# Estimating retail gasoline price dynamics: The effects of sample characteristics and research design

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# Estimating Retail Gasoline Price Dynamics:
# The Effects of Sample Characteristics and Research Design*

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**Abstract**

The study shows that much of the variation in the findings of the literature on retail gasoline price dynamics is systematic rather than sample variation from using different data. Estimates of pass-through rates depend systematically on research design and features of the data, such as the sampling frequency, the choice of upstream price, whether taxes are included or not, the sample length, and the postulated lag structure. In addition, there are systematic differences between time periods and countries. Using a 20 year-long dataset of 28 European Union countries we quantify the extent of estimate variation that arises from the choice of data structure from that arising from temporal and country heterogeneity and sampling variation. We also show that country heterogeneity itself has systematic components, with wealthier countries experiencing slower adjustments. Our results inform the interpretation of results on pass-through rates derived from Error Correction Models. They are also of relevance for the broader literature estimating the transmission of price shocks in the economy.

J.E.L. Codes: L11, L16.

Keywords: Rockets and Feathers, Cost Pass-through, Price Adjustment and Inflation, Error Correction Model.

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# 1. INTRODUCTION

There are hundreds of academic papers on the asymmetric response of retail gasoline price to changes in the wholesale price or the price of crude oil. In part, this is because the literature is broad in its relevance, being pertinent to search theory, dynamic competition (e.g., Edgeworth cycles), pricing, pass-through (including foreign exchange and tax through), inflation dynamics, tacit collusion, market power, and the link between information and consumer demand, among others.[1] The topic has become of interest to economists in a number of fields including Industrial Organization, Macroeconomics, and Applied Econometrics, which, along with the availability of data, helped spawn a large empirical literature (and also a number of important theoretical contributions). This literature spans almost 30 years, dozens of countries, uses data at various level of spatial aggregation (from individual gas stations to continent-size countries, like the US), covers periods of less than one year to longer than a decade, ranges in frequency from a single day to one month, considers both pre-tax or after-tax prices, which are sometimes in logs and sometimes in levels. Methodologically, most of it employs variations of the standard error correction model.

Though this literature has made a number of important contributions, the basic question of how large these asymmetries are, say, one or two months after an input price shock, has drawn widely different answers. Part of the reason is that different markets exhibit different price dynamics because they differ along relevant characteristics, such as competitiveness. But part of the reason may simply come down to differences in the data structure, e.g., data frequency, spatial aggregation, and price definition, or to minor differences in specification, e.g., lag structure. Indeed, Bachmeier and Griffin (2003) provide evidence that these factors can, on their own, materially affect the conclusions drawn by some of the seminal studies. If different data structures tend to provide different estimates of pass-through asymmetries, then much of what seems like divergence in point estimates across studies might disappear if the underlying data were similarly configured. In addition to this, there seems to be a tendency for some recent contributions to find limited or no asymmetries; this might be because they are becoming less important over time, but could also be because authors

[1] Among the first studies on the topic are Karrenbrock (1991), Bacon (1991), who coined the commonly used term "rockets and feathers," indicating a faster retail price response to input price increases than to input price decreases, and Borenstein, Cameron, and Gilbert (1992, 1997).

look at new locations, or because results are more likely to be considered a publishable contribution when they differ from prior findings.

Knowing how data structures affect passthrough estimates would allow for a more accurate comparison among studies. In fact, it could be a pre-requisite to assessing how much heterogeneity there is in the price process across different countries and over time. Measuring the extent of such heterogeneity would require using the same yardstick, i.e., the same type and amount of data, and the same econometric specification. Knowing how data structures affect estimates of asymmetries would also be useful prospectively. For example, if using a weekly frequency or tax inclusive prices leads to relatively smaller estimates, a researcher doing so can take this into consideration in interpreting his/her results and comparing with prior research. Identifying a possible trend in the extent of the asymmetries would also be useful in assessing whether this was a temporally transient phenomenon that is disappearing, possibly because it has become prominently highlighted. In principle, one could try to identify a possible connection between the data structure and measured asymmetries through meta-analysis, such as in Perdiguero-Garcia (2013). But doing so would require disentangling all the other sources of variation in the estimates, and would also implicitly assume that the size of the estimated effects does not impact the likelihood of a journal publication.

Addressing these issues is of value beyond the narrow question of cost passthrough in gasoline markets. Asymmetric price adjustment is not unique to these markets. Peltzman (2000) examines prices in over 200 industries and finds evidence of asymmetric adjustment in a significant fraction of them. In addition, Goodwin and Holt (1999) and Goodwin and Harper (2000) estimate asymmetric price adjustment in the U.S. beef and pork industries, O'Brian (2006) estimates asymmetric adjustment in interest bearing deposit accounts, and McShane et al. (2016) finds evidence of an asymmetric pass-through in retail prices for the packaged goods industry. The literature on the passthrough to upstream price shocks is broader still. Many of these studies employ similar methodologies and research design to that used in the gasoline price adjustment literature, and thus passthrough estimates may relate to the research design in a qualitatively similar manner.

There are also implications beyond the confines of Industrial Organization. As Alvarez et al (2006), among others, point out, the speed of adjustment of inflation and the Consumer Price Index (CPI) to economic shocks, including input price shocks, is directly linked to the speed of individual price adjustment. Though many studies have looked at a broad range of prices, focusing on the gasoline industry has the advantage that it allows us to study directly the transmission of upstream price shocks downstream; this cannot be easily done for most products, and is certainly not feasible for a study that combines a large number of them. The fuel sector is one where heterogeneity is easier to detect from relatively high frequency upstream cost changes because prices change much more frequently than in the non-energy sector (e.g., see Bils and Klenow, 2004, for the US, and Altissimo, Ehrmann and Smets, 2006, for Europe). The value of this paper is not in helping us understand the effect of oil price changes on inflation; this effect is rather small (see Alvarez et al, 2011).[2] It is to contribute to our general understanding of heterogeneity in passthrough estimates and their dependence on the data structure; this heterogeneity and data dependence is likely relevant for a broad swath of industries, which in aggregate have a material impact on inflation.[3]

The first contribution of this paper is to measure the variability of the passthrough estimates and associated asymmetries using a single parent dataset. Our second contribution is to identify linkages between those estimates and the data configuration, the estimation window, and variant of estimation technique and specification. Our final contribution is to partial out the country specific systematic component of passthrough rate heterogeneity and relate it to country-specific characteristics such as the level of economic development and the importance of the personal motor vehicle market.

We implement our analysis using a single long panel of European countries, which spans more than 20 years, covers 28 countries, includes both pre-tax and tax-inclusive prices, and is collected weekly.[4] We combine this data with two different upstream prices: crude oil and wholesale regular

[2] It is known that the effect of an oil shock on output and inflation differs across countries (e.g., see Kilian 2008). Though there are many reasons for these differences, the upstream to downstream pass-through channel certainly plays a contributory role.

[3] Though "price rigidities" were a controversial topic in macroeconomics, it has become less so in recent years, in part because of the preponderance of evidence about their presence. Moreover, As pointed in Christiano, Eichenbaum, and Evans (2005), nominal rigidities play a crucial role in helping reproduce the inflation and output dynamics of the US economy. Though wage rigidities are more important than those of prices (of either intermediate or final goods), the latter are also an important contributing factor.

[4] There is a trend in recent studies towards using daily data (e.g., Remer, 2015; Chesnes, 2016). But similar issues arise there, as well.

gasoline. Finally, we construct an aggregated version of the data, temporally aggregating to the monthly level. We estimate time series specifications at the country level as well as panel specifications at the European level. Our specifications include many commonly used versions of error correction models both in levels and in logs, and cover different spans of the 20-year period in our disposal, centered in different years and varying in length. For each combination of econometric model and data configuration, we estimate the pass-through rate at the one and two-month intervals under symmetric and asymmetric specifications, thus establishing the relationship between these pass-through rates, the data structure (including the estimation window) and the econometric specification. For the final component of our analysis, we use as country characteristics the per capita income, the number of personal motor vehicles per capita, and the number of gas stations per capita, all averaged over the relevant estimation window.

We find that passthrough rates can differ substantially across estimation runs. The dispersion is generally higher for log specifications. The dispersion double or triple the size of the confidence intervals reported in the literature from single estimation runs. It is not surprising that the confidence intervals tend to understate the degree of uncertainty as measured by a random choice of data and specification, because the former hold the sample and specification fixed, removing one source of variability that is faced by researchers when starting a research project. However, the magnitude of the difference is surprising. Interestingly, passthrough rates do not generally appear to be asymmetric when looking across all estimation runs.

Estimated passthrough rates are generally higher for later sample periods, for specifications with longer lags, when the data is of monthly frequency, and when an error correction model is used. These effects are sometimes quantitatively important. For example, holding every other feature of the data and specification constant, a difference of one decade in the sample mid-point can affect passthrough rates by ten percent. The sample length and the choice of upstream price do not seem to have important effects. Though asymmetries in passthrough tend to be generally absent, some specifications tend to deliver the familiar “rocket-and-feathers” pattern reported by many studies in the literature. These are specifications using monthly, pre-tax data with no error correction term and prices measured in currency units (instead of logs). Most of the other elements of econometric specification and data structure have no effect on the estimated asymmetries of passthrough rates.

Moreover, country heterogeneity in passthrough rates is quantitatively very important. To assess the importance of observed characteristics, we obtain the passthrough rates for each country for non-overlapping six-year periods. We then partial out the contribution of all other elements that can affect passthrough estimates, such as the time period, the data structure and the econometric specification. We finally regress these adjusted passthrough rates on the average value of country characteristics for each time period. We show that countries with higher per capita income during a time period exhibit slower passthrough rates. Controlling for per capita income, the importance of the car market and gasoline industry (as measured by the number of cars per capita and the number of stations per capita) seems to have no effect. Though we cannot ascertain the source of this correlation, our results are indicative of systematic variation in the pass-through rates across countries and time. This analysis is reminiscent of findings in the literature that explain the systematic time variation in pass-through rates. For example, Taylor (2000) shows that low and stable inflation can lead to a reduction to cost or competitor driven pass-throughs. Unfortunately, we cannot perform a similar analysis in our own data as inflation tends to be rather stable for most of time period in our sample, and any change in inflation tends to be strongly correlated with a simple time trend. However, the importance of inflation could also be investigated using our approach using a longer time series.

The rest of this paper is structured as follows. Section 2 outlines the econometric framework and conceptual design of this study. Section 3 presents the data and the sample variables used in the empirical models, while Section 4 discusses key features of the distribution of passthrough estimates. Section 5 investigates the linkages between research design and the passthrough estimates. Section 6 analyzes the main determinants of country heterogeneity and Section 7 concludes the paper.

## 2. FRAMEWORK

### *2.1. Econometric Specifications*

We consider the most common specifications employed by the retail gasoline price adjustment literature. The simplest of these is the Distributed Lag (DL) model. The symmetric adjustment version of this model, estimated using a panel of EU countries, takes the form

$$\Delta R_{j,t} = a_j + a_s + \sum_{l=0}^{L} b_l \Delta C_{t-l} + \varepsilon_{j,t} \tag{1a}$$

where $R_{j,t}$ is the retail price of gasoline in country *j* and period $t$, $\Delta R_{j,t}$ is the change in the retail price from period $t$-1 to period $t$ in country *j*, $C_t$ is the upstream input price (common for every country), $\Delta C_t$ is the change in the upstream input price from period $t$-1 to period $t$, $L$ is the number of lags in the upstream price, $a_j$ is a set of country dummy variables, and $a_s$ is a set of seasonal dummy variables. This regression, like all those described in this paper, can be estimated for a panel of countries or county-by-country, i.e., permitting every parameter estimate to vary by country. This yields the following specification

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j} \Delta C_{t-l} + \varepsilon_{j,t} \tag{1b}$$

The asymmetric adjustment versions of these models, which allow for increases in upstream prices to exhibit a different adjustment process than decreases, are given by:

$$\Delta R_{j,t} = a_j + a_s + \sum_{l=0}^{L} b_l^+ \Delta C_{t-l}^+ + \sum_{l=0}^{L} b_l^- \Delta C_{t-l}^- + \varepsilon_{j,t} \tag{1c}$$

and

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j}^+ \Delta C_{t-l}^+ + \sum_{l=0}^{L} b_{l,j}^- \Delta C_{t-l}^- + \varepsilon_{j,t} \tag{1d}$$

respectively, where $\Delta C_{t-l}^+ = \Delta C_{t-l}$ if $\Delta C_{t-l} \geq 0$ and zero otherwise, $\Delta C_{t-l}^- = \Delta C_{t-l}$ if $\Delta C_{t-l} < 0$ and zero otherwise. The asymmetric DL specification was introduced by Karrenbrock (1991) and has been adopted in a large number of papers since. The DL model does not take into consideration that lagged changes in retail prices may be associated with future price increases due to autocorrelation or that the upstream and downstream prices may be cointegrated. If that is the case, including autoregressive terms and incorporating the long-run relationship between these prices in the short-term dynamics through an "error correction term" provides a more accurate representation of the price adjustment process. Let this long run relationship be given by the equation

$$R_{j,t} = k_j + mC_t + u_t \tag{2}$$

Then, the symmetric version of the Error Correction Model (ECM) estimated from the entire panel of countries is given by:

$$\Delta R_{j,t} = a_j + a_s + \sum_{l=0}^{L} b_l \Delta C_{t-l} + \sum_{l=1}^{L} c_l \Delta R_{j,t-l} + d\left(R_{j,t-1} - k_j - mC_{t-1}\right) + \varepsilon_{j,t} \tag{3a}$$

where the parameter $d$ is the speed at which the retail price returns to its long run equilibrium value. When this estimation is done country-by-country, this parameter and also the long-run relationship between upstream and downstream prices (the parameter $m$) take different values for each country, i.e., the model becomes

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j} \Delta C_{t-l} + \sum_{l=1}^{L} c_{l,j} \Delta R_{j,t-l} + d_j\left(R_{j,t-1} - k_j - m_j C_{t-1}\right) + \varepsilon_{j,t} \tag{3b}$$

These specifications, and their asymmetric variants which we describe below, were first adopted by Borenstein, Cameron, and Gilbert (1992), and since used by many others in this literature. The long-run relationship can be estimated simultaneously with the short-run dynamics, through the regressions

$$\Delta R_{j,t} = a_j - k_j d + a_s + \sum_{l=0}^{L} b_l \Delta C_{t-l} + \sum_{l=1}^{L} c_l \Delta R_{j,t-l} + dR_{j,t-1} - dmC_{t-1} + \varepsilon_{j,t} \tag{3c}$$

when using all countries in the panel, and

$$\Delta R_{j,t} = a_j - k_j d_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j} \Delta C_{t-l} + \sum_{l=1}^{L} c_{l,j} \Delta R_{j,t-l} + dR_{j,t-1} - d_j m_j C_{t-1} + \varepsilon_{j,t} \tag{3c}$$

when estimating them country-by-country. Note that the country fixed effects (or regression constant) are composite terms each component of which is not separately identified in the one-step regression. However, this is not important for assessing the price dynamics or for performing simulations of the retail price response to upstream price changes. The econometric models (3a) and (3b) can also be estimated in two steps. In the first step, one estimates the co-integration relationship (2), or its country-by-country counterpart, obtaining the residuals $\widehat{u_{j,t}}$. The short run dynamics for the panel model are estimated in a second step using the regression

$$\Delta R_{j,t} = a_j + a_s + \sum_{l=0}^{L} b_l \Delta C_{t-l} + \sum_{l=1}^{L} c_l \Delta R_{j,t-l} + d\hat{u}_{j,t-1} + \varepsilon_{j,t} \tag{3d}$$

and similarly for the country-by-country version. Note that all parameters are identified in the two-step approach, though this is of no relevance for the simulation of the price dynamics. The asymmetric county-by-country model with short-run dynamics is of the form:

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j}^{+} \Delta C_{t-l}^{+} + \sum_{l=0}^{L} b_{l,j}^{-} \Delta C_{t-l}^{-} + \sum_{l=1}^{L} c_{l,j}^{+} \Delta R_{j,t-l}^{+} + \sum_{l=1}^{L} c_{l,j}^{-} \Delta R_{j,t-l}^{-} + d_j\left(R_{j,t-1} - k_j - m_j C_{t-1}\right) + \varepsilon_{j,t} \tag{3e}$$

with the panel version incorporating the parameter restrictions, as shown in the symmetric specification of this model. The asymmetric specification can be estimated using both the one step and the two step approaches outlined above. There is also a variant of the error correction model that allows for asymmetries in the speed of adjustment towards the long-run equilibrium values. Under this specification model (3e) becomes

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j}^{+} \Delta C_{t-l}^{+} + \sum_{l=0}^{L} b_{l,j}^{-} \Delta C_{t-l}^{-} + \sum_{l=1}^{L} c_{l,j}^{+} \Delta R_{j,t-l}^{+} + \sum_{l=1}^{L} c_{l,j}^{-} \Delta R_{j,t-l}^{-} + d_j^{+}\left(R_{j,t-1} - m_j C_{t-1}\right)^{+} + d_j^{-}\left(R_{j,t-1} - m_j C_{t-1}\right)^{-} + \varepsilon_{j,t} \tag{4}$$

where $\left(R_{j,t-1} - m_j C_{t-1}\right)^{+} = R_{j,t-1} - m_j C_{t-1}$ if $R_{j,t-1} - m_j C_{t-1} \geq 0$ and zero otherwise, while $\left(R_{j,t-1} - m_j C_{t-1}\right)^{-} = R_{j,t-1} - m_j C_{t-1}$ if $R_{j,t-1} - m_j C_{t-1} < 0$ and zero otherwise. This last model, and its panel variant, must be estimated using a two-step method, since the one step method represents a fundamentally non-linear equation that cannot be estimated via linear regression.

Of intermediate complexity between the DL and ECM specifications is the Autoregressive Distributed Lag model (ARDL). This model, also often used in the literature, consists of the ECM specification without the error correction term, i.e., it is the Distributed Lag model augmented by the series of the lagged dependent variable. Its symmetric specification, estimated country-by-country, is given by

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j} \Delta C_{t-l} + \sum_{l=1}^{L} c_{l,j} \Delta R_{j,t-l} + \varepsilon_{j,t}$$

while the asymmetric specification is given by

$$\Delta R_{j,t} = a_j + a_{j,s} + \sum_{l=0}^{L} b_{l,j}^{+} \Delta C_{t-l}^{+} + \sum_{l=0}^{L} b_{l,j}^{-} \Delta C_{t-l}^{-} + \sum_{l=1}^{L} c_{l,j}^{+} \Delta R_{j,t-l}^{+} + \sum_{l=1}^{L} c_{l,j}^{-} \Delta R_{j,t-l}^{-} + \varepsilon_{j,t}$$

Because the ARDL model is intermediate to the DL and ECM specifications, there is only limited value in considering it for the purposes of this study.

After any of these models is estimated, the predicted price path for a one-time change in the upstream price can be calculated. For concreteness, take equation (3a), and assume $\Delta C_t = 1$ for some time period $t$, starting from a long run equilibrium. Then, the contemporaneous effect on the retail price is $\Delta R_{j,t} = b_{0,j}$. Changes in the retail price because of changes in the seasonal effects are ignored, because they are not driven by the change in the upstream price, i.e., they are not part of the counterfactual simulation. For the next period, $t$+1, there will be an additional change in the retail price. This will have three components: one component is due to the non-zero value of $\Delta R_{j,t}$ (which is equal to $b_{0,j}$), one from the non-zero value of $\Delta C_t$ (which is equal to 1), and the last from the non-zero value of $R_{j,t} - k_j - m_j C_t$, (which recalling that we start from a long run equilibrium is now equal to $b_{0,j} - m_j 1$). Multiplying these terms with the corresponding coefficients, we obtain the second period change in the retail price to be $\Delta R_{j,t+1} = b_{1,j} + c_{1,j} b_{0,j} + d_j (b_{0,j} - m_j)$. One can iterate forward to obtain the retail price changes for period $t$+2, $t$+3, and so on. Analogous expressions can be derived for any of the models described here.

### *2.2. Other Elements of the Research Design*

An important choice for each researcher is the econometric specification, with those described in the preceding section being some of the most commonly chosen ones. Within each specification, an important decision is the lag length, $L$. This is either chosen to follow other papers in the literature, or on the basis of some criterion that balances parsimony with goodness of fit, e.g., Akaike Information Criterion and the Schwarz Criterion. But in practice, this choice varies from paper to paper, even when using data from the same country.

There are a number of other choices that need to be made, which may depend on the object of interest to the researcher, and for which econometrics provides no guidance. Paramount among them is the choice of the downstream and upstream prices. Most papers use the pre-tax value of the retail gasoline as the downstream price; but not all do (see Table 2). Though pre-tax values are appropriate when the researcher wants to investigate how margins are affected by input price changes, from the point of view of consumers and price index dynamics post-tax prices are more relevant. Upstream price choices vary from using the price of crude oil, to using the price of gasoline at the terminal. The latter is often not available (and in fact, it is not available for this study, either); a substitute is the price of wholesale gasoline at a large market, e.g., New York. Regardless of the choice of price series, a researcher assesses the degree of asymmetric responses based on the series he or she is using, without considering the possibility that the choice of data has impacted the relevant estimates.

Other elements of the research design are dictated by data availability. For example, in some countries, data is available only in a monthly frequency, while in other countries, data is available in weekly frequency (and industry micro-data sometimes are available daily). Researchers often use the most temporally disaggregated data available to them. Almost never do they compare their estimates with those obtained at higher levels of aggregation of the same dataset. Similarly, data is sometimes available for short time periods, while other times it is available for longer time periods. Often, researchers do not use the longest possible length for the data on the specific country, because doing so may require combining information from different sources. Regardless of the reason, the length of the price series used varies substantially from study to study. The econometric specification, the lag structure, the choice of downstream and upstream price series, the pre-tax vs post-tax choice, the frequency of the data, and the length of the sample are the elements of research design we consider in this paper. In addition to heterogeneity due to the research design, there is additional heterogeneity from the use of data from different countries and different time periods (e.g., using recent versus older data).

## 3. Data and Subsamples

Our empirical analysis is based on an unbalanced panel dataset of retail gasoline prices comprising of weekly observations spanning the period from January 1994 to January 2015. The sample includes all 28 European Union countries, but the coverage for each country varies, largely because of differences in accession dates into the EU. Moreover, the coverage period for the tax-inclusive gasoline price (price at the pump) is more limited than the coverage period for the pre-tax (net) retail gasoline price. The data coverage for the gasoline price series is shown in Table 1.[5]

We use two different measures of upstream prices: the first is the price of crude oil, as reflected in the Brent benchmark; the second is the price of wholesale gasoline, proxied by the New York spot price. These weekly price series are obtained from the U.S. Energy Information Administration.[6] Upstream and downstream prices are converted to the same volumetric and monetary units (Euros/1000 liters).[7] The downstream price series contain occasional gaps reflecting weeks when there is no data collection (typically over the Christmas/New Year's holidays). When data is missing for a week, we impute the average value of the adjacent weeks. Because we perform econometric analysis using this data at both a weekly and a monthly frequency, we create a monthly version of the price dataset by averaging all weekly entries that belong to a month, mimicking the process through which monthly data is often put together.[8]

In addition to price series and exchange rates, we also utilize in some of the analysis measures of observed country heterogeneity. One such measure is the per capita income of the country, capturing a key measure of economic development.[9] A second possibly important measure would reflect the importance of the personal car market, conditional on per capita income. We capture this by the number of personal motor vehicles per 1,000 inhabitants. This variable is taken by the Eurostat database.[10] A third measure is the number of gas stations per capita.[11] Controlling for income and

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[5] The source of the retail data is the Weekly Oil Bulletin (http://ec.europa.eu/energy/en/data-analysis/weekly-oil-bulletin).

[6] https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm. The price of Brent better reflects refinery input costs in the Europe. Bulk conventional unleaded gasoline is a homogeneous product with well-integrated markets. For example, the New York and Gulf hub price have a correlation of 0.99, despite the large physical distance between them (see Borenstein, Cameron and Gilbert, 1997). The hub price of gasoline represents 96 percent of the wholesale price (see Douglas and Herrera, 2010).

[7] The Brent crude oil price is originally in US dollars per barrel, while the New York gasoline price is originally in US dollars per gallon. The retail prices of gasoline originally are in local currency per 1000 liters.

[8] For example, the monthly series provided by the US Energy Information Administration is obtained through the averaging of data collected over three different time periods during the month.

[9] This variable is available at http://data.worldbank.org/indicator/NY.GDP.PCAP.KD. This raw data series is in 2005 US dollars; we scale it to thousands of dollars for the analysis.

[10] The term "*passenger car*" also covers microcars (small cars which, depending on individual member state legislation, may need no permit to be driven and/or benefit from lower vehicle taxation), taxis and other hired passenger cars, provided that they have fewer than 10 seats. This variable is obtained from http://ec.europa.eu/eurostat/statistics-explained/index.php?title=Passenger_transport_statistics.

[11] This data is obtained from Eurostat's Structural Business Statistics.

ownership, this variable may reflect the competitive conditions of the retail market. However, a high per capita number of stations under free entry may also be correlated with high profit margins, since those would be needed to ensure breakeven for retail stations that each has a smaller share of the retail market. All these country-level variables are reported at an annual frequency.

This dataset is used in its entirety to estimate the models described in Section 2. But we also construct a set of subsamples as follows. We specify a list of sample start years: 1996, 1998, 2000, 2002, 2004, 2006, and 2008. For each start year, we specify a sample length of 6 years, 10 years, 14 years, or 18 years. Each combination of start year and sample length gives a sub-sample. Observe that some of the subsamples are overlapping, while some are not. We account for the sample overlap, when comparing passthrough estimates over these samples. For the analysis that aims to explain country heterogeneity, only the non-overlapping samples are used.[12]

## 4. THE DISTRIBUTION OF PASS-THROUGH ESTIMATES

### *4.1. Estimating Passthrough Rates.*

We perform the following notional "experiment." A researcher arrives and obtains a sample from one of those described above. The researcher makes downstream price choice, $R_{j,t}$, i.e., chooses to use either the pre-tax or the after-tax retail price series. He or she then chooses the upstream price series, $C_t$, which is either the Brent crude oil price of the NY spot gasoline price. The data series can be either in weekly or in monthly frequency, something chosen by "nature." The researcher estimates both symmetric and asymmetric models, after making the appropriate specification choice. This includes deciding to use a distributed lag model, or an error correction model (in the latter case, the model can be estimated via and one-step or a two-step procedure). It also includes a choice of the lag length. There is no randomness in this process: we consider all possible combinations of dataset configurations and research design choices.

[12] For some countries, the duration of day for some of these subsamples was substantially shorter than the specified sample length because of the date at which the European Union started collecting the relevant data series (mainly driven by the accession date of the country to the EU). When this was the case, these subsamples were not used.

For each researcher's parameter estimates, we compute the passthrough for the first month (the month of impact of upstream price change) and the second month (the post-impact month). When the data frequency is monthly, these passthrough rates are well defined. Things are a bit more complicated when the underlying models are estimated under a weekly frequency. Being able to compare weekly and monthly estimates of passthrough speed is valuable. A researcher using data from country X may, for example, only have monthly data available for analysis. Any estimates may need to be compared with those from other studies on countries for which weekly data was available. Obtaining the parent data, aggregating to monthly frequency, and re-estimating it is one way to make a comparison; but it is certainly far easier to know ex ante the direction and magnitude of any bias.

A conversion of weekly passthrough rates into monthly frequency is not as straightforward, as it might at first appear. We do not aim to convert the estimates obtained from data of different frequencies so that they are "equivalent" in some sense. This is a complicated exercise and would require assuming a particular data generating process. Rather, we want to convert the estimates to monthly values in ways that the typical researcher would in order to compare the speed of price adjustment for two different countries, one that has monthly data and one that has weekly data. There are two such conversion approaches of weekly passthrough rates to monthly frequencies, and we perform them both. In the first approach, the passthrough in the impact month is the average of the passthrough rate of weeks 4 and 5, and the passthrough in the post-impact month the passthrough in week 9 (a month has on average almost four and a half weeks). This is the most natural comparison. In the second approach, the passthrough in the impact month is the weighted average of the weeks 1 through 5 (with week 5 having half the weight of the other weeks), while the passthrough in the post-impact month is the weighted average of weeks 5 through 9 (again, week 5 has half the weight of the other weeks). Though averaging might seem appealing in some respects, it turns out that it results in large and systematic biases. The conversion method used has no material impact on the regression coefficients, other than the indicator variable for the data frequency. Therefore, we present in the main body of the paper the results for the first conversion method, and provide results for the other conversion method in two Appendix tables.

*4.2. Heterogeneity in Passthrough Estimates*

The summary statistics of the passthrough estimates obtained by our hypothetical researchers are reported in Table 3. The table consists of two panels; one that reports passthrough estimates when all prices are in levels, the second with passthrough estimates when all prices are in logs. Looking at Panel A of Table 3, we observe that impact month passthrough estimates obtained in the hypothetical studies average around 0.6 for the impact month and around 0.85 for the post-impact month. They are generally higher when the data is estimated in a panel. The range of passthrough estimates greatly exceeds the typical confidence intervals reported in the literature. The implied standard errors from those confidence intervals are only about 5 percent of the passthrough point estimates.[13] But the standard deviation of the estimates reported in Table 3 are approximately 15% of the point estimates. One would expect the standard deviation in the passthrough estimates over a number of different simulated studies to exceed the standard error in a single study, because they also include variation due to the research design. However, the difference is much higher than we expected, with the minor variations in the research design we consider being twice as important as sampling variation. The ratio of the standard deviation of pass-through estimates to the mean estimated value is even larger when prices are is logs. Examining panel B of Table 3, we observe that this ratio is approximately equal to 40%, with the mean pass-through estimates in the 0.3 to 0.45 range.

Upstream price increases result in approximately equally rapid downstream prices changes as do upstream price decreases. The average “asymmetry” is, if anything, negative in the EU data, whether it is analyzed as a single panel or country-by-country. But there is wide variation in those estimates from sub-sample to sub-sample and across different research designs. Though most studies would not confirm the “rocket-and-feathers” pattern of asymmetric response, many would. As we see in the next section, the studies that are more likely to yield such a pattern have a specific profile.

[13] See, for example, the estimates in Lewis and Noel (2011), Bachmeier and Griffin (2003), and Balmaceda and Soruco (2008) which have confidence intervals in the range of plus/minus 10% of the point estimate.

## 5. PASSTHROUGH AND RESEARCH DESIGN

We now investigate how the research design and the sample characteristics affect the passthrough estimates. To do so, we estimate regressions of the form

$$PSTR_{s,d,\tau} = \alpha + \beta X_s + \gamma\, Z_d + e_{s,d,\tau} \tag{5a}$$

where $PSTR_{s,d,\tau}$ is the passthrough for sample $s$, research design $d$, for month $\tau$, where $\tau = 1$ indicates the impact month and $\tau = 2$ indicates the post-impact month. These passthrough estimates are obtained using the coefficients of econometric specifications of the form (1a), (1b), (3a) and (3b) for the samples described in Section 3. The vector $X_s$ includes all the characteristics of the sample, such the duration in years, the sample mid-year, whether the data is of monthly or weekly frequency, and country dummies (if passthrough estimates where obtained from country-by-country regressions). The vector $Z_d$ includes all the characteristics of the research design, such as the lag length, whether an error correction model was used, whether pre-tax or post-tax data is used, whether the upstream price is wholesale gasoline or the price of crude oil. Because the passthrough estimates obtained from overlapping samples are clearly correlated, we cluster standard errors at the country and sample midyear levels.

We also estimate similar specifications in which we explain the degree of asymmetry in the passthrough estimates. These regressions are of the form

$$ASYM_{s,d,\tau} = \alpha + \beta X_s + \gamma\, Z_d + e_{s,d,\tau} \tag{5b}$$

where $ASYM_{s,d,\tau}$ is the difference in the passthrough to price increases minus the passthrough for price decreases, from the estimation of asymmetric econometric specifications of the form (1c), (1d), (3e), and (4). The parameter vectors $X_s$ and $Z_d$ are as defined in the passthrough regression (5a), except that $Z_d$ also includes a dummy for whether the asymmetric models were estimated in one step or in two steps.

The results for the passthrough speed analysis are reported in Table 4 Panel A (for regressions using prices in levels) and Panel B (prices in logs). We discuss these results variable-by-variable. The pass-through rate seems to be completely unaffected by the length of the sample. However, later samples exhibit higher passthrough rates, especially when the price change models are estimated in logs, for which point estimates average around 0.017. Thus, our latest samples exhibit passthrough rates that are approximately 0.2 higher than our earliest samples, a quantitatively very important result. Impact and post-impact passthrough rates are equally affected, which implies that the incremental passthrough increase from the first to second month is unaffected by the time period. Employing a lag length of two months, rather than one, also leads to higher passthrough rates, but the effect is quantitatively much smaller.

The tax treatment of the price series is of large quantitative importance, and its effect depends on whether the underlying price data is logs or levels. When the price series is in levels, using pre-tax data results in smaller pass-through estimates by around 0.15 eurocents on the euro. However, when the price series is in logs, using pre-tax data results in pass-through elasticities that are higher by approximately 0.30. To understand why, it is important to note that taxes in the European Union consist of both an ad valorem component and a proportional VAT component. A change in a firm's price-cost margin has no effect on the ad valorem component of the tax, but it does affect the VAT component. A reduction in the price-cost margin reduces the VAT tax by reducing firm profits; the opposite happens when the price-cost margin increases. Because price fluctuations, on average, are likely to increase industry segment profits, they also increase the VAT tax collected and the post-tax passthrough rates. When prices are measured in logs, the passthrough rates reflect percentage changes in downstream prices due to a one percent increase in the upstream price. The presence of a fixed ad valorem tax reduces the percentage increase in the tax-inclusive price for any value of a pre-tax passthrough elasticity.

Using wholesale gasoline price as the upstream input price results in higher passthrough rates when the underlying price series is in levels, but has no effect when the price adjustment model is estimated in logs. Recall that input prices are converted so that they equivalent in terms of volume. However, crude oil is broken up into many fuels, and thus an increase in the oil price does not necessarily translate into an equally large increase in the price of wholesale gasoline. With the wholesale gasoline price being more closely coupled to gas station marginal cost than the price of crude, we would expect the use of the former to result in passthrough rates that are no smaller than those based on the latter. When the underlying data series has a monthly frequency, impact month passthroughs are lower, but post-impact month passthroughs higher. Finally, specifications that include an error correction term lead to higher passthrough estimates, but the effect is quantitatively large only for the post impact month.

The results for the analysis of asymmetric response are reported in Table 5. Very few aspects of the research design appear to have a consistent statistically significant effect on measured asymmetries. Generally, later periods result in smaller asymmetries, consistent with the perception that such asymmetries were easier to detect in earlier studies. For the post-impact month, this effect exceeds 0.1 eurocents on the euro among the latest and earliest sample periods; however, it is not always statistically significant. Pre-tax data yields larger measured asymmetries when prices are measured in levels, but smaller when measured in logs. Using the wholesale gasoline price instead of the price of oil also results in higher measured asymmetries. These observations might explain why some of the seminal papers in the asymmetries literature employed pre-tax data in levels, with wholesale gasoline as the upstream price. The frequency of the data appears to be of little relevance. The use of error correction terms results in smaller asymmetries, but the effect is quantitatively very small when these models are estimated in one-step, as is common practice (the only exception to this is the panel-based estimates when prices are in levels).

These findings are all based on the end-of-month conversion method, under which the passthrough rates based on weekly frequencies are converted to monthly frequency on the basis of the average of week four and five (for the first month) and week nine (for the second month). We have also re-estimated all regressions using as a conversion method the average passthrough rate of the weeks in each month for the respective monthly passthrough rates. This results in qualitative similar estimates for all parameters except the one pertaining to data frequency. For completeness, we report these results in the Appendix Tables 1-A and 2-A.

## 6. Country Heterogeneity of Passthrough Rates

Much of the variation in the passthrough rate estimates is due to variation in the sample. Some of this is random sampling variation: even if the data is generated from the same underlying statistical process, a different sample drawn from that process will yield different estimates. But some of this variation may be systematic, i.e., it can be linked to underlying characteristics of the countries. In fact, this is suggested from the finding that passthrough rates tend to become faster over time. This might be a secular trend, but it alternatively it might be linked to underlying changes in the European economies.

We formally investigate this possibility as follows. From the samples described in Section 3, we retain only those of six years of length that are non-overlapping. There are three such sets of samples, centered in 1999, 2005, and 2011. We estimate symmetric and asymmetric adjustment models from those samples, and obtain pass through estimates and estimates of passthrough asymmetries. Our task here is to investigate to what extent these passthrough and asymmetry estimates depend on country characteristics. We purge variation based on research design by estimating regressions (5a) and (5b), albeit with a somewhat reduced variable set. For example, sample length is not part of the regressor set since all samples are of the same length; neither is the sample midyear. We do, however, include exhaustive interactions between the country dummies and indicator variables for each of samples.

$$PSTR_{s,d,\tau} = \alpha_{j,1999} + \alpha_{j,2005} + \alpha_{j,2011} + \beta M_s + \gamma\, Z_d + e_{s,d,\tau} \tag{5c}$$

and

$$ASYM_{s,d,\tau} = \alpha_{j,1999} + \alpha_{j,2005} + \alpha_{j,2011} + \beta M_s + \gamma\, Z_d + e_{s,d,\tau} \tag{5d}$$

where $M_s$ is an indicator variable of whether the data frequency is monthly, $\alpha_{j,1999}$ is a set of indicator variables for country $j$ when the sample is centered in 1999 (and takes the value of zero for all other samples), $\alpha_{j,1999}$ is a similar set of indicators for samples centered in 2005, $\alpha_{j,2011}$ is the corresponding set of indicators for samples centered in 2011, and $Z_d$ is as defined in the preceding section. The country-cross-sample-year dummies represent the country-specific effect on the passthrough speed and asymmetry. We then regress these effects on country characteristics for the corresponding time period. This yields the regression

$$\alpha_{j,y}^{P} = c^{P} + h_1^{P} CARSPC_{j,y} + h_2^{P} GDPPC_{j,y} + h_3^{P} STAPC_{j,y} + \varepsilon_{j,y} \tag{6a}$$

and

$$\alpha_{j,y}^{A} = c^{A} + h_1^{A} CARSPC_{j,y} + h_2^{A} GDPPC_{j,y} + h_3^{A} STAPC_{j,y} + \varepsilon_{j,y} \tag{6a}$$

where $y$ indicates the sample mid-year, $\alpha_{j,y}^{P}$ are the country-specific effects from regression (5c), $\alpha_{j,y}^{A}$ are the country-specific effects from regression (5d), $CARSPC_{j,y}$ is the number of passenger cars per capita, $GDPPC_{j,y}$ is the country GDP per capita, and $STAPC_{j,y}$ is the number of retail gasoline gas stations per capita; these country characteristics are all averaged over the years of the sample period with mid-year $y$.

These variables are rough proxies for factors that could have a systematic effect in explaining country heterogeneity in the retail price dynamics. The GDP per capita is the single most important proxy for the economic development of a country, and is also correlated with the quality of institutions including those relevant for market regulation. The number of cars per capita, conditional on the GDP per capita, reflects the importance of the private motor vehicle in the economy. In countries where this variable is high, public transport may be less developed and car use may be more frequent. This might lead to greater importance and higher salience of the retail gasoline price for consumers. The number of retail stations per capita, controlling for the other two variables, could reflect the competitiveness of the retail gasoline market.

The results are reported in Table 6. As in the prior tables of results, we report figures for analysis in logs and levels in separate panels. Notice that the number of observations is very small, since the dimension of the data is the number of countries times the number of six year periods; moreover, data for many countries are only available for one of those periods. We find that higher income economies experience slower adjustment process (panels A and B), and also faster price decreases relative to price increases (panels C and D). The number of stations per capita also leads to slower passthrough rates, but the effect is only statistically significant when prices are measured in logs. Though these variables explain a very small part of passthrough heterogeneity (typically less than 10% as reflected by the R-squared). However, their effect is quantitatively material. An increase in per capita income by twenty thousand (deflated) US dollars decreases passthrough speeds and asymmetries by approximately 0.04. More economically advanced economies experience slower price adjustment, which seems to be entirely driven by slower adjustment to price increases. The number of stations per capita have a quantitatively equally large effect. The standard deviation of this variable is approximately equal to 0.12. When this variable is statistically significant, i.e., for the passthrough rate when prices are measured in logs, a standard deviation in the concentration of gas stations reduces pass-through by approximately 0.014 for the impact month and 0.018 for the post-impact month. However, this result is non-robust across specifications.

Overall, these variables account for less than ten percent of the country heterogeneity in passthrough rates. Other factors, such as the availability and usage of price comparison platforms, the number of miles driven by each driver, the quality of road network and even traffic patterns (which can affect substitutability between stations) may have a bigger impact on competitiveness and passthrough rates. Unfortunately, we have not identified a consistently collected data on these variables for the European Union countries. However, some insights might be obtained on some of them (e.g., on the advent of price comparison websites) through difference-in-difference analysis for country pairs, since, for example, these websites were introduced at different times in different countries.[14]

## 7. Concluding Remarks

In an empirically oriented literature with little theoretical guidance for functional form and where a variety of econometric specifications and other research design features are frequently chosen, much of the difference in findings may stem from those choices. We have shown this to be the case in the gasoline price adjustment literature, where some features of the research design, such as the sampling frequency, the choice of upstream price, whether taxes are included or not, the sample length, and the postulated lag structure, can affect passthrough estimates by quantitatively very large values. These values exceed the typical standard error of individual studies, and thus can be source of different conclusions by contributors to this literature. Indeed, our findings can be interpreted as

[14] The very recent study of Lemus and Luco (2018) is using two such changes in the Chilean price monitoring website to study changes in the price setting of the retail gasoline industry.

suggesting that much of the variation in the findings of the literature on retail gasoline price dynamics is systematic rather than sample variation from using different data. Moreover, the variation in the conclusions of existing studies that stems from using different data is also to some extent systematic, and driven by differences in observable market characteristics.

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**Table 1. Data Coverage: Countries and Years.**

| Year | Aus. | Bel. | Bul. | Cro. | Cyp. | Cze. | Den. | Est. | Fin. | Fra. | Ger. | Gre. | Hun. | Irel. | Ita. | Latv. | Lith. | Lux. | Mal. | Neth. | Pol. | Port. | Rom. | Slov. | Slov. | Sp. | Swe. | U. K. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1994 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1995 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1996 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1997 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1998 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 1999 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2000 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2001 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2002 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2003 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2004 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2005 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2006 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2007 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2008 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2009 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2010 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2011 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2012 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2013 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2014 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

Notes: Dark shaded areas when both pre-tax and post-tax data are available. Light shaded areas when only pre-tax or post-tax data are available. Unshaded areas when no data are available.

**Table 2. Selected Papers by Model, Country Coverage, Data Fequency and Tax Status.**

| Papers (listed alphabetically by author) | Model | Countries | Data Frequency | Pre-tax | Post-tax | Cointegration | Passthrough |
|---|---|---|---|---|---|---|---|
| Asplund, Eriksson, and Friberg (2000) | ECM | Sweden | Monthly | X | | Yes | Symmetric |
| Bachmeier and Griffin (2003) | ECM | USA | Weekly | X | X | Yes | Mixed |
| Bacon (1991) | PAM | UK | Biweekly | X | | Not tested | Asymmetric |
| Bagnai, Ospina and Alexander (2015) | NARDL | Italy | Monthly | X | | Yes | Asymmetric |
| Balmaceda and Soruco (2008) | ECM | Chile | Weekly | X | | Yes | Asymmetric |
| Bermingham and O'Brien (2011) | ECM | Ireland/UK | Monthly | X | | Yes | Symmetric |
| Bettendorf, Van der Geest and Varkevisser (2003) | ECM | Netherlands | Weekly | X | X | Yes | Mixed |
| Borenstein and Shepard (1996) | ECM | USA | Monthly | X | | Not tested | Asymmetric |
| Borenstein and Shepard (2002) | PAM/VAR | USA | Weekly | X | X | Yes | Asymmetric |
| Borenstein, Cameron and Gilbert (1997) | ECM | USA | Biweekly | X | | Not tested | Asymmetric |
| Bumbass, Ginn and Tuttle (2015) | TAR | USA | Monthly | | X | Yes | Symmetric |
| Deltas (2008) | ECM | USA | Monthly | X | | Not tested | Asymmetric |
| Duffy-Deno (1996) | DL | USA | Weekly | X | | Not tested | Asymmetric |
| Eckert (2002) | ECM | Canada | Weekly | X | | Yes | Asymmetric |
| Galeotti, Lanza and Manera (2003) | ECM | 5 EU countries | Monthly | X | | Yes | Mixed |
| Godby, Lintner, Stengos and Wandschneider (200C | TAR | Canada | Weekly | X | | Yes | Symmetric |
| Grasso and Manera (2007) | ECM/DRS | 5 EU countries | Monthly | X | X | Yes | Asymmetric |
| Greenwood-Nimmo and Shin (2013) | NARDL | UK | Monthly | X | | Not tested | Symmetric |
| Hosken, McMillan and Taylor (2008) | ECM | Northern Virginia | Weekly | | X | Not tested | Asymmetric |
| Johnson (2002) | ECM | USA | Weekly | X | | Yes | Asymmetric |
| Karrenbrock (1991) | DL | USA | Weekly | X | | Not tested | Symmetric |
| Kirchgaassner and Kubler (1992) | VECM | Germany | Monthly | X | | Yes | Mixed |
| Kristoufek and Lunackova (2015) | ECM | 6 EU countries/USA | Weekly | X | | Yes | Symmetric |
| Lewis (2011) | ECM/DRS | USA | Weekly | X | | Yes | Asymmetric |
| Liu, Margaritis and Tourani-Rad (2010) | ECM | New Zealand | Weekly | X | | Yes | Mixed |
| Noel (2007) | ECM | Canada | Weekly | X | | Not tested | Asymmetric |
| Polemis (2012) | ECM | Greece | Monthly | X | | Yes | Asymmetric |
| Polemis and Tsionas (2017) | TPVECM | USA | Monthly | X | X | Not tested | Asymmetric |
| Radchenko and Tsurumi (2006) | VAR | USA | Monthly | X | | Not tested | Symmetric |
| Verlinda (2008) | ECM | USA | Weekly | X | | Not tested | Asymmetric |
| Wlazlowski, Giulietti, Binner and Milas (2012) | STAR ECM | EU | Monthly | X | | Not tested | Asymmetric |

Notes: The econometric models estimated in the listed studies are Partial Adjustment Model (PAM), Distributed Lag (DL), Vector Error Correction Model (VECM), Vector Autoregression (VAR), Deterministic Regime Switching (DRS), Threshold Autoregression (TAR), Threshold Vector Error Correction Model (TPVECM), Smooth Transition Autoregressive Error Correction Model (STAR ECM), and Non-linear Autoregressive Distributed Lag Model (NARDL).

## Table 3. Passthrough Estimates - Summary Statistics.

| | Month | Panel-based Estimates Mean | Std. Dev. | Min | Max | Obs | Country-by-Country based Estimates Mean | Std. Dev. | Min | Max | Obs |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Pass-through based on price changes in levels | | | | | | | | | | | |
| Symmetric | Impact | 0.669 | 0.092 | 0.495 | 0.933 | 544 | 0.589 | 0.068 | 0.438 | 0.897 | 6792 |
| | post-Impact | 0.856 | 0.117 | 0.496 | 1.116 | 544 | 0.843 | 0.115 | 0.511 | 1.116 | 6792 |
| Price Increases | Impact | 0.633 | 0.109 | 0.260 | 0.955 | 816 | 0.553 | 0.078 | 0.294 | 0.870 | 10144 |
| | post-Impact | 0.832 | 0.126 | 0.392 | 1.269 | 816 | 0.817 | 0.125 | 0.392 | 1.269 | 10144 |
| Price Decreases | Impact | 0.707 | 0.112 | 0.433 | 1.049 | 816 | 0.624 | 0.086 | 0.402 | 0.919 | 10144 |
| | post-Impact | 0.899 | 0.145 | 0.296 | 1.288 | 816 | 0.885 | 0.138 | 0.441 | 1.231 | 10144 |
| Asymmetry | Impact | -0.074 | 0.112 | -0.625 | 0.283 | 816 | -0.072 | 0.094 | -0.625 | 0.213 | 10144 |
| | post-Impact | -0.067 | 0.130 | -0.592 | 0.782 | 816 | -0.067 | 0.124 | -0.617 | 0.782 | 10144 |
| Panel B: Pass-through based on price changes in logs | | | | | | | | | | | |
| Symmetric | Impact | 0.343 | 0.134 | 0.130 | 0.640 | 544 | 0.301 | 0.115 | 0.118 | 0.573 | 6792 |
| | post-Impact | 0.441 | 0.169 | 0.131 | 0.754 | 544 | 0.435 | 0.167 | 0.135 | 0.754 | 6792 |
| Price Increases | Impact | 0.326 | 0.133 | 0.055 | 0.628 | 816 | 0.285 | 0.113 | 0.055 | 0.628 | 10144 |
| | post-Impact | 0.415 | 0.155 | 0.086 | 0.728 | 816 | 0.410 | 0.153 | 0.086 | 0.728 | 10144 |
| Price Decreases | Impact | 0.353 | 0.136 | 0.120 | 0.731 | 816 | 0.311 | 0.116 | 0.120 | 0.566 | 10144 |
| | post-Impact | 0.463 | 0.179 | 0.080 | 0.866 | 816 | 0.454 | 0.177 | 0.105 | 0.866 | 10144 |
| Asymmetry | Impact | -0.027 | 0.055 | -0.260 | 0.178 | 816 | -0.025 | 0.046 | -0.233 | 0.178 | 10144 |
| | post-Impact | -0.048 | 0.075 | -0.409 | 0.211 | 816 | -0.045 | 0.073 | -0.409 | 0.211 | 10144 |

Notes: See text for details on the data and econometric specifications from which these passthrough rates have been computed.

## Table 4. Symmetric Passthrough Rates

| | Panel-based Estimates | | | | Country-by-Country based Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Impact Month | | Post-Impact Month | | Impact Month | | Post-Impact Month | |
| Variables | Estimate | St. Err. (a) | Estimate | St. Err. (a) | Estimate | St. Err. (b) | Estimate | St. Err. (b) |
| Panel A: Pass-through based on price changes in levels | | | | | | | | |
| Sample Length | 0.0005 | *0.0004* | 0.0009 | *0.0012* | 0.0004 | *0.0009* | 0.0000 | *0.0016* |
| Sample Midyear | **0.0051** | ***0.0007*** | 0.0038 | *0.0020* | **0.0093** | ***0.0044*** | 0.0001 | *0.0045* |
| Lag Length (months) | **0.0054** | ***0.0012*** | **0.0425** | ***0.0019*** | **0.0043** | ***0.0017*** | **0.0325** | ***0.0071*** |
| Pre-tax | **-0.1140** | ***0.0033*** | **-0.1433** | ***0.0067*** | **-0.1297** | ***0.0128*** | **-0.1658** | ***0.0111*** |
| Brent | **-0.0494** | ***0.0092*** | **-0.1011** | ***0.0123*** | **-0.0615** | ***0.0146*** | **-0.1138** | ***0.0157*** |
| Monthly Frequency | **-0.1067** | ***0.0088*** | **0.0857** | ***0.0055*** | **-0.0921** | ***0.0235*** | **0.0702** | ***0.0104*** |
| Error Correction Model | **0.0272** | ***0.0024*** | **0.0506** | ***0.0041*** | **0.0301** | ***0.0046*** | **0.0562** | ***0.0083*** |
| Constant | 0.7537 | *0.0148* | 0.8194 | *0.0263* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.8410 | | 0.7945 | | 0.8264 | | 0.7468 | |
| Observations | 544 | | 544 | | 6,792 | | 6,792 | |
| Panel B: Pass-through based on price changes in logs | | | | | | | | |
| Sample Length | -0.0001 | *0.0005* | 0.0007 | *0.0010* | -0.0022 | *0.0007* | -0.0008 | *0.0015* |
| Sample Midyear | **0.0142** | ***0.0006*** | **0.0164** | ***0.0014*** | **0.0205** | ***0.0028*** | **0.0180** | ***0.0033*** |
| Lag Length (months) | **0.0028** | ***0.0003*** | **0.0208** | ***0.0013*** | **0.0029** | ***0.0010*** | **0.0171** | ***0.0046*** |
| Pre-tax | **0.2420** | ***0.0096*** | **0.3109** | ***0.0101*** | **0.2798** | ***0.0182*** | **0.3378** | ***0.0155*** |
| Brent | **0.0100** | ***0.0079*** | -0.0007 | *0.0072* | 0.0130 | *0.0114* | 0.0003 | *0.0094* |
| Monthly Frequency | **-0.0539** | ***0.0036*** | **0.0468** | ***0.0025*** | **-0.0517** | ***0.0125*** | **0.0437** | ***0.0067*** |
| Error Correction Model | **0.0108** | ***0.0019*** | **0.0214** | ***0.0021*** | **0.0137** | ***0.0025*** | **0.0284** | ***0.0041*** |
| Constant | 0.1709 | *0.0068* | 0.1380 | *0.0112* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.9599 | | 0.9654 | | 0.8594 | | 0.8716 | |
| Observations | 544 | | 544 | | 6,792 | | 6,792 | |

Notes: (a) Heteroskedasticity-consistent standard errors clustered at the sample midpoint; (b) Two way clustering of heteroskedasticity-consistent standard errors at the sample midpoint and at the country levels. Entries in bold indicate statistical significance at the 5% level. See text for details.

**Table 5. Asymmetries in Passthrough Rates**

| | Panel-based Estimates | | | | Country-by-Country based Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Impact Month | | Post-Impact Month | | Impact Month | | Post-Impact Month | |
| Variables | Estimate | St. Err. (a) | Estimate | St. Err. (a) | Estimate | St. Err. (b) | Estimate | St. Err. (b) |
| Panel A: Asymmetries based on price changes in levels | | | | | | | | |
| Sample Length | 0.0038 | *0.0021* | 0.0021 | *0.0024* | 0.0023 | *0.0034* | 0.0028 | *0.0039* |
| Sample Midyear | 0.0059 | *0.0033* | **-0.0105** | ***0.0054*** | 0.0020 | *0.0063* | -0.0100 | *0.0073* |
| Lag Length (months) | 0.0050 | *0.0065* | 0.0032 | *0.0122* | 0.0106 | *0.0094* | -0.0130 | *0.0121* |
| Pre-tax | **0.0443** | ***0.0230*** | **0.0552** | ***0.0229*** | 0.0317 | *0.0191* | **0.0739** | ***0.0304*** |
| Brent | **-0.0355** | ***0.0128*** | -0.0397 | *0.0206* | -0.0327 | *0.0224* | -0.0400 | *0.0332* |
| Monthly Frequency | -0.0102 | *0.0274* | 0.0226 | *0.0223* | 0.0077 | *0.0433* | 0.0188 | *0.0291* |
| Error Correction Model | **-0.0586** | ***0.0085*** | **-0.0885** | ***0.0122*** | **-0.0532** | ***0.0082*** | **-0.0619** | ***0.0124*** |
| One Step | 0.0000 | *0.0080* | -0.0065 | *0.0119* | **0.0244** | ***0.0109*** | **0.0451** | ***0.0173*** |
| Constant | -0.1068 | *0.0267* | 0.0000 | *0.0222* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.1769 | | 0.2366 | | 0.2039 | | 0.2152 | |
| Observations | 816 | | 816 | | 10,144 | | 10,144 | |
| Panel B: Asymmetries based on price changes in logs | | | | | | | | |
| Sample Length | -0.0006 | *0.0008* | -0.0024 | *0.0014* | -0.0016 | *0.0017* | -0.0037 | *0.0027* |
| Sample Midyear | -0.0001 | *0.0017* | **-0.0060** | ***0.0024*** | -0.0020 | *0.0038* | -0.0075 | *0.0053* |
| Lag Length (months) | **0.0148** | ***0.0032*** | -0.0026 | *0.0039* | **0.0160** | ***0.0053*** | -0.0062 | *0.0088* |
| Pre-tax | -0.0040 | *0.0118* | **-0.0304** | ***0.0177*** | -0.0105 | *0.0119* | **-0.0374** | ***0.0141*** |
| Brent | **-0.0195** | ***0.0071*** | **-0.0389** | ***0.0139*** | -0.0131 | *0.0119* | -0.0344 | *0.0184* |
| Monthly Frequency | 0.0002 | *0.0167* | -0.0114 | *0.0141* | 0.0057 | *0.0297* | -0.0108 | *0.0203* |
| Error Correction Model | **-0.0218** | ***0.0057*** | **-0.0381** | ***0.0060*** | **-0.0179** | ***0.0089*** | **-0.0247** | ***0.0102*** |
| One Step | -0.0014 | *0.0055* | -0.0061 | *0.0104* | -0.0019 | *0.0055* | 0.0018 | *0.0094* |
| Constant | -0.0166 | *0.0134* | 0.0773 | *0.0128* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.0869 | | 0.2451 | | 0.1620 | | 0.1989 | |
| Observations | 816 | | 816 | | 10,144 | | 10,144 | |

Notes: (a) Heteroskedasticity-consistent Standard errors clustered at the sample midpoint; (b) Two way clustering of heteroskedasticity-consistent standard errors at the sample midpoint and at the country levels. Entries in bold indicate statistical significance at the 5% level. See text for details.

## Table 6. Heterogeneity and Country Characteristics.

| | Impact Month | | Post-Impact Month | |
|---|---|---|---|---|
| Variables | Estimate | St. Err. | Estimate | St. Err. |
| Panel A: Pass-through based on price changes in levels | | | | |
| Cars per Capita | 0.0908 | *0.2225* | 0.0696 | *0.2282* |
| Per Capita Income | **-0.0023** | ***0.0011*** | **-0.0023** | ***0.0011*** |
| Stations per Capita | -0.0223 | *0.2391* | -0.0068 | *0.2487* |
| R-squared | 0.0425 | | 0.0391 | |
| Panel B: Pass-through based on price changes in logs | | | | |
| Cars per Capita | 0.1801 | *0.1048* | 0.2157 | *0.1133* |
| Per Capita Income | **-0.0017** | ***0.0007*** | **-0.0018** | ***0.0008*** |
| Stations per Capita | **-0.1235** | ***0.0598*** | **-0.1494** | ***0.0634*** |
| R-squared | 0.1127 | | 0.1157 | |
| Panel C: Asymmetries based on price changes in levels | | | | |
| Cars per Capita | 0.1738 | *0.2040* | 0.2018 | *0.1993* |
| Per Capita Income | **-0.0026** | ***0.0011*** | **-0.0027** | ***0.0011*** |
| Stations per Capita | -0.0827 | *0.2030* | -0.1032 | *0.1914* |
| R-squared | 0.0588 | | 0.0650 | |
| Panel D: Asymmetries based on price changes in logs | | | | |
| Cars per Capita | 0.0095 | *0.1041* | -0.0259 | *0.1123* |
| Per Capita Income | **-0.0012** | ***0.0006*** | -0.0011 | *0.0006* |
| Stations per Capita | 0.0007 | *0.1047* | 0.0265 | *0.1203* |
| R-squared | 0.0610 | | 0.0504 | |

Notes: Heteroskedasticity-consistent (robust) standard errors clustered at the country level reported. Entries in bold indicate statistical significance at the 5% level. The number of observations is equal to 55 for all regressions. A constant is included in every specification, but its value is not directly interpretable because it depends on scaling of the origin. See text for details.

**Table 1-A. Symmetric Passthrough Rates - Using Monthly Average Conversion of Weekly Estimates.**

| | Panel-based Estimates | | | | Country-by-Country based Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Impact Month | | Post-Impact Month | | Impact Month | | Post-Impact Month | |
| Variables | Estimate | St. Err. (a) | Estimate | St. Err. (a) | Estimate | St. Err. (b) | Estimate | St. Err. (b) |
| <u>Panel A: Pass-through based on price changes in levels</u> | | | | | | | | |
| Sample Length | 0.0000 | *0.0003* | 0.0009 | *0.0010* | 0.0004 | *0.0008* | 0.0001 | *0.0013* |
| Sample Midyear | **0.0030** | ***0.0004*** | **0.0042** | ***0.0016*** | **0.0108** | ***0.0042*** | 0.0010 | *0.0046* |
| Lag Length (months) | **0.0055** | ***0.0009*** | **0.0308** | ***0.0017*** | **0.0041** | ***0.0016*** | 0.0232 | *0.0048* |
| Pre-tax | **-0.1040** | ***0.0016*** | **-0.1421** | ***0.0064*** | **-0.1155** | ***0.0132*** | **-0.1631** | ***0.0114*** |
| Brent | **-0.0342** | ***0.0078*** | **-0.0930** | ***0.0113*** | **-0.0433** | ***0.0137*** | **-0.1045** | ***0.0148*** |
| Monthly Frequency | **0.0530** | ***0.0042*** | **0.1099** | ***0.0053*** | **0.0529** | ***0.0115*** | **0.0929** | ***0.0069*** |
| Error Correction Model | **0.0214** | ***0.0019*** | **0.0423** | ***0.0036*** | **0.0246** | ***0.0040*** | **0.0478** | ***0.0065*** |
| Constant | 0.5989 | *0.0090* | 0.8104 | *0.0237* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.8422 | | 0.8444 | | 0.8810 | | 0.7943 | |
| Observations | 544 | | 544 | | 6,792 | | 6,792 | |
| <u>Panel B: Pass-through based on price changes in logs</u> | | | | | | | | |
| Sample Length | -0.0002 | *0.0004* | 0.0006 | *0.0009* | -0.0022 | *0.0006* | -0.0009 | *0.0013* |
| Sample Midyear | **0.0123** | ***0.0005*** | **0.0164** | ***0.0013*** | **0.0203** | ***0.0027*** | **0.0183** | ***0.0033*** |
| Lag Length (months) | **0.0029** | ***0.0003*** | **0.0151** | ***0.0007*** | **0.0028** | ***0.0009*** | **0.0125** | ***0.0029*** |
| Pre-tax | **0.2113** | ***0.0090*** | **0.3064** | ***0.0100*** | **0.2503** | ***0.0183*** | **0.3343** | ***0.0162*** |
| Brent | **0.0136** | ***0.0070*** | 0.0018 | *0.0078* | 0.0172 | *0.0103* | 0.0040 | *0.0101* |
| Monthly Frequency | **0.0287** | ***0.0024*** | **0.0588** | ***0.0023*** | **0.0318** | ***0.0061*** | **0.0562** | ***0.0046*** |
| Error Correction Model | **0.0084** | ***0.0015*** | **0.0173** | ***0.0022*** | **0.0112** | ***0.0023*** | **0.0235** | ***0.0034*** |
| Constant | 0.1124 | *0.0070* | 0.1386 | *0.0108* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.9665 | | 0.9694 | | 0.8792 | | 0.8847 | |
| Observations | 544 | | 544 | | 6,792 | | 6,792 | |

Notes: (a) Heteroskedasticity-consistent standard errors clustered at the sample midpoint; (b) Two way clustering of heteroskedasticity-consistent standard errors at the sample midpoint and at the country levels. Entries in bold indicate statistical significance at the 5% level. See text for details.

## Table 2-A. Asymmetries in Passthrough Rates - Using Monthly Average Conversion of Weekly Estimates.

| | Panel-based Estimates | | | | Country-by-Country based Estimates | | | |
|---|---|---|---|---|---|---|---|---|
| | Impact Month | | Post-Impact Month | | Impact Month | | Post-Impact Month | |
| Variables | Estimate | St. Err. | Estimate | St. Err. | Estimate | St. Err. | Estimate | St. Err. |
| Panel A: Asymmetries based on price changes in levels | | | | | | | | |
| Sample Length | 0.0027 | *0.0020* | 0.0023 | *0.0023* | 0.0015 | *0.0033* | 0.0026 | *0.0038* |
| Sample Midyear | 0.0066 | *0.0035* | -0.0083 | *0.0049* | 0.0047 | *0.0063* | -0.0089 | *0.0071* |
| Lag Length (months) | 0.0034 | *0.0044* | 0.0036 | *0.0090* | 0.0048 | *0.0062* | -0.0067 | *0.0101* |
| Pre-tax | 0.0330 | *0.0174* | **0.0517** | ***0.0231*** | 0.0272 | *0.0172* | **0.0634** | ***0.0288*** |
| Brent | **-0.0362** | ***0.0080*** | -0.0368 | *0.0215* | -0.0251 | *0.0186* | -0.0451 | *0.0352* |
| Monthly Frequency | -0.0144 | *0.0243* | 0.0239 | *0.0254* | 0.0042 | *0.0414* | 0.0125 | *0.0305* |
| Error Correction Model | **-0.0434** | ***0.0074*** | **-0.0872** | ***0.0113*** | **-0.0458** | ***0.0069*** | **-0.0617** | ***0.0116*** |
| One Step | 0.0031 | *0.0055* | -0.0069 | *0.0113* | **0.0146** | ***0.0072*** | **0.0425** | ***0.0162*** |
| Constant | -0.0987 | *0.0148* | -0.0143 | *0.0195* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.1897 | | 0.2244 | | 0.1941 | | 0.2097 | |
| Observations | 816 | | 816 | | 10,144 | | 10,144 | |
| Panel B: Asymmetries based on price changes in logs | | | | | | | | |
| Sample Length | -0.0009 | *0.0009* | -0.0020 | *0.0013* | -0.0019 | *0.0016* | -0.0034 | *0.0026* |
| Sample Midyear | 0.0014 | *0.0018* | **-0.0054** | ***0.0023*** | 0.0003 | *0.0036* | -0.0071 | *0.0051* |
| Lag Length (months) | **0.0091** | ***0.0018*** | **0.0057** | ***0.0028*** | **0.0103** | ***0.0034*** | 0.0028 | *0.0071* |
| Pre-tax | -0.0059 | *0.0085* | -0.0298 | *0.0176* | -0.0060 | *0.0112* | **-0.0381** | ***0.0124*** |
| Brent | **-0.0216** | ***0.0057*** | **-0.0331** | ***0.0130*** | -0.0125 | *0.0103* | -0.0319 | *0.0185* |
| Monthly Frequency | -0.0045 | *0.0142* | -0.0175 | *0.0155* | 0.0006 | *0.0274* | -0.0190 | *0.0215* |
| Error Correction Model | **-0.0168** | ***0.0047*** | **-0.0371** | ***0.0060*** | **-0.0148** | ***0.0072*** | **-0.0248** | ***0.0101*** |
| One Step | 0.0009 | *0.0038* | -0.0058 | *0.0099* | -0.0017 | *0.0035* | 0.0017 | *0.0087* |
| Constant | -0.0093 | *0.0080* | 0.0609 | *0.0118* | na | | na | |
| Country Fixed Effects | na | | na | | included | | included | |
| R-squared | 0.1201 | | 0.2307 | | 0.1648 | | 0.1855 | |
| Observations | 816 | | 816 | | 10,144 | | 10,144 | |

Notes: (a) Heteroskedasticity-consistent standard errors clustered at the sample midpoint; (b) Two way clustering of heteroskedasticity-consistent standard errors at the sample midpoint and at the country levels. Entries in bold indicate statistical significance at the 5% level. See text for details.