Asymmetric price transmission in the US and German fuel markets: A quantile autoregression approach*

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Abstract

This paper proposes a new econometric model for asymmetric price transmissions. We estimate long-run equilibrium equations between upstream and downstream prices and use quantile autoregression to estimate a quantile-dependent adjustment behavior for lower and upper quantiles of the residual process. We develop a bootstrap cointegration test which is suitable for cointegration relationships that exhibit quantile-dependent adjustment. Furthermore, we introduce the appropriate statistical tests for across-quantile comparisons and overall quantile effects. The methodology is applied to the US and German gasoline and diesel markets. Our empirical results suggest that asymmetries can be found in the early stages of the production chain but are not completely transferred to retail prices.

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1 Introduction

The relationship between upstream and downstream fuel prices is one of the most commonly studied topics in asymmetric pricing. Starting with Bacon (1991) and Manning (1991), a steadily growing literature has emerged (see, among others (Kaufmann and Laskowski, 2005; Grasso and Manera, 2007; Al-Gudhea et al., 2007; Meyler, 2009; Douglas, 2010; Douglas and Herrera, 2010; Fosten, 2012)), trying to determine whether price decreases in upstream markets are adjusted in downstream markets differently to price increases. Previous empirical studies find mixed evidence for price asymmetries depending on the methodology used, on the country or regional market under investigation and on the stage of the supply chain. Perdiguero-García (2013) conducts a meta-analysis of empirical studies on price asymmetries in the oil market from 1991 until 2011. He finds that the research design contributes substantially to finding asymmetries. Also, the level of competition seems to be a key factor for the existence of asymmetries in the market.

Several concepts of asymmetry in price transmissions are found in the literature (see Meyer and Cramon-Taubadel (2004) for a comprehensive survey on asymmetric pricing and Frey and Manera (2007) for an overview of econometric approaches). The specific type of asymmetry we focus on in this paper is long-run asymmetry, where we investigate the reaction times of a cointegrated system after equilibrium errors. Because the cost function for retail fuel is primarily determined by the price of crude oil, we expect fuel markets to be strongly vertically linked. Hence, upstream and downstream prices are expected to maintain a long-run equilibrium which implies that either the upstream or the downstream prices have to adjust in response to equilibrium errors. In this context, asymmetric pricing refers to a situation in which the rate of price adjustment differs, depending on the size or the sign of the deviation from equilibrium.

Long-run asymmetry has a negative effect on consumer welfare if positive equilibrium errors (downstream prices are too high relative to the long-run equilibrium) are not adjusted as quickly as negative equilibrium errors (upstream prices are too high relative to the long-run equilibrium).

Most studies on asymmetric pricing are conducted under a similar framework: A long-run relationship between upstream and downstream prices is estimated by least squares as the first step of the Engle-Granger two-step cointegration procedure. The resulting residual process is separated into two or more regimes and the speed of adjustment in each regime is measured. Significantly different adjustment rates over at least two regimes may be considered as evidence for long-term asymmetry in the cointegrating relationship. The methodological aspects of testing for cointegration with threshold effects have been developed by Enders and Siklos (2001). Although the latter framework is appealing due to its straightforward implementation, it yields contradictory results in a number of studies.[1] These ambiguities may be related to difficulties for the researcher in correctly determining the boundaries of the regimes. Chan (1993) shows that searching over the set of possible threshold values so as to minimize the sum of squared residuals yields a consistent estimate of the threshold parameter. However, it is possible that multiple local extrema can be found and the global extremum might not necessarily be the only reasonable parameter choice from an economic perspective. Additionally, it is not quite clear how many regimes should be used to quantify the degree of asymmetric pricing. Taking into account the existence of transaction costs, it might be reasonable to model the price adjustment process with three regimes - one regime for small equilibrium errors with weak or insignificant adjustment and one regime for large positive and negative equilibrium errors, respectively. However, the standard literature on threshold cointegration (Enders and Siklos, 2001; Hansen and

[1] Compare for example the results in (Al-Gudhea et al., 2007; Douglas, 2010).

Seo, 2002) tends to restrict the analysis to only two regimes. Therefore, a certain degree of subjective judgement is involved in all threshold cointegration models.

Typically, the comparison of adjustment rates between regimes is based on a comparison of conditional-means. Because the analysis is restricted to the mean behaviour of the residual process in each regime, specifying the threshold parameter correctly exerts a substantial influence on the outcomes. Consider, for instance, a residual process that exhibits gradually increasing mean-reversion starting with low mean-reversion for negative deviations up to high mean-reversion for positive deviations, i.e. the adjustment rates do not follow a piecewise linear step-function but rather a monotonically increasing continuous function. In this case, the threshold cointegration approach is not able to produce robust results since the aforementioned adjustment process requires a large number of regimes and hence a correspondingly large number of thresholds to be estimated.[2] Alternatively, the class of smooth transition autoregressive (STAR) models may be used for modelling nonlinear regime-dependent processes (see (Terasvirta, 1994; van Dijk et al., 2002) for an overview). In particular, a logistic transition function could provide an adequate fit for the above described process. However, the recent literature points to severe identification problems associated with STAR models (Ekner and Nejstgaard (2013)).

In line with the majority of papers on the subject, we use Engle-Granger cointegration as a starting point and focus on the mean-reversion of the residual process. But instead of piecewise linear models, we propose a quantile autoregression model. This model expresses the τ-th conditional-quantile function of the response as a linear function of the lagged values of the response. Using quantile autoregression, we are able to analyze different parts of the response distribution and thereby use information that would not be accessible in a conditional-mean paradigm. This is also done

[2] Honarvar (2010) shows in a series of simulation experiments how an incorrect threshold biases the estimated coefficients.

without separating the process into sub-processes in a subjective manner. Since the equilibrium error series - obtained as least squares residuals from the cointegrating regression - are centered around zero by construction, a natural interpretation for the conditional-quantiles applies: Lower quantiles correspond to large negative deviations from the long-run equilibrium and upper quantiles to large positive deviations. A comparison of quantile-dependent autoregressive coefficients enables us to assess the degree of asymmetry more thoroughly.

We apply this new approach to price relationships in the US and German fuel markets. So far it has not been possible to draw any conclusive statement about whether or not prices are adjusted asymmetrically in these fuel markets. We consider the two major fuel types, gasoline (regular grade for the US market and Euro Super95 for Germany) and diesel, and follow the supply chain disaggregation by Grasso and Manera (2007) to track the price transmission at the different stages of the production chain from crude oil to retail prices. The German fuel market has a distinctly different market structure as compared to the US market hence we seek to provide new insights as to how the potential asymmetries are formed.

This article provides two main contributions. First, we develop a new methodology that is able to model asymmetric price adjustments in a more flexible way. Second, we apply this new methodology to the US and German fuel markets and study the price transmission channel between different stages of the supply chain. Comparing the results for two major fuel markets allows us to draw conclusions on how the different market structures may be related to the potentially different degrees of asymmetric price transmission.

The remainder of the paper is organized as follows. Section 2 summarizes the unique characteristics of the US and German fuel markets. Section 3 outlines the quantile regression methodology by Koenker and Xiao (2006) and discusses its applicability in a cointegration model for asymmetric pricing. In Section 4, we apply these techniques to assess the degree of asymmetric price transmission in the US and German fuel markets and Section 5 offers a conclusion.

2 A brief description of the US and German fuel markets

Gasoline and diesel play a primary role in transportation and the economy in general. As liquid fuels, they are derived from crude oil in a refinery process, are stored in fuel depots and are finally distributed to local filling stations. To reveal the potentially asymmetric price transmission in the fuel markets, we follow Grasso and Manera (2007) and analyze individual steps of the transmission chain. At the first stage of the production chain, the price transmission occurs from crude oil to ex-refinery prices. We refer to this as the *first stage* or refining stage price transmission. The *second stage* price transmission then occurs when wholesale price changes affect the cost structure for retailers. We refer to this as the *second stage* or distribution stage price transmission. The refined fuel is transported to the filling stations and priced depending on the fuel grade. Additionally, we consider a *single stage* transmission, directly from crude oil prices to retail prices. Concerning the retail price, one has to distinguish between prices that exclude (PTD) and prices that include tax and duty (ITD). Hence, the taxation structure might have an influence on whether price transmissions are asymmetric.

In this study, we examine two fuel markets which are geographically separated and feature distinct market structures. The US fuel market is characterized by a large dependence on gasoline, with 137.8 billion gallons of gasoline consumption in 2010 whereas diesel consumption amounted to only 49.2 billion gallons (US Energy Information Agency (2015)). The share of diesel-engined retail car sales is generally low in the US.[3] The preference for gasoline can in parts be explained by a higher federal excise tax burden on diesel fuel (24.4 cents per gallon) in comparison to gasoline (18.4 cents per gallon). State and local state taxes and fees amount to a national average total of 49.44 cents per gallon for gasoline and 55.41 cents per gallon for diesel (American Petroleum Institute (2017)). Diesel is almost exclusively consumed by professional users (e.g. truck companies, heavy-duty machinery). Approximately 85% of gasoline sold is of regular grade, therefore we do not consider midgrade and premium gasoline.

US refineries mostly use North American crude oil that is considered light and sweet making it a high quality crude. The price for North American crude oil (WTI) is formed in a trading hub in Cushing, Oklahoma. An ex-refinery price can be stated for the West coast (Los Angeles), East Coast (New York Habor) and the Gulf Coast region. The retail price is then derived from a sample of filling stations throughout the country.

Northern and Central European countries utilize primarily crude oils for which the North Sea crude oil Brent serves as a benchmark. The crude oil production is delivered to the Antwerp-Rotterdam-Amsterdam (ARA) oil hub and transported to nearby refineries. For the retail price of fuel we concentrate on Germany as a major automotive market in Europe and analyze the country-specific fuel prices. A Europe-wide analysis would only be feasible as a panel of individual country data (see Grasso and Manera (2007) or Meyler (2009)) since the market structures and taxing schemes vary greatly. European transportation relies much more on diesel-powered engines than the US. Around half of all new passenger cars sold in 2013 were diesel-powered (Eurostat (2017)). Including industrial use, the overall diesel consumption of 31.3 million tons in 2009 was higher than the gasoline consumption of 20.2 million tons (Statista (2010)). The retail fuel tax in Germany is a compound of a fixed mineral oil tax (diesel 47.04 cents per litre, gasoline 65.45 cents per litre) and a value added tax (VAT) applied to

[3] The share of diesel cars sales rose to an all-time high with 2.94% in 2009 but then dropped back down to 0.33% in 2012 (US Department of Energy (2013)).

both the fuel itself and the mineral oil tax.[4]

3 A quantile-dependent error correction mechanism

The starting point for the empirical analysis of asymmetric price adjustments in this paper is the residual-based cointegration framework developed by Engle and Granger (1987). Two individually integrated time series, y_t and x_t, are said to be cointegrated if they form a linear combination that is stationary. In our empirical application, y_t describes the downstream price and x_t corresponds to the upstream price. In the first step, the long-run equilibrium equation

$$y_t = \beta_0 + \beta_1 x_t + z_t \tag{1}$$

is estimated by least squares to obtain the cointegrating vector. In the second step, a stationarity test is applied on the least squared residual series z_t to ascertain whether the latter indeed constitutes a stationary equilibrium error.[5] The ADF-type Engle-Granger cointegration test assesses the significance of the reversion of the residual process towards its mean.

The majority of studies on asymmetric price adjustment focusses on the mean-reversion property of the cointegration residuals. In order to allow for asymmetric adjustment, the residual process is divided into sub-processes at one or more threshold values. Instead, we propose a quantile autoregression model that is able to measure nonlinear effects in the adjustment process using repeated estimation of a linear model. We assume an autoregressive process of order p and use the following linear function

[4] The mineral tax in Germany has changed five times during our sample. At the beginning of our sample in 1999 the mineral tax for gasoline (diesel) was 50.11 (31.70) cents. It increased by 3.07 cents in April 1999 and then in January of each following year to reach 65.45 (47.04) cents in 2003. The VAT increased in 2007 from 16% to 19%.

[5] The disequilibirum series, although estimated, will be denoted z_t for simplicity.

(see Koenker and Xiao (2006)) for the residuals z_t,

$$z_t = \mu_0 + \alpha_{1,t} z_{t-1} + \alpha_{2,t} z_{t-2} + \cdots + \alpha_{p,t} z_{t-p} + u_t \tag{2}$$

with $\mu_0 = E\left[\theta_0(U_t)\right]$, $u_t = \theta_0(U_t) - \mu_0$ and $\alpha_{j,t} = \theta_j(U_t)$ for $j = 1, \ldots, p$. The θ_j's are real-valued functions $[0,1] \rightarrow \mathbb{R}$ of standard uniform random variables U_t. The functions are unknown and have to be estimated. u_t is a sequence of independently identical distributed random variables with distribution function $F(\cdot) = \theta_0^{-1}(\cdot + \mu_0)$. The autoregressive coefficients $\alpha_{j,t}$ depend on the quantile $\tau \in [0,1]$ of the error term via the function $\theta_j(U_t)$, allowing them to change from one period to the next.

The residual process z_t is assumed to follow a globally covariance-stationary process under the alternative that is allowed to exhibit some locally persistent or even explosive behavior. However, significant mean-reversion is required in some quantiles to ensure overall stability of the process. Estimation of (2) requires solving

$$\min_{\alpha_t \in \mathbb{R}^{p+1}} \left[\sum_{t \in \{t: z_t \geq \mathbf{X}_t \boldsymbol{\alpha_t}\}} \tau |z_t - \mathbf{X}_t \boldsymbol{\alpha_t}| + \sum_{t \in \{t: z_t < \mathbf{X}_t \boldsymbol{\alpha_t}\}} (1-\tau) |z_t - \mathbf{X}_t \boldsymbol{\alpha_t}| \right] \tag{3}$$

with $\mathbf{X}_t = (1, z_{t-1}, \ldots, z_{t-p})$ and $\boldsymbol{\alpha_t} = (\mu_0, \alpha_{1,t}, \ldots, \alpha_{p,t})'$ by using linear programming techniques (see (Koenker and d'Orey, 1987; Portnoy and Koenker, 1997)).
The quantile autoregression can equivalently be written in the random-coefficient notation which will be hereafter referred to as the QAR(p) model,

$$z_t = \mu_0 + \rho_t z_{t-1} + \sum_{j=1}^{p} \gamma_{j,t} \Delta z_{t-j} + \epsilon_t \tag{4}$$

where the additional p lags are included to accommodate the dynamics of the process. The analysis continues to focus on the quantile-dependent autoregressive coefficient ρ_t

or equivalently the mean-reversion $1 - \rho_t$ of the τth conditional-quantile of z_t.[6] Since we are interested in a quantile-dependent error correction mechanism, we apply the QAR(p) model to the least squared residuals resulting from the long-run equation in (1). The coefficient ρ_t is estimated for a sequence of quantiles so that the mean-reversion behaviour can be studied for disequilibria of different signs and magnitudes.

3.1 Testing for cointegration

We test for stationarity of the residual series z_t by applying a modified version of the quantile unit root test developed by Koenker and Xiao (2004). For that purpose, equation (4) is estimated for a range of quantiles (in our case $\mathcal{T} = (0.01, 0.02, \ldots, 0.99)$) and the t-statistic for the null hypothesis of no cointegration, $\rho_t(\tau) = 1$, is computed by

$$t_n(\tau) = \frac{f(\widehat{F^{-1}(\tau)})}{\sqrt{\tau(1-\tau)}}(\mathbf{Z_{-1}}'\mathbf{P}_\Delta \mathbf{Z_{-1}})^{1/2}(\hat{\rho}_t(\tau) - 1) \tag{5}$$

where $\mathbf{Z_{-1}}$ is the vector of the lagged variable z_{t-1} and $\mathbf{P}_\Delta$ is the projection matrix onto the space orthogonal to $\Delta = (1, \Delta z_{t-1}, \ldots, \Delta z_{t-p})'$. $f(\widehat{F^{-1}(\tau)})$ can be written as $f(\widehat{F^{-1}(\tau)}) = (\tau_i - \tau_{i-1})/(\widehat{Q}_{z_t}(\tau_i|\mathbf{X}_t) - \widehat{Q}_{z_t}(\tau_{i-1}|\mathbf{X}_t))$ where $\widehat{Q}_{z_t}(\tau_i|\mathbf{X}_t)$ represents the conditional-quantile of z_t given the information set at point t. The difference quotient, $f(\widehat{F^{-1}(\tau)})$, estimates the conditional density of z_t for some appropriately chosen sequence of τ's. Since the residual process maintains stationarity in the long-run despite the fact that it may display persistence for some quantiles, we use a test statistic that focuses on the overall mean-reversion. For that matter, we employ a quantile Kolmogorov-Smirnov test

$$QKS = \sup |t_n(\tau)| \tag{6}$$

[6] Note that the quantile autoregression should not be estimated in the usual mean-reversion notation since the application of the nonparametric quantile function on the response Δz_t is not equivalent to the application on the response z_t. The former could be used to model momentum shifts in the adjustment process.

for the t-ratios in (5). Large values of QKS signal a strong overall mean-reversion behaviour of the residual process and should therefore lead to a rejection of the hypothesis of no cointegration.

The limiting distributions of the individual t-statistics are nonstandard so that we follow Koenker and Xiao (2004) and use a re-sampling procedure for inference based on the QKS statistic. However, a bootstrap design has to account for the fact that residuals from the cointegrating regression in (1) are used. The existing literature on bootstrapping cointegrating regressions points to some difficulties related to nuisance dependencies between the error term and the regressor(s) in the cointegrating regression (see (Li and Maddala, 1997; Chang et al., 2006)). However, bootstrapping cointegrating regressions is mostly used to test linear hypothesis on the cointegrating vector, whereas in our study we seek to test whether the variables are cointegrated with a potentially time-varying mean-reversion behaviour. The error term in (1) is not well defined under the null of no cointegration so that a contemporaneous dependence structure between z_t and the x_t variable(s) cannot exist. We therefore propose a modification of the bootstrap unit root test in Koenker and Xiao (2004) in order to make it applicable in cointegration testing. In step (4) of the bootstrap algorithm (see below) the cointegrating regression is re-estimated to mimic the data more closely. The algorithm then proceeds as follows:

(1) Fit the pth order autoregression

$$\Delta z_t = \sum_{j=1}^{p} \eta_j \Delta z_{t-j} + u_t \tag{7}$$

by least squares and obtain the parameter estimates $\hat{\eta}_j$ as well as the residuals $\hat{u}_t$.

(2) Draw iid variables u_t^* from the centered residuals $\hat{u}_t$ and generate Δz_t^* using the estimates from the fitted autoregression so that

$$\Delta z_t^* = \sum_{j=1}^{p} \hat{\eta}_j \Delta z_{t-j}^* + u_t^*. \tag{8}$$

(3) Generate z_t^* under the null restriction of a unit root

$$z_t^* = z_{t-1}^* + \Delta z_t^* \tag{9}$$

with $z_1^* = z_1$.

(4) Regard the exogenous cointegration variables as fixed and generate $y_t^* = \hat{\beta}_0 + \hat{\beta}_1 x_t + z_t^*$. Estimate

$$y_t^* = \beta_0^* + \beta_1^* x_t + z_t^{**} \tag{10}$$

by least squares and obtain the residuals z_t^{**}.

(5) Estimate

$$z_t^{**} = \mu_0 + \rho_t z_{t-1}^{**} + \sum_{j=1}^{p} \gamma_{j,t} \Delta z_{t-j}^{**} + \epsilon_t \tag{11}$$

to obtain the bootstrap estimates and test statistics.

The bootstrap estimates for QKS allow to construct p-values for the empirically observed statistic. If the QKS test confirms global stationarity of the residuals we assume a long-run cointegrating relationship and proceed with the analysis of the degree of asymmetry in the adjustment path, especially as to how the mean-reversion parameter differs for different signs and sizes of the shock.

3.2 Testing for quantile effects

Inferential evidence for an asymmetric adjustment behavior is obtained by evaluating the difference in the autoregressive coefficients across quantiles. Least squares residuals are centered around zero by construction so that lower quantiles of z_t refer to large negative and upper quantiles of z_t to large positive deviations. Thus we seek to test the equality of two autoregressive coefficients at the left and right tail of the conditional distribution, for example, according to the null hypothesis $H_0 : \rho_t(\tau_5) = \rho_t(\tau_{95})$ or more generally, we compare a range of coefficients across quantiles with $H_0 : \rho_t(\tau_5) + \cdots + \rho_t(\tau_l) = \rho_t(\tau_u) + \cdots + \rho_t(\tau_{95})$. In both cases, we use a Wald statistic that imposes the corresponding restrictions on the coefficients. The computation of the test statistic requires estimation of the covariance matrix of the estimators.

Cointegration residuals, although covariance-stationary, potentially display a large degree of dependence. Therefore, to account for potentially autocorrelated errors in (4), we suggest a block bootstrapping procedure to estimate the covariance matrix.[7] Evaluating the Wald statistic becomes a direct test for asymmetric adjustment in the cointegration relationship.[8]

Furthermore, we are interested in a comparison of the quantile-dependent coefficients with the conditional-mean coefficient. The corresponding null hypothesis of the constancy of the autoregressive coefficient can be formulated as $\rho_t(\tau_i) = \rho_M$ for all $\tau_i \in [\tau_L, \tau_U] = \mathcal{T}$, where ρ_M is the least squares estimate for ρ in (4). Following Bera et al. (2014), we estimate a sequence of Wald tests with the null hypothesis $\rho_t(\tau_i) = \rho_M$ and compute a Kolmogorov-Smirnov type statistic. The practical application requires an estimate of the joint covariance matrix for the QAR- and AR-parameters. For that purpose we use the above outlined block bootstrap set-up and include the calculation of the least squares estimate for ρ_M. Through resampling we can then calculate the bootstrap variance for ρ_M and subsequently the covariance, $\text{cov}(\rho_M, \rho_t(\tau_i))$ for $L \leq i \leq U$. The Wald statistic is computed for each i. To evaluate the resulting Wald process, we

[7] We intend to retain the dependence structure of the data by choosing a replication with an average block length of $l = 2m$ where m is the most distant lag that still shows a significant impact in the autocovariance function of z_t (see Politis and Romano (1994)). We use 600 replications of the disequilibrium series z_t to estimate the covariance matrix.

[8] The interpretation of the quantile approach, unfortunately, suffers from subjective decision-making in that we have to determine which across-quantile comparison are most relevant. For the empirical part, we therefore display a battery of Wald tests as well as plots of the estimates of ρ_t to depict the adjustment behaviour as accurately as possible.

consider the supremum statistic,

$$W_n := \sup_{\tau \in \mathcal{T}} W(\tau), \tag{12}$$

where W_n does not follow a standard χ^2_p-distribution. The proposed method in Bera et al. (2014) uses an approximation by Davies (1987) that provides an upper boundary for the p-value. The boundary takes the form of

$$\Pr(W_n > u) \leq \Pr(\chi^2_p > u) + \frac{u^{\frac{p-1}{2}}}{e^{\frac{u}{2}} 2^{\frac{p}{2}} \Gamma(\frac{p}{2})} \int_{\mathcal{T}} E \left| \frac{\partial W^{\frac{1}{2}}(\tau)}{\partial \tau} \right| d\tau \tag{13}$$

where p denotes the number of restrictions. Davies (1987) estimates $\int_{\mathcal{T}} E \left| \frac{\partial W^{\frac{1}{2}}(\tau)}{\partial \tau} \right| d\tau$ from the total variation of the Wald process,

$$V = \left| W^{\frac{1}{2}}(\tau_1) - W^{\frac{1}{2}}(\tau_L) \right| + \left| W^{\frac{1}{2}}(\tau_2) - W^{\frac{1}{2}}(\tau_1) \right| + \cdots + \left| W^{\frac{1}{2}}(\tau_U) - W^{\frac{1}{2}}(\tau_k) \right|, \tag{14}$$

where $\tau_1, \tau_2, \ldots, \tau_k$ are the turning points of $W^{\frac{1}{2}}(\tau)$ and L and U are the lower and upper bound of τ, respectively.

3.3 Monte Carlo simulation results

In this section, we use Monte Carlo experiments to examine the properties of the modified QKS test applied to residuals of a cointegrating regression. The Engle-Granger cointegration test based on the ADF statistic and the threshold cointegration test with TAR adjustment serve as benchmarks. We generate series of length $T \in \{100, 500\}$, representing small and medium-sized samples, according to the model

$$\begin{aligned} y_t &= 5 + 2x_t + u_t \qquad u_t = \rho_t u_{t-1} + \vartheta_t \qquad \vartheta_t \sim N(0,1) \\ x_t &= x_{t-1} + \epsilon_t \qquad\qquad\qquad\qquad\qquad\quad \epsilon_t \sim N(0,1) \end{aligned} \tag{15}$$

to investigate the empirical size and power of the cointegration tests. We discard additional 100 observations to randomize initial values. The theoretical justification of the Monte Carlo approach rests on asymptotic results which means that the number of replications, R, should be large for the Monte Carlo experiment to approximate the distribution of a test statistic. However, the QKS test involves a bootstrap procedure and the number of bootstrap replications B are required to be large for the test to be valid. Therefore, a Monte Carlo experiment concerned with bootstrap procedures has to fulfil $B, R \to \infty$. Assuming that the number of bootstrap replications is fixed at $B = 600$, every added Monte Carlo iteration contributes multiplicatively to the overall computational cost. To avoid this inefficiency, we refer to the 'Warp-speed' bootstrap described by Giacomini et al. (2013). The authors provide formal results that it is sufficient to use only one bootstrap replication in each Monte Carlo replication. The critical values are then computed from the empirical distribution of the R bootstrap test statistics. We draw $R = 5,000$ replications from (15) in each experiment.

Setting $\rho_t = \rho = 1$ gives the empirical size of the tests. We compare the power of the tests according to four different choices of the autoregressive coefficient ρ_t: First, we consider constant adjustment $\rho_t = \rho = 0.9$. Second, we generate data according to threshold autoregressive adjustment

$$\rho_t = \begin{cases} \rho_1 = 0.95 & u_{t-1} \geq 0 \\ \rho_2 = 0.75 & u_{t-1} < 0 \end{cases} \tag{16}$$

where negative shocks are adjusted at a faster rate. Finally, we specify a quantile-dependent adjustment behaviour. For that matter, we set $\rho_t = \theta(\vartheta_t) = \min\{c + F(\vartheta_t), 0.95\}$, $c \in \{0.7, 0.8.0.9\}$, where $F(\cdot)$ is the standard-normal cumulative distribution function. The speed of adjustment is inversely related to the magnitude of shocks with an upper boundary of $\rho_t = 0.95$. Furthermore, we use the specification $\rho_t = \tilde{\theta}(\vartheta_t) = \min\{c + F(\vartheta_t), 1\}$, $c \in \{0.5, 0.6.0.7\}$. This specification allows for persistence in case of large positive shocks and moderate mean-reversion for negative shocks.[9]

Table 1 Empirical size and power of the cointegration tests.

	$T = 100$				$T = 500$			
ρ_t	EG	TAR	QKS	QKS^*	EG	TAR	QKS	QKS^*
Size (5%):								
$\rho = 1$	0.054	0.055	0.036	0.078	0.050	0.050	0.050	0.069
Power:								
$\rho = 0.9$	0.218	0.229	0.067		1	1	0.814	
$\rho_1 = 0.95, \rho_2 = 0.75$	0.217	0.246	0.078		0.998	1	0.738	
$\theta(\vartheta_t)$								
$c = 0.7$	0.168	0.178	0.114		0.996	0.999	0.995	
$c = 0.8$	0.119	0.122	0.055		0.959	0.961	0.825	
$c = 0.9$	0.103	0.103	0.048		0.879	0.880	0.287	
$\tilde{\theta}(\vartheta_t)$								
$c = 0.5$	0.359	0.392	0.345		1	1	1	
$c = 0.6$	0.190	0.202	0.242		0.987	0.992	1	
$c = 0.7$	0.101	0.104	0.132		0.786	0.786	0.998	

Note: The data generating process in (15) along with different specifications of ρ_t is used for the size and power experiments. EG denotes the Engle-Granger test. TAR denotes the threshold cointegration test with TAR adjustment. The quantile unit root test by Koenker and Xiao (2006), QKS^*, without a modification for the use of cointegration residuals is only reported for the size experiment. The QKS test is accommodated for small sample sizes, i.e. we estimate the deciles for $T = 100$ instead of percentiles for $T = 500$.

The results are reported in Table 1. We find that the modified QKS test is slightly undersized for small sample sizes but has correct size for $T = 500$. The quantile unit root test by Koenker and Xiao (2006) without a modification for the use of cointegration residuals is still oversized for $T = 500$. The QKS test lacks power in situations of constant or TAR adjustment. Changing the autoregressive parameter ρ_t to a quantile-

[9]Using the symmetry of the standard-normal distribution, we can easily generate data so that positive shocks are reverted and large negative shocks persist. The autoregressive coefficient ρ_t then follows the function $\theta(\vartheta_t) = \min\{c + F(-\vartheta_t), 1\}$. However, the results are virtually identical.

dependent adjustment scheme does not lead to a superior performance of the QKS test compared to the benchmark cointegration tests if a mean-reversion tendency is assured over the whole distribution of shocks. However, the QKS test clearly outperforms the Engle-Granger and threshold cointegration tests if large positive shocks persist.

4 Empirical analysis

Economic theory strongly suggests that a cointegrating relationship between prices of upstream and downstream fuel markets exists since the prices of downstream goods are largely influenced by upstream prices. Meyler (2009) decomposes EU petrol and diesel prices from 2008 and finds that 75% of petrol and 62% of diesel are accounted for by the crude oil price. The decomposition for the US fuel market shows a similar result with crude oil accountable for 72% of petrol and 61% of diesel prices. It is therefore not unrealistic to assume that crude oil and fuel prices share a common stochastic trend. In what follows, we will first have to test the individual series for their order of integration. After confirmation of their $I(1)$ property, we will estimate the first step of the Engle-Granger cointegration procedure to obtain the equilibrium error series z_t on which we will then apply the above outlined quantile autoregression approach to cointegration.

4.1 Data, unit root and cointegration tests

Our data cover the period from January 1999 until November 2013 with weekly observations. For the crude oil price we use WTI as a proxy for the North American market and Brent for the European market.[10] Both series are taken from the Federal Reserve Economic Database (FRED) and are converted into cents per litre in their respective

[10]The properties of different crude oil benchmarks have been discussed in the literature (see Fattouh (2006) for an extensive exposition). WTI and Brent have been chosen since they are the crude oils primarily utilized in US and European refineries, respectively. However, switching the benchmarks or using a third benchmark (Dubai) instead, did not change the qualitative interpretation of our results.

currencies. The US ex-refinery price for Los Angeles, New York Habor and the Gulf Coast as well as the retail prices for gasoline and diesel are obtained from Thomson Reuters Datastream. We use the spot prices at the ARA oil hub for the ex-refinery prices in Europe. Since regular gasoline is rarely used in Europe, we focus on premium gasoline. Gasoil, a prestage for diesel, serves as the proxy for the ex-refinery diesel price. The German gasoline (Super95) and diesel prices with tax and duty excluded/included (PTD/ITD) are taken from the Weekly Oil Bulletin of the European Commission.

The prices for crude oil and its derivatives experienced a sudden slump during the financial crisis. This break in the series may influence the statistical properties of unit root tests which do not account for structural breaks and could lead to a false rejection of a unit root. Therefore, we choose the unit root test by Busetti and Harvey (2001) which allows for a structural break in the intercept as well as in the slope coefficient in both the null hypothesis and alternative. The test is based on the KPSS framework which tests for random walk components while assuming (trend-) stationarity with a potential break under the null hypothesis. The results for the Busetti-Harvey (BH) test suggests a unit root in all available series.[11] The differenced time series are deemed stationary in all cases. The results of the unit root tests are depicted in Table 2.[12]

Next, we estimate the cointegrating regressions (1) for each stage of the price transmission and test for the stationarity of the residual process z_t, using the EG test and the modified QKS test. Since prices of US retail fuel excluding tax and duty are not available, we estimate the *second stage* and *single stage* for the US and German fuel market directly for prices that are observed at the pump. Hence, we use a log-transformation of the prices in these regressions to capture the fact that the mark-up is increasing in costs

[11]Estimated breakpoints become irrelevant if the null hypothesis of the BH test is rejected.

[12]The unit root test results for log-transformed prices lead to the same test decision but are not reported here to conserve space.

Table 2 Unit root tests of individual price series.

	BH			ADF	
	$\xi(l)$	break		t-stat	lags
Crudes					
Brent	0.204***	02/2002	Δ Brent	−19.50***	1
WTI	0.103***	02/2005	Δ WTI	−20.88***	1
Ex-refinery prices					
Diesel (ARA)	0.206***	02/2004	Δ Diesel (ARA)	−18.87***	1
Gasoline (ARA)	0.199***	06/2011	Δ Gasoline (ARA)	−19.37***	1
Diesel (US)	0.156***	10/2004	Δ Diesel (US)	−18.94***	1
Gasoline (US)	0.125***	09/2004	Δ Gasoline (US)	−20.58***	1
Retail prices					
Diesel (US)	0.154***	10/2004	Δ Diesel (US)	−10.58***	2
Gasoline (US)	0.140***	10/2004	Δ Gasoline (US)	−9.89***	2
Diesel (GER)	0.136***	05/2009	Δ Diesel (GER)	−20.86***	1
Gasoline (GER)	0.100***	02/2009	Δ Gasoline (GER)	−19.51***	1
PTD retail prices					
Diesel (GER)	0.228***	09/2009	Δ Diesel (GER)	−21.06***	1
Gasoline (GER)	0.182***	04/2011	Δ Gasoline (GER)	−19.86***	1

Note: BH denotes the Busetti-Harvey test. The BH test equation includes a constant and a linear time trend. Critical values are 10%: 0.033, 5%: 0.041, 1%: 0.054. The ADF test equation includes a constant. The number of lags is based on the Bayesian Information Criterion (BIC). Critical values are 10%: −2.57, 5%: −2.86, 1%: −3.43.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

due to the VAT.[13] However, this does not allow to isolate the effects of the taxation structure. To further investigate this issue, we compare the results for German ITD prices with the German PTD prices. The mark-up for spot fuel prices and retail prices excluding tax and duty does not increase in costs, hence we use a linear specification in these instances.[14] The results are presented in Table 3.

The cointegration tests indicate an overall mean-reversion behaviour, with the exception of the German diesel spot/diesel ITD relationship where we find evidence for EG cointegration but cannot reject the null hypothesis of no quantile-dependent cointe-

[13]Estimating the cointegration regressions in a linear specification yields qualitatively identical results for the asymmetry patterns.

[14]Likewise, a log-specification does not alter the results substantially.

gration. This discrepancy can be explained with the Monte Carlo simulation results in Subsection 3.3 in which the QKS test has lower power than the EG test if adjustment is symmetrical. We therefore conjecture the residual process z_t to be a globally stationary process which implies a cointegrating price relationship. In the next section, we proceed with the estimation of the quantile autoregressive model and test the resulting quantile-dependent coefficients for their degree of asymmetry.

Table 3 Estimates of the equilibrium equations and residual-based cointegration tests.

	Intercept	Slope	EG	QKS
First stage				
Diesel^{ARA}	1.096	1.128	-5.377^{***}	10.360^{***}
Gasoline^{ARA}	3.412	1.149	-6.609^{***}	8.603^{***}
Diesel^{US}	-2.967	1.289	-5.095^{***}	6.183^{**}
Gasoline^{US}	0.919	1.130	-6.278^{***}	10.530^{***}
Second stage				
Diesel^{GER}	3.034	0.469	-4.311^{***}	4.949
Gasoline^{GER}	3.467	0.381	-4.769^{***}	6.016^{**}
Diesel^{US}	1.576	0.693	-7.408^{***}	6.907^{**}
Gasoline^{US}	1.591	0.682	-10.040^{***}	9.714^{***}
Single stage				
Diesel^{GER}	3.123	0.464	-4.654^{***}	5.581^{*}
Gasoline^{GER}	3.658	0.352	-5.132^{***}	6.365^{**}
Diesel^{US}	1.474	0.755	-5.384^{***}	7.555^{**}
Gasoline^{US}	1.690	0.681	-5.716^{***}	5.751^{**}

Note: EG denotes the Engle-Granger test. The number of lags is based on the Bayesian Information Criterion (BIC). Critical values are taken from MacKinnon (2010), 10%: -3.05, 5%: -3.35, 1%: -3.91. QKS denotes the modified quantile Kolmogorov-Smirnov test with 600 bootstrap replications.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2 Quantile autoregression results

For the empirical analysis, we apply the QAR(p) model in (4) to US fuel market data and German fuel market data. The residuals in both cases originate from the estimates of the long-run equilibrium equation (1). We use the modified Barrodale and Roberts algorithm for the quantile regression (Koenker and d'Orey (1987)). The estimated quantile-dependent coefficients are plotted for quantiles between 0.05 and 0.95 (see Figure 1 and Figure 2). The remaining quantiles are not displayed since solving (3) results in increasingly inaccurate estimates for tail quantiles and the overall pattern is already sufficiently revealed by the constrained quantile sequence.

We begin with the *first stage* of the price transmission chain in the US market. We restrict the empirical analysis to the Gulf coast prices since the US refinery industry is concentrated in this region.[15] The estimated autoregressive coefficients (ρ_t) for disequilibria series of the diesel/WTI and gasoline/WTI relationships are plotted in the upper panel of Figure 1. We observe a upward-sloping curve for the quantile-dependent coefficients in both relationships. The estimated autoregressive coefficient is visibly smaller than one for lower quantiles, corresponding to large negative deviations. This means that disequilibria induced by crude oil prices that are higher in relation to the ex-refinery prices are adjusted relatively fast over time. Conversely, the point estimates for upper quantiles are close to one indicating that adjustment is slow when crude oil prices are too low.

Generally, the speed of pass-through is quite slow (see Table 4). The half-life period (50% of pass-through reached) of shocks to the diesel/WTI relationship is 7.9 weeks for negative deviations from the long-run equilibrium (25% quantile) and 44.6 weeks for positive deviations from the long-run equilibrium (75% quantile). 90% of a shock is passed through after 26.2 weeks for negative deviations and 148 weeks for positive devi-

[15] The results for Los Angeles and New York Habor prices display a similar pattern.

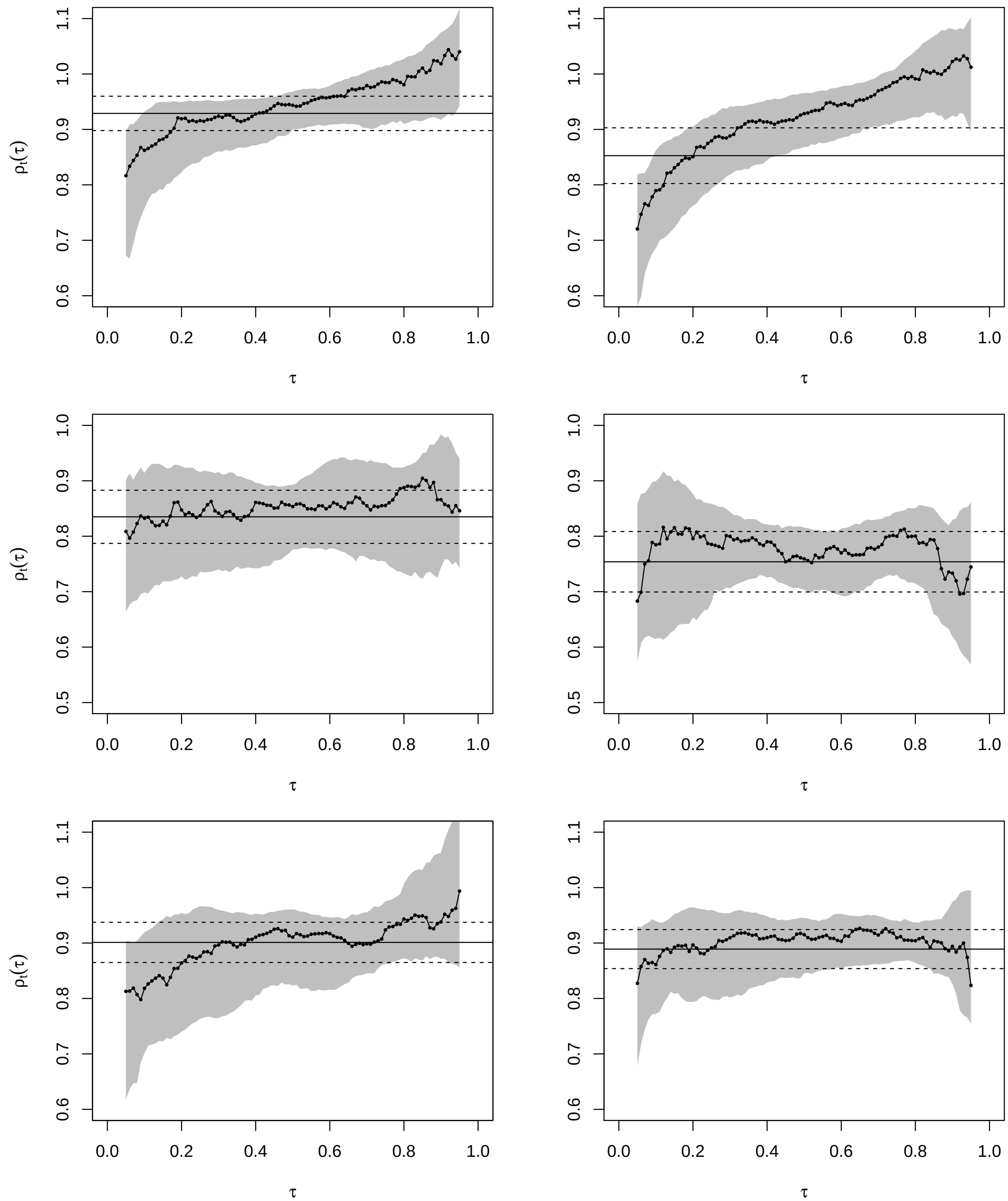

Fig. 1 Estimation results for the quantile-dependent adjustment coefficient $\rho_t(\tau)$ in the US fuel market. The upper panel, middle panel and lower panel display the *first stage*, *second stage* and *single stage*, respectively. Diesel prices are on the left and gasoline prices are on the right. Shaded areas correspond to a 95% bootstrap confidence interval.

ations. Correspondingly, the half-life period of shocks to the gasoline/WTI relationship is 5.4 weeks for negative deviations and 48.8 weeks for positive deviations while 90% of the shock is passed through after 17.9 weeks for negative deviations and 162 weeks for positive deviations.

Table 4 Pass-through of long-run equilibrium shocks in weeks.

	lower tail					upper tail				
	50%	60%	70%	80%	90%	50%	60%	70%	80%	90%
First stage										
Diesel^{ARA}	4.5	5.9	7.8	10.4	14.9	253	335	440	588	842
Gasoline^{ARA}	3.6	4.8	6.3	8.4	12.0	10.2	13.5	17.7	23.7	33.9
Diesel^{US}	7.9	10.4	13.7	18.3	26.2	44.6	58.9	77.4	104	148
Gasoline^{US}	5.4	7.1	9.4	12.5	17.9	48.8	64.6	84.8	113	162
Second stage										
Diesel^{GER}	1.7	2.3	3.0	4.0	5.7	2.2	2.9	3.8	5.1	7.3
Gasoline^{GER}	2.2	2.9	3.8	5.1	7.3	2.3	3.1	4.1	5.4	7.8
Diesel^{US}	3.9	5.2	6.8	9.0	12.9	4.4	5.9	7.7	10.3	14.8
Gasoline^{US}	2.9	3.8	5.0	6.7	9.5	3.1	4.1	5.4	7.2	10.3
Single stage										
Diesel^{GER}	2.9	3.8	5.0	6.7	9.6	4.6	6.1	7.9	10.6	15.2
Gasoline^{GER}	4.1	5.5	7.2	9.6	13.7	4.2	5.6	7.4	9.9	14.1
Diesel^{US}	5.2	6.9	9.1	12.1	17.4	8.7	11.5	15.1	20.2	27.0
Gasoline^{US}	6.0	8.0	10.5	14.0	20.0	7.3	9.6	12.7	16.9	24.2

Note: The pass-through durations for the lower tail are based on the 25% conditional-quantile estimations, while the upper tail results are estimated based on the 75% quantile. The durations are computed for the hypothetical case that the quantile-dependent adjustment coefficients stay at the 25% (75%) quantile. It needs to be emphasized that this situation is unrealistic since the coefficients are allowed to change every period.

Interestingly, the point estimates indicate that extreme positive shocks are not reverted at all. The QAR(p) model in principle allows for a locally persistent or locally explosive behavior of z_t as long as the disequilibrium process is globally mean-stationary.

However, in this case the confidence bands for tail quantiles are relatively wide and include values below one so that we do not find significant statistical evidence for a lack of adjustment. A notion which is supported by the results of the EG and QKS cointegration test rejecting the null of no cointegration for all *first stage* relationships (Table 3).

The point estimates for gasoline (right panel) show slightly stronger asymmetric behaviour than the point estimates for diesel (left panel). The supremum Wald test for equality of conditional-mean and quantile effects, depicted in Table 5, signals that the quantile-dependent coefficients are significantly different from the coefficients of the conditional-mean model only for gasoline/WTI. A comparison of the tails of the distribution points towards a strong asymmetry for diesel and gasoline. This is in line with the graphical illustration. The results for the *first stage* suggest that the refinery sector is able to delay the pass-through of price decreases in the US crude oil market, while price increases are passed through at a significantly faster rate.

In the *second stage*, we analyze the transmission from ex-refinery prices to retail prices at the pump. The point estimates, depicted in the middle panel of Figure 1, are more concentrated around the baseline conditional-mean value. The conditional-mean estimates indicate that shocks are passed through faster in the gasoline market than in the diesel market. The half-life period of shocks to the diesel/ex-refinery relationship is 3.9 weeks for negative deviations and 4.4 weeks for positive deviations. The half-life period of shocks to the gasoline/ex-refinery relationship is 2.9 weeks for negative deviations and 3.1 weeks for positive deviations. The supremum Wald test supports the hypothesis that the quantile effects are not statistically different from the conditional-mean effect and a comparison at the tails indicates no asymmetries.

In the *single stage* transmission process, we find a slightly upward-sloping curve for the diesel/WTI relationship while the estimated quantile-dependent adjustment coefficients for the gasoline/WTI relationship largely coincide with the conditional-mean estimate (lower panel of Figure 1). The supremum Wald test for equality and the asymmetry tests do not reveal any asymmetries at reasonable significance levels. As expected, the speed of adjustment is slower than in the *second stage*. 50% (90%) of a shock to the diesel/WTI relationship is adjusted after 5.2 (17.4) weeks for negative deviations and 8.7 (27.0) weeks for positive deviations, while 50% (90%) of a shock to the gasoline/ex-refinery relationship is 6.0 (20.0) weeks for negative deviations and 7.3 (24.2) weeks for positive deviations.

Table 5 Supremum Wald test for equality of mean and quantile effects and single Wald tests for equality of the autoregressive coefficients across quantiles.

	W_n	$W(\tau_{15}=\tau_{85})$	$W(\tau_{10}=\tau_{90})$	$W(\tau_5=\tau_{95})$	$W(R1)$	$W(R2)$
First stage						
Diesel^{ARA}	17.00***	16.07***	15.34***	12.55***	14.17***	15.54***
Gasoline^{ARA}	10.36**	7.46***	6.99***	9.54***	8.63***	8.37***
Diesel^{US}	6.58	5.48**	5.87**	5.34**	6.47**	6.80***
Gasoline^{US}	18.37***	7.99***	12.44***	13.72***	17.07***	14.30***
Second stage						
Diesel^{GER}	6.56	2.07	1.77	1.70	2.07	2.34
Gasoline^{GER}	1.87	0.15	0.56	0.00	0.26	0.27
Diesel^{US}	1.89	0.84	0.14	0.16	0.18	0.31
Gasoline^{US}	3.97	0.07	0.28	0.27	0.04	0.17
Single stage						
Diesel^{GER}	6.28	1.53	3.11*	4.65**	4.80**	4.25**
Gasoline^{GER}	7.49	0.05	0.16	3.05*	1.46	0.35
Diesel^{US}	4.54	1.94	1.40	1.94	1.43	1.43
Gasoline^{US}	3.59	0.06	0.29	0.00	0.06	0.08

Note: W_n denotes the supremum Wald test for equality of mean and quantile effects with null hypothesis $\rho_M = \rho_t(\tau_5) = \rho_t(\tau_6) = \cdots = \rho_t(\tau_{95})$. The Wald tests $W(\tau_{15}=\tau_{85})$, $W(\tau_{10}=\tau_{90})$ and $W(\tau_5=\tau_{95})$ test the null hypothesis $\rho_t(\tau_{15}) = \rho_t(\tau_{85})$, $\rho_t(\tau_{10}) = \rho_t(\tau_{90})$ and $\rho_t(\tau_5) = \rho_t(\tau_{95})$, respectively. $W(R1)$ corresponds to a Wald test under the hypothesis $\rho_t(\tau_5)+\cdots+\rho_t(\tau_9) = \rho_t(\tau_{91})+\cdots+\rho_t(\tau_{95})$ and $W(R2)$ to a Wald test under the hypothesis $\rho_t(\tau_5)+\cdots+\rho_t(\tau_{14}) = \rho_t(\tau_{86})+\cdots+\rho_t(\tau_{95})$.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

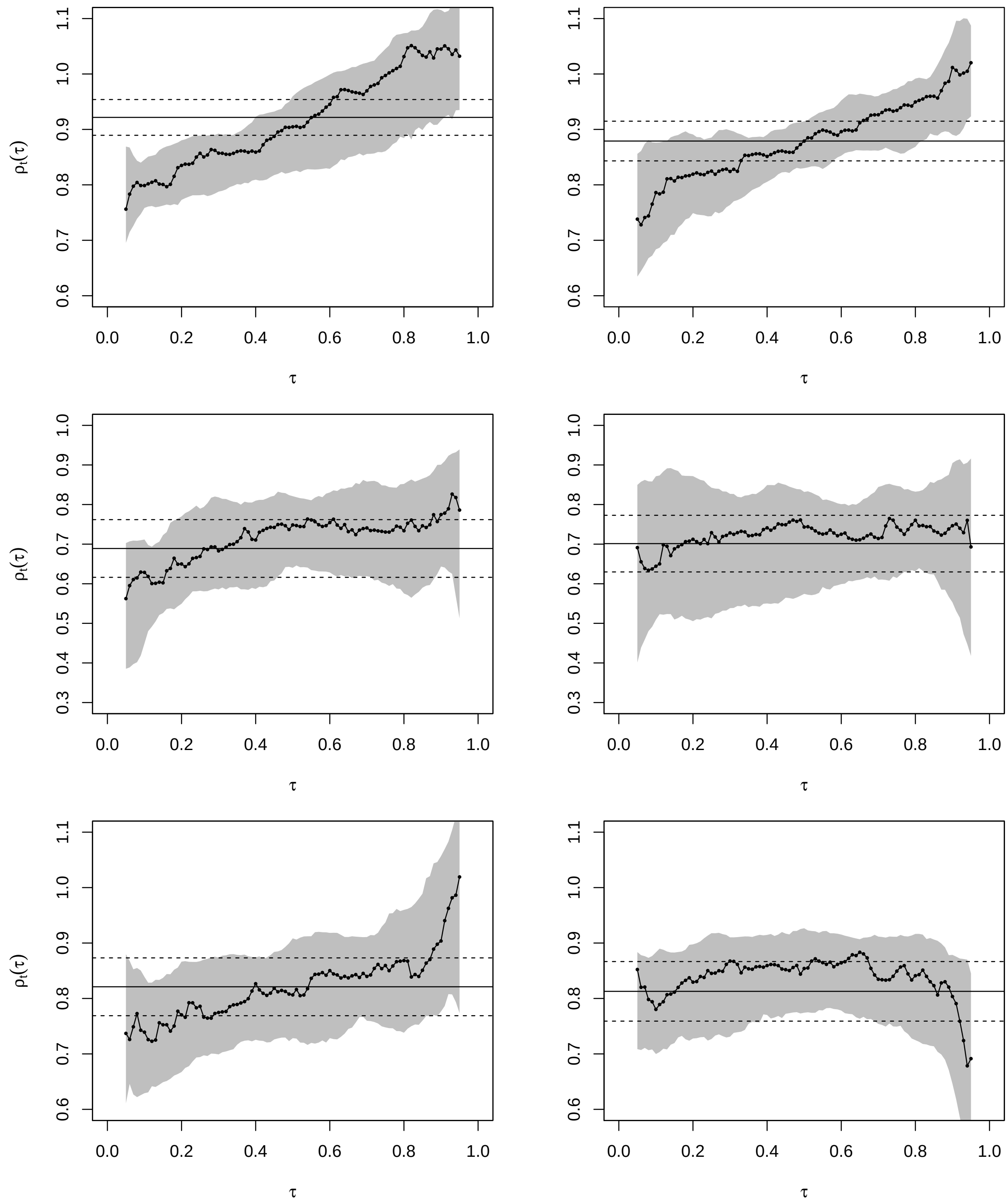

Fig. 2 Estimation results for the quantile-dependent adjustment coefficient $\rho_t(\tau)$ in the German fuel market. The upper panel, middle panel and lower panel display the *first stage*, *second stage* and *single stage*, respectively. Diesel prices are on the left and gasoline prices are on the right. Shaded areas correspond to a 95% bootstrap confidence interval.

We now turn to the German fuel markets. The quantile-dependent adjustment coefficients in the *first stage* transmission are depicted in the upper panel of Figure 2 and show a similar pattern compared to their US counterparts. Gasoil and premium gasoline at the ARA hub display a steep upward-directed slope. Since the null hypothesis of equality of the conditional-mean coefficient and all quantile-dependent coefficients is rejected, we find significant quantile effects. Also, the across quantiles comparison are highly significant. The half life of shocks to the gasoil/Brent relationship is 4.5 weeks for negative deviations and 253 weeks for positive deviations. This means that large positive deviations are not effectively adjusted by the system. Premium gasoline is adjusted at a faster rate so that we estimate the half life of shocks to the premium gasoline/Brent relationship to be 3.6 weeks for negative deviations and 10.2 weeks for positive deviations.

A possible source for the strong signs of asymmetry in the *first stage* in Europe and the US might be the fact that the oil refinery market has a relatively small number of competitors due to the capital-intensive nature of this industry. In 2013, the refining capacity of the US was spread across 57 refinery companies operating 139 refineries (US Energy Information Agency (2013)), while 106 refineries were operated in Europe (FuelsEurope (2014)). Large vertically integrated operations which are involved in several upstream activities might also reduce competition. Additionally, the price formation process in the crude oil and fuel spot markets is unusual. The product is sold in large quantities and trading in the ex-refinery petroleum market depends highly on the benchmark prices provided by price reporting agencies (PRA). Platts, the leading PRA, collects prices by a window or market-on-close process (MOC) in which bids, offers and the trade volume are assessed and prices are published as an end-of-day value. The system has been harshly criticized lately since it rests on voluntary and selective disclosure as well as subjective judgement of the PRA. Even without proclaiming intentional manipulation or collusive action, the MOC price formation is far from a full information pricing and opens up opportunities for delayed price reactions.

Next, we analyze the prices transmissions for German ITD prices. Since the mineral oil tax and the VAT have changed during our sample, we have to control for structural breaks in the intercept by including the appropriate dummy variables and interaction terms.[16] The *second stage* transmission does not reveal significant asymmetries. The estimated conditional-mean adjustment rates for Super95 and diesel are nearly identical while the confidence bands for Super95 tend to be wider for the lower tail of the distribution. The half life of shocks to the diesel/gasoil relationship is 1.7 weeks for negative deviations and 2.2 weeks for positive deviations. Similarly, the half life of shocks to the Super95/premium gasoline relationship is 2.2 weeks for negative deviations and 2.3 weeks for positive deviations.

The results for the *single stage* are depicted in the lower panel of Figure 2. The curve is slightly upward-sloping for diesel so that crude oil price reductions are delayed. In contrast, we find a downward-sloping curve for upper quantiles in the Super95/Brent relationship corresponding to a situation in which the customers experience an immediate retail price decrease caused by lower crude oil prices, but price increases are delayed. Equality across quantiles can only be rejected for diesel. The differences between the *second stage* and the *single stage* are more pronounced compared to the US market. This might be explained by the higher concentration of the European refinery sector leading to stronger asymmetries in the *first stage* price transmission. Differences between gasoline and diesel might be explained by the fact that EU refineries were initially configured to produce large amounts of gasoline and fuel oil but have struggled to meet

[16]The cointegration tests are performed without controlling for structural breaks in the intercept since the modified QKS test in Subsection 3.1 does not account for structural shifts in the long-run equilibrium relationship. However, since the timing of the breaks is known beforehand and the adjustment rates increase after inclusion of the dummy variables, we can interpret the p-values in Table 3 as upper bounds.

an increasing demand for diesel after the introduction of favourable diesel excise taxes.

The results in this section are robust to a sample split at the time of the financial crisis. Furthermore, we find only minor violations of the monotonicity requirement on the conditional-quantile functions (see (Koenker and Xiao, 2006; Chernozhukov et al., 2010)).

4.3 Effects of the taxation structure on fuel price transmissions

In contrast to the US market, fuel prices excluding tax and duty are available for the German market. Hence, we are now able to investigate whether the tax structure masks any asymmetries in the distribution stages. Greenwood-Nimmo and Shin (2013) study fuel price adjustments in the UK and find that the tax structure masks asymmetries at the pump. However, the UK uses an escalator type fuel duty policy which is different from the fixed sum mineral oil tax in Germany. It is therefore of interest to find out whether the same difference between PTD and ITD prices exist in the German fuel market. Also, we are able to check whether the change from a log specification to a linear specification has any influence on the speed of pass-through and the adjustment patterns.

The cointegration equation for PTD prices is estimated in a linear specification and the results for the *second stage* and *single stage* are displayed in the upper and lower panel of Figure 3, respectively. Prices before tax and duty and prices at the pump are on average adjusted at a similar rate. However, the results reveal small differences between the adjustment patterns for PTD and ITD prices. In case of diesel, the half life of shocks in the *second stage* is 3.1 weeks for negative deviations and 1.8 weeks for positive deviations. For Super95, the half life of shocks in the *second stage* is 2.8 weeks for negative deviations and 1.8 weeks for positive deviations.

In the *second stage*, we find downward-sloping conditional-quantile curves for diesel and Super95, but only the differences across quantiles for Super95 are statistically significant. The reaction to increases in production costs and subsequent adjustment of retail prices seem more difficult for the retailers in the Super95 market. A higher price elasticity of demand for gasoline could imply that customers postpone refuelling their cars when they use them for expendable activities or they switch to alternative modes of transportation. This pattern is not found in the *single stage* where the conditional-quantile curve is again upward-sloping for diesel and almost flat for Super95. Since the differences between PTD and ITD prices are small, we find no evidence that the tax structure in Germany allows retailers to delay prices decreases.

5 Conclusion

The quantile autoregression approach to asymmetric pricing in the US and German fuel markets leads to new insights about the pricing mechanisms. Using quantile regression techniques, we are able to quantify the degree of asymmetric price transmission without explicitly specifying distinct regimes and estimating the associated threshold values, or without specifying a particular parametric smooth transition framework. Therefore, the estimations are free of subjectivity and the employed model is parsimonious in nature. Applying this methodology to two large, geographically separated fuel markets, we are able to relate potential similarities or differences in the empirical findings to the specific structures of the two markets.

Our results highlight the importance of separating the price transmission chain in individual steps. The price transmission at the *second stage* and *single stage* turn out to be mostly symmetric, while we find evidence for a strong degree of asymmetry in the *first stage* of both markets. This finding might be related to indirect price discovery through a price reporting agency and the strong vertical integration in the US and European refinery sectors. Furthermore, the literature points to oligopolistic structures and the storage capacity to have some influence on the price transmission process from crude oil prices to the fuel spot markets (Bacon, 1991; Manning, 1991; Kaufmann and Laskowski, 2005). However, we are not able to identify the source of asymmetry in this paper and leave this open for further research.

Interestingly, the asymmetries found for the refinery stage seem to vanish when we turn to direct adjustment of retail prices to upstream products. This is a surprising result considering that the meta-analysis by Perdiguero-García (2013) reports a greater likelihood of price asymmetries for the retail price segment. A contributing factor could have been the fact that we use prices at the pump which include tax and duty. However, further analysis of German fuel prices excluding tax and duty reveals that the tax structure in Germany does not significantly affect the pass-through of price changes. In terms of asymmetric adjustment behaviour, the retail fuel prices in Germany, particularly Super95, show a pattern which contradicts the widespread perceptions. Indeed, not the decreases in fuel spot prices are adjusted at a slower rate but rather the increases appear to be delayed. This has a positive effect on customer welfare and signals a highly competitive fuel market. However, the differences in pass-through are not statistically significant for retail diesel prices.

For the US retail fuel market, we find no statistically significant asymmetry in both gasoline and diesel. This has to be considered a surprising result in the context of previous studies that argue for market power as a possible explanation for empirically observed asymmetric adjustments (Fosten (2012) and Perdiguero-García (2013)). Although the smaller diesel demand side consists almost exclusively of professional users and small-scale enterprises which are usually not able to delay their purchase in times of increasing fuel prices, we find no evidence that retailers are able to exploit the market structure.

In summary, it can be stated that fuel spot prices are asymmetrically adjusted to crude oil prices both in Europe and the US but we find no convincing evidence that these asymmetries are passed on to the retail fuel markets.

6 Appendix

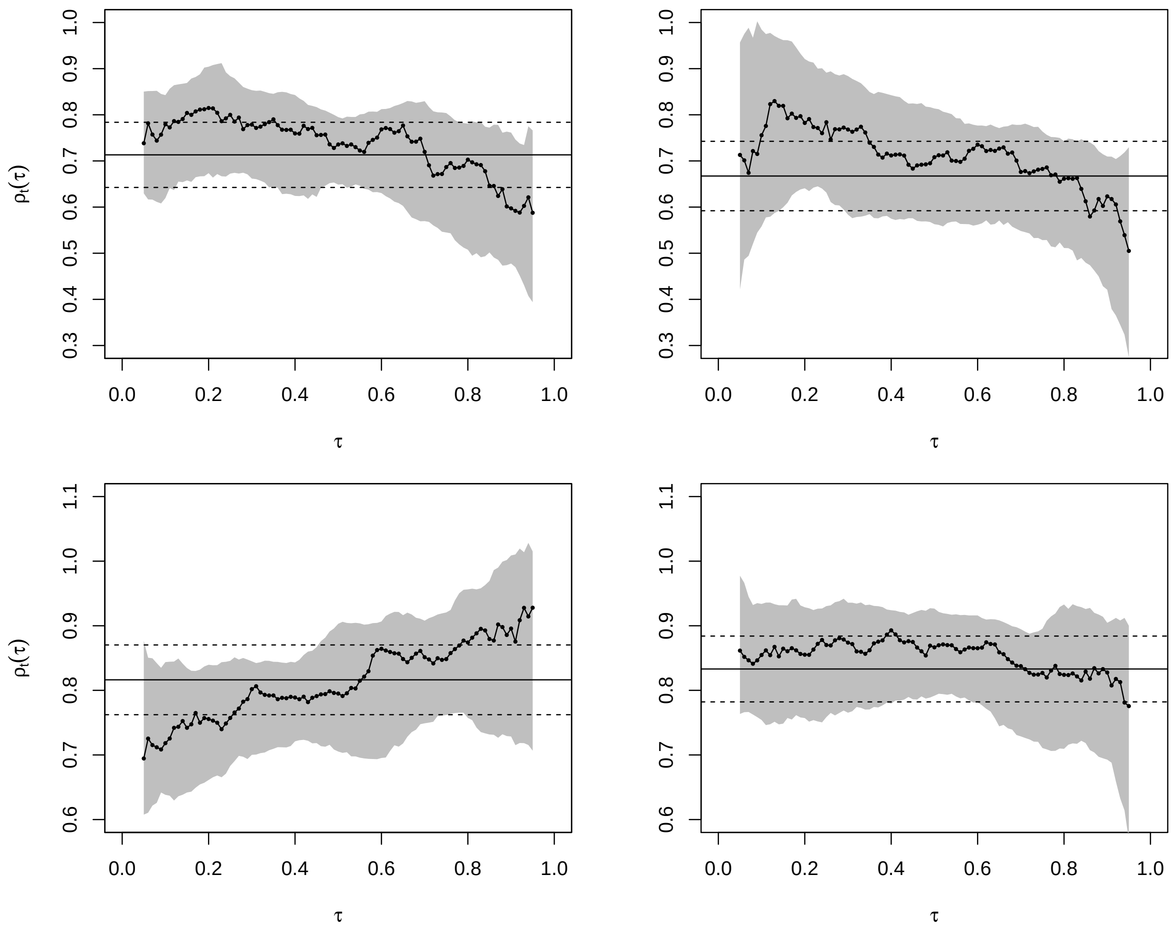

Fig. 3 Estimation results for the quantile-dependent adjustment coefficient $\rho_t(\tau)$ in the German fuel market (excluding tax and duty). The upper panel and lower panel display the *second stage* and *single stage*, respectively. Diesel prices are on the left and gasoline prices are on the right. Shaded areas correspond to a 95% bootstrap confidence interval.

Table 6 Additional estimations and tests for German fuel prices excluding tax and duty.

	Intercept	Slope	EG	QKS	W_n	$W(\tau_{15}=\tau_{85})$	$W(\tau_{10}=\tau_{90})$	$W(\tau_5=\tau_{95})$	$W(R1)$	$W(R2)$
Second stage										
Diesel^{GER}	7.774	1.098	-8.672^{***}	6.970^{**}	11.59^{**}	4.15^{**}	4.19^{**}	4.55^{**}	4.29^{**}	6.13^{**}
Gasoline^{GER}	7.232	0.945	-9.413^{***}	9.252^{***}	11.59^{**}	4.38^{**}	1.15	2.13	1.24	2.24
Single stage										
Diesel^{GER}	8.874	1.242	-6.997^{***}	8.365^{**}	2.68	0.18	0.10	0.57	0.29	0.22
Gasoline^{GER}	10.303	1.092	-6.554^{***}	7.577^{**}	6.24	2.53	2.63	3.77^{*}	3.03^{*}	2.93^{*}

Pass-through of long-run equilibrium shocks in weeks

	lower tail					upper tail				
	50%	60%	70%	80%	90%	50%	60%	70%	80%	90%
Second stage										
Diesel^{GER}	3.1	4.1	5.4	7.2	10.3	1.8	2.4	3.2	4.3	6.1
Gasoline^{GER}	2.8	3.8	4.9	6.6	9.5	1.8	2.4	3.2	4.2	6.0
Single stage										
Diesel^{GER}	2.5	3.3	4.3	5.8	8.3	4.2	5.6	7.3	9.8	14.0
Gasoline^{GER}	5.0	6.6	8.7	11.6	16.7	3.6	4.8	6.3	8.5	12.1

Note: EG denotes the Engle-Granger test. The number of lags is based on the Bayesian Information Criterion (BIC). Critical values are taken from MacKinnon (2010), 10%: -3.05, 5%: -3.35, 1%: -3.91. QKS denotes the modified quantile Kolmogorov-Smirnov test with 600 bootstrap replications. W_n denotes the supremum Wald test for equality of mean and quantile effects with null hypothesis $\rho_M = \rho_t(\tau_5) = \rho_t(\tau_6) = \cdots = \rho_t(\tau_{95})$. The Wald tests $W(\tau_{15} = \tau_{85})$, $W(\tau_{10} = \tau_{90})$ and $W(\tau_5 = \tau_{95})$ test the null hypothesis $\rho_t(\tau_{15}) = \rho_t(\tau_{85})$, $\rho_t(\tau_{10}) = \rho_t(\tau_{90})$ and $\rho_t(\tau_5) = \rho_t(\tau_{95})$, respectively. $W(R1)$ corresponds to a Wald test under the hypothesis $\rho_t(\tau_5)+\cdots+\rho_t(\tau_9) = \rho_t(\tau_{91})+\cdots+\rho_t(\tau_{95})$ and $W(R2)$ to a Wald test under the hypothesis $\rho_t(\tau_5)+\cdots+\rho_t(\tau_{14}) = \rho_t(\tau_{86})+\cdots+\rho_t(\tau_{95})$. The pass-through durations for the lower tail are based on the 25% quantile, while the upper tail results are estimated based on the 75% quantile. The durations are computed for the hypothetical case that the quantile-dependent adjustment coefficients stay at the 25% (75%) quantile. It needs to be emphasized that this situation is unrealistic since the coefficients are allowed to change every period.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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