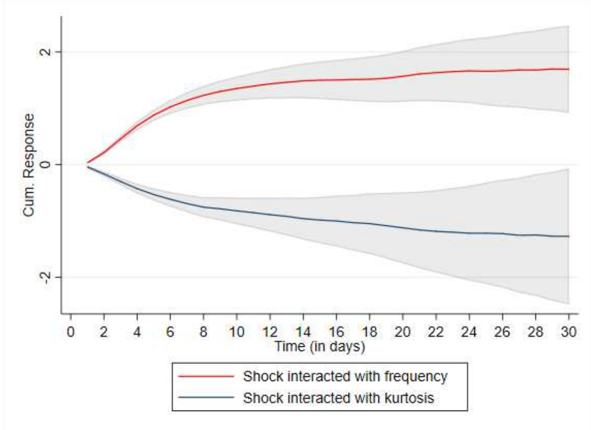


Figure C.4 – Shock interacted with frequency and kurtosis (C_H and D_H)



Note: these figures plot the estimated coefficients of equation (14) where we relate the cumulated price changes over horizon H to the shock (coefficient A_H – left panel), to the shock interacted with $\frac{F_i}{F}$ (coefficient C_H – red line, right panel) and the shock interacted with $\frac{K_i}{K}$ (coefficient D_H – red line, right panel). The x axis gives the horizon H at which we estimate the coefficients. Gray shaded areas give the 95% confidence intervals. The sample is restricted to gas stations with more than 6 years of opening days.

Baseline shock – Coefficients of the placebo test over horizon H (constrained model)

Figure C.5 – Shock (A_H)

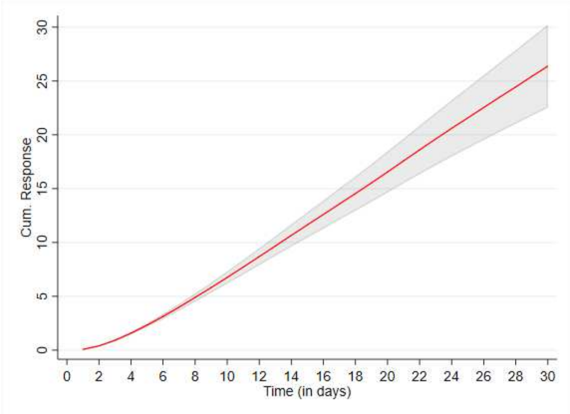


Figure C.6 – Shock interacted with the ratio kurtosis over frequency (B_H)

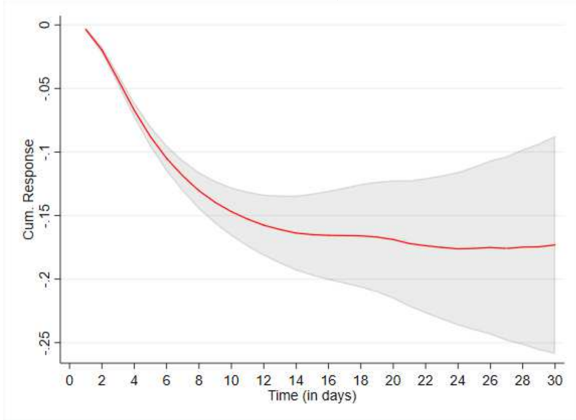


Figure C.7 - Shock interacted with mean (E_H)

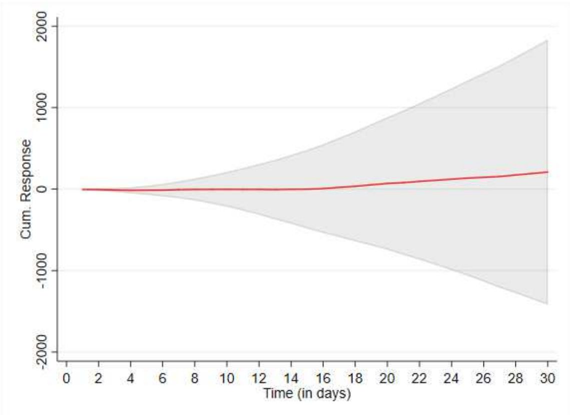


Figure C.8 – Shock interacted with standard deviation (F_H)

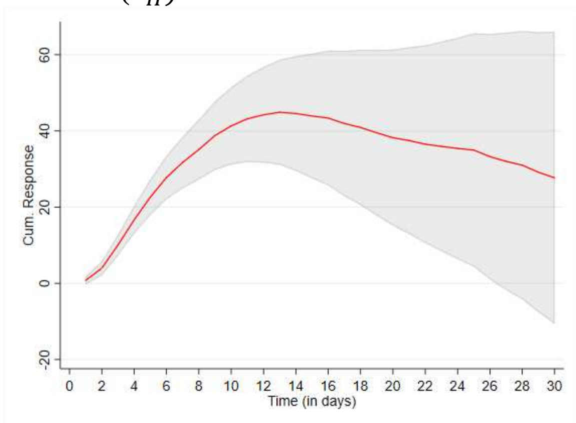
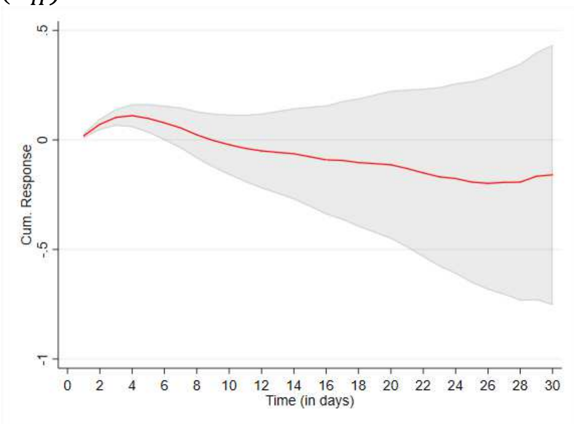


Figure C.9 – Shock interacted with skewness (G_H)



Note: these figures plot the estimated coefficients of equation (15) where we relate the cumulated price changes over horizon H to the shock (coefficient A_H – top left panel), to the shock interacted with K/F (coefficient B_H – top right panel) and to the shock interacted with other moments. The x axis gives the horizon H at which we estimate the coefficients. Gray shaded areas give the 95% confidence intervals. The sample is restricted to gas stations with more than 6 years of opening days.

Baseline shock – Coefficients of the placebo test over horizon H (unconstrained model)

Figure C.10 – Shock (A_H)

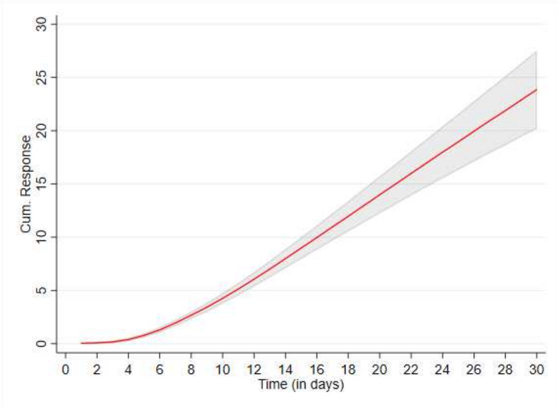


Figure C.11 – Shock interacted with the frequency and kurtosis (C_H and D_H)

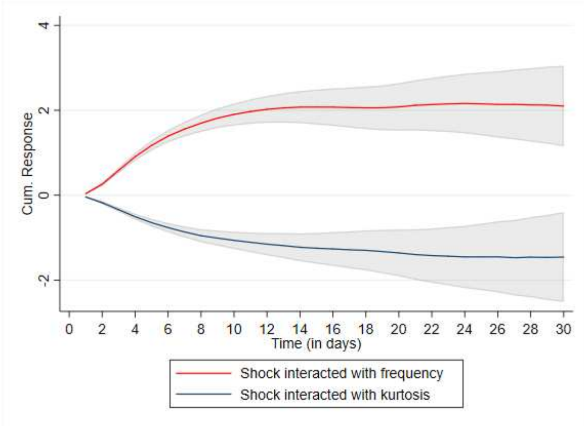


Figure C.12 - Shock interacted with mean (E_H)

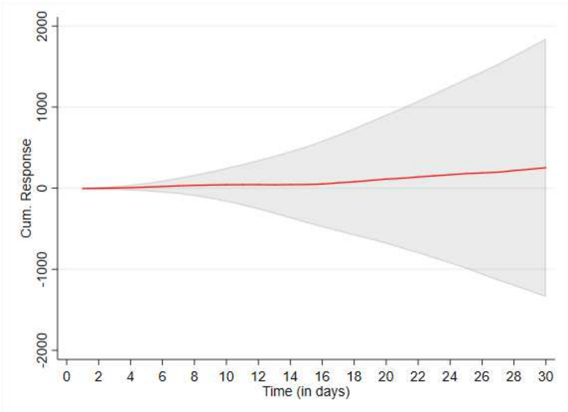


Figure C.13 – Shock interacted with standard deviation (F_H)

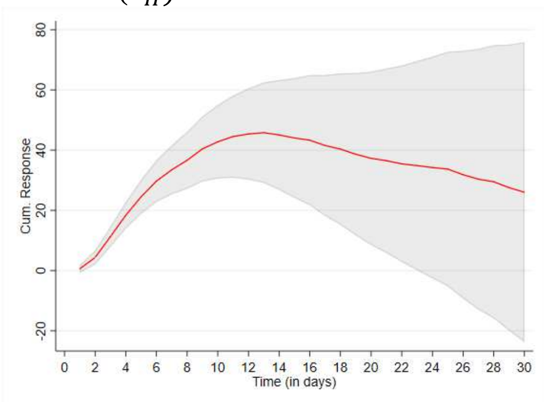
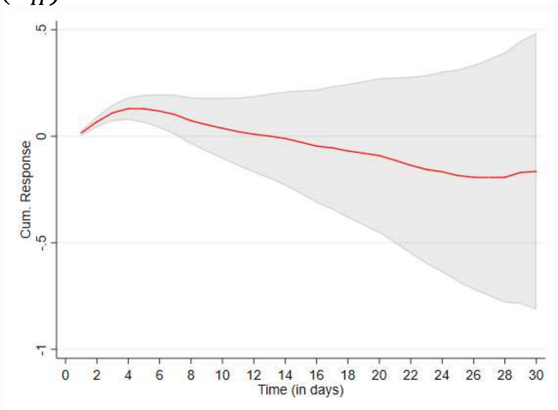


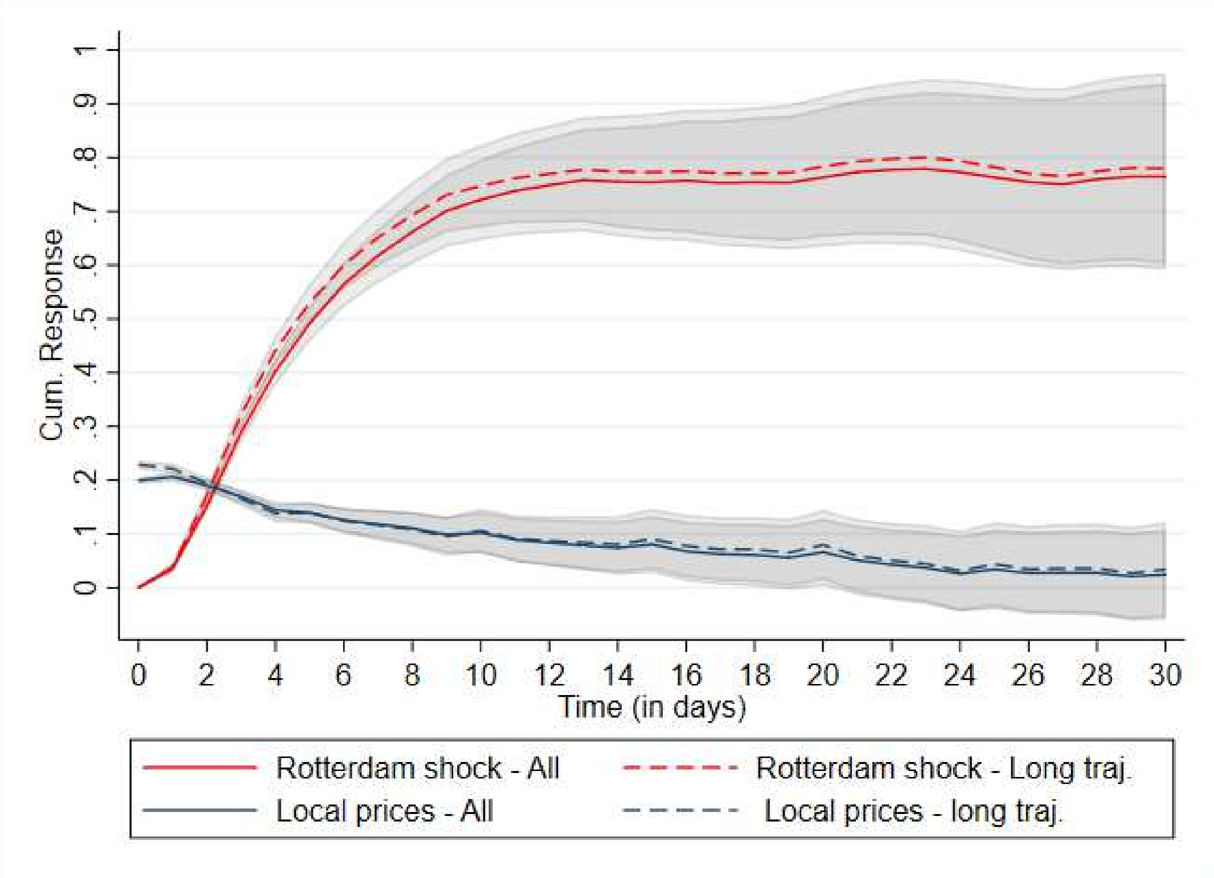
Figure C.14 – Shock interacted with skewness (G_H)



Note: these figures plot the estimated coefficients of equation (15) where we relate the cumulated price changes over horizon H to the shock (coefficient A_H – top left panel), to the shock interacted with $\frac{F_i}{\overline{F}}$ (coefficient C_H – red line, top right panel), the shock interacted with $\frac{K_i}{\overline{K}}$ (coefficient D_H – red line, top right panel) and the shock interacted with other moments (other panels). The x axis gives the horizon H at which we estimate the coefficients. Gray shaded areas give the 95% confidence intervals. The sample is restricted to gas stations with more than 6 years of opening days.

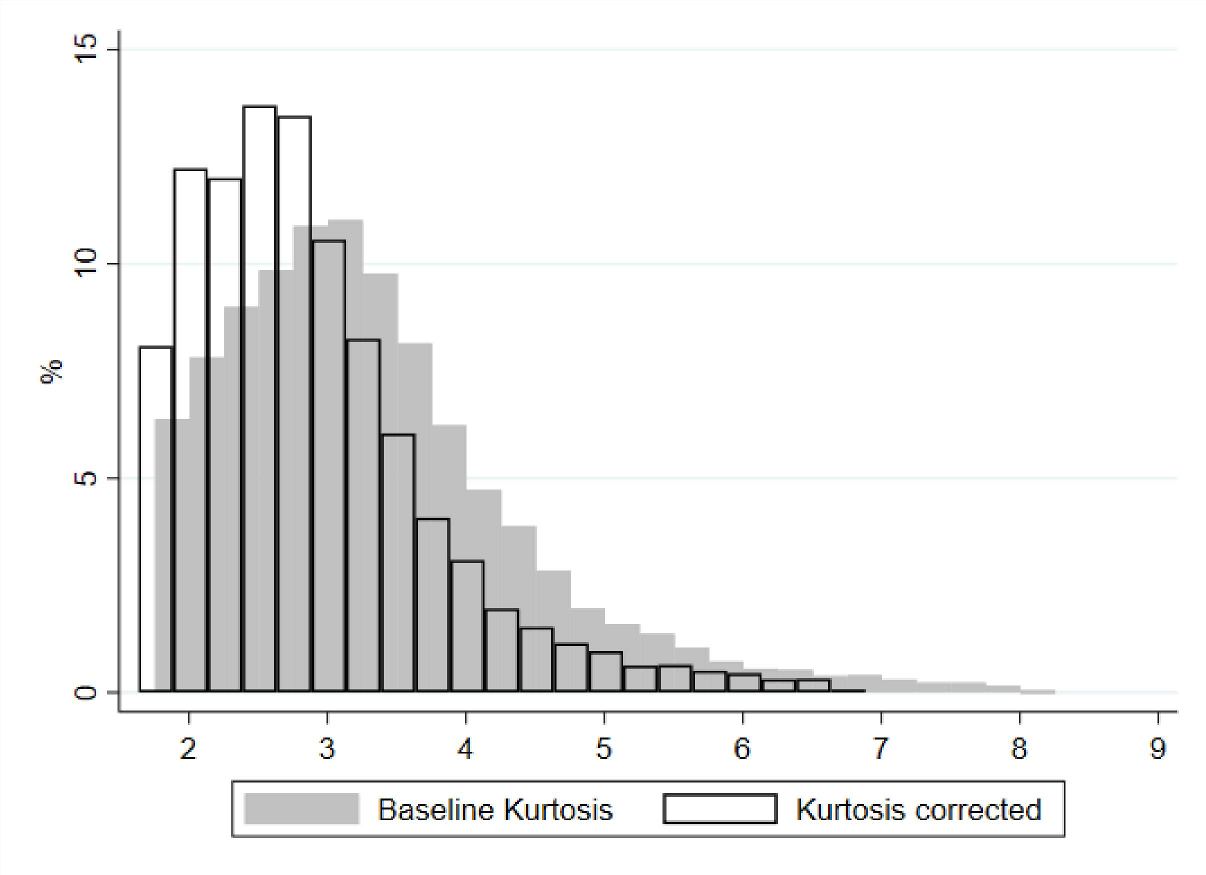
Appendix C – Robustness Analysis

Figure D.1: Impulse Reaction Function of Prices to a Cost Shock – Robustness



Note: this figure plots the impulse response function of diesel retail prices to a 1% shock in Rotterdam wholesale price (red line), a 1% shock on average local price (defined as the average price changes of the 10 closest gas stations) (blue line). Grey areas correspond to the 95% confidence intervals. Regressions control for up to 5 lags of shocks on Rotterdam wholesale price and average local price, as well as up to 5 lags of the average diesel retail price change and include station fixed effects. Standard errors are clustered by date. "All" correspond to the sample restricted to gas stations with more than 2 years of opening days while "Long traj." correspond to the sample restricted to gas stations with more than 6 years of opening days.

Figure D.2: Distribution of Kurtosis Across Gas Stations – including or not correction for unobserved heterogeneity



Note: this figure plots in grey the distribution of the kurtosis and in white the distribution of the corrected kurtosis for unobserved heterogeneity (we allow 15 lags for the covariance term in the corrected measure of kurtosis (Alvarez et al.,2021a)).

Table D.1: Distribution of kurtosis after correction for unobserved heterogeneity

	Average	P25	P50	P75	Correlation
Kurtosis (no correction)	3.31	2.56	3.15	3.83	1
Kurtosis incl correction (10 lags)	2.80	2.20	2.66	3.19	0.87
Kurtosis incl correction (15 lags)	2.85	2.23	2.71	3.27	0.89
Kurtosis incl correction (20 lags)	2.90	2.25	2.74	3.32	0.90

Note: we first calculate for every gas station the kurtosis of non-zero price changes and then we report in this table the average and the percentiles of the distribution of kurtosis over gas stations. The first line corresponds to the case using raw price data without any correction, the second line reports results where we allow 10 lags for the covariance term in the corrected measure of kurtosis (Alvarez et al. 2021a), the second line reports results taking into account 15 lags for the correction and the last line allows for 20 lags.

Table D.2: OLS cross section regressions linking CIRP and ratio – Log specifications

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Ratio (Kur./Freq.)	-0.0825	-0.0835	-0.0657	-0.0670
	(-26.00)	(-25.86)	(-22.62)	(-22.19)
Intercept	3.175	3.186	3.382	3.402
	(434.1)	(426.0)	(498.6)	(481.7)
R2	0.201	0.198	0.160	0.155
Unconstrained regression				
Frequency	0.088	0.089	0.071	0.071
	(24.4)	(24.1)	(21.0)	(20.2)
Kurtosis	-0.072	-0.073	-0.057	-0.059
	(-15.97)	(-16.17)	(-14.02)	(-14.12)
Intercept	3.169	3.180	3.377	3.398
	(418.8)	(413.7)	(486.4)	(469.2)
R2	0.204	0.201	0.163	0.157

Note: in this table, we report the results of the regression of the log of CIRP on the log of the ratio kurtosis over frequency (top panel) and of the regression of the log of the CIRP on the log of kurtosis and the log of frequency (bottom panel). We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table D.3: Placebo - OLS cross section regressions linking CIRP and ratio – kurtosis corrected for unobserved heterogeneity

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Constrained regression				
Ratio (Kur./Freq.)	-0.204	-0.212	-0.193	-0.206
	(-21.18)	(-21.17)	(-16.98)	(-17.33)
Mean	262.1	364.6	129.6	314.4
	(6.45)	(8.30)	(2.67)	(6.19)
Standard Deviation	44.88	46.54	25.84	27.24
	(8.20)	(7.92)	(3.82)	(3.81)
Skewness	0.172	0.139	-0.137	-0.189
	(1.56)	(1.25)	(-1.10)	(-1.36)
Intercept	20.58	20.76	26.38	26.87
	(248.2)	(238.8)	(255.4)	(247.0)
R2	0.212	0.221	0.154	0.166
Unconstrained regression				
Frequency	2.094	2.171	1.954	2.028
	(20.87)	(20.72)	(16.87)	(16.40)
Kurtosis	-1.253	-1.285	-1.268	-1.384
	(-13.81)	(-14.03)	(-11.60)	(-12.37)
Mean	310.3	415.3	168.8	351.0
	(7.01)	(9.12)	(3.38)	(6.76)
Standard Deviation	42.52	43.86	23.58	23.40
	(7.85)	(7.59)	(3.60)	(3.36)
Skewness	0.197	0.169	-0.133	-0.189
	(1.73)	(1.46)	(-0.95)	(-1.31)
Intercept	17.98	18.05	24.03	24.48
	(96.39)	(92.58)	(110.2)	(104.2)
R2	0.202	0.210	0.148	0.156

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency and other moments (mean, standard deviation, skewness) in the top panel and of the regression of the CIRP on the rescaled kurtosis and frequency and other moments (mean, standard deviation, skewness) in the bottom panel. The kurtosis that we compute is corrected for heterogeneity (Alvarez et al., 2021a).We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table D.4: Placebo OLS cross section regressions linking CIRP and ratio – Brent oil price

CIRP period	14 days	18 days	24 days	30 days
Long term definition	15-19 days	19-24 days	25-30 days	31-36 days
Constrained regression				
Ratio (Kur./Freq.)	-0.135	-0.118	-0.147	-0.087
	(-25.76)	(-19.98)	(-20.70)	(-11.09)
Mean	-213.4	-241.6	329.1	-159.2
	(-7.45)	(-7.12)	(8.14)	(-3.29)
Standard Deviation	44.13	33.63	28.24	17.90
	(13.38)	(10.21)	(6.66)	(3.60)
Skewness	0.024	0.222	0.012	0.037
	(0.329)	(2.42)	(0.106)	(0.283)
Intercept	10.52	13.73	19.86	23.84
	(190.0)	(223.1)	(267.4)	(266.4)
R2	0.272	0.187	0.202	0.062
Unconstrained regression				
Frequency	1.700	1.448	1.662	1.054
	(25.25)	(18.84)	(18.34)	(9.91)
Kurtosis	-0.979	-0.894	-1.336	-0.788
	(-16.25)	(-12.81)	(-15.86)	(-8.36)
Mean	-176.1	-213.8	343.5	-146.3
	(-5.84)	(-6.05)	(8.21)	(-2.97)
Standard Deviation	43.60	32.08	22.82	16.55
	(12.18)	(9.02)	(5.20)	(3.07)
Skewness	0.079	0.261	0.001	0.028
	(1.028)	(2.74)	(0.010)	(0.210)
Intercept	8.332	11.92	18.03	22.64
	(67.85)	(88.03)	(114.9)	(114.5)
R2	0.249	0.169	0.178	0.058

Note: in this table, we report the results of the regression of the CIRP on the ratio kurtosis over frequency and other moments (mean, standard deviation, skewness) in the top panel and of the regression of the CIRP on the rescaled kurtosis and frequency and other moments (mean, standard deviation, skewness) in the bottom panel. We consider four horizons for the calculation of the CIRP and the long-term pass through 18 days (first column), 24 days (second column), 30 days (third column), 36 days (fourth column); the long-term horizon then corresponds to the maximum on the five following days. The CIRP is computed with respect to a cost shock measured by the Brent oil price. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.

Table D.5: Placebo - OLS cross section regressions linking CIRP and ratio – Mis-specified models

Long-term	24 days		30 days	
	Baseline	Moving Average Shock	Baseline	Moving Average Shock
Frequency	1.665	1.733	1.524	1.559
	(18.00)	(18.08)	(14.20)	(13.61)
Mean	355.3	462.0	215.8	402.6
	(7.80)	(9.83)	(4.20)	(7.43)
Standard Deviation	21.37	22.23	2.39	0.292
	(4.55)	(4.49)	(0.42)	(0.048)
Skewness	0.533	0.513	0.204	0.178
	(4.380)	(4.179)	(1.40)	(1.18)
Intercept	17.64	17.70	23.68	24.10
	(98.26)	(94.37)	(111.3)	(105.4)
R2	0.144	0.153	0.104	0.108
Kurtosis	-0.715	-0.719	-0.765	-0.826
	(-8.43)	(-8.48)	(-7.78)	(-8.14)
Mean	218.0	320.4	84.6	266.0
	(4.46)	(6.36)	(1.61)	(4.83)
Standard Deviation	-22.97	-23.95	-37.97	-40.69
	(-6.27)	(-6.37)	(-8.43)	(-8.77)
Skewness	0.405	0.387	0.0522	0.009
	(3.22)	(3.03)	(0.350)	(0.061)
Intercept	20.99	21.16	26.85	27.38
	(182.8)	(181.0)	(196.0)	(189.9)
R2	0.059	0.064	0.054	0.063

Note: in this table, we report the results of the regression of the CIRP on the rescaled frequency and other moments (mean, standard deviation, skewness) in the top panel and of the regression of the CIRP on the rescaled kurtosis and other moments (mean, standard deviation, skewness) in the bottom panel. We consider two horizons for the calculation of the CIRP (24 days for the first 2 columns, and 30 days for the last 2 columns). We consider two measures of the shock: the observed change in Rotterdam prices (baseline) or the gap between the current Rotterdam price and the moving average on the last 3-weeks. T-statistics of the estimates are reported in parentheses. The sample is restricted to gas stations with more than 6 years of opening days.