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Asymmetric Diesel Retail Pricing Strategies: Depending on Brands and Population Densities?

Sebastian Kreuz (BTU Cottbus-Senftenberg), sebastian.kreuz@b-tu.de, sebastian.kreuz@gmail.com

Prof. Dr. Felix Müsgens (BTU Cottbus-Senftenberg), felix.muesgens@b-tu.de

Chair of Energy Economics
Brandenburg University of Technology Cottbus-Senftenberg
Prof. Dr. Felix Müsgens
http://www.b-tu.de/fg-energiewirtschaft/

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ABSTRACT

Asymmetric cost pass-through between crude oil and retail fuel prices ("Rockets and Feathers") has been analysed for different countries and time periods. However, few studies have been conducted for the German market. Furthermore, this study differentiates between company types and regions in this context. We compare price setting behaviour of independent and major brand stations following oil price changes. Furthermore, we differentiate between regions with higher and lower population densities. We establish an error correction model with a novel data set from the years 2011 to 2012. Our results confirm significant differences between price setting behaviour after oil price changes of major brand stations and other stations.

Keywords: *diesel price; error correction model; oil price, retail fuel; rockets and feathers; spatial analysis*

1 INTRODUCTION

Transport is an essential good. Within individual transport, fuel costs have one of the highest shares of all cost components (Belzowski, 2015, Hagman et al., 2016). Retail fuel prices also influence consumption and investment decisions in the transport sector and beyond (Moutinho et al., 2017). Not surprisingly, retail fuel pricing strategies are the topic of intense and controversial public and political discussions in many countries of the world.

In the German market, such discussions lead to an analysis of the retail fuel sector and its mechanisms of competition by the Federal Cartel Authorities (FCO, 2011). The authors conclude that five major brands have a market dominating position on the German retail fuel market. This result is opposed by the International Energy Agency (IEA, 2014) which states that ‘Germany has a highly deregulated and competitive oil market’ characterized by a ‘large number of independents in the […] retail sector’. The German government established a market transparency platform for fuel within the FCO in 2013, but the debate is still ongoing.

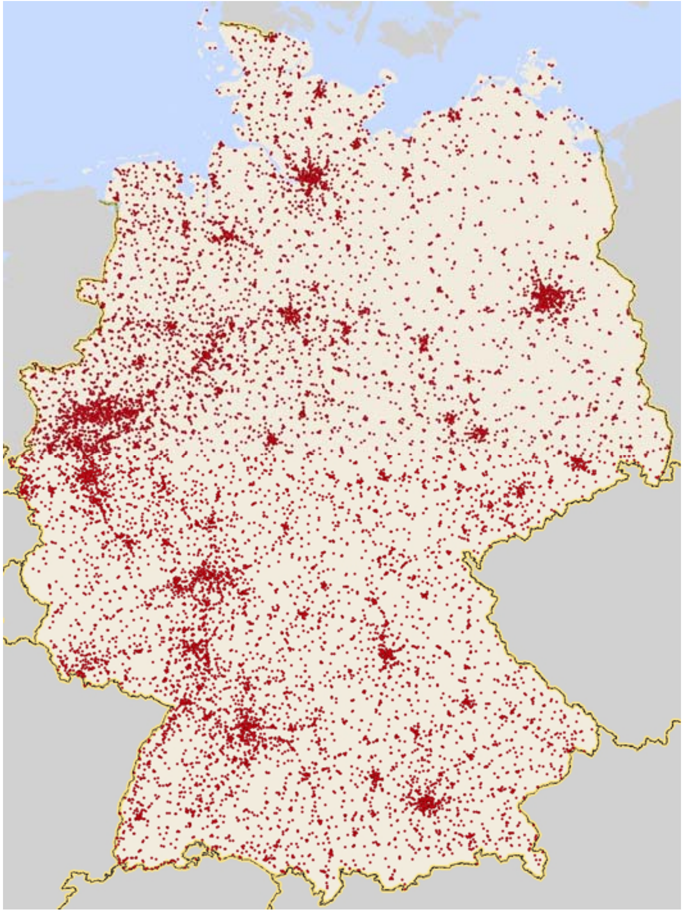
One way to analyse price setting behaviour is to compare input costs and prices. In the context of fuel prices, it is often analysed whether fuel prices increase faster than they decrease after oil price changes (which are a major driver of retail gasoline price developments). Such asymmetric cost pass-through, also referred to as “Rockets and Feathers”, can be interpreted as evidence for market power even though other factors also contribute to asymmetric price movements (see e.g. Borenstein et al., 1997, Balke et al., 1998, Brown and Yücel, 2000, Kaufmann and Laskowski, 2005).

Our paper analyses asymmetric cost pass-through in the German diesel retail market. The main contribution is that our data set enables us to differentiate between brand stations (e.g. Aral, Esso or Shell) and independent petrol stations (IPS), as well as between petrol stations in densely and less densely populated areas. On this basis, we contribute to the controversy whether the German diesel retail market is “dominated by the top 5 stations” or “competitive”. Furthermore, an analysis of differences in pricing strategies between IPS and brand stations as well as by population density is interesting in an international context as many markets have both IPS and brands as well as more and less densely populated areas.

We adapt an error correction model (ECM) to test whether German diesel prices increase or decrease at the same speed after corresponding oil price changes. With the help of this model, we can test for potential positive asymmetries, i.e. diesel prices responding faster to increasing oil prices than to decreasing oil prices (the “Rockets and Feathers” hypothesis). To analyse our main research questions, we separate the diesel price data of five brands (Aral, Jet, Esso, Shell and Total) from the other data, because the former are considered the dominant firms by FCO, 2011. Similarly, we separate price data for IPS, also referred to as no-logo retailer networks, from all other data. These have more autonomy than brand stations with respect to pricing and marketing strategies (FCO, 2011). Furthermore, IPS might have different incentives for strategic price setting behaviour: unlike brand stations, IPS may have lower incentives to increase prices because they do not control other stations profiting from higher prices and thus have lower incentives for strategic behaviour (see e.g. Ausubel and Cramton, 2002). For both subsets, we a) test whether they differ in average prices, b) test for (asymmetric) cost pass-through and c) compare adjustment speed levels after oil price increases and decreases between the respective subset and the remaining stations.

Furthermore, we also analyse whether population density influences results by splitting our data set into two subgroups (one with high and one with low population density). Regional population densities in Germany vary between urban and rural areas. While urban districts have high population densities (Munich having the highest density with 4,668 inhabitants per km2), rural areas have significantly lower population densities (the lowest in the Prignitz in north-east Germany with 36 inhabitants per km2, Federal Statistical Office, 2015). The distribution of petrol stations in Germany correlates with population densities (see data and maps from FIPR, 2015). Hence, Figure 1 shows a higher concentration of stations in urban areas such as Berlin, Munich, Hamburg, Frankfurt and the Ruhr area. In contrast, in more rural areas, petrol stations are more sparsely distributed and, therefore, there may be lower competition intensity between stations. In analogy to station types, our paper analyses whether population density per km2 in a district, as an indicator of station density, affects a) average prices, b) (asymmetric) cost pass-through and c) adjustment speed levels after oil price increases and decreases.

Figure 1: Distribution of petrol stations in Germany (map by authors, data from ESRI, 2015).



The remainder of this paper is organised as follows: Chapter 2 gives an overview of the literature related to our analysis. Chapter 3 explains major characteristics of our data set. In chapter 4, we test our data set on the cointegration relationship between diesel prices and oil prices and establish an ECM to determine whether there are asymmetries in cost pass-through. Chapter 5 presents the results. We also discuss the most relevant findings of our analysis in that chapter. Chapter 6 concludes and identifies areas of further research.

2 LITERATURE

The high public and political interest in retail fuel prices is reflected in a large and varied literature. Eckert (2013) performed a literature overview and found 26 articles on asymmetries and pass-through of shocks and 24 on station level price dispersion and price differentials. Most of the 26 articles on asymmetries confirm some form of asymmetries of retail prices after upstream price adjustments. However, more than 80 % of the studies analysed in that overview use data from North America (USA or Canada).

Given the large and varied literature on gasoline retailing, we will restrict our literature survey based on the focus of our paper. We start with a discussion of asymmetries and - after a brief introduction on the relationship between retail fuel and oil prices - concentrate on 'semi-asymmetric' error correction models. As we also analyse differences between brands and non-brand asymmetric pricing strategies as well as population density, we continue with a discussion of the few papers analysing differences in asymmetries in combination with either population density and/or brands. Lastly, we discuss studies on the German market.[1]

The relationship between retail fuel and crude oil prices - or other input products - can be analysed with different methodological approaches. Frey and Manera (2007) as well as Perdiguero-García (2013) differentiate five main methods to analyse asymmetric cost pass-through in the retail fuel market: autoregressive distributed lag models, partial adjustment models, error correction models, regime switching models and as a last subgroup their multivariate extensions (e.g. vector autoregressive models). Error correction models (ECM) are one of the most widely used methods. Engle and Granger (1987) describe the idea of error correction simply as 'a proportion of the disequilibrium from one period is corrected in the next period'. Therefore, error correction models disclose adjustment speeds back towards the long-term equilibrium. They can be established in multiple ways. Usually, error correction models contain residuals as error correction terms which are estimated from a cointegration relationship. To detect asymmetries, specific parts, e.g. the error correction or distributed lag terms can be decomposed with the help of threshold values.

A subgroup of asymmetric ECMs are 'semi-asymmetric' ECMs (Balaguer and Ripollés, 2012). These were used in a similar context by Granger and Lee (1989), Bachmeier and Griffin (2002), Kaufman and Laskowski (2005), Contín-Pilart et al. (2009) and Balaguer and Ripollés (2012). The distinguishing feature of this approach is that it analyses potential asymmetries of the cointegration relationship's lagged residuals only, i.e. the error correction terms.[2] Therefore, a semi-asymmetric ECM tests for potential asymmetries on the long-term equilibrium adjustment parameters (error correction terms). Focussing on literature applying semi-asymmetric ECMs to test for asymmetries, Kaufman and Laskowski (2005) use a model similar to our paper for monthly US gasoline data (in 12 US states for the years from 1986 to 2002). The threshold value they use to decompose the error correction terms is the lagged crude oil price change. Results show that symmetric price responses of retail fuel are present in most of the analysed US states. Contín-Pilart et al. (2009) and Balaguer and Ripollés (2012) use ECMs for the analysis of the Spanish market. Contín-Pilart et al. (2009) conclude, based on weekly data, that gasoline prices in Spain respond symmetrically to gasoline spot prices from 1993 to 2004. Balaguer and Ripollés (2012), based on daily data, also do not find asymmetries for the years 2006 to 2009 between wholesale prices for refined oil and retail gasoline and diesel prices.

[1] We also include research results for the German gasoline market because literature on German diesel price characteristics is currently rare.

[2] We also analysed an asymmetric model approach (see appendix A.5) and found comparable results to the reference case presented in chapter 5.

In terms of our research questions, few studies evaluated the influence of station brands and/or spatial distribution on asymmetric pricing strategies.[3] Verlinda (2008) analyses comparable characteristics with a weekly station level data set from Orange County[4] over nine months in the years 2002 and 2003. Price-response asymmetry is given for the aggregated data set. Furthermore, the author shows that brand stations have higher price-response asymmetries than unbranded stations but concludes that he cannot measure any effect between population size and asymmetries. Balmaceda and Soruco (2008) analyse weekly station level data from 44 petrol stations in Santiago[5] between 2001 and 2004. The authors find asymmetries regarding retail prices after wholesale price changes in their data set. Furthermore, the results show that brand stations have a stronger price-adjustment asymmetry than unbranded stations. It is noteworthy that their results are derived in an “unusual”[6] market environment as stations in their data set usually adjust prices once a week (after the monopolistic refinery supplier announces recent price changes). Faber (2015) also uses an asymmetric ECM for the Dutch market from 2006 to 2008. His station-specific results show that 38 % of the stations in the data set do respond asymmetrically for the market of retail gasoline. Furthermore, the author found asymmetric behaviour of certain brands, but there was no correlation with regions or population sizes in the Dutch market.

In the German context, our paper is the first to analyse the rockets and feathers hypothesis differentiated by brands and population density. The following eight papers analyse asymmetric cost pass-through in Germany – but without the latter differentiation. Kirchgässner and Kübler (1992) analysed price adjustment effects of West-German gasoline and its relationship with spot prices from the Rotterdam fuel market. They draw on 216 monthly data observations from 1972 to 1989 and find asymmetries during the 1970s but symmetry for the 1980s. Lanza (1991) analyses the situation in West-Germany from 1980 to 1990, finding asymmetry between retail and refinery gasoline prices. Galeotti et al. (2003) investigate price setting characteristics for crude oil and retail gasoline prices from Germany and four other European countries with ECMs. The German sample comprises the period from 1985 to 1997. The authors conclude that there are asymmetries between these prices in Germany. Grasso and Manera (2007) use three different ECM approaches (asymmetric, threshold autoregressive and threshold cointegration) with monthly data for the period from 1985 to 2003. The authors find evidence of asymmetry for Germany for the first two models. Kristoufek and Lunackova (2015) analyse weekly gasoline and oil prices for Germany and six other countries for the years 1996 to 2014. The authors introduced two new test formats in addition to a more standard ECM (based on Galeotti et al., 2003). Their results do not show asymmetric adjustments for their preferred test

3 Many studies however analyse that retail prices in general are influenced by such characteristics (see e.g. Barron et al., 2004, Firgo et al., 2015 and the literature cited therein).

4 Orange County is a county in California, USA, comprising 2,460 km^2, i.e. less than 1 % of the German landmass.

5 Santiago is the capital of Chile with a landmass of 641 km^2 (the Santiago Metropolitan Region comprises 15,403 km^2).

6 See ibid, p. 630.

methodology in any country. However, standard ECM calculation showed asymmetric characteristics for Germany and Belgium. Asane-Otoo and Schneider (2015) analyse German gasoline and diesel prices on a weekly level. In the case of diesel, the authors found positive asymmetries between 2003 and 2007 (more rapid price reactions to Brent crude oil price increases than decreases) and symmetric adjustment for 2009-2013. They also analyse city level data for the four largest German cities but do not compare it to other regions. Bagnai and Ospina (2016) use monthly retail fuel and crude oil data from 1999 to 2015 for different European countries, including Germany. With the recently introduced approach of nonlinear autoregressive distributed lag (NARDL) the authors show for the German case that over the full time period a negative asymmetry is given. Kreuz and Müsgens (2016) analysed asymmetries in the German diesel retail market for the period from 2011 to 2012. However, the paper also does not analyse spatial characteristics like urban and rural diesel retail prices and the pricing patterns of the five mayor brands. The last two papers in this literature discussion differentiate brands and spatial effects but not with an ECM. Kihm et al. (2016) use quantile regressions to analyse deviations from cost-based pricing in a station-specific panel of German retail stations. They conclude that low and high priced stations pass on more of input price increases than station with average prices. Haucap et al. (2017) analyse causes for specific price levels of German retail stations. The authors show that premium brands charge the highest prices, while increased competition (i.e. heterogeneous stations in close proximity) decreases absolute price levels.

3 DATABASE

Haucap et al. (2017) argue that historically, ‘comprehensive pricing data sets for empirical investigations have been difficult to obtain as gasoline and diesel are sold through numerous local gas stations’. Nowadays, fuel pricing data is more widely available in many countries. One main reason for the increase in data quality is that private websites publish retail prices which customers can update with their smartphones when refuelling. Consumers can also provide location data and brand names.

We use such a bottom-up data set for the following analysis. The information set was gathered from an online platform (http://www.benzinpreis-aktuell.de) where users can voluntarily report information. We concentrate our analysis on retail diesel, which is the petroleum product with the highest consumption in Germany (IEA, 2014) and Europe (Eurostat, 2016). Our database comprises 25,616 diesel data points for the two calendar years 2011 and 2012 (on average about 35 reported prices each day). Prices are reported fairly identical over the weekdays, with slightly more prices for Mondays.[7] A data point comprises a price (in Euros per litre), a point in time (yyyy,mm,dd,hh,mm,ss), a postal code (five digits) and a station brand.[8] Note that specific

[7] More reported prices on Monday may be explained by higher demand on Mondays (FCO, 2011).

[8] When data points did not include specific brand names, we included them in Non IPS and Non Top Five subsets. This is a cautious approach as we may underestimate differences between subsets.

stations cannot always be unambiguously identified based on postal codes and brands. In contrast to earlier work carried out in this period, our data enables us to differentiate between brands and regions.

We analyse seven different price data series consisting of different (sub-)sets. We start using all diesel price data (All Data). In addition, we establish two time series to analyse independent petrol stations: one time series with the prices from all IPS (subset IPS) and another series from the remaining data, i.e. all other stations (Non IPS). IPS prices have a share of 20 % of all data points (compared to a market share of about 18 % for those years, based on the German Petroleum Industry, 2012). Furthermore, we generate two time series by isolating the price data from the five major brands in the German retail fuel market, which we call Top Five: Aral, Shell, Total, Esso and Jet. Again, we complement the Top Five time series with another series consisting of all other stations (Non Top Five). Finally, we analyse two more subsets related to prices from administrative districts in Germany with either high or low population densities (PopDens high and PopDens low). Low population densities are assumed in districts with less than 1,000 people per square kilometre and higher population densities for districts above that threshold.

In each data (sub-)set, 104 weekly diesel data points (52 weeks in 2011 and 2012) are calculated as the average of seven consecutive days starting on Mondays. Each daily value is the average of all prices reported for that day in the respective data series. We use weekly data for our analysis due to a lack of data for several days in all (sub-)sets. The following Table 1 shows both the mean of each category's weekly averages as well as the number of data points in each. Looking at the means, we can confirm that IPS are cheaper than Non IPS stations. Furthermore, the Top-Five Brands are on average more expensive than Non Top Five and prices in districts with high population density (PopDens high) are lower than in areas with low population density (PopDens low). However, we discovered through two-sample-t-tests that we cannot reject the null hypothesis of identical price averages between two subsets (last three lines of Table 1).

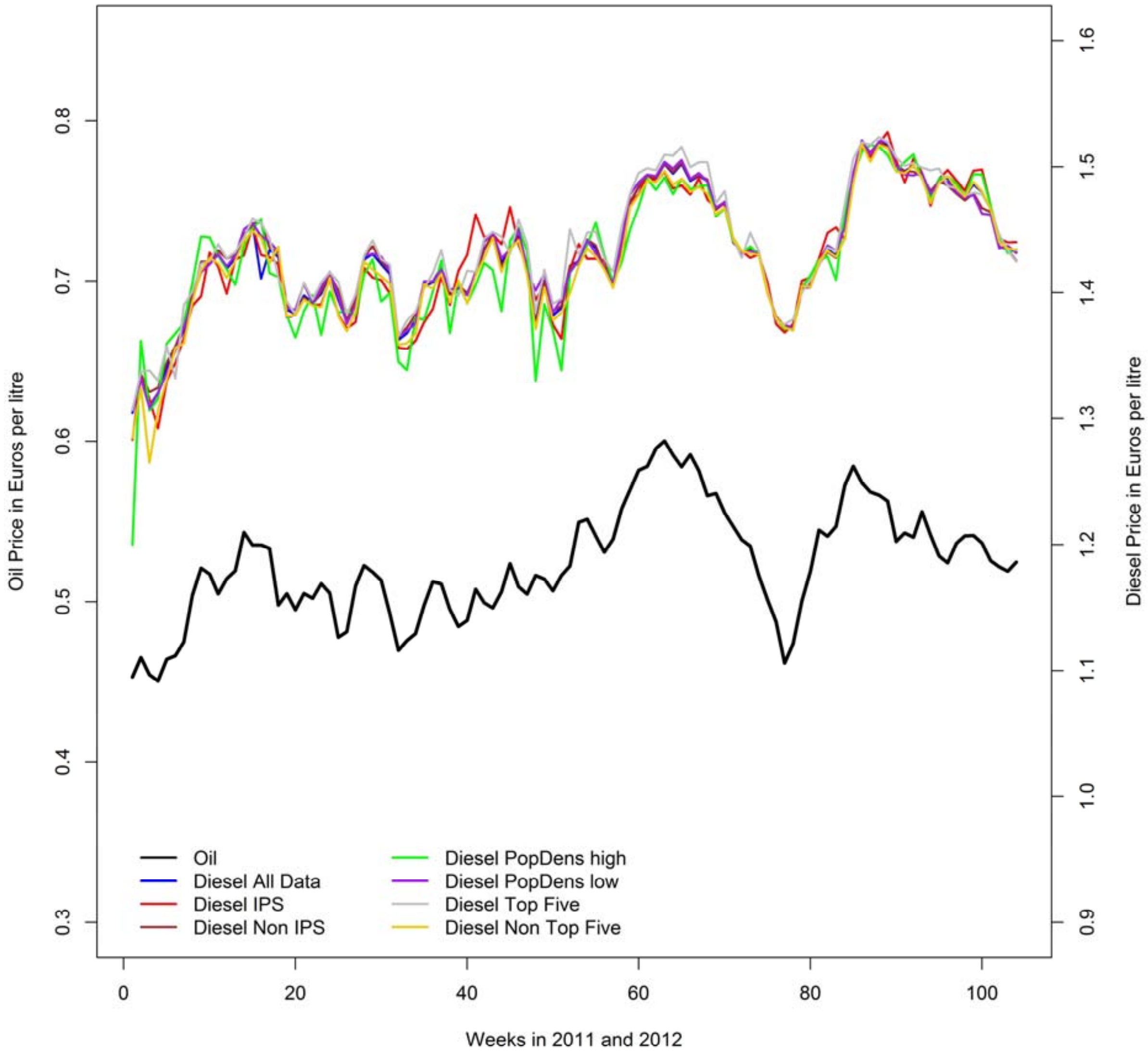
Data	Mean of weekly averages [€ per litre]	Number of price observations
All Data	1.4301	25,616
IPS	1.4280	5,173
Non IPS	1.4311	20,443
Top Five	1.4364	9,161
Non Top Five	1.4258	16,455
PopDens high	1.4249	7,768
PopDens low	1.4313	17,848
Two-sample-t-test		
IPS vs. Non IPS	-0.45 (0.6532)	
Top Five vs. Non Top Five	1.5658 (0.1189)	
PopDens high vs. PopDens low	-0.9149 (0.3613)	

Table 1: Data characteristics. Notes: for two-sample-t-test, p-value in brackets ( ), significance codes: 0.01 (***), 0.05 (**), 0.1 (*).

The weekly crude oil data series is calculated from daily closing prices of Brent oil (in Euros per litre). As no oil prices are quoted for weekends, we assume oil prices on Saturdays are equal to the closing price on the Friday before. For Sundays, we assume the opening price of the following Monday. This step harmonises oil data with diesel data.[9] Figure 2 shows resulting weekly prices for the seven diesel time series and oil prices over the years 2011 and 2012. The oil price time series and different diesel categories show comparable price movements.

[9] Using daily opening prices (instead of closing prices) does not change our results in a meaningful way.

Figure 2: Weekly diesel and Brent oil prices for the years 2011 and 2012.



As people voluntarily report prices, our online sample is not necessarily unbiased. However, Atkinson (2008) compares an online data set for Guelph, Ontario, with balanced panel collected data and concludes that 'spotters [i.e. voluntarily reported online data] do not tend to report a station's price more often if its price is higher or lower relative to the citywide mode or mean prices.' Furthermore, Kihm et al. (2016) also work with data gathered from a German online platform ('Clever Tanken'). They argue that the average monthly deviation between online price data and representative market prices is less than 1 %. To further evaluate our data set, we also compared it with an official weekly benchmark from the European Commission (note that this can only be done for all data, as more disaggregated data is not available from the European Commission) as well as with 'Clever Tanken's data. Some statistics for both comparisons are shown in the following Table 2. In particular, the mean absolute percentage error, i.e. the average deviation between our data and both the European Commission data as well as Clever Tanken is below 2 % - on a weekly level.

	Diesel price data (used in this paper)	European Commission	Clever Tanken
Mean	1.4301	1.4376	1.4555
Standard deviation	0.0479	0.0694	0.053
Mean squared error	-	0.0011	0.0008
Mean absolute percentage error [%]	-	1.99	1.73

Table 2: Descriptive statistics and comparison between the used data in this paper and the diesel data from the European Commission (2018) and Clever Tanken (2018).

4 METHODOLOGY

To establish our ECM, the following procedure is carried out: We firstly test our data for cointegration with the help of the Engle-Granger two-step cointegration procedure (Engle and Granger, 1987). The first part includes testing the original data and first differences for unit roots and stationarity with the help of the Augmented Dickey-Fuller test (ADF-test). Results need to show that all data series in levels are non-stationary and differences are stationary on the same order of integration, e.g. I(1). The second part of the Engle-Granger procedure contains the test for stationarity of the residuals of the long-term relationship between the two possibly cointegrated time series which, in our case, are diesel and crude oil prices. If the residuals of the long-term relationship are stationary, the two time series are cointegrated. Subsequently we use the estimated residuals as error correction term for the ECM. The calculation for the cointegration relationship and the construction of the ECM will be presented in this chapter, the test for stationarity of the original data and its first differences is included in the appendix. We use the statistical software 'R' to implement our work (R Core Team, 2016).

4.1 Cointegration Relationship

With the help of the Engle-Granger two-step cointegration procedure, we test crude oil prices (as independent variable) and the respective diesel data (sub-)set (as dependent variable) for cointegration, i.e. a stable long-term relationship between diesel and oil prices. Tests are often done with the help of OLS, however, following Contín-Pilart et al. (2009) we chose a DOLS also including lagged oil price changes (see Eq. 1). Results for the OLS are presented in the appendix. In (1), τ_t are the residuals and θ is a constant, n is the number of lags with the latter determined based on the BIC.

$$diesel_t = \theta + \mu\, oil_t + \sum_{i=0}^{n} \beta_i\, \Delta oil_{t-i} + \tau_t \tag{1}$$

Table 3 shows the optimal cointegration relationships, which maximises the absolute value of the BIC for each of the seven data series. With the residuals of (1), we again use the ADF-test to test for the stationarity of the time series without intercepts or trends. If the residuals τ_t are stationary, we can assume a long-term relationship exists. The results in Table 3 show that the residuals are indeed stationary. Therefore, we can conclude that diesel and oil price data are cointegrated.

	All Data	IPS	Non IPS	Top Five	Non Top Five	PopDens high	PopDens low
θ	0.8045*** (0.0336)	0.7945*** (0.0416)	0.8166*** (0.0318)	0.8011*** (0.0324)	0.7876*** (0.0374)	0.7932*** (0.0425)	0.8033*** (0.0315)
oil_t	1.1974*** (0.06384)	1.2127*** (0.07911)	1.1761*** (0.0605)	1.2158*** (0.0616)	1.2215*** (0.0711)	1.21*** (0.0809)	1.2018*** (0.06)
Δoil_t	-0.7427*** (0.1634)	-0.6962*** (0.2026)	-0.7607*** (0.1549)	-0.7278*** (0.1578)	-0.7474*** (0.1821)	-0.7301*** (0.2072)	-0.7313*** (0.1535)
Adj. R^2	0.78	0.70	0.79	0.79	0.75	0.69	0.80
BIC	-478.1006	-434.3437	-489.0982	-485.311	-456.0903	-429.6965	-491.8856
ADF-test [lags]	-3.8151*** [0]	-3.4683** [0]	-3.7926*** [0]	-3.2179** [1]	-4.6738*** [1]	-3.5504*** [1]	-3.8223*** [0]

Table 3: Cointegration relationship (DOLS) with 102 observations for each data set. Notes: standard errors in parenthesis ( ), significance codes: 0.01 (***), 0.05 (**), 0.1 (*), ADF-test for cointegration without constant and trend, optimal lag length for the cointegration relationship and ADF-test chosen by BIC, critical values from MacKinnon (1991).

4.2 Error Correction Model

Once cointegration is confirmed, an error correction model (ECM) can be established. An ECM describes a dynamic adaptation process between cointegrated variables, in our case diesel and oil prices.

$$\Delta diesel_t = \gamma\tau_{t-1} + \sum_{j=0}^{K} \vartheta_{1,j}\Delta oil_{t-j} + \sum_{i=1}^{L} \vartheta_{2,i}\Delta diesel_{t-i} + \varepsilon_t \tag{2}$$

The ECM relationship expressed in (2) defines the relationship between changes in diesel prices and (lagged) oil price changes and lagged diesel price changes. The short-term impact of lagged oil price changes and lagged diesel price changes is measured by ϑ_1 and ϑ_2. K and L are the respective lag length. Furthermore, τ_{t-1} are the lagged residuals from the cointegration relationship between diesel and oil prices (see Equation (1)). The coefficient γ is a long-term equilibrium adjustment parameter, which measures the significance of one-period lagged residuals. It determines the speed of adjustment between oil and diesel prices (cointegration relationship). Therefore, it should always be negative in sign.

Our aim is to analyse asymmetries of diesel price changes after oil prices have increased or decreased. Therefore, we have to differentiate between positive and negative changes of oil prices (also used in Bachmeier and Griffin, 2002, Kaufman and Laskowski, 2005, Contín-Pilart et al., 2009, Balaguer and Ripollés, 2012). This is achieved by decomposing τ in equation (3), which shows our semi-asymmetric ECM. The threshold variable for the distinction (decomposition) of the residual time series τ_t is the sign of the change of the Brent oil price (Δoil_t). Positive changes correspond to oil price increases and vice versa. The model evaluates the potential asymmetry of the adjustment speed back into the long-term equilibrium with the help of the error correction terms gained from (1). The coefficient γ^+ (γ^-) estimates the adjustment speed if oil prices are increasing (decreasing). The optimal lag length is again determined based on the BIC.

$$\Delta diesel_t = \gamma\tau_{t-1} + \sum_{j=0}^{K} \vartheta_{1,j}\Delta oil_{t-j} + \sum_{i=1}^{L} \vartheta_{2,i}\Delta diesel_{t-i} + \varepsilon_t \tag{3}$$

where

$$\tau_t^+ = \tau_t \wedge \tau_t^- = 0, if\ \Delta oil_t > 0,$$

$$\tau_t^- = \tau_t \wedge \tau_t^+ = 0, if\ \Delta oil_t \leq 0,$$

$$\Delta oil_t = oil_t - oil_{t-1}$$

The crucial question in terms of asymmetric price adjustment is whether γ^+ and γ^- are different. We use the Wald-test (F-test) to test for the null hypothesis of $\gamma^+ = \gamma^-$. As Cook et al. (1999) discuss the relatively low strength of the F-test in the context of ECMs, we bootstrap the F-statistics with the help of residual bootstrapping (see comparable adaptations in Galeotti et al., 2003, Grasso and Manera, 2007 and the discussion in Contín-Pilart et al., 2009). This bootstrapping approach increases the reliability of tests for symmetry with restricted data sets by calculating replications with the help of random sampling with replacement. The following method for residual bootstrapping was used to bootstrap the F-test for the ECM (see e.g. Mooney and Duval, 1996): (a) Calculate the model with original data; (b) calculate residuals of the model $\varepsilon_i = Y_i - \hat{Y}_i$; (c) resample residuals randomly with replacements; (d) generate a bootstrapped vector of the dependent variable by adding the resampled vector of residuals to the fitted dependent values $Y_b^* = \hat{Y} + \widehat{\varepsilon_b^*}$; (e) regressing Y_b^* on the exogenous variables; (f) conduct hypothesis test for bootstrapped estimators - in our case, the Wald-test (F-test) for the error correction parameters. We obtained newly simulated dependent variables, estimated model parameters and computed the F-statistic 1,000 times. Higher levels of replications do not show significantly different results.

Finally, we conduct two-sample-t-tests, both for the original data and bootstrapped data, to test for the null hypothesis of $\gamma_x^+ = \gamma_y^+$ ($\gamma_x^- = \gamma_y^-$) between IPS and Non IPS, Top Five and Non Top Five, as well as for PopDens high and PopDens low.

5 RESULTS

Table 4 shows the results for our seven ECMs (containing All Data as well as subsets for IPS, Non IPS, Top Five, Non Top Five, regions with high and low population densities). We find that changes in the crude oil price are the major driver for short-term diesel price changes in our model (rows one and two). Lagged diesel price differences (row three) do not have enough explanatory power to be included when parameters are selected according to BIC.

The results with respect to asymmetric price adjustments will be analysed in two steps: In a first step, we will compare γ^{+} and γ^{-} for all seven data series and analyse the Rockets and Feathers hypothesis. We provide test results both based on data sets before and after bootstrapping results. In a second step, we will discuss differences in adjustment speeds between the three data sets IPS, Top Five and PopDens high and the remaining stations in each subset (Non IPS, Non Top Five and PopDens low respectively), e.g. comparing adjustment speed levels of diesel prices after oil price increases between IPS and Non IPS.

A comparison of the two parameters γ^{+} and γ^{-} (row four and five) shows that γ^{+} has higher absolute values in all (sub-)sets, meaning that oil price increases are faster transferred to diesel prices than oil price decreases.[10] However, based on the results of the Wald test, we cannot reject the null hypothesis of equal error correction terms ($\gamma^{+} = \gamma^{-}$) in six categories (row nine). The exception are the Top-Five-brands, which show asymmetry on the 10 % significance level. Table 4 also shows the number of rejections in percentage terms after 1,000 replications (bootstrapping) with a significance level of 5 % (Bootstrapped $\gamma^{+} = \gamma^{-}$ in [%], row ten). We interpret high rejection frequencies as larger than 15 % of all calculated cases (see Cook et al., 1999, Galeotti et al., 2003, Grasso and Manera, 2007). Based on these assumptions, we reject the null hypothesis of equal error correction parameters in six out of seven categories (the exception being Non Top Five stations) and conclude that there is asymmetric price setting in those cases.

Based on results both before and after bootstrapping, we deduce the following: The Rockets and Feathers hypothesis is confirmed for the dominant Top Five stations. For these stations, we can reject $\gamma^{+} = \gamma^{-}$ both before and after bootstrapping. This is especially noteworthy in comparison to the Non Top Five, where we can reject the null hypothesis of $\gamma^{+} = \gamma^{-}$ neither before nor after bootstrapping. In all other cases, despite observing that γ^{+} has higher absolute values, we can reject the null hypothesis of $\gamma^{+} = \gamma^{-}$ only after bootstrapping.

10 The Durbin-Watson statistic (DW-test, row 7) is applied to analyse autocorrelation of the error terms. The DW-test finds no evidence of autocorrelation.

	All Data	IPS	Non IPS	Top Five	Non Top Five	PopDens high	PopDens low
Δoil_t	0.3937*** (0.1007)	0.4668*** (0.1226)	0.3662*** (0.0982)	0.4312*** (0.1179)	0.4009*** (0.109)	0.3943** (0.1612)	0.4398*** (0.0913)
Δoil_{t-1}	0.7455*** (0.1006)	0.6265*** (0.1225)	0.7547*** (0.0981)	0.6599*** (0.1178)	0.7375*** (0.1087)	0.7805*** (0.1617)	0.7166*** (0.0911)
$\Delta diesel_{t-1}$	-	-	-	-	-	-	-
γ^+	-0.3051*** (0.0947)	-0.2977*** (0.0866)	-0.3267*** (0.0978)	-0.5001*** (0.1147)	-0.2695*** (0.0957)	-0.4447*** (0.1075)	-0.3007*** (0.0957)
γ^-	-0.1525* (0.0816)	-0.1444* (0.083)	-0.158* (0.0828)	-0.2096** (0.0961)	-0.1937** (0.0832)	-0.2736** (0.1122)	-0.1456* (0.077)
Adj. R^2	0.51	0.40	0.52	0.44	0.47	0.37	0.56
DW-test	2.1	2.1	2.16	2.23	2.3	2.18	2.14
BIC	-567.2634	-527.9382	-572.4459	-535.8472	-552.0267	-472.3857	-587.1351
p-value $\gamma^+ = \gamma^-$	0.2253	0.2046	0.1914	0.055*	0.5519	0.2745	0.2104
Bootstrapped $\gamma^+ = \gamma^-$ [%]	25.2	28.1	28.2	49.5	9.7	20.0	24.1
t-value $\gamma_x^+ = \gamma_y^+$	-	2.22**		-15.44***		-10.01***	
(Bootstrapped)	(-)	(2.16**)		(-15.35***)		(-10.63***)	
t-value $\gamma_x^- = \gamma_y^-$	-	1.16		-1.25		-9.41***	
(Bootstrapped)	(-)	(1.5)		(-1.59)		(-9.55***)	

Table 4: Estimates for the error correction model with 100 observations for each data set. Notes: lag length chosen by BIC, standard error in parentheses, significance codes: 0.01 (***), 0.05 (**), 0.1 (*), bootstrapping: bootstrapped $\gamma^+ = \gamma^-$ [%] gives the percentages of rejections of the null hypothesis of equal error correction terms with a significance level of 5 %, bootstrapped $\gamma_x^+ = \gamma_y^+$ and $\gamma_x^- = \gamma_y^-$ [%] gives the test results for model characteristics after 1,000 replications of both models.

After bootstrapping, our general findings are in line with the work by Galeotti et al. (2003). Compared to Asane-Otoo and Schneider (2015), we find more asymmetries. For their weekly German diesel data set, they found positive asymmetry for the period from 2003 to 2007 but not for the time period 2009 to 2013.

The last four rows in Table 4 analyse the relationship between complementary subsets. In particular, they show the results of the two-sample-t-tests with the null hypothesis of identical adjustment speeds (e.g. $\gamma_{IPS}^{+} = \gamma_{Non\ IPS}^{+}$) between different subsets. While results in row four show that Top Five adjust faster after oil price increases than Non Top Five stations, row eleven confirms this by rejecting the null hypothesis of identical γ^{+} between Top Five and Non Top Five (-15.44, significant on the 1 % level). Thus, the dominating players – Aral, Shell, Total, Esso and Jet – increase prices faster after oil price increases than all other stations. This outcome correlates with the findings of Verlinda (2008) for Orange County, Balmaceda and Soruco (2008) for Santiago and the FCO (2011) for Germany. The latter concludes that price changes are often initiated by Aral or Shell and rapidly adopted by the other three top brands. Interestingly, our results show that while γ^{+} is significantly different between Top Five and Non Top Five, γ^{-}show comparable adjustment speed levels. Hence, the Top Five stations are not as fast to pass on oil prices decreases into lower diesel prices and show comparable characteristics like all other stations.

Analysing differences in price setting strategies between petrol stations in densely and less densely populated areas, we find that stations in regions with higher population densities show significantly faster adjustment speed levels, both after oil price increases and after oil price decreases. This might result from an easy monitoring of prices for both retail stations and customers from numerous close competitors and hence rapidly following individual price adaptations. On the contrary, less densely populated regions show lower adjustment speed levels after oil price changes (Kihm et al., 2016). Comparing our results regarding population densities to Asane-Otoo and Schneider (2015), they found that retail prices in extremely densely populated metropolitan areas (Berlin and Munich) have lower adjustment speeds to wholesale price increases compared to decreases. However, they did not compare this to data from less densely populated areas or their German average as they used a different data set (daily diesel prices from December 2013 to September 2014 in Berlin and Munich compared to weekly data from 2003 to 2013 for all of Germany).

Lastly comparing adjustment speeds between IPS and Non IPS, adjustments after oil price increases (γ^{+}) are different on the 5 % level (1.984), with IPS showing lower adjustment speeds. No significant differences can be found after oil price decreases. Hence, IPS' lower reaction speed on oil price increases seems the only difference between IPS and Non IPS. These results may be caused by the same pricing strategies being profit-maximizing for both categories, or by IPS simply mirroring the pricing strategies of the market. Alternatively, dependence on main petrol brands may drive IPS to follow, e.g. due to the influence of vertically integrated market players on refinery prices (FCO, 2011), although they follow less fast after oil price increases.

We also tested the robustness of our results with model variations and present the results in the appendix. To begin with, our main conclusions based on the reference model (Table 4) do not significantly change when using price data in logs instead of levels (see Table A.4 in the appendix). In addition, we calculated an asymmetric model (see Eq. A.4, instead of our semi-asymmetric reference in Eq. 3). Table A.5 shows the model selected by BIC. It confirms again a relatively low explanatory power of lagged diesel price changes as they are omitted by BIC.

In terms of asymmetric price adjustment, the model shows comparable results to our main findings.

6 CONCLUSION

This paper analyses asymmetries in the German diesel retail market for the calendar years 2011 and 2012. We use weekly diesel prices from a countrywide bottom-up data set and analyse the price relationship with Brent crude oil prices. Our disaggregated data enables us to separate the data set into subsets. Thus, we quantified the impact of the oil price on seven different diesel price data (sub-)sets: all diesel prices in our data set, diesel prices from independent petrol stations (IPS) and all Non IPS respectively, diesel prices from the five dominant brands (Top Five) and all Non Top Five stations respectively, as well as diesel prices from regions with higher and lower population densities.

Our results show that diesel prices follow increases in oil prices faster than decreases in all cases. Before bootstrapping results, testing for significance of these asymmetries confirms them for Top Five stations only. After bootstrapping the ECM and testing for significant asymmetries, the results show asymmetric price setting behaviour in six out of seven cases: All Stations, IPS, Non IPS, Top Five, as well as stations in high and low population areas.

Hence, we find significant differences in price setting behaviour between Top Five stations and other stations. This confirms their influence as price setters during price increases: They follow oil price increases faster and more pronounced than the other stations. However, results do not confirm such behaviour after oil price reductions. Our results reveal little differences in asymmetric cost pass-through between IPS and Non IPS. We offered profit maximizing by IPS as well as dominant firms' influence on IPS as possible explanations. Furthermore, petrol stations in regions with higher population densities and lower population densities differ with respect to their adjustment speeds: petrol stations in regions with higher population densities react both significantly faster to oil price increases as well as to oil price decreases. Further research may analyse the relationship between brands and their spatial distribution in more detail (certain brands may be found more often in less densely populated areas).

In terms of policy implications, we find evidence for asymmetric cost pass-through in the German diesel retail market. Furthermore, asymmetric cost pass-through is most significant for stations from the Top Five brands – which have the highest market share and thus may be particularly interested in strategic pricing behaviour. In the light of these results, the introduction of the market transparency platform by FCO seems a step in the right direction.

Further research might focus on the analysis of structural changes of pricing patterns before and after market transparency changes. Those might occur because of (1) technological innovations or (2) regulatory changes. While the technological innovations within recent years enabled researchers to work with bottom-up data with higher frequencies in more regions, regulatory changes might modify the transparency of a market for both suppliers and customers. Therefore, analysis might concentrate on the comparison of pricing patterns before and after those changes.

In the case of Germany, future work could in particular focus on the analysis of the symmetry of pricing patterns after the full establishment of the mentioned market transparency platform in late 2013.

APPENDIX A: TEST FOR STATIONARITY AND COINTEGRATION

Establishing an ECM with cointegrated time series data requires tests for the original data's order of integration. We need to know the order of integration to ensure that the two possibly cointegrated time series have the same order of integration. We test with the (Augmented) Dickey-Fuller test (ADF-test) whether the relevant time series is stationary, which is commonly used in those methodological approaches and introduced by Dickey and Fuller (1979). We use the ADF-test with a constant and a trend for data in levels, because of trend characteristics and significances (equation A.1) and without a constant or trend (equation A.2) for first differences (see Figure 2 for raw data).

$$\Delta y_t = \alpha_0 + \alpha_1 t + \beta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(Eq. A.1)}$$

$$\Delta y_t = \beta y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \qquad \text{(Eq. A.2)}$$

The variable y_t represents the price data for oil or diesel. α_0 is a constant, that is needed because the plotted data in levels show a nonzero mean, and α_1 is the trend for the data in levels. No constant and trend need to be included for the data of first differences. The reminder of both equations is identical. ε is the error term. If β is 0, the process is non-stationary (null hypothesis). If we reject the null hypothesis, we can conclude that our data is stationary. To test stationarity, we compare the t-statistics for β against a non-standard distribution (Pfaff, 2008). We use the BIC for the optimal lag length. The outcomes (Table A.1) show that all seven time series are stationary for their first differences while they are not stationary at levels. Hence, we can assume they are I(1). We also controlled with the help of the KPSS Unit Root Test (alternative hypothesis: no stationarity) and obtained comparable results (integration order of I(1), see Table A.2).

Table A.3 gives the results for the cointegration relationship estimated with OLS and Equation A.3. Results show that residuals are stationary, as in the case of DOLS. Therefore, we can conclude that a cointegration relationship exists between diesel and oil prices.

$$diesel_t = \theta + \mu\, oil_t + \tau_t \qquad \text{(Eq. A.3)}$$

	Oil	D(Oil)	Diesel	D(Diesel)
All Data	-2.9159	-6.7101***	-2.9467	-7.0347***
IPS	-2.9159	-6.7101***	-3.1024	-7.0693***
Non IPS	-2.9159	-6.7101***	-2.8711	-6.5139***
Top Five	-2.9159	-6.7101***	-2.6962	-6.6104***
Non Top Five	-2.9159	-6.7101***	-2.8938	-6.6777***
PopDens high	-2.9159	-6.7101***	-3.1042	-7.9302***
PopDens low	-2.9159	-6.7101***	-2.9917	-6.7383***

Table A.1: Results of ADF-tests with 104 observations for each data set (respectively 103 for first differences). significance codes: 0.01 (***), 0.05 (**), 0.1, optimal lag length for all cases is 1 – chosen by BIC.

	Oil	D(Oil)	Diesel	D(Diesel)
All Data	1.32***	0.0885	1.6982***	0.1348
IPS	1.32***	0.0885	1.8619***	0.1357
Non IPS	1.32***	0.0885	1.5323***	0.1411
Top Five	1.32***	0.0885	1.7266***	0.1412
Non Top Five	1.32***	0.0885	1.5592***	0.1519
PopDens high	1.32***	0.0885	1.7441***	0.2073
PopDens low	1.32***	0.0885	1.57***	0.1366

Table A.2: Results of KPSS-test with lags equal 2 with 102 observations for each data set (respectively 101 for first differences), significance codes: 0.01 (***), 0.05 (**), 0.1 (*).

	All Data	IPS	Non IPS	Top Five	Non Top Five	PopDens high	PopDens low
θ	0.8279*** (0.0363)	0.8164*** (0.0433)	0.84057*** (0.03486)	0.8241*** (0.0351)	0.81120*** (0.03975)	0.8162*** (0.0444)	0.8264*** (0.0344)
oil_t	1.1519*** (0.069)	1.17*** (0.0823)	1.12948*** (0.06629)	1.1712*** (0.0668)	1.17573*** (0.07560)	1.1653*** (0.0844)	1.157*** (0.0653)
Adj. R^2	0.73	0.67	0.74	0.75	0.71	0.65	0.76
BIC	-463.4035	-427.4701	-471.4758	-470.0756	-444.6812	-422.2712	-474.4615
ADF-test [lags]	-3.493*** [1]	-3.1966** [1]	-3.5089*** [1]	-3.5574*** [1]	-3.4757** [1]	-3.8013*** [1]	-4.4156*** [0]

Table A.3: OLS cointegration relationship with 102 observations for each data set. Notes: ADF-test for the residuals of the OLS relationship without constant or trend, optimal lag length chosen by BIC, critical values from MacKinnon (1991), standard errors in parenthesis ( ), significance codes: 0.01 (***), 0.05 (**), 0.1 (*).

APPENDIX B: FURTHER ROBUSTNESS CALCULATION OF ECM

Table A.4 shows results for the reference ECM but with all price data entering in logs.

	All Data	IPS	Non IPS	Top Five	Non Top Five	PopDens high	PopDens low
Δoil_t	0.3991*** (0.1007)	0.4731*** (0.1226)	0.3717*** (0.0983)	0.4397*** (0.1174)	0.4078*** (0.1090)	0.4041** (0.1618)	0.4451*** (0.0914)
Δoil_{t-1}	0.7397*** (0.1007)	0.6209*** (0.1225)	0.7489*** (0.0982)	0.6507*** (0.1173)	0.7297*** (0.1089)	0.769*** (0.1614)	0.7113*** (0.0913)
$\Delta diesel_{t-1}$	-	-	-	-	-	-	-
γ^+	-0.4412*** (0.1367)	-0.4304*** (0.1247)	-0.4686*** (0.1411)	-0.7403*** (0.1647)	-0.3827*** (0.1379)	-0.6391*** (0.1516)	-0.4302*** (0.139)
γ^-	-0.2210* (0.1194)	-0.2087* (0.1213)	-0.2307* (0.121)	-0.3037** (0.1398)	-0.2860** (0.1218)	-0.3969** (0.1633)	-0.215* (0.1126)
Adj. R^2	0.51	0.40	0.52	0.45	0.47	0.37	0.55
DW-test	2.09	2.1	2.15	2.2	2.28	2.16	2.13
BIC	-567.2253	-527.9637	-572.3054	-536.7919	-551.8906	-472.8794	-586.915
p-value $\gamma^+ = \gamma^-$	0.228	0.2057	0.2039	0.0458**	0.6005	0.2803	0.2325
Bootstrapped $\gamma^+ = \gamma^-$ [%]	23.4	26.5	26.6	56.8	8.1	19.2	21.4
t-value $\gamma_x^+ = \gamma_y^+$ (Bootstrapped)	- (-)	2.03** (2.21**)		-16.65*** (-17.47***)		-10.15*** (-10.78***)	
t-value $\gamma_x^- = \gamma_y^-$ (Bootstrapped)	- (-)	1.28 (1.19)		-0.95 (-1.28)		-9.17*** (-9.32***)	

Table A.4: Estimates for the error correction models with logged data with 100 observations for each data set. Notes: lag length chosen by BIC, standard error in parentheses, significance codes: 0.01 (***), 0.05 (**), 0.1 (*), bootstrapping: bootstrapped $\gamma^+ = \gamma^-$ [%] gives the percentages of rejections of the null hypothesis of equal error correction terms with a significance level of 5 %, bootstrapped $\gamma_x^+ = \gamma_y^+$ and $\gamma_x^- = \gamma_y^-$ [%] gives the test results for model characteristics after 1,000 replications of both models.

Table A.5 shows results for an asymmetric ECM selected by BIC.

$$\Delta diesel_t = \gamma^+\tau^+_{t-1} + \gamma^-\tau^-_{t-1} + \sum_{m=0}^{K} \vartheta^+_{1,m}\Delta oil^+_{t-m} + \sum_{m=0}^{K} \vartheta^-_{1,m}\Delta oil^-_{t-m} \qquad \text{(Eq. A.4)}$$

$$+ \sum_{n=1}^{L} \vartheta^+_{2,n}\Delta diesel^+_{t-n} + \sum_{n=1}^{L} \vartheta^-_{2,n}\Delta diesel^-_{t-n} + \varepsilon_t$$

$$\Delta oil^+_t = \Delta oil_t \wedge \Delta oil^-_t = 0 \; if \; \Delta oil_t > 0,$$

$$\Delta oil^-_t = \Delta oil_t \wedge \Delta oil^+_t = 0 \; if \; \Delta oil_t < 0;$$

$$\Delta diesel^+_t = \Delta diesel_t \wedge \Delta diesel^-_t = 0 \; if \; \Delta diesel_t > 0,$$

$$\Delta diesel^-_t = \Delta diesel_t \wedge \Delta diesel^+_t = 0 \; if \; \Delta diesel_t < 0$$

	All Data	IPS	Non IPS	Top Five	Non Top Five	PopDens high	PopDens low
Δoil_t^+	0.4372*** (0.1585)	0.4279** (0.1928)	0.4209*** (0.1544)	0.3452* (0.1854)	0.5018*** (0.171)	0.5288** (0.227)	0.5076*** (0.1289)
Δoil_t^-	0.3463** (0.1669)	0.5087** (0.2034)	0.3049* (0.1626)	0.5213*** (0.1949)	0.2877 (0.1797)	0.229 (0.234)	0.3716*** (0.1321)
Δoil_{t-1}^+	0.7173*** (0.1579)	0.6557*** (0.1924)	0.7278*** (0.1538)	0.7336*** (0.1849)	0.6916*** (0.17)	0.8611*** (0.2231)	0.6777*** (0.1264)
Δoil_{t-1}^--	0.7731*** (0.1675)	0.597*** (0.2039)	0.7793*** (0.1631)	0.5839*** (0.1957)	0.7783*** (0.1805)	0.657*** (0.2374)	0.7497*** (0.1346)
γ^+	-0.304*** (0.0957)	-0.2969*** (0.0876)	-0.3252*** (0.0988)	-0.4968*** (0.1158)	-0.2648*** (0.0966)	-0.4396*** (0.1078)	-0.2964*** (0.0966)
γ^-	-0.1527* (0.0824)	-0.1444* (0.0838)	-0.1574* (0.0836)	-0.2086** (0.097)	-0.194** (0.0838)	-0.2651** (0.1128)	-0.1425* (0.0777)
Adj. R²	0.4966	0.387	0.5072	0.4303	0.4646	0.3648	0.548
DW-test	2.1	2.1	2.2	2.2	2.3	2.2	2.1
BIC	-558.1901	-518.8019	-563.483	-527.0423	-543.5209	-464.8965	-578.5476
p-value $\gamma^+ = \gamma^-$	0.2342	0.2117	0.1981	0.0592*	0.5822	0.2661	0.218
p-value $\Delta oil_t^+ = \Delta oil_t^-$	0.7204	0.7941	0.6395	0.5536	0.4351	0.36	0.463
p-value $\Delta oil_{t-1}^+ = \Delta oil_{t-1}^-$	0.8264	0.8498	0.8352	0.6153	0.7517	0.5326	0.6971
Bootstrapped $\gamma^+ = \gamma^-$ [%]	22.5	25.7	25.8	50.1	7.0	18.5	23.5
t-value $\gamma_x^+ = \gamma_y^+$	-	2.14**		-15.38***		-9.89***	
(Bootstrapped)	(-)	(1.93*)		(-16.33***)		(-10.41***)	
t-value $\gamma_x^- = \gamma_y^-$	-	1.1		-1.14		-8.95***	
(Bootstrapped)	(-)	(1.58)		(-1.01)		(-9.84***)	

Table A.5: Estimates for the asymmetric error correction models with one lag and short-run asymmetries with 100 observations for each data set. Notes: lag length chosen by BIC, standard error in parentheses, significance codes: 0.01 (***), 0.05 (**), 0.1 (*), bootstrapping: bootstrapped $\gamma^+ = \gamma^-$ [%] gives the

percentages of rejections of the null hypothesis of equal error correction terms with a significance level of 5 %, bootstrapped $\gamma_x^+ = \gamma_y^+$ and $\gamma_x^- = \gamma_y^-$ [%] gives the test results for model characteristics after 1,000 replications of both models.

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