Title
Demand and Price Volatility: Rational Habits in International Gasoline Demand

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Abstract

The combination of habits and a forward outlook suggests that consumers will be sensitive not just to prices but to price *dynamics*. In particular, rational habits models suggest *1.* that price volatility and uncertainty will reduce demand for a habit-forming good and *2.* that such volatility will dampen demand's responsiveness to price. These two implications can be tested by augmenting a traditional partial-adjustment or error-correction model of demand. I apply this augmented model to data on gasoline consumption, as rational habits provide a succinct representation for the investment and behavioral decisions that determine gasoline usage. The trade-offs among 2SLS, system GMM, and pooled mean group (PMG) estimators are considered, and my preferred PMG estimator provides evidence for the two implications of rational habits in a panel of 29 countries for the years 1990-2009. The sensitivity of certain results to the choice of estimator offers a cautionary illustration of the cost of assumptions such as coefficient heterogeneity. Given the evidence uncovered in favor of rational gasoline habits, such habits may help to explain some of the cross-country variation in "total" price elasticity. These habits also imply that the effect of price volatility must be taken into account when projecting the impacts of potential policies on gasoline consumption.

1 Introduction

The same consumer behavior that shapes gasoline demand also shapes the effectiveness of policies for controlling gasoline demand. Reducing this demand has become a widespread policy goal, driven by environmental concerns both global and local; and the intricacies of demand behavior are now of very practical interest.

Although this interest has generated a great deal of empirical work measuring the effects of income and prices on gasoline consumption, less attention has been devoted to the deeper behaviors underlying gasoline demand. Consumers may purchase fuel at the pump, but in fact they make their gasoline-buying decisions almost everywhere but the gas station. They make these decisions in the form of discrete, infrequent choices about what type of vehicle to buy and where to live in relation to work, as well as in nearly-continuous choices about daily routines—carpooling, driving style, how much non-essential travel to undertake and whether to cycle or take the car. The investment nature of the former decisions and the habitual nature of the latter help to explain consumers' sluggish responses to changes in the gasoline price, and also suggest that models of gasoline demand should allow for the effects of long-run choices.

One way to incorporate these effects is a rational habits model, in which consumers' utility for a particular good—in this case, gasoline—is a function of how much of the good they consumed in the past.

Since past investment decisions affected past consumption, the habit setup captures both investment- and habit-influenced behaviors. The model assumes consumers are 'rational', or forward-looking; and therefore when deciding their current gasoline consumption, they consider how this consumption will affect their future utility. The future burden of a gasoline habit depends upon future market conditions, and so demand in this model depends upon consumers' expectations of the future, particularly of future prices.

If rational habits do in fact shape gasoline demand, then studies that confine themselves to the effects of income and contemporary prices on demand may overlook nuances of behavior that are relevant to policy. Given rational habits, demand will be affected by the *process* by which prices are generated as well as by the current price level, and differences in price elasticity across countries may be driven by differences in price regimes as well as by differences in environment and infrastructure.

The ideal way to examine the hypothesis of rational habits would be to estimate or calibrate a structural model, such as the one introduced in Scott (2010). Unfortunately, this model can only be solved numerically, and so its parameters cannot not be estimated using traditional estimation methods. More problematically, the model contains too many parameters to be calibrated precisely using available data—eight, plus any parameters necessary to model the gasoline price process. Even to identify each of these parameters would be a stretch.

Fortunately, however, rational habits models suggest two implications that are easily testable by augmenting a traditional demand model with extra variables. If consumers are forward-looking,

1. demand for a habit-forming good will decline with the uncertainty in its (future) price, and
2. responsiveness to price changes will be dampened by price uncertainty and the expectation that price changes will be short-lived.

The first of these implications is proved by Coppejans et al. (2007), who consider a mean-preserving spread in the distribution of future prices and find that this reduces consumption of the habit-forming good. This first implication is also demonstrated in Scott (2010), where the level of demand is shown to decline with the variance of future prices (Figure 2.10). To test whether price uncertainty in fact reduces demand for gasoline, I introduce a measure of price uncertainty into a traditional, non-structural dynamic model of gasoline demand. Coppejans et al. take a similar approach in examining the effect of price uncertainty on smoking behavior, augmenting a static demand model with an estimate of the expected one-period-ahead standard deviation of price.

The second implication above is demonstrated in Scott (2010), where the magnitude of price elasticity is shown to be negatively related to the variance of the future price distribution (Figures 2.8 and 2.9) and positively related to the expected duration of price changes (Figure 2.7). To test whether price uncertainty dampens consumers' responsiveness to prices in practice, I augment my demand model with an interaction between a price-uncertainty measure and the gasoline price. The "total" elasticity with respect to price is therefore given by a combination of the price and interaction coefficients.

To capture the sluggish adjustment associated with any habits model, rational or myopic, I can add these two rational-habits regressors to a partial-adjustment, or ADL, model. Partial-adjustment models are frequently used to estimate gasoline demand, and my augmented version takes the form

$$g_{it} = \lambda g_{i,t-1} + \delta_1 y_{it} + \delta_2 p_{it} + \delta_3 \widehat{\sigma}_{it} + \delta_4 \left(p_{it} - \overline{p}_i\right) \widehat{\sigma}_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where g is log gasoline consumption per capita, y_{it} is log real income or expenditure per capita, p is the log real gasoline price, and $\widehat{\sigma}$ is a measure of price uncertainty. For simplicity I will sometimes refer to the de-meaned gasoline price, $(p_{it} - \overline{p}_i)$, as $\widetilde{p}_{it}$. (Coefficients in (1) are restricted to be homogeneous across countries; later I will relax this assumption.) The rational habits model implies that δ_3 should be negative, with price uncertainty discouraging gasoline consumption, and δ_4 should be positive, with the interaction term offsetting some of the negative effect of prices:

$$g_{it} = \underbrace{\lambda}_{+,<1} g_{i,t-1} + \underbrace{\delta_1}_{+} y_{it} + \underbrace{\delta_2}_{-} p_{it} + \underbrace{\delta_3}_{-} \widehat{\sigma}_{it} + \underbrace{\delta_4}_{+} (p_{it} - \overline{p}_i) \widehat{\sigma}_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

Short-run income elasticity is given here by δ_1; short-run "uncertainty elasticity", by δ_3; and short-run "total" price elasticity, by

$$\frac{\partial g_{it}}{\partial p_{it}} = \delta_2 + \delta_4 \widehat{\sigma}_{it}$$

Corresponding long-run elasticities are calculated, of course, by dividing each short-run elasticity by $1 - \lambda$.

Estimating this model entails some complications, and to address these I will reparameterize (1) into an error-correction model. I discuss alternative formulations of the model in Section 4.3. For now, I begin with a brief review of the literature on estimating gasoline demand and a discussion of my data set, which is a country-level panel. I then revisit the specification of my model and consider possible estimation methods, weighing the advantages and disadvantages of three approaches: least squares and system GMM estimation of the ADL model in (1) and maximum-likelihood estimation of an error-correction model allowing for coefficient heterogeneity. My preference is for the error-correction model with heterogeneous short-run coefficients, but I report the results of all these estimators in order to be transparent about the sensitivity of my results to the specification of the model—and to illustrate the potential pitfalls of certain approaches. For ease of comparison with the literature, I also estimate a "standard", non-habits version of the error-correction specification. Before concluding, finally, I use country-specific price volatilities to interpolate country-specific price elasticities, and I consider the extent to which cross-country variation in price volatility predicts cross-country variation in elasticity.

2 Gasoline Demand Literature Review

The predominant focus in the gasoline demand literature is on measuring the effects of income and prices on consumption. Little attention has been directed at structural models in which consumers choose consumption to maximize expected utility.

Neither myopic nor rational habits have been investigated as a potentially demand-shaping behavior. Although Breunig and Gisz (2009) use an unobservable habit stock variable in a petrol demand regression, they insert this directly into a nonstructural demand model rather than into the consumer's utility-maximization problem. The habit stock in this scenario simply substitutes for the ADL model's directly-observed lags of consumption, allowing for gradual adjustment. Breunig and Gisz focus on the econometric complications generated by this unobserved stock, which implies that the error terms have a moving-average form. This correlation of the errors across time is analogous to that implied by the inclusion of lagged consumption in the usual ADL model (see Section 4). Breunig and Gisz estimate an ECM-type model using maximum likelihood to account for moving-average errors, and argue that, because this approach yields less precise elasticities than OLS estimates of an ADL-type model, the latter must be spuriously precise. Yet they do not establish that the OLS estimates owe their precision to a disregard of intertemporal error correlations rather than to their basis in a model with ten fewer parameters. Across the standard ADL and Breunig and Gisz's model, moreover, point estimates of long-run elasticities are about the same: -0.25 and -0.20, respectively, for price; and 0.34 and 0.27, respectively, for income.

Table 1: Average elasticities in gasoline demand literature reviews

Study	Average **price** elasticity Short run	Average **price** elasticity Long run	Average **income** elasticity Short run	Average **income** elasticity Long run
Dahl and Sterner (1991)[a]	-0.24	-0.80	0.45	1.31
Goodwin (1992)[b]	-0.27	-0.71		
Espey (1998)	-0.26	-0.58	0.42	0.88
Goodwin, Dargay and Hanly (2004)[c]	-0.25	-0.64	0.39	1.08
Brons et al. (2008)	-0.34	-0.84		

[a]Lagged endogenous models, annual. [b]Time series models

[c]Price: time series models; income: dynamic models

As a determinant of gasoline demand, therefore, habits have not been introduced into the literature; and the effects of habit-related variables such as price uncertainty and price expectations remain unexamined. The typically-acknowledged determinants of demand—income and price—have received wide attention, however; and studies measuring income and price elasticities abound. In her 1998 meta-analysis, for instance, Espey (1998) considers 363 short- or medium-run and 277 long-run price elasticity estimates, along with similar numbers of income elasticity estimates. In the past there have been so many studies that simultaneous literature reviews have even managed, as Goodwin (1992) recalls, to draw on nearly-disjoint sets of papers. More recently, simultaneous reviews by Goodwin, Dargay and Hanly (2004) and Graham and Glaister (2004), commissioned by the same source for the same purpose, have continued to draw from a pool of literature large enough to allow substantial differences in their samples.

In this large literature, gasoline demand elasticities have run a wide gamut, with own-price elasticity estimates ranging from 0 to -1.36 in the short run and 0 to -2.72 in the long run, and income elasticities ranging from 0 to 2.91 in the short run and 0 to 2.73 in the long run (Espey 1998). Overall, however, the reviews are in basic agreement about average elasticities. Average own-price elasticity, these reviews find, is around -0.25 to -0.30 in the short run and -0.6 to -0.8 in the long run; average income elasticity is around 0.4 in the short run and somewhere around unit elastic in the long run. Some of these averages are summarized in Table 1.

Although much of the variation in estimated elasticities has not been explained—and may, in fact, arise from rational habits and variation in price volatility—literature surveys have uncovered some trends. Studies based on a panel of countries, for instance, tend to produce price elasticities that are similar to single-country elasticities for the long run but of higher magnitude for the short run (Espey 1998). Short-run price responsiveness seems to be relatively low in the United States and relatively high in Europe (Espey 1998). Including a measure of vehicle ownership and/or the characteristics of the vehicle stock affects the resulting estimates (Dahl and Sterner 1991, Espey 1998). And price elasticities may be changing over time: Espey (1998) observes that short-run price elasticities appear to have decreased in magnitude, and long-run price elasticities *increased* in magnitude, since the 1970s and 1980s. Hughes, Knittel and Sperling (2006) corroborate this shift in short-run price elasticities for the U.S.

The majority of the studies summarized in these reviews are based on partial adjustment models. In recent years, increasing attention has been diverted toward error-correction models and questions of cointegration. So far it seems all these studies have looked at single countries (or the world as a whole) rather than panels, and their estimates are summarized in Table 2. The most striking difference between these ECM-based price elasticity estimates and the average elasticities reported in the literature reviews is that the ECM-based elasticities are generally smaller in magnitude. Whether the ECM model is actually responsible for this difference, however, is not clear: the preponderance of single-country ECM studies and the tendency for single-country studies to yield smaller-magnitude short-run price elasticities (Espey

Table 2: Gasoline demand studies based on cointegration and error-correction models

Study	Country	Price elasticity Short run	Price elasticity Long run	Income elasticity Short run	Income elasticity Long run
Akinboade, Ziramba and Kumo (2008)	South Africa		-0.47		0.36
Alves and Bueno (2003)	Brazil	-0.0919	-0.465	0.122[g]	0.122[g]
Bentzen (1994)[a]	Denmark	-0.32	-0.41	0.89	1.04
Cheung and Thomson (2004)	China	-0.19	-0.56	1.64	0.97
De Vita, Endresen, and Hunt (2006)[b]	Namibia		-0.794		0.957
Eltony and Mutairi (1995)	Kuwait	-0.37	-0.46	-0.47	0.92
Krichene (2002)[c]	World	-0.02	-0.005	1.54	1.2
Nadaud (2004)[d]	France	-0.06	-0.09	0.27	0.28
Polemis (2006)	Greece	-0.10	-0.38	0.36	0.79
Ramanathan (1999)	India	-0.209	-0.319	1.178	2.682
Ramanathan and Subramanian (2003)[d]	Oman	-0.05	-0.52	0.35	0.96
Rao and Rao (2009)	Figi		-0.159 to -0.244		0.427 to 0.462
Samimi (1995)[e]	Australia	-0.2	-0.12	0.25	0.52
Wadud, Graham, and Noland (2009)[f]	US	-0.085	-0.116	0.520	0.592

[a]Elasticities with respect to vehicles per capita substituted for income elasticities.
[b]1990q1-2002q4
[c]Estimates elasticity of demand for crude oil, not gasoline. Results for 1973-1999.
[d]As reported in Wadud, Graham, and Noland (2009).
[e]Energy for transport, not just gasoline.
[f]Single-step nonlinear least squares, post-1978.
[g]Reported short- and long-run elasticities in fact the same.

1998) might also explain some of the difference. In Section 5 I will report ECM results that are consistent with a story in which the panel dimension, rather than the choice of an ECM, drives this difference. Not only do my panel-based ECM price estimates turn out to be relatively high in magnitude, but those of my estimators that exploit cross-section variation (PMG and DFE) yield elasticities that are higher in magnitude than those elasticities based on single-country regressions (MG). The differences between these estimators will be explored in Section 4.

3 Data and Specification of Variables

3.1 Data

My data set consists of a panel of 29 countries for the period 1990-2009. As price data for some countries is limited, the actual series length ranges from fifteen to twenty years, with an average of 18.7 years. A list of included countries is provided in Appendix 7.

In order to focus as much as possible on passenger vehicles rather than freight, data is isolated to gasoline, not diesel. Information on gasoline consumption[1] is taken from the International Energy Agency (IEA)'s *Oil Information* (2009) and transformed into per capita terms using annual population estimates from the UN's *World Population Prospects* (2009). Only annual consumption data is provided; quarterly observations are not available. Data on gasoline prices and taxes, broken down by product and grade, is taken from the IEA's *Energy Prices and Taxes* (2009Q4). International differences in product definitions and regulations mean that data availability for each product varies by country. Depending on

[1]This series ("motor gasoline demand") explicitly excludes aviation gasoline.

this availability, I use either regular unleaded or 95 RON to create a price series for each country. These choices are discussed further in Appendix 7.

As a measure of income, I take GDP from the World Bank's *World Development Indicators* (2009) and transform this into real per capita terms. When crude oil prices are used, these are the spot prices for the Brent stream, taken again from the IEA's *Energy Prices and Taxes* (2009Q4). I concentrate on this stream because the Brent is used extensively as a pricing benchmark.[2]

For reasons explained below, I consider regressions based both in a common currency and in real local currencies. When dealing in a common currency, I convert the IEA's USD-denominated series into real 2005 USD. When dealing in local currencies, I convert all prices and income from nominal to real terms using country-specific CPIs taken from the IEA's *Energy Prices and Taxes* (2009Q4).

Further specifics about my data and data sources are provided in Appendix 7.

3.2 Measuring Price Volatility

In order to begin examining the model in (1), I need a measure of the price uncertainty or volatility faced by gasoline consumers. The simplest measure of volatility would, of course, be the country-specific variance or standard deviation of the (log) gasoline price. Such a measure, taken over the entire sample period and constant over time, however, would hold two disadvantages: first, it would imply that consumers had information about future prices that they do in reality not have; and second, it would make identification of price volatility effects impossible without restrictive assumptions. Instead, I use a measure of the *rolling* standard deviation of log prices. This constrains consumers' information about volatility to current and past prices, and also captures the evolution in price volatility over time.

Annual price observations mask volatility within each year. In the extreme case, two countries with identical annual price series could have wildly different price paths from month to month or quarter to quarter. Relying on annual data to construct a measure of price volatility, therefore, may yield a measure that is biased toward zero, with the size of the 'bias' increasing with 'true' volatility. To mitigate this problem, I exploit the availability of quarterly price data to construct the rolling standard deviation measure. This has the added advantage of allowing me to keep several years of data at the beginning of the period that I would otherwise lose to measuring volatility.

I construct the rolling standard deviation for each quarter, denoted $\widehat{\sigma}_{iq}$, as

$$\begin{aligned} \widehat{\sigma}_{iq} &= \sqrt{\widehat{\sigma}^2_{iq}}, \text{ where} \\ \widehat{\sigma}^2_{iq} &= \frac{1}{x}\sum_{j=1}^{x}\left(p_{i,q-j}-\overline{p}_{iq}\right)^2 \\ \text{and } \overline{p}_{iq} &= \frac{1}{x}\sum_{j=1}^{x}p_{i,q-j+1} \end{aligned} \tag{3}$$

where x is the number of quarters in the rolling window and p_{iq} is the log real price of gasoline in quarter q. As a sensible default, I choose $x = 4$. In this case, the fourth-quarter rolling standard deviation in any year is the standard deviation of the year's prices from their year-long mean, and it is this that I use as my measure of annual rolling standard deviation. As an alternative, one could average $\widehat{\sigma}_{iq}$ over the quarters in each year. (The chief difference of this alternative method lies in the mean price, $\overline{p}_{iq}$, from which each quarter's deviations are calculated: in the alternative method, prices are always compared to a *past* average. In the default measure, each quarter's price is compared to the mean price for the entire

[2] The West Texas Intermediate (WTI) stream is widely used in North America. Using this stream instead of or alongside the Brent, however, makes little difference in the resulting estimates.

year, which for the first three quarters includes *lead* prices.) As an alternative, one could, of course, lengthen the window of the rolling standard deviation beyond $x = 4$.

A further alternative would be to consider price *predictability* rather than volatility—that is, to measure the performance of price forecasts in each country. This would entail modelling each country's price series, generating rolling forecasts, and calculating root mean squared forecasting error for each period. One could also consider modelling the evolution of price volatility over time and incorporating price-volatility forecasts into the demand model. This would be a particularly worthwhile exercise as the theory developed in Scott (2010) posits a relationship between demand and expected *future* price volatility, not current volatility: the rolling-volatility measure used at present functions as a proxy for expected future volatility, a very simple forecast. Better volatility forecasts may be possible, particularly if gasoline prices follow an ARCH-type process and tend to move between periods of high and low volatility. If consumers are aware of better forecasts, then the current proxy may contain substantial measurement error. Even if this measurement error is white noise, it will bias estimates of volatility's effects toward 0. The rolling-volatility proxy may, therefore, render the current model susceptible to underestimating the influence of uncertainty on demand. Although I stick to the rolling-volatility measure for now, price forecastability measures and explicit volatility forecasts are well worth examining in the future.

One extension I do consider now is the use of before-tax prices rather than total prices to calculate $\widehat{\sigma}_{iq}$. This variation is of interest because "volatility" is not synonymous with "uncertainty": tax increases may, for example, contribute to price volatility within the year they come into effect but actually lead to a *reduction* in price uncertainty. If this is the case, then there is, in effect, a systematic measurement error in $\widehat{\sigma}_{iq}$ that will bias the coefficient on the interaction term downward and make consumers' price elasticity appear less sensitive to price volatility. Using before-tax prices to construct $\widehat{\sigma}_{iq}$ circumvents this danger, and so I will consider this alternative definition as a check.

3.3 Currency Issues

The international nature of the panel leads to an additional consideration, namely how to deal with prices, price volatility, and income denominated in different currencies. These variables must be treated in a way that allows comparisons across countries, and ideally they should capture real prices and income, and variation therein, as perceived locally.

One approach is to transpose all variables into a common currency. Indeed, this is the approach toward which convention in the gasoline- and energy demand literature leans,[3] and it is the approach I shall adopt for my main discussion. Measuring all monetary variables in the same units (in this case, real (2005) US dollars) has the advantage that it does not introduce restrictions on the type of estimator that can be deployed; and it has the side benefit, of course, of allowing easy comparisons of price and income levels across countries.

Provided care is taken in the choice of estimator, however, another option is to work in log real local currency. As a check on my common-currency findings, I also estimate local-currency versions, with results reported in Appendix 8. To see that the local-currency approach can be valid, imagine that each country i has a real gasoline price P_{it}, denominated in real local currency units, and let the real exchange rate with respect to some common currency be given by $r_t = r_i e_{it}$. The time-invariant component, r_i, represents the long-run exchange rate, and e_{it} represents fluctuations away from relative PPP. At any

[3] See, for example, Angelier and Sterner (1990), Baltagi and Griffin (1983, 1997), Dahl (2011), Johanssen and Schipper (1997), Judson, Schmalensee, and Stoker (1999), Narayan and Smyth (2007), Nguyen-Van (2010), and Storchmann (2005).

time, country i's gasoline price can be written in real common-currency units as

$$P_{it} r_i e_{it}$$

The log of this real common-currency price is

$$\ln P_{it} + \ln r_i + \ln e_{it}$$

and so the log real local-currency price, $\ln P_{it}$, can be thought of as

$$\ln P_{it} = \ln (\text{real common-currency price}) - \ln r_i - \ln e_{it}$$

This log *local* currency measure therefore removes $\ln e_{it}$, the fluctuations from relative PPP that might otherwise contribute noise to a measure of locally-perceived prices. The removal of this noise is the chief advantage of using log real common-currency prices. Unfortunately, in addition to $\ln e_{it}$, the log local currency measure also removes $\ln r_i$, the term that allows us to compare prices across countries. Essentially we could think of each log real local-currency price $\ln P_{it}$ as containing a measurement-error term, $-\ln r_i$, which pushes $\ln P_{it}$ away from a measure that would be comparable across countries.

Fortunately, since $-\ln r_i$ is a constant, it disappears as soon as $\ln P_{it}$ is de-meaned or differenced. Any estimator that does so, therefore, will be immune to this "measurement-error" problem. A fixed-effects (within-groups) estimator, for example, will remove $-\ln r_i$ by subtracting the country-specific mean from each variable; the pooled mean groups estimator discussed in Section 4.3 removes $-\ln r_i$ by differencing. In these types of estimators, prices and income become unitless, measured in percentage changes or percentage deviations. Only when an estimator exploits cross-sectional variation but fails to de-mean or difference is the "measurement-error" problem really a problem, biasing estimates of the coefficients on prices and income toward 0. This bias will be apparent in the pooled 2SLS estimators that I use to establish an upper bound for λ (Tables 12 and 22), where the local-currency versions find smaller-magnitude price and income elasticities than their common-currency counterparts.

As an aside, it should be noted that the inclusion or exclusion of $\ln r_i$ does not influence the volatility measure $\widehat{\sigma}_{it}$, as standard deviation is unaffected by a constant. Similarly, the long-run exchange rate does not affect the interaction term $\widehat{\sigma}_{it}\widetilde{p}_{it}$, as $\widehat{\sigma}_{it}$ is not affected by a constant and $\widetilde{p}_{it} = \ln P_{it} - \overline{\ln P_i}$ removes any effect of $\ln r_i$ by de-meaning.

There is, of course, a trade-off when choosing which approach to take toward currency. The chief disadvantage of the common-currency approach is that my USD-denominated variables incorporate exchange rate volatility that may not be reflected in local perceptions of prices and income. On the other hand, since oil is generally imported from abroad, exchange rate fluctuations will in fact be passed along into the gasoline price. The USD-denominated price therefore actually removes some of the exchange-rate driven fluctuation in the locally-perceived price, providing a measure that focuses on price changes driven by the world crude oil price rather than by exchange-rate fluctuations. Depending on how consumers think about oil prices and price expectations, USD-denominated prices may in fact be more appropriate in this sense. More to the point, if converting to USD affected results by introducing exchange-rate noise into the price and income measures, then price and income elasticities should be of lower magnitude when estimated in a common currency than in local currencies—and this is not the case. Overall, therefore, the common-currency approach is both clear and appropriate.

3.4 A Brief Overview of the Data

Gasoline consumption per capita shows a reasonable amount of variation, both across countries and over time. Annual consumption in the sample ranges from a low of 31.7 kg per person (Turkey, 2008) to a high of 1352.4 kg per person (Luxembourg, 1994), with an overall mean of 295.9 kg per person. Over time, per-capita consumption has been slightly decreasing in most countries, and the 1990 average of 37.5 kg per person has fallen to a 2008 average of 34.4 kg. Figure 2 plots the path of log gasoline consumption over time for each of the 29 countries in the sample.

Prices, like consumption, have shown considerable variation, with much of the cross-sectional variation driven by tax differences (see Figure 1) and much of the variation over time driven by fluctuations in the crude oil price. The overall mean real price in the sample is 1.11 Y2005-USD per liter, and country-averaged prices range from 0.47 Y2005-USD per liter in the United States to 1.52 Y2005-USD per liter in Norway. The volatility measure, too, has both cross-sectional and cross-time variation that should allow us to identify its effect. The four-period rolling standard deviation of price, as defined in (3), has an average over all observations of 0.048 Y2005-USD per liter, with a comparatively-high standard deviation of 0.037. Country-specific mean volatilities range from a low of 0.035 for Mexico to a high of 0.063 for the United States, and annual average volatility ranges from low of 0.022 in 1998 to a high of 0.14 in 2008. The time paths of the gasoline price and the volatility measure are plotted in Figures 3 and 4, respectively.

Income per capita, finally, has generally been increasing, and this upward trend is depicted in Figure 6.

Figure 1: Mean gasoline prices, by tax- and non-tax components

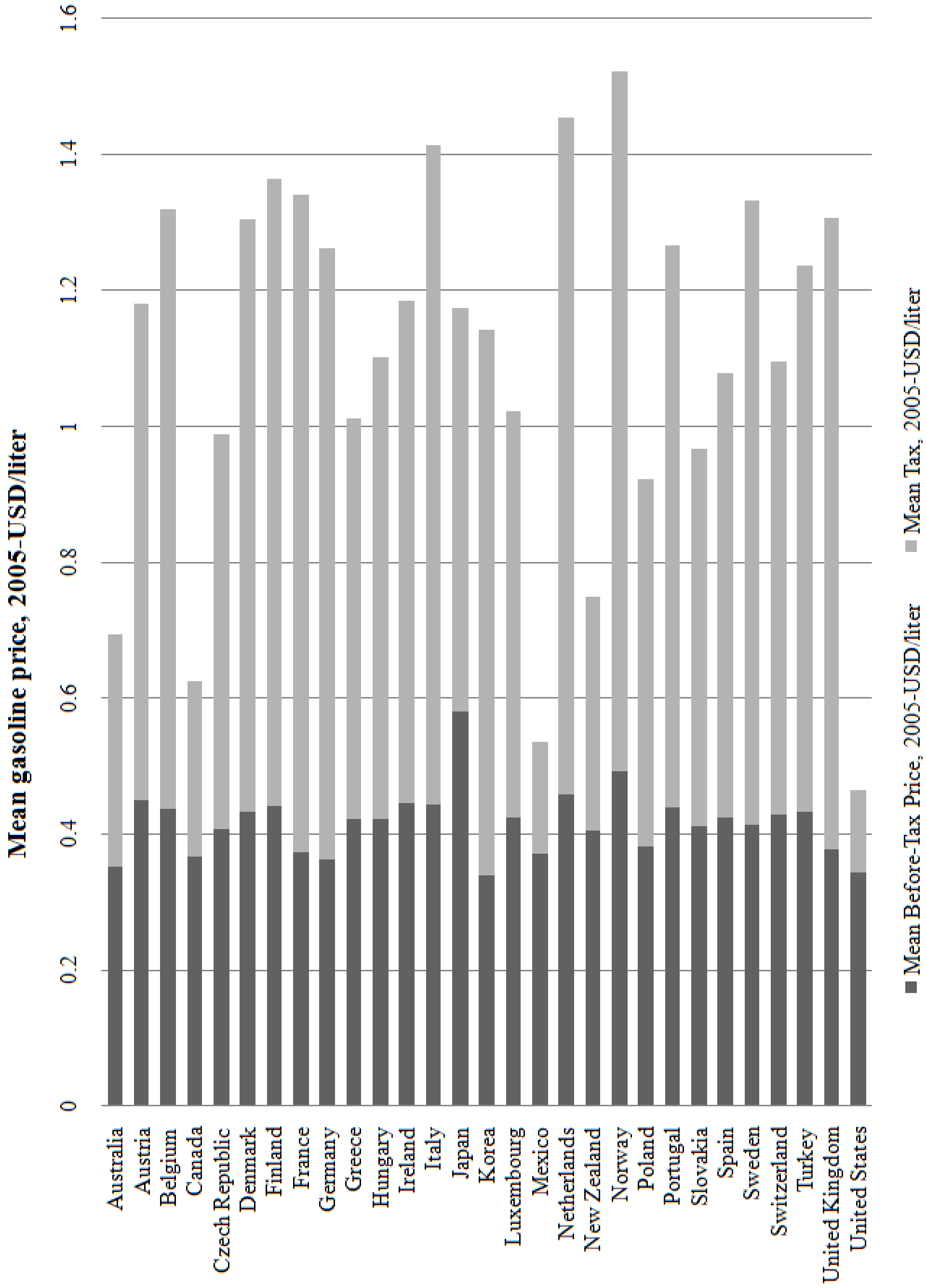


Figure 2: Gasoline consumption per capita, by country

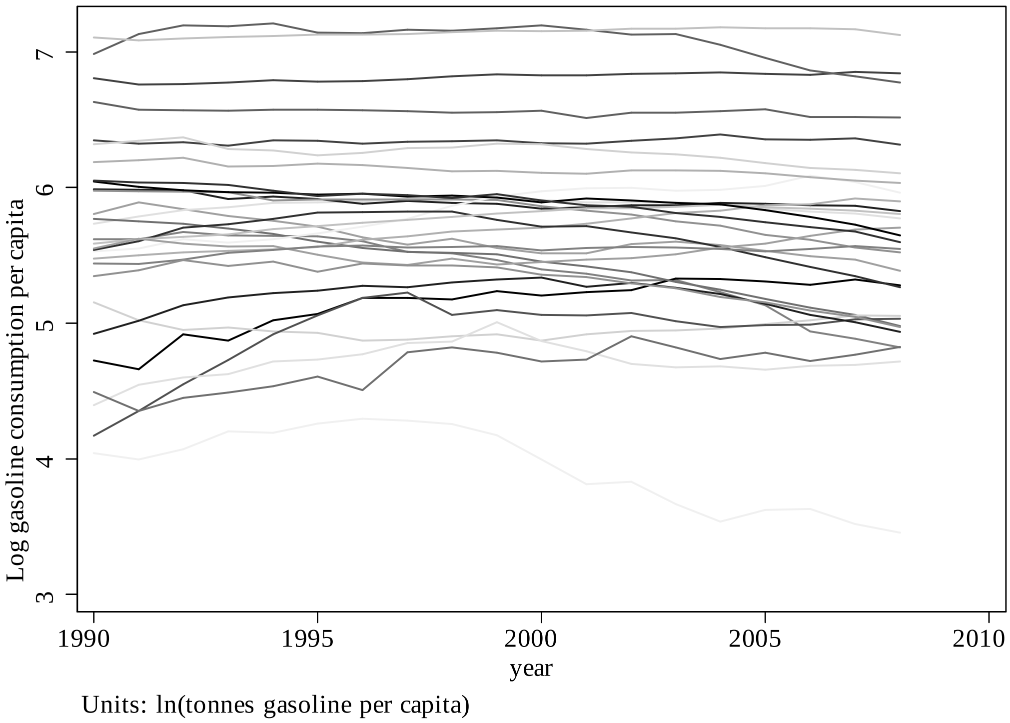


Figure 3: Real log gasoline prices, by country

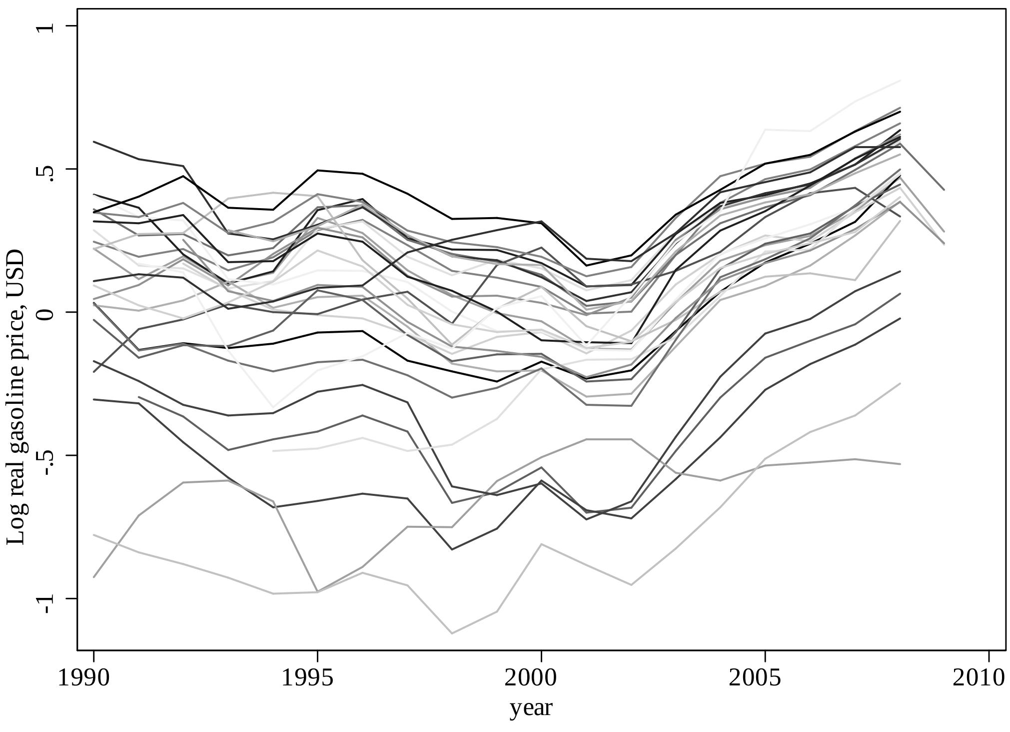
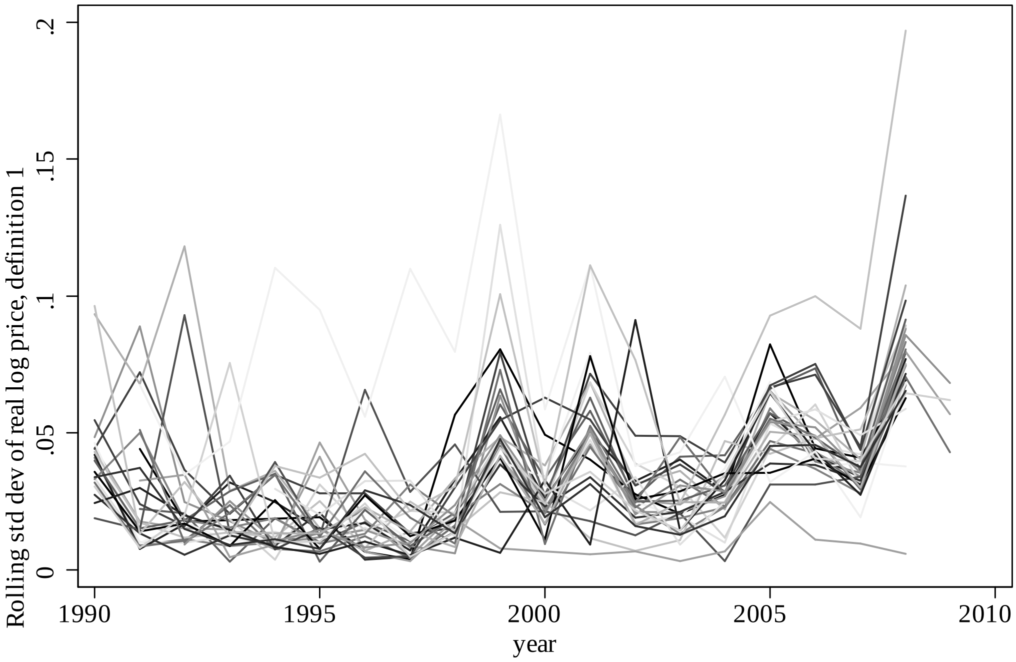


Figure 4: Gasoline price volatility, by country



Volatility measure: rolling standard deviation of log real (Y2005-USD) gasoline price. Omitting 1990 outliers for Czech Republic and Slovkia

Figure 5: Interaction between de-meaned log real price and price volatility measure (USD), by country

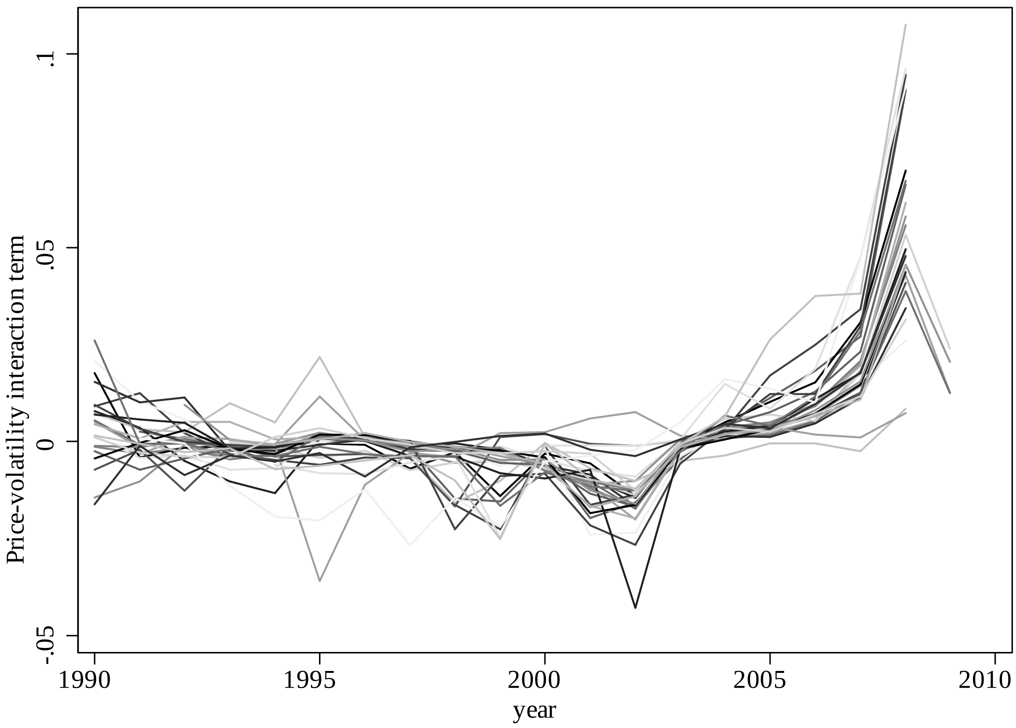
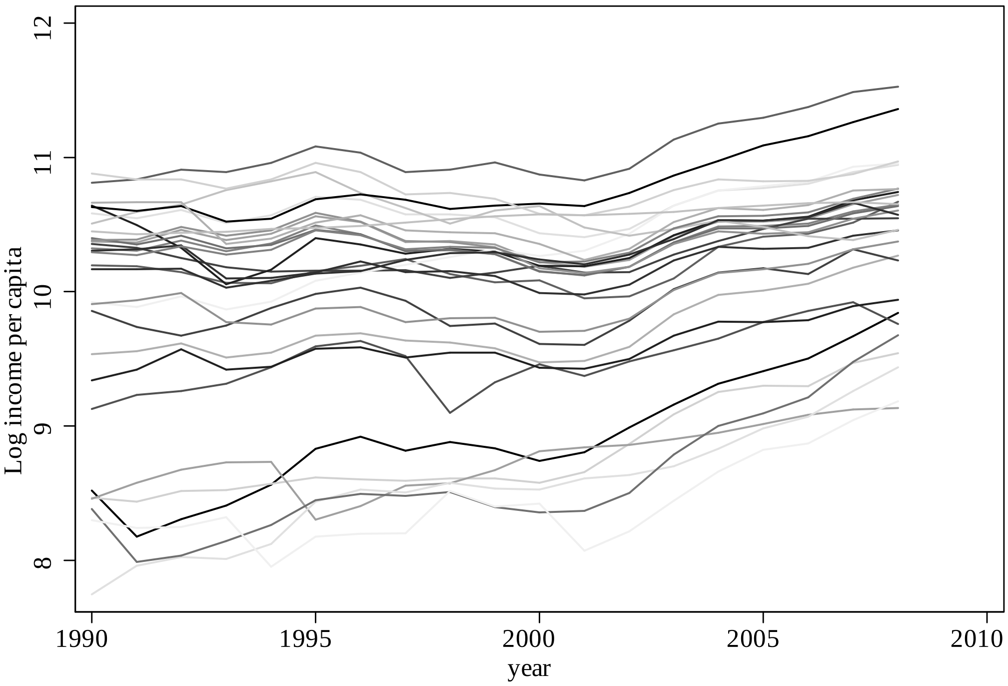


Figure 6: Real income per capita, by country



Income measure: log GDP per capita, real USD

4 Models and Estimation

I consider several strategies to examine gasoline demand for the effects implied by a rational habits model. These strategies vary by model specification as well as by estimation method. To start, I estimate a partial adjustment (ADL) model using standard least-squares panel methods. Next I estimate the same model using Arellano & Bover (1995) and Blundell and Bond's (1998) system GMM estimator. Finally I turn to an error-correction version of the model, which I estimate under a range of coefficient-homogeneity restrictions using Pesaran and Smith's (1995) mean groups method; Pesaran, Shin, and Smith's (1999) pooled mean group method; and a dynamic fixed effects method. Each of these ways of specifying and estimating the model has its advantages and trade-offs, but, as I will discuss in Section 5, the least-squares and GMM methods' weaknesses are troublesome in this application, and I prefer the pooled mean group estimator of the ECM.

4.1 Least Squares

The model laid out in Section 1 was formulated as a partial adjustment model—specifically, as an ADL(1,**0**) model:

$$g_{it} = \lambda g_{i,t-1} + \delta_1 y_{it} + \delta_2 p_{it} + \delta_3 \widehat{\sigma}_{it} + \delta_4 \left(p_{it} - \overline{p}_i\right) \widehat{\sigma}_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

where g is log per-capita gasoline consumption, y is log per-capita income, p is the log real gasoline price, $\widehat{\sigma}$ is a measure of volatility in the log real gasoline price, and μ_i is a time-invariant country-specific effect. I shall also consider a version of this model that includes a common time trend,

$$g_{it} = \lambda g_{i,t-1} + \delta_1 y_{it} + \delta_2 p_{it} + \delta_3 \widehat{\sigma}_{it} + \delta_4 \left(p_{it} - \overline{p}_i\right) \widehat{\sigma}_{it} + \delta_5 t + \mu_i + \varepsilon_{it} \tag{5}$$

and a version that includes country-specific time trends,

$$g_{it} = \lambda g_{i,t-1} + \delta_1 y_{it} + \delta_2 p_{it} + \delta_3 \widehat{\sigma}_{it} + \delta_4 \left(p_{it} - \overline{p}_i\right) \widehat{\sigma}_{it} + \delta_{5i} t + \mu_i + \varepsilon_{it} \tag{6}$$

Short-run elasticities in these models are given by the δ coefficients, and long-run elasticities can be calculated as $\frac{\delta}{1-\lambda}$.

On each of these models I first employ a within-groups (fixed-effects) estimator, eliminating the fixed effects μ_i by de-meaning each variable by its country-specific average. A within-groups estimator makes more sense in this situation than a GLS/random-effects estimator because, even putting aside the issue of the lagged endogenous variable, the country-specific effects are likely to be correlated with the other regressors. Indeed, a Hausman test soundly rejects the equivalence of fixed- and random-effects estimates of a static version of (4); see Table 3. (The same non-equivalence holds for the dynamic version of the model.) Since the random-effects estimator of the static model is consistent only if μ_i is in fact random in relation to the exogenous variables, and the fixed-effects estimator is consistent either way, rejecting the equivalence of the resulting estimates confirms that μ_i is not random.

4.1.1 Addressing Price Endogeneity

The simple within-groups estimator is still afflicted by two problems. The first of these is the potential endogeneity of prices: unless the gasoline supply schedule is flat, any positive demand shock will drive up prices, and vice versa. The gasoline supply schedule is unlikely to be flat when 'individuals' are national aggregates rather than single households, and so causality runs *from* consumption *to* prices as

Table 3: Random- vs. fixed-effects estimator, static model, USD

		(1) Static Random effects	(2) Static Fixed effects	(3) Dynamic Random effects	(4) Dynamic Fixed effects
g_{t-1}	λ			0.957**	0.906**
				(0.0113)	(0.0175)
				[0.000]	[0.000]
y	δ_1	0.523**	0.372**	0.0284**	0.0428**
		(0.0329)	(0.0368)	(0.0107)	(0.0156)
		[0.000]	[0.000]	[0.008]	[0.006]
p	δ_2	-0.574**	-0.419**	-0.0717**	-0.0894**
		(0.0508)	(0.0515)	(0.0177)	(0.0207)
		[0.000]	[0.000]	[0.000]	[0.000]
$\widehat{\sigma}$	δ_3	0.0418	-0.0280	-0.118+	-0.105
		(0.182)	(0.172)	(0.0714)	(0.0729)
		[0.818]	[0.871]	[0.098]	[0.151]
$\widehat{\sigma}\widetilde{p}$	δ_4	-2.348**	-2.197**	-0.132	-0.236
		(0.479)	(0.453)	(0.172)	(0.175)
		[0.000]	[0.000]	[0.444]	[0.179]
R^2		0.8558	0.8564	0.9949	0.9947
Hausman test[a]		77.85 [0.000]		19.07 [0.002]	

Standard errors in parentheses; P-values in brackets.
** p<0.01, * p<0.05, + p<0.1
[a]Under H_0 that random- and fixed-effects estimates equivalent, $\chi^2(4)$ for static model, $\chi^2(4)$ for dynamic.

well as from prices to consumption. Ignoring this endogeneity may lead us to underestimate consumers' responsiveness to price changes.

Fortunately, a strength of the current approach is that it allows us to address the endogeneity of prices by instrumenting for them using outside variables. Two obvious instrument candidates are the tax level and the crude oil price. Both should be highly relevant, as they are major determinants of the local gasoline price. Both should also be exogenous, insofar as an individual country's demand does not drive its tax level or the world crude oil price. (Exogeneity may, of course, be violated if demand-driven political pressure affects the tax level or if an individual country's gasoline consumption is great enough to affect the world oil market.) I use tax instruments and crude-price instruments, therefore, to estimate 2SLS within-groups versions of (4) through (6).

The use of log prices slightly complicates the specification of these instruments. In order to create a good first-stage fit for log prices, note that the real price level P_{it} can be decomposed into the tax level, Tax_{it}, and the before-tax price level, $BeforeTax_{it}$:

$$P_{it} = Tax_{it} + BeforeTax_{it}\text{ , or}$$

$$P_{it} = \left(1 + \frac{Tax_{it}}{BeforeTax_{it}}\right) BeforeTax_{it}$$

$$p_{it} = \ln P_{it} = \ln\left(1 + \frac{Tax_{it}}{BeforeTax_{it}}\right) + \ln BeforeTax_{it} \tag{7}$$

Assuming the crude oil price is linearly related to the before-tax gasoline price, the log real crude oil price is a sensible instrument for the second term in (7). In the first term, the appearance of the before-tax price means the tax component of log price is still endogenous—assuming, of course, that taxes are levied predominantly as level amounts rather than as percentages. To eliminate the endogeneity introduced by the before-tax price, I define the tax instrument as

$$TaxIV_{it} = \ln\left(1 + \frac{Tax_{it}}{\widehat{BeforeTax}_{it}}\right)$$

where $\widehat{BeforeTax}_{it}$ is predicted using the coefficients estimated by a fixed-effects regression of $BeforeTax_{it}$ on the crude oil price:

$$BeforeTax_{it} = \beta_0 + \beta_1 crude_{(i)t} + \mu_i + e_{it}$$

Note that when the model is estimated using local-currency data, the real crude oil price ($crude_{it}$) differs across countries; when a common currency is used, the real crude oil price ($crude_t$) is the same for all.

As instruments for the price-volatility interaction term, finally, I construct interactions between the volatility measure $\widehat{\sigma}_{it}$ and a de-meaned version of each of the price instruments.

The resulting estimates of models (4) through (6) are reported in Table 11 (USD) and Table 21 (local currencies). All least-squares estimates are computed in Stata using Schaffer's (2010) *xtivreg2*.

4.1.2 An Aside on the Potential Reverse Causality of Price Volatility

At this point it is worth considering the potential for the causality between price volatility and price elasticity to run in reverse. In a closed market, if a country with an inherently low elasticity experiences a supply shock, its prices will have to undergo relatively large changes in order to re-balance supply and demand. In this sense, price elasticity could actually be driving price volatility, rather than the reverse.

Fortunately, by and large the integration of the world oil market rescues the original interpretation of causality. Oil is a globally-traded commodity: following a supply shock (or a global demand shock), it is the world crude oil price that must change in order to re-balance world supply and demand. In response to such a shock, therefore, the change in a country's gasoline price should not depend much on the country's individual price elasticity.

Of course, this only applies to shocks that are in fact global: local supply shocks, for example refinery disruptions, may feed into gasoline price changes that vary with local price elasticity. Refining shocks, however, do not seem to be the major source of gasoline price variation, at least at the annual level; Kilian (2010), for example, finds that on a 12-month horizon, only 11% of variability in the U.S. gasoline price can be attributed to refining shocks. Reverse causality, therefore, is likely to explain at most a small portion of the correlation between price volatility and elasticity.

4.1.3 Lagged Endogenous Variable and the Small-T Bias

The second problem afflicting the within-groups estimator of the ADL model is the small-T bias that arises because lagged gasoline consumption is included as a regressor. To see why this occurs, observe that, by definition, lagged gasoline consumption is positively correlated with the fixed effect μ_i and the idiosyncratic error term $\varepsilon_{i,t-1}$:

$$g_{i,t-1} = \lambda g_{i,t-2} + \delta_1 y_{i,t-1} + \delta_2 p_{i,t-1} + \delta_3 \widehat{\sigma}_{i,t-1} + \delta_4 \left(p_{i,t-1} - \overline{p}_i\right) \widehat{\sigma}_{i,t-1} + \mu_i + \varepsilon_{i,t-1}$$

The within-groups transformation removes μ_i from the model, but introduces all years' idiosyncratic error into the modified error term. Writing out the within-transformation of model (4), it becomes clear that transformed lagged consumption is correlated with the transformed error term:

$$\begin{aligned} g_{it} - \overline{g}_i &= \underbrace{\lambda\left(g_{i,t-1} - \frac{1}{T}\sum_{t=1}^{T} g_{i,t-1}\right)}_{\widetilde{g}_{i,t-1}} + \delta_1\left(y_{it} - \overline{y}_i\right) + \delta_2\left(p_{it} - \overline{p}_i\right) + \delta_3\left(\widehat{\sigma}_{it} - \overline{\widehat{\sigma}}_i\right) \\ &\quad + \delta_4\left(\left(p_{it} - \overline{p}_i\right)\widehat{\sigma}_{it} - \frac{1}{T}\sum_{t=1}^{T}\left(p_{it} - \overline{p}_i\right)\widehat{\sigma}_{it}\right) + \underbrace{\left(\varepsilon_{it} - \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{it}\right)}_{\widetilde{\varepsilon}_{it}} \end{aligned}$$

$$\begin{aligned} g_{it} - \overline{g}_i &= \lambda\left(g_{i,t-1} - \frac{1}{T}g_{i0} - \frac{1}{T}g_{i1} - \ldots - \frac{1}{T}g_{it} - \ldots - \frac{1}{T}g_{i,T-1}\right) + \delta_1\left(y_{it} - \overline{y}_i\right) + \delta_2\left(p_{it} - \overline{p}_i\right) \\ &\quad + \delta_3\left(\widehat{\sigma}_{it} - \overline{\widehat{\sigma}}_i\right) + \delta_4\left(\left(p_{it} - \overline{p}_i\right)\widehat{\sigma}_{it} - \frac{1}{T}\sum_{t=1}^{T}\left(p_{it} - \overline{p}_i\right)\widehat{\sigma}_{it}\right) \\ &\quad + \left(\varepsilon_{it} - \frac{1}{T}\varepsilon_{i1} - \frac{1}{T}\varepsilon_{i2} - \ldots - \frac{1}{T}\varepsilon_{it} - \ldots - \frac{1}{T}\varepsilon_{iT}\right) \end{aligned}$$

There will be $T-1$ pairwise correlations between the terms comprising $\widetilde{g}_{i,t-1}$ and $\widetilde{\varepsilon}_{it}$. $T-2$ of them are positive and of order $\frac{1}{T^2}$ (by definition, $-\frac{1}{T}g_{i1}$ is correlated with $-\frac{1}{T}\varepsilon_{i1}$, and so on), and one of them is negative and of order $\frac{1}{T}$ ($g_{i,t-1}$ is correlated with $-\frac{1}{T}\varepsilon_{it}$). As Bond (2002) notes, the negative bias of order $\frac{1}{T}$ will be larger in magnitude than the sum of the positive biases, and altogether the within-groups estimator of λ will be biased downward.

Although the within-groups estimator will be consistent as $T \to \infty$, the size of the bias may still be significant for a panel of length $T = 15$ to 20. For an autoregressive model without outside regressors (i.e. equation (4) with all $\delta = 0$), Nickell (1981) derives the small-T bias as

$$\underset{N\to\infty}{p\lim}\left(\widehat{\lambda} - \lambda\right) = \left\{\frac{2\lambda}{1-\lambda^2} - \left[\frac{1}{\frac{1+\lambda}{T-1}\left(1 - \frac{1}{T}\frac{1-\lambda^T}{1-\lambda}\right)}\right]\right\}^{-1} \tag{8}$$

In the same paper Nickell derives a more opaque expression for the small-T bias in a model that includes additional regressors. He shows that the downward bias of $\widehat{\lambda}$ should be even greater in this case, and so (8) may be used to establish the minimum size of the bias. Given a true λ near 0.7, as suggested by the estimates in Table 11 (column 3), and setting T equal to its average of 18.6, (8) suggests the bias in $\widehat{\lambda}$ is about -0.10. Since the size of the bias increases in λ, and the true λ is suspected to be greater than the estimate $\widehat{\lambda} \approx 0.7$, the minimum small-sample bias of $\widehat{\lambda}$ may be even larger than 0.1. In other words, the bias is unlikely to be trivial. We can, however, put a bound on it: as Bond (2002) notes, the positive correlation between the lagged endogenous variable and the fixed effect μ_i means that the OLS estimator of λ in the untransformed model will be biased *upward*. In Tables 12 and 22, therefore, I report time- and country-pooled 2SLS estimates for models (4) through (6). The coefficient on lagged consumption—around 0.9 if country-specific time trends are included and just below 1 otherwise—represents an upper bound on λ. This should quiet any fears of a unit root for λ, which would have troubling implications for the long-run interpretation of the model.

Finally, note that spurious regression—a concern that is at the forefront of much of the recent literature—is not a problem in this model. Spurious regression may indeed arise in models where the dependent variable and its regressors are nonstationary. In such a case, a regression may attribute the variables' similar but unrelated evolution over time to a relationship amongst the variables. In fact, as I'll show in section (4.3), both my dependent variable g and several of the explanatory variables are nonstationary in levels. Because these $I(1)$ variables are cointegrated, however (see Section (4.3)), the relationships estimated amongst these variables are not spurious; and as Pesaran and Shin (1999) and Bentzen and Engsted (2001) demonstrate, the ADL model remains valid.

4.2 System GMM

To address the bias generated by the inclusion of lagged endogenous variables in models such as (4), the dynamic panel literature has come up with several alternative estimators. The first of these was Anderson and Hsiao's (1981) estimator, which in this case calls for differencing the model and then using the second lag of the *level* of consumption as an instrument for the included endogenous variable, which has been transformed into the first lag of *differenced* consumption. This instrument should be both relevant and exogenous, as $g_{i,t-2}$ is correlated with $\Delta g_{i,t-1} = g_{i,t-1} - g_{i,t-2}$ by definition but uncorrelated (provided the model is properly specified) with the contemporary error term $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$. Subsequent papers (e.g., Holtz-Eakin, Newey and Rosen 1988 and Arellano and Bond 1991) pointed out that all lags of the endogenous variable beyond the first should be independent of the contemporary differenced error term, and that this independence could be exploited using GMM.

Even more moment conditions were suggested by Ahn and Schmidt (1995) and Arellano and Bover (1995)—nonlinear moment conditions in the case of Ahn and Schmidt, and "levels" moment conditions in the case of Arellano and Bover. These latter "levels" moment conditions are particularly useful in cases where the coefficient on the lagged endogenous variable is near 1, which is exactly the case at hand. In such a situation, Blundell and Bond (1998) point out, the included endogenous variable's *level* provides little information about its future *evolution*, and so lags of the endogenous variable are weak instruments. By contrast, lagged differences of the included endogenous variable *will* be informative about its future level, and this relationship can be used to construct a set of moment conditions for the non-differenced model. Combining these "levels" moment conditions with Arellano and Bond's (1991) "difference" moment conditions yields the "system GMM" estimator. Blundell, Bond, and Windmeijer (2000) show using Monte Carlo simulations that system GMM is more precise and less biased than difference GMM when λ is high and the model includes outside regressors.

I therefore construct a system GMM estimator for (4) based on these difference and level moment conditions, as well as on additional "IV-style" moment conditions based upon the outside instruments for the gasoline price and price-volatility interaction term:

$$\textbf{Difference moment conditions: } E\left[g_{i,t-k}\Delta\varepsilon_{it}\right] = 0,\ k = 2, ..., T \tag{9}$$

$$\textbf{Levels moment conditions: } E\left[\left(\mu_i + \varepsilon_{it}\right)\Delta g_{i,t-1}\right] = 0 \tag{10}$$

$$\textbf{IV-style moment conditions: } E\left[\Delta w_{it}\Delta\varepsilon_{it}\right] = 0\ \forall\ t \text{ and } E\left[w_{it}\varepsilon_{it}\right] = 0\ \forall\ t \tag{11}$$

where w represents each of the price instruments discussed in Section 4.1.1. The validity of the difference moment conditions requires that the ε_{it} are not serially correlated; the levels moment conditions further require that the relationship between g_{it} and the fixed effect μ_i is constant over time; and the IV-style moment conditions require that each w fulfills the standard conditions for 2SLS instruments.

Estimates based on this system GMM estimator, computed in Stata using Roodman's (2011) *xtabond2*, are reported in Tables 13 (USD) and 24 (local currencies). The two-step version of the system GMM estimator is known to produce downward-biased standard errors (Arellano and Bond 1991, Blundell and Bond 1998), so I apply Windmeijer's (2005) correction. To address the problem of overfitting, which arises in difference and system GMM when moment conditions proliferate (Roodman 2006, 2007), I also report a version in which the difference moment conditions are restricted to $k = 2, 3, 4$ and a version based on a 'collapsed' instrument matrix. The meaning and implications of collapsing the instrument matrix are discussed in Roodman (2007).

Discussion of the system GMM results is postponed to Section 5. For now, note that addressing the endogeneity of lagged consumption has cost us considerable precision. Few of the coefficients in the system GMM estimates differ significantly from 0, even those coefficients that the least-squares estimates found to be highly significant. Despite the bias inherent in estimates that do not specifically address the endogeneity of $g_{i,t-1}$, therefore, these methods are more informative—and probably preferable, as the nature of the bias is known.

4.3 Heterogeneous Coefficients and the Error-Correction Model

Neither the least-squares nor the GMM methods discussed above allow for cross-country heterogeneity in the coefficients. If coefficients indeed vary by country and regressors are autocorrelated, then, as Pesaran and Smith (1995) prove, estimators that assume homogeneity will be biased and inconsistent. In particular, fixed-effects models such as (4), which constrain all coefficients except the country-fixed effects to be the same across countries, will produce downward-biased estimates for the coefficients on the outside regressors ($\delta_1, ..., \delta_4$). The fixed-effects model will also yield a biased estimate of the coefficient on the lagged endogenous variable (λ), the direction of which will be positive if the autocorrelations of the other regressors are positive. These biases do not go away as the sample size and sample period increase, and their practical effect will be to exaggerate the difference between short- and long-run responses. The intuition for this practical effect is simple: if the coefficient on lagged consumption is biased upward, the speed of adjustment will appear slower, and this will magnify artificially-small short-run responses into artificially-large long-run responses.

If regressors are I(1), moreover, these biases are potentially severe. As the autocorrelation coefficient of an outside regressor approaches a unit root, Pesaran and Smith (1995) show, the estimator for the coefficient on the lagged endogenous variable converges in probability to 1, while the estimators for the coefficients on the outside regressors converge to 0. Many of my regressors are in fact I(1), as I'll show shortly, and so the consequences of coefficient heterogeneity are potentially grave.

To address the problem of coefficient heterogeneity, Pesaran, Shin and Smith (1999) suggest a pooled-mean group (PMG) estimator that allows short-run responses to vary across individuals. Since the PMG estimator and its alternatives are derived and discussed in the literature in terms of an error-correction model, I turn to an ECM model of gasoline demand—the unrestricted version of which is equivalent to an ADL(1,**1**). To demonstrate the relationship between the former ADL(1,**0**) specification and the ECM and the ECM's equivalence to an ADL(1,**1**), I first re-write the existing model (4) to allow coefficients to vary by country:

$$g_{it} = \lambda_i g_{i,t-1} + \delta_{1i} y_{it} + \delta_{2i} p_{it} + \delta_{3i} \widehat{\sigma}_{it} + \delta_{4i} \left(\widehat{\sigma}\widetilde{p}\right)_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

(For notational simplicity, define $\widetilde{p}_{it} = p_{it} - \overline{p}_{i\cdot}$.) Next, subtracting $g_{i,t-1}$ from each side of (12), then adding and subtracting $\delta_{1i} y_{i,t-1}$, $\delta_{2i} p_{i,t-1}$, $\delta_{3i} \widehat{\sigma}_{i,t-1}$, and $\delta_{4i} \widehat{\sigma}\widetilde{p}_{i,t-1}$ from the right-hand side, yields

$$\begin{aligned} \Delta g_{it} \quad = \quad & (\lambda_i - 1) \, g_{i,t-1} + \delta_{1i} y_{i,t-1} + \delta_{2i} p_{i,t-1} + \delta_{3i} \widehat{\sigma}_{i,t-1} + \delta_{4i} \left(\widehat{\sigma}\widetilde{p}\right)_{i,t-1} \\ & + \delta_{1i} \Delta y_{it} + \delta_{2i} \Delta p_{it} + \delta_{3i} \Delta \widehat{\sigma}_{it} + \delta_{4i} \Delta \left(\widehat{\sigma}\widetilde{p}\right)_{it} + \mu_i + \varepsilon_{it} \end{aligned}$$

which can be factored into

$$\Delta g_{it} = \underbrace{-\left(1-\lambda_{it}\right)}_{\phi_i}\left[g_{i,t-1} - \underbrace{\frac{\delta_{1i}}{1-\lambda_i}}_{\theta_{1i}} y_{i,t-1} - \underbrace{\frac{\delta_{2i}}{1-\lambda_i}}_{\theta_{2i}} p_{i,t-1} - \underbrace{\frac{\delta_{3i}}{1-\lambda_i}}_{\theta_{3i}} \widehat{\sigma}_{i,t-1} - \underbrace{\frac{\delta_{4i}}{1-\lambda_i}}_{\theta_{4i}} \left(\widehat{\sigma}\widetilde{p}\right)_{i,t-1}\right] \quad (13)$$
$$+\delta_{1i}\Delta y_{it} + \delta_{2i}\Delta p_{it} + \delta_{3i}\Delta\widehat{\sigma}_{it} + \delta_{4i}\Delta\left(\widehat{\sigma}\widetilde{p}\right)_{it} + \mu_i + \varepsilon_{it}$$

This is an ECM with no coefficient-homogeneity restrictions, but it can be factored just as easily into ADL(1,**1**) form:

$$g_{it} = \left(\phi_i + 1\right) g_{i,t-1} + \delta_{1i} y_{it} - \left(\phi_i\theta_{1i} + \delta_{1i}\right) y_{i,t-1} + \delta_{2i} p_{it} - \left(\phi_i\theta_{2i} + \delta_{2i}\right) p_{i,t-1} \quad (14)$$
$$+\delta_{3i}\widehat{\sigma}_{it} - \left(\phi_i\theta_{3i} + \delta_{3i}\right)\widehat{\sigma}_{i,t-1} + \delta_{4i}\left(\widehat{\sigma}\widetilde{p}\right)_{it} - \left(\phi_i\theta_{4i} + \delta_{4i}\right)\left(\widehat{\sigma}\widetilde{p}\right)_{i,t-1} + \mu_i + \varepsilon_{it}$$

Estimates based on the ECM differ from those based on ADL(1,**0**) by virtue of slightly different underlying models, therefore, as well as by different coefficient-homogeneity restrictions.

In the unrestricted ECM given by (13), the new coefficient ϕ_i is the error-correction term. It should be negative, and its magnitude is the speed of adjustment, or the portion of long-run adjustment that takes place during the first period after a change in one of the regressors. The new coefficients θ_{1i} through θ_{4i} are long-run elasticities, and as before the coefficients δ_{1i} through δ_{4i} are short-run elasticities.

Although Pesaran, Shin and Smith's (1999) estimator allows regressors to be I(0) or I(1), it does require a cointegrating relationship among I(1) variables—that is, it requires a stable long-run relationship between the dependent and explanatory variables. Before checking for cointegration, I check the order of integration of each of my variables.

The classical tests for a unit root in a *single* time series are the Dickey-Fuller and Augmented Dickey-Fuller, which test for the stationarity of an AR(1) and an AR(p) process, respectively. The Dickey-Fuller tests $H_0 : \rho - 1 = 0$ (nonstationarity) vs. $H_a : |(\rho - 1)| < 0$ (stationarity) in the transformed model

$$\Delta x_t = (\rho - 1)\, x_{t-1} + (\alpha_0 + \alpha_1 t) + \varepsilon_t$$

whereas the Augmented Dickey-Fuller uses the same null and alternative hypotheses for the transformed model

$$\Delta x_t = (\rho - 1)\, x_{t-1} + \sum_{i=j}^{p-1} \beta_i \Delta x_{t-j} + (\alpha_0 + \alpha_1 t) + \varepsilon_t$$

Alternately, the Phillips-Perron (1988) test makes it possible to test for nonstationarity in an AR(p) process without knowing p. In this test, corrections for serial correlation in ε_t allow $\widehat{\rho}$ estimated for an AR(1) to be used to to test $\rho = 1$ for any AR(p).

When x is a panel variable, the cross-section dimension introduces several complications, which have prompted the development of a variety of panel unit root tests.[4] One complication is whether to consider a single autocorrelation coefficient for the panel as a whole or to consider each individual i as a separate time series with its own coefficient ρ_i. Tests taking the former route include Levin, Lin, and Chu (2002) and Harris and Tzavalis (1999). Tests taking the latter route include Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001), all of which involve performing a separate test for each individual and aggregating the results. Im, Pesaran and Shin (2003) perform this aggregation by averaging the *test statistics* for individual (A)DF tests; Maddala and Wu (1999) and Choi (2001) perform the aggregation over the *p-values* associated with (A)DF or other individual unit root tests. These tests

[4] For a thorough overview of these tests, see Baltagi and Kao (2000).

based on p-values are known collectively as Fisher-type tests, and weigh a null hypothesis that all panels are *nonstationary* against the alternative that one or more panels are stationary.

To explore the order of integration of my variables, I use a Fisher-type test based on individual Phillips-Perron tests, with and without a trend. The choice of the Phillips-Perron test protects my results from the ADF's sensitivity to the choice of lag length p. The choice of a Fisher-type test has the advantages of high power compared to tests based on ADF test statistics (Choi 2001) and, crucially, the flexibility to deal with series whose length varies across individuals. Results of these tests, performed using Stata's (2009) *xtunitroot*, are reported in Tables 4 and 5. Where the test does not reject a variable's nonstationarity in levels, I repeat the test on first differences. In each instance the second test does reject nonstationarity, and so for the USD-denominated variables I am able to conclude that volatility is I(0) with or without trend and the remaining variables are I(1) with or without trend. For the common-currency variables, results are somewhat different: g and p are I(1) with or without trend; y is I(1) without trend and I(0) with; and $\widehat{\sigma}$ and $\widehat{\sigma}\widetilde{p}$ are I(0) with or without trend.

Table 4: Fisher-style Phillips-Perron unit root tests, currency in USD

Without trends

	Level		First Difference		
Variable	Test Statistic*	P-Value	Test Statistic*	P-Value	Order of Integration
g	68.0062	0.1732	364.1834	0.0000	$I(1)$
p	17.8696	1.0000	148.7426	0.0000	$I(1)$
y	11.8702	1.0000	220.1072	0.0000	$I(1)$
$\widehat{\sigma}$	190.6238	0.0000			$I(0)$
$\widehat{\sigma}\widetilde{p}$	19.1043	1.0000	199.4135	0.0000	$I(1)$

With time trends

	Level		First Difference		
Variable	Test Statistic*	P-Value	Test Statistic*	P-Value	Order of Integration
g	71.6704	0.1071	507.0169	0.0000	$I(1)$
p	14.6156	1.0000	136.2582	0.0000	$I(1)$
y	24.2946	1.0000	156.7488	0.0000	$I(1)$
$\widehat{\sigma}$	195.1116	0.0000			$I(0)$
$\widehat{\sigma}\widetilde{p}$	12.0569	1.0000	211.9994	0.0000	$I(1)$

*Inverse $\chi 2$ with 58 degrees of freedom.
Phillips-Perron tests conducted using 3 lags for the Newey-West standard errors.

Since a regression involving nonstationary variables may be spurious, and since Pesaran, Shin and Smith's (1999) estimator requires cointegration of any I(1) variables, I turn now to checking for cointegration. One approach to cointegration testing involves estimating a static model and then checking the residuals for nonstationarity. This was in fact the first approach to cointegration testing, introduced by Engle and Granger (1987) for single time series and later adapted to panels by Kao (1999) and others. Pedroni (2004) expanded this two-step, residual-based approach to allow for cross-sectional heterogeneity of coefficients. Meanwhile, a second approach to cointegration testing has been to check whether the error-correction term in an ECM—e.g., ϕ_i in (13), or α_i in (15)—is zero. Banerjee, Dolado and Mestre (1998) develop this approach for single time series, and Westerlund (2007) adapts it to panels, basing his tests on a model of the form

$$\Delta y_{it} = \alpha_i y_{i,t-1} + \lambda_i^{'} \mathbf{x}_{i,t-1} + \sum_{j=1}^{q_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q_i} \gamma_{ij}^{'} \Delta \mathbf{x}_{i,t-j} + \mu_i + \pi_i t + \varepsilon_{it} \tag{15}$$

Table 5: Fisher-style Phillips-Perron unit root tests, local currencies

	Level		First Difference		
	Without trends				
Variable	Test Statistic*	P-Value	Test Statistic*	P-Value	Order of Integration
g	68.0062	0.1732	364.1834	0.0000	$I(1)$
p	72.0861	0.1010	343.6998	0.0000	$I(1)$
y	21.1883	1.0000	412.3704	0.0000	$I(1)$
$\widehat{\sigma}$	313.8033	0.0000			$I(0)$
$\widehat{\sigma}\widetilde{p}$	183.9754	0.0000			$I(0)$
	Fisher-style unit root tests on models **With time trends**				
	Level		First Difference		
Variable	Test Statistic*	P-Value	Test Statistic*	P-Value	Order of Integration
g	71.6704	0.1071	507.0169	0.0000	$I(1)$
p	81.6818	0.0219	316.9540	0.0000	$I(1)$
y	165.6083	0.0000			$I(0)$
$\widehat{\sigma}$	450.9815	0.0000			$I(0)$
$\widehat{\sigma}\widetilde{p}$	229.8273	0.0000			$I(0)$

*Inverse $\chi 2$ with 58 degrees of freedom.
Phillips-Perron tests conducted using 3 lags for the Newey-West standard errors.

where $\mathbf{x}$ and y comprise the variables to be examined for possible cointegration. Westerlund's approach has the advantages of high power and flexibility: not only does it allow cross-sectional heterogeneity in coefficients, but, unlike the two-step residual-based approaches, it does not impose a common factor restriction on the relationship between short- and long-run adjustment. For these reasons I choose Westerlund's test to check for cointegration of my I(1) variables.

Westerlund's (2007) test actually has several varieties. The "group mean" variety (G) allows the error-correction term to vary across individuals, and tests against the alternative hypothesis that the error-correction term is smaller than zero for at least one individual; the "panel" variety (P), by contrast, constrains the error-correction term to be the same across individuals, testing against the alternative hypothesis that this single term is smaller than zero. In both cases, the null hypothesis is that the error-correction term is zero, and that the variables in question are not cointegrated. Given my small sample size, the extra precision afforded by constraining the error-correction term to be constant across countries appears to be important, and so I focus on this variety. For each of these varieties, Westerlund suggests two different test statistics: a t-statistic version, denoted with the subscript τ, which is simply the estimated error-correction term divided by its standard error (or, for the group mean version, the average of these quotients); and a less intuitive version, denoted with the subscript α, that controls for the panel length $T_{(i)}$. I report both of these test statistics.

Tests are performed in Stata with Persyn and Westerlund's (2008) *xtwest*, using standard errors that have been bootstrapped to allow cross-sectional dependence (see Westerlund 2007 and Persyn and Westerlund 2008). Results are reported in Tables 6 and 7. Note that some countries' series are insufficiently long to be used in certain versions of the tests; these omissions are listed in the tables. Using the panel-variety tests, I can clearly reject the hypothesis of non-cointegration of the I(1) variables in the local-currency version of the model. In the common-currency version, the panel-variety tests reject the hypothesis of non-cointegration provided that the lag q_i in (15), chosen for each country using the AIC, is allowed to be as high as 2.[5,6]

Table 6: Cointegration tests, USD

Variables	Lag length q_i	Omitted Countries	Test	Value	P-Value	Bootstrapped[a] p-value
g, y, p, $\widehat{\sigma}\widetilde{p}$	Chosen by AIC from 0 and 1	*Czech Republic*	G_τ	-0.036	1.000	1.000
			G_α	-0.203	1.000	1.000
			P_τ	-1.431	1.000	0.720
			P_α	-0.427	0.999	0.730
g, y, p, $\widehat{\sigma}\widetilde{p}$	Chosen by AIC from 0-2	*Australia, Czech Republic, Hungary, Mexico, Poland, Spain, Sweden, Turkey*	G_τ	-1.991	0.103	0.390
			G_α	-0.057	1.000	0.630
			P_τ	-0.144	1.000	0.010
			P_α	-0.051	0.999	0.010
g, y, p, $\widehat{\sigma}\widetilde{p}$	Chosen by AIC from 0 and 1	*Australia, Czech Republic, Hungary, Mexico, Poland, Spain, Sweden, Turkey*	G_τ	-0.071	1.000	0.990
			G_α	-0.091	1.000	1.000
			P_τ	-1.708	1.000	0.580
			P_α	-0.566	0.996	0.560

[a]100 draws

Table 7: Cointegration tests, local currencies

Variables	Lag length q_i	Omitted Countries	Test	Value	P-Value	Bootstrapped[a] p-value
g, y, p	Chosen by AIC from 0 and 1	none	G_τ	-1.460	0.344	0.340
			G_α	-3.833	0.975	0.320
			P_τ	-9.074	0.001	0.000
			P_α	-3.501	0.136	0.050
g, y, p	Chosen by AIC from 0-2	none	G_τ	-1.540	0.207	
			G_α	-3.244	0.995	
			P_τ	-9.074	0.001	
			P_α	-3.501	0.136	
g, y, p	Chosen by AIC from 0-3	Australia, Hungary, Poland, Spain, Sweden, Turkey	G_τ	-1.311	0.627	0.420
			G_α	-0.961	1.000	0.260
			P_τ	-6.129	0.109	0.000
			P_α	-2.520	0.492	0.000

[a]100 draws

Given this evidence that a long-run relationship amongst the variables of my model does exist, I move on to estimating the ECM. Pesaran, Shin and Smith's (1999) pooled mean group estimator uses maximum likelihood, based on the assumption that the ε_{it} are independent and normal, to estimate

$$\begin{aligned}\Delta y_{it} &= \phi_i \left[g_{i,t-1} - \theta_1 y_{i,t-1} - \theta_2 p_{i,t-1} - \theta_3 \widehat{\sigma}_{i,t-1} - \theta_4 \left(\widehat{\sigma}\widetilde{p}\right)_{i,t-1} \right] \\ &\quad + \delta_{1i} \Delta y_{it} + \delta_{2i} \Delta p_{it} + \delta_{3i} \Delta \widehat{\sigma}_{it} + \delta_{4i} \Delta \left(\widehat{\sigma}\widetilde{p}\right)_{it} + \mu_i + \varepsilon_{it}\end{aligned} \tag{16}$$

[5]Allowing q_i to be as high as 2, unfortunately, forces me to drop several countries from the sample. It does not appear to be the omission of these countries that is responsible for the rejection of non-cointegration, however, as running the test for $q_i \leq 1$ with the same countries omitted does not lead to rejection.

[6]Persyn and Westerlund (2008) observe that the Westerlund tests are sensitive to their specification in "small" T situations. As my T is only two thirds that of Persyn and Westerlund's example, and I am attempting to test for cointegration amongst a larger number of variables, I suspect that my inability to reject non-cointegration in certain specifications (e.g., $q_i \leq 1$) arises from this sensitivity and relatively low power, and not from a lack of a long-run relationship amongst the variables. The strong rejection of non-cointegration amongst the local-currency variables, moreover, suggests that a cointegrating relationship does exist.

Table 8: Restrictions on the error-correction model

Model	Restrictions
Pooled mean-group (PMG)	Long-run parameters homogenous: $\theta_{1i} = \theta_1, \theta_{2i} = \theta_2, \theta_{3i} = \theta_3, \theta_{4i} = \theta_4$
Mean-Group (MG)	None
Dynamic Fixed-Effect (DFE)	All parameters homogenous: $\theta_{1i} = \theta_1, \theta_{2i} = \theta_2, \theta_{3i} = \theta_3, \theta_{4i} = \theta_4$; $\delta_{1i} = \delta_1, \delta_{2i} = \delta_2, \delta_{3i} = \delta_3, \delta_{4i} = \delta_4; \phi_i = \phi$

Note that (16) is simply the general ECM from (13) with the long-run coefficients θ_{1i}, θ_{2i}, θ_{3i}, and θ_{4i} constrained to be equal across individuals.

The resulting pooled mean group estimates are reported in Tables 14, 15, and 25. Table 14 reports results for all countries; Table 15 reports results when the four countries with the worst fit from the ADL are omitted. The short run elasticities ($\widehat{\delta}_1$ through $\widehat{\delta}_4$) reported in these tables are the *means* of the country-specific short-run elasticities; individual short-run elasticities are reported in Appendix 10.

To examine the value of the assumption that the long-run coefficients are homogenous (which drastically reduces the number of parameters to be estimated), I also report mean group estimates of the ECM model. The mean group estimator simply estimates (13) separately for each country and forms an average of the resulting coefficient estimates. To examine the value and cost of restricting both the long- *and* the short-run coefficients to be homogenous, as the ADL inherently did, I also estimate a dynamic fixed-effects version of the ECM. The restrictions imposed by these various estimators are summarized in Table 8. Results are reported alongside the PMG results.

All estimates of the ECM—pooled mean groups, mean groups, and dynamic fixed-effects—are computed in Stata using Blackburne and Frank's (2007b) *xtpmg*.

5 Results and Discussion

Results, particularly with respect to the habits-related parameters, vary considerably across these model specifications and estimation methods. Although each approach does have its advantages (summarized in Table 9), not all the advantages are equal; and after weighing each approach's advantages and disadvantages, my preference is for the pooled mean group estimates of the error-correction model.

Table 9: Advantages of various estimation approaches

Advantage	Fixed-effects 2SLS with instrumenting for price	GMM	Pooled mean group estimator of ECM
Corrects for endogeneity of prices	✓		
Addresses endogeneity of g_{t-1}		✓	
Addresses coefficient heterogeneity			✓
Precision	✓		✓

5.1 Least-Squares Estimates of the ADL Model

The unique advantage of the fixed-effects estimator of the ADL model is that it allows me to use outside instruments to address the endogeneity of the price variables. In practice, however, it is not clear that instrumenting for prices is very valuable. Tests for endogeneity[7] do, by and large, reject that prices are exogenous, and may or may not, depending on the specification of the trend, reject that price and the price-volatility interaction are jointly exogenous. The instruments used to address the apparent endogeneities, moreover, do appear to be relevant, as underidentification is rejected[8] no matter how the trend is specified. The problems arise when it comes to the instruments' exogeneity: overidentifying restrictions tests strongly reject that all the instruments are exogenous. The endogeneity, it becomes clear when the regressions are re-run using subsets of the instruments, lies in the instruments based on crude oil prices. Unfortunately, omitting the crude-oil instruments and basing price identification solely on the tax instruments yields estimates that are nonsensical and uninformative, with most coefficients' p-values around 0.9.

In theory, it's possible that an instrument that is not *perfectly* exogenous may nonetheless remove some of the instrumented variable's endogeneity, and therefore retain some value. Alas, this is not such a case. Any endogeneity in the price should bias its coefficient upwards towards 0, and yet the price coefficients in the non-instrumented ADL models (Table 10) are more negative than their instrumented counterparts. The implied long-run price elasticity from the instrumented version of the individual-trend model, moreover, is of a smaller magnitude than the long-run elasticity estimated using PMG on the error-correction model. Though price endogeneity is an issue, it appears we are better off ignoring it than addressing it—or, rather, better off merely acknowledging it than addressing it using the instruments at hand.

The actual fixed-effects 2SLS estimates, it should be noted, are nonsensical unless country-specific trends are included. With no trend or a homogenous trend, prices have no statistically-significant effect; and with no trend, even income does not have a statistically-significant effect. Moreover, *none* of the fixed-effects 2SLS results—common or local currency, with or without any type of trend—finds the rational-habits variables, $\widehat{\sigma}$ and $\widehat{\sigma}\widetilde{p}$, to have a statistically-significant effect. Although this might ordinarily be taken as a sign that $\widehat{\sigma}$ and $\widehat{\sigma}\widetilde{p}$ are not relevant to gasoline demand, the weakness of the price and income effects suggests that the estimated effects of $\widehat{\sigma}$ and $\widehat{\sigma}\widetilde{p}$ should not be trusted, either. Overall, I discount the findings of the fixed-effects 2SLS estimator of the ADL.

5.2 System GMM Estimates of the ADL Model

The unique advantage of the system GMM estimator is that it addresses the endogeneity of lagged consumption. That endogeneity should, as previously discussed, bias the coefficient on lagged consumption upward, and therefore make adjustment seem slower than it truly is. As expected, the system GMM estimates of λ are higher than the least-squares estimates. Troublingly, in fact, the GMM estimates of λ are in most cases higher than 1. But although these estimates have been pushed upward by the removal of a downward bias, they have also been pushed upward by the GMM estimator's own shortcomings. One of these shortcomings is that the system GMM estimator, like the least-squares estimator, imposes homogeneity of coefficients across countries. Given that the other regressors are positively autocorrelated, this will lead to an upward bias on $\widehat{\lambda}$ (Pesaran and Smith 1995). Another shortcoming is that, unlike the least-squares estimator, the system GMM estimator does not allow me to identify a model with country-specific trends,[9] which in the least-squares case reduced $\widehat{\lambda}$ considerably. The GMM estimator merely trades one bias for another, therefore, and it does so at an incredibly high cost of precision: in

[7] That is, difference-in-Sargan/Hansen tests comparing a regression in which the variable(s) in question are treated as endogenous to a regression in which they are assumed to be exogenous.

[8] Kleibergen-Paap (2006) tests are used to test for underidentification.

[9] Country-specific trends require the estimation of an extra 28 parameters, which system GMM cannot handle given my sample size.

Table 10: Within-groups (fixed-effects) estimates, USD

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}	λ	0.911**	0.888**	0.727**
		(0.0249)	(0.0230)	(0.0372)
		[0.000]	[0.000]	[0.000]
y	δ_1	0.0404+	0.105**	0.183**
		(0.0217)	(0.0233)	(0.0318)
		[0.064]	[0.000]	[0.000]
p	δ_2	-0.117**	-0.135**	-0.198**
		(0.0312)	(0.0299)	(0.0331)
		[0.000]	[0.000]	[0.000]
$\widehat{\sigma}$	δ_3	-0.178+	-0.0470	-0.0592
		(0.0931)	(0.0904)	(0.0792)
		[0.056]	[0.604]	[0.455]
$\widehat{\sigma}\widetilde{p}$	δ_4	0.260	0.263	-0.00520
		(0.288)	(0.275)	(0.244)
		[0.367]	[0.340]	[0.983]
t			-0.00426**	
			(0.000524)	
			[0.000]	
R^2		0.891	0.904	0.938

Robust standard errors in parentheses;
P-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 11: Within-groups (fixed effects) estimates with 2SLS instrumenting for price, USD

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}	λ	0.941**	0.922**	0.681**
		(0.0288)	(0.0274)	(0.0417)
		[0.000]	[0.000]	[0.000]
y	δ_1	0.0347	0.0770**	0.196**
		(0.0251)	(0.0265)	(0.0368)
		[0.167]	[0.004]	[0.000]
p	δ_2	0.0479	0.0361	-0.168**
		(0.101)	(0.0928)	(0.0520)
		[0.635]	[0.698]	[0.001]
$\widehat{\sigma}$	δ_3	0.283	0.342	0.0906
		(0.318)	(0.295)	(0.142)
		[0.374]	[0.248]	[0.525]
$\widehat{\sigma}\widetilde{p}$	δ_4	-2.313	-2.062	-0.868
		(1.572)	(1.442)	(0.680)
		[0.142]	[0.153]	[0.202]
t			-0.00364**	[country-specific trends]
			(0.000550)	
			[0.000]	
R^2		0.871	0.886	0.934
Implied long-run elasticities				
y	$\frac{\delta_1}{1-\lambda}$	0.585	0.983*	0.614**
		(0.462)	(0.422)	(0.125)
		[0.207]	[0.020]	[0.000]
p	$\frac{\delta_2}{1-\lambda}$	0 .807	0.460	-0.528**
		(1.762)	(1.208)	(0.165)
		[0.647]	[0.703]	[0.001]
Tests				
Endogeneity: price[a]		4.081	0.297	7.396
		[0.0434]	[0.5859]	[0.0065]
Endogeneity: price & interaction[b]		4.230	4.477	7.675
		[0.1206]	[0.1066]	[0.0215]
Underidentification[c]		8.159	8.341	19.689
		[0.0428]	[0.0395]	[0.0002]
Exogeneity[d]		22.997	7.175	7.919
		[0.000]	[0.0277]	[0.0191]

Robust standard errors in parentheses; p-values in brackets.

** p<0.01, * p<0.05, + p<0.1

[a]Difference-in-Sargan/Hansen $\chi^2(1)$ under H_0.

[b]Difference-in-Sargan/Hansen $\chi^2(2)$ under H_0.

[c]Kleibergen-Paap (2006) rk statistic; $\chi^2(3)$ under H_0.

[d]Overidentifying restrictions test (Hansen J statistic); $\chi^2(2)$ under H_0.

Table 12: Pooled estimates with 2SLS instrumenting for prices, USD

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}	λ	0.997**	0.991**	0.924**
		(0.00957)	(0.00910)	(0.0143)
		[0.000]	[0.000]	[0.000]
y	δ_1	-0.00216	0.00318	0.0569**
		(0.00879)	(0.00834)	(0.0122)
		[0.806]	[0.703]	[0.000]
p	δ_2	-0.0292*	-0.0341*	-0.0806**
		(0.0140)	(0.0134)	(0.0181)
		[0.037]	[0.011]	[0.000]
$\widehat{\sigma}$	δ_3	-0.0575	-0.0309	-0.0247
		(0.0957)	(0.0953)	(0.0889)
		[0.548]	[0.746]	[0.781]
$\widehat{\sigma}\widetilde{p}$	δ_4	-0.260	0.0969	0.201
		(0.209)	(0.224)	(0.228)
		[0.213]	[0.666]	[0.379]
t			-0.00223**	[country-specific trends]
			(0.000503)	
			[0.000]	
R^2		0.996	0.996	0.997

Robust standard errors in parentheses;
p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

nearly all variants of the system GMM estimator, in fact, $\widehat{\lambda}$ is the *only* coefficient that's statistically significantly different from 0. Overall, the system GMM estimates are useless in this application.

Table 13: System GMM, USD

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		No trend	With trend	No trend Collapsed IV matrix	With trend Collapsed IV matrix	No trend Reduced IV count	With trend Reduced IV count	No trend No outside IVs	With trend No outside IVs
g_{t-1}	λ	1.031**	1.010**	1.085**	1.055**	1.042**	1.032**	0.995**	0.966**
		(0.0331)	(0.0240)	(0.0532)	(0.0693)	(0.0402)	(0.0326)	(0.0359)	(0.0337)
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
y	δ_1	-0.0394+	-0.0177	-0.0451	-0.0116	-0.0445	-0.0158	-0.000187	0.0354
		(0.0220)	(0.0168)	(0.0432)	(0.0325)	(0.0262)	(0.0190)	(0.0302)	(0.0327)
		[0.084]	[0.301]	[0.306]	[0.725]	[0.101]	[0.414]	[0.995]	[0.288]
p	δ_2	0.0233	-0.00381	0.0740	0.0435	0.0345	0.0139	-0.0758	-0.108**
		(0.0383)	(0.0282)	(0.0624)	(0.0633)	(0.0478)	(0.0328)	(0.0485)	(0.0380)
		[0.548]	[0.894]	[0.246]	[0.498]	[0.476]	[0.675]	[0.129]	[0.008]
$\widehat{\sigma}$	δ_3	-0.145	-0.0776	0.0843	0.160	-0.0232	0.0671	-0.133	-0.0168
		(0.123)	(0.121)	(0.204)	(0.225)	(0.146)	(0.155)	(0.0890)	(0.108)
		[0.248]	[0.527]	[0.683]	[0.483]	[0.875]	[0.668]	[0.145]	[0.877]
$\widehat{\sigma}\widetilde{p}$	δ_4	-0.201	0.119	-0.824	-0.450	-0.421	-0.103	0.237	0.563
		(0.296)	(0.263)	(0.592)	(0.651)	(0.318)	(0.341)	(0.346)	(0.340)
		[0.503]	[0.653]	[0.175]	[0.496]	[0.196]	[0.765]	[0.498]	[0.109]
t			-0.00215*		-0.00280		-0.00276*		-0.00367*
			(0.00103)		(0.00175)		(0.00106)		(0.00142)
			[0.046]		[0.120]		[0.014]		[0.015]
Sargan		377.2	368.4	97.30	86.25	267.3	253.3	427.4	391.3
Sargan df		169	168	17	16	64	63	165	164
Sargan P		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hansen		25.39	23.91	22.65	23.51	25.89	22.26	26.10	25.42
Hansen df		169	168	17	16	64	63	165	164
Hansen P		1	1	0.161	0.101	1.000	1.000	1	1
AR(2) test		-0.522	-0.495	-0.596	-0.556	-0.550	-0.528	-0.283	-0.304
AR(2) P		0.602	0.621	0.551	0.578	0.582	0.597	0.778	0.761

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

5.3 Error-Correction Model

Turning to the error correction model, note that pooled mean group, mean group, and dynamic fixed effects estimators are all affected by the endogeneity of lagged consumption, just as the least squares estimators of the ADL were. It would be ideal to correct for the resulting biases, and this may become possible as relevant bias corrections are developed in the literature. At the moment, however, it does not seem that appropriate corrections have been derived. Bias corrections for the (*not*-pooled) mean group estimator are worked out in Pesaran and Zhao (1999); these corrections perform well when $\lambda < 0.8$

but not at all when $\lambda \geq 0.8$, which appears likely in the case of gasoline demand. Moreover, the assumption of homogeneity of the long-run coefficients appears to be important in this application (as will be discussed shortly), and so a mean group estimator that allows heterogeneity of the long-run coefficients is inappropriate. Recent work by Choi, Mark and Sul (2010) offers bias corrections that constrain the long-run coefficients to be homogenous, but unfortunately they also constrain the *short-run* coefficients and speed of adjustment to be homogenous. For now, I will have to accept estimates of the ECM (and ADL) as they are.

Despite the endogeneity of g_{t-1}, pooled mean group estimates of the ECM yield reasonable results. As expected, the speed of adjustment implied by PMG estimates based on all countries (with or without trend) is slightly faster than the speed of adjustment implied by 2SLS on the ADL. This is because the PMG approach is not susceptible to the false assumption of coefficient homogeneity that biases the 2SLS estimate of λ upward. Similarly, the PMG estimates of the error-correction model imply slightly faster adjustment than their DFE (dynamic fixed effects) counterparts. (That is, the PMG estimates of the error-correction term ϕ are more negative than the DFE estimates.) Although the PMG estimates imply slightly faster adjustment, however, the difference is not so great as to beggar belief. The pooled 2SLS estimates of the ADL (Table 12) establish lower bounds for the speed of adjustment of 0.3 to 7.6 percent in the first year, and we know that these estimates are biased toward 0 in *two* ways. In that light, the speeds of adjustment estimated by PMG—5.4 to 33.7 percent of adjustment occurring in the first year—do not seem suspiciously fast.

My preferred specification is, therefore, the pooled mean group estimator of the ECM. The PMG estimator's distinct advantage, as has been mentioned, is that by allowing for heterogeneity in the short-run coefficients, it avoids some of the heterogeneity-induced bias of least squares or system GMM. The PMG estimator does, of course, restrict long-run coefficients to be the same across countries; and another matter to consider is whether this restriction is acceptable. A Hausman test comparing the common-currency PMG and MG estimates fails to reject the hypothesis that the estimates are equivalent for the model without trend ($p = 0.71$) but squarely rejects the equivalence of the models with trend ($p = 0.00$), so it is not clear whether the restrictions are entirely true. The efficiency gains offered by the long-run restrictions if they are true, however, are huge; and without them, the MG estimator has trouble even establishing statistically-significant price effects. This is unsurprising, as the MG estimator is based on individual regressions in which time series of 15 to 19 observations are used to estimate the short- and long-run effects of four different variables, plus intercept and time trend. The relatively short length of this panel makes the restrictions necessary, whether or not the long-run coefficients are purely homogenous. On a positive note, PMG does at least introduce a considerable relaxation of homogeneity in comparison to estimators that assume homogeneity of *all* coefficients; and as Pesaran, Shin and Smith (1999) observe, PMG is not as sensitive to outliers as MG.

Although PMG is not as sensitive to outliers as MG, it is not entirely insensitive to them, either; and so in addition to estimates based on all countries in my data set (Table 14), I report estimates omitting the four countries that consistently suffered the worst fit in least-squares estimates—the Czech Republic, Poland, Slovakia, and Turkey (Table 15). The latter three countries are, incidentally, the three poorest in my sample,[10] and the Czech Republic is the sixth-poorest. The first three, moreover, were beginning their political and economic transformations away from communism at the beginning of the sample period in 1990, and so it is not surprising that their gasoline-consumption patterns would be atypical of the broader sample. In response to the removal of these four countries, the PMG estimates do in fact change a bit, with the long-run income, price, and price-volatility interaction elasticities increasing in magnitude. Unless otherwise noted, the following discussion refers to the PMG estimates with these

[10] As measured by mean real GDP per capita, USD, over the course of the sample.

outlier countries removed.

By and large, my long-run coefficients are not out of line with the literature. To facilitate comparisons, I report estimates of an ECM in the form of (16) with price volatility and the price-volatility interaction term omitted (Tables 16, 17, and 26). The resulting model contains only the variables standardly included in gasoline demand models. The PMG estimates of this model, omitting the four worst-fitting countries (Table 17), suggest a long-run income elasticity of 0.7 to 1. These nearly-unit-elastic estimates fit neatly within the values usually estimated in the literature. Meanwhile, the estimated long-run price elasticities, ranging from -0.6 to -1.3, span the middle to upper end (in magnitude) of estimates in the literature. Although the PMG estimator is more reliable in its long-run than its short-run estimates, the short-run elasticities in Table 17 are plausible, with short-run income elasticities somewhat lower than the literature's averages and short-run price elasticities ranging from low (in magnitude) to average.

Returning to the model that includes the rational-habits variables, long-run results with respect to income and prices appear, again, reasonable. In the no-trend and homogenous-trend models, long-run income elasticities of 0.8 and 0.9 closely match the literature. In the same models, long-run "total" price elasticities are again on the high-magnitude end, hovering around unit elastic. Since these high-magnitude price elasticities are also found in the "standard" model without the rational-habits variables, the difference from the literature can be ascribed to my panel data set and the choice of an ECM with heterogeneous short-run coefficients rather than to the inclusion of $\widehat{\sigma}$ and $\widehat{\sigma}\widetilde{p}$. In the model with heterogeneous trends, results look somewhat different but still plausible, with long-run income elasticity on the low end and long-run price elasticity near the literature average.

The parameters of primary interest are, of course, the coefficients on price volatility and the price-volatility interaction term, which allow us to test for the behaviors implied by a rational habits model. The rational habits model implies, first, that price uncertainty should reduce demand for the habit-forming good, and this is indeed borne out by the regressions: trend or no trend, all countries or all-but-four, the PMG estimate of the long-run effect of price volatility, θ_3, is negative and statistically significant. Depending on the specification, values of $\widehat{\theta}_3$ range from -0.7 to -1.9, suggesting that a 0.1 increase in $\widehat{\sigma}$ is associated with a 7 to 19% reduction in gasoline consumption.

Evidence on rational habits' second implication, that the magnitude of price elasticity should decline with price uncertainty, is not clear-cut. When a time trend is included in the USD-denominated model, the PMG estimate of the long-run coefficient on the price-volatility interaction term, $\widehat{\theta}_4$, is not statistically significant. Absent the trend, $\widehat{\theta}_4$ is positive and highly significant when the four outlier-countries are omitted but not statistically significant when they are included.[11] Given that these four countries experienced some of the highest price volatilities in the sample at a time when their economies were rapidly expanding, it is easy to imagine that they might skew the effect of volatility on price elasticity. It seems reasonable, therefore, to put greater faith on the estimates of $\widehat{\theta}_4$ that omit these countries.

Recall the possibility that tax changes might contribute to measured price volatility while actually decreasing price uncertainty. To check whether this problem is hiding some of the effect of price volatility on price elasticity, I estimate a version of the model in which before-tax prices are used to construct an alternative measure of price volatility, $\widehat{\sigma}_{BT}$. In Table 18 I report results using the before-tax volatility term *a.* both in the interaction term and on its own and *b.* only in the interaction term, with total-price volatility used on its own. Continuing to use total-price volatility on its own seems reasonable, as rational habits imply that it is *overall* price volatility that dampens consumption—that is, high volatility that

[11] In the local-currency models (Table 25), as in the USD-denominated models, the coefficient on the interaction term is sensitive to the specification of the trend. With no trend, $\widehat{\theta}_4$ in the local-currency model is not statistically significant; with a homogenous trend, it is very negative; and with heterogenous trends, it is positive. This pattern is, confusingly enough, nearly opposite to that in the USD-denominated models, where $\widehat{\theta}_4$ is only positive and statistically significant if the trend is excluded.

Table 14: Estimates of the error-correction model, all countries, USD

		(1) PMG No trend	(2) PMG Homogenous trend	(3) PMG Heterogenous trends	(4) MG No trend	(5) MG (Heterogeneous) trends	(6) DFE No trend	(7) DFE (Homogenous) trend
t			-0.0473**	-0.00507*		-0.0129*		-0.0481*
			(0.00303)	(0.00228)		(0.00651)		(0.0219)
			[0.000]	[0.026]		[0.048]		[0.028]
Long run								
y	θ_1	0.555**	0.774**	0.388**	0.752*	0.313	0.0812	0.746*
		(0.0306)	(0.0905)	(0.0412)	(0.335)	(0.209)	(0.579)	(0.372)
		[0.000]	[0.000]	[0.000]	[0.025]	[0.134]	[0.888]	[0.045]
p	θ_2	-0.693**	-0.981**	-0.626**	-0.945+	-0.466	-2.046	-1.585*
		(0.0755)	(0.122)	(0.0398)	(0.495)	(0.400)	(1.488)	(0.744)
		[0.000]	[0.000]	[0.000]	[0.056]	[0.244]	[0.169]	[0.033]
$\widehat{\sigma}$	θ_3	-1.249**	-1.464**	-0.881**	-0.653	-0.411	-4.456	-2.551
		(0.249)	(0.353)	(0.100)	(1.067)	(0.678)	(4.013)	(1.727)
		[0.000]	[0.000]	[0.000]	[0.540]	[0.545]	[0.267]	[0.140]
$\widehat{\sigma}\widetilde{p}$	θ_4	0.816	-0.307	-0.0718	6.402	-1.075	22.64	12.63
		(1.205)	(1.872)	(0.520)	(10.63)	(6.308)	(22.87)	(10.01)
		[0.498]	[0.870]	[0.890]	[0.547]	[0.865]	[0.322]	[0.207]
Short run								
EC term	ϕ	-0.142**	-0.133**	-0.337**	-0.300**	-0.604**	-0.0534	-0.0789+
		(0.0530)	(0.0326)	(0.0733)	(0.0934)	(0.0918)	(0.0501)	(0.0415)
		[0.007]	[0.000]	[0.000]	[0.001]	[0.000]	[0.287]	[0.057]
Δy	δ_1	0.184**	0.162**	0.0901*	0.130*	0.0173	0.225**	0.177**
		(0.0472)	(0.0344)	(0.0420)	(0.0543)	(0.0526)	(0.0396)	(0.0317)
		[0.000]	[0.000]	[0.032]	[0.016]	[0.742]	[0.000]	[0.000]
Δp	δ_2	-0.177**	-0.108**	-0.0415	-0.102+	0.0217	-0.131+	-0.0683
		(0.0543)	(0.0389)	(0.0356)	(0.0553)	(0.0556)	(0.0690)	(0.0607)
		[0.001]	[0.006]	[0.245]	[0.065]	[0.697]	[0.058]	[0.261]
$\Delta\widehat{\sigma}$	δ_3	0.0180	0.148*	0.169**	0.0864	0.224*	0.130	0.215*
		(0.0654)	(0.0579)	(0.0640)	(0.124)	(0.108)	(0.109)	(0.0911)
		[0.783]	[0.011]	[0.008]	[0.486]	[0.038]	[0.232]	[0.019]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	δ_4	-0.318	0.151	0.0938	0.275	0.351	-1.258	-0.903
		(0.228)	(0.231)	(0.235)	(1.014)	(0.862)	(0.785)	(0.706)
		[0.163]	[0.513]	[0.690]	[0.786]	[0.684]	[0.109]	[0.200]

Standard errors in parentheses; p-values in brackets.

** p<0.01, * p<0.05, + p<0.1

Table 15: Estimates of the error-correction model, USD, omitting 4 worst-fit countries*

		(1) PMG No trend	(2) PMG Homo-genous trend	(3) PMG Hetero-genous trends	(4) MG No trend	(5) MG (Hetero-geneous) trends	(6) DFE No trend	(7) DFE (Homo-geneous) trend
t			-0.0491**	-0.00586*		-0.0190**		-0.0525
			(0.00374)	(0.00241)		(0.00587)		(0.0340)
			[0.000]	[0.015]		[0.001]		[0.122]
Long run								
y	θ_1	0.893**	0.782**	0.350**	0.803*	0.401*	0.363	1.042+
		(0.0767)	(0.110)	(0.0516)	(0.385)	(0.202)	(0.625)	(0.564)
		[0.000]	[0.000]	[0.000]	[0.037]	[0.047]	[0.562]	[0.065]
p	θ_2	-1.295**	-0.971**	-0.593**	-1.021+	-0.535	-2.949	-2.233+
		(0.118)	(0.154)	(0.0458)	(0.572)	(0.453)	(2.963)	(1.222)
		[0.000]	[0.000]	[0.000]	[0.074]	[0.237]	[0.320]	[0.068]
$\widehat{\sigma}$	θ_3	-0.731**	-1.904**	-0.942**	-1.090	-0.985+	-1.564	-1.071
		(0.261)	(0.410)	(0.106)	(1.203)	(0.589)	(2.433)	(1.763)
		[0.005]	[0.000]	[0.000]	[0.365]	[0.095]	[0.520]	[0.544]
$\widehat{\sigma}\widetilde{p}$	θ_4	7.879**	-2.120	-0.213	8.537	-0.0767	36.01	21.10
		(1.913)	(2.526)	(0.631)	(12.31)	(7.251)	(41.90)	(14.48)
		[0.000]	[0.401]	[0.736]	[0.488]	[0.992]	[0.390]	[0.145]
Short run								
EC term	ϕ	-0.0542	-0.100**	-0.283**	-0.283**	-0.597**	-0.0416	-0.0617
		(0.0354)	(0.0296)	(0.0767)	(0.0918)	(0.0933)	(0.0600)	(0.0508)
		[0.126]	[0.001]	[0.000]	[0.002]	[0.000]	[0.488]	[0.225]
Δy	δ_1	0.228**	0.182**	0.133**	0.168**	0.0587	0.214**	0.177**
		(0.0488)	(0.0369)	(0.0412)	(0.0585)	(0.0565)	(0.0425)	(0.0327)
		[0.000]	[0.000]	[0.001]	[0.004]	[0.299]	[0.000]	[0.000]
Δp	δ_2	-0.214**	-0.148**	-0.0897**	-0.145*	-0.0402	-0.139*	-0.0838
		(0.0567)	(0.0327)	(0.0297)	(0.0588)	(0.0510)	(0.0643)	(0.0571)
		[0.000]	[0.000]	[0.003]	[0.014]	[0.430]	[0.030]	[0.142]
$\Delta\widehat{\sigma}$	δ_3	-0.154**	0.113*	0.107+	0.0521	0.170	-0.156+	-0.0230
		(0.0506)	(0.0534)	(0.0596)	(0.137)	(0.117)	(0.0806)	(0.0780)
		[0.002]	[0.034]	[0.074]	[0.703]	[0.146]	[0.053]	[0.768]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	δ_4	-0.537	0.374	0.129	0.555	0.807	-1.394*	-1.047**
		(0.344)	(0.299)	(0.273)	(1.002)	(0.897)	(0.607)	(0.389)
		[0.118]	[0.211]	[0.635]	[0.580]	[0.368]	[0.022]	[0.007]

Standard errors in parentheses; p-values in brackets.

** p<0.01, * p<0.05, + p<0.1

* *Czech Republic, Poland, Slovakia, and Turkey*

Table 16: Estimates of error-correction model with only the standard regressors, USD

		(1) PMG No trend	(2) PMG Homo-genous trend	(3) PMG Hetero-geneous trends	(4) MG No trend	(5) MG (Hetero-geneous) trends	(6) DFE No trend	(7) DFE (Homo-genous) trend
t			-0.0523**	-0.00558**		0.0261		-0.0446*
			(0.00432)	(0.00169)		(0.0465)		(0.0200)
			[0.000]	[0.001]		[0.575]		[0.025]
Long run								
y	θ_1	-0.908**	0.863**	0.647**	0.0733	-0.712	0.0468	0.786**
		(0.140)	(0.117)	(0.0658)	(0.429)	(0.851)	(0.526)	(0.277)
		[0.000]	[0.000]	[0.000]	[0.864]	[0.403]	[0.929]	[0.005]
p	θ_2	0.139	-1.075**	-0.834**	-0.302	0.0632	-1.039*	-0.985**
		(0.129)	(0.0961)	(0.0567)	(0.336)	(0.363)	(0.454)	(0.261)
		[0.282]	[0.000]	[0.000]	[0.369]	[0.862]	[0.022]	[0.000]
Short run								
EC term	ϕ	-0.0505+	-0.116**	-0.286**	-0.288**	-0.480**	-0.0557	-0.0822+
		(0.0282)	(0.0263)	(0.0527)	(0.0649)	(0.0746)	(0.0523)	(0.0435)
		[0.073]	[0.000]	[0.000]	[0.000]	[0.000]	[0.287]	[0.059]
Δy	δ_1	0.272**	0.164**	0.0819*	0.137*	0.0260	0.222**	0.173**
		(0.0365)	(0.0339)	(0.0404)	(0.0547)	(0.0537)	(0.0382)	(0.0340)
		[0.000]	[0.000]	[0.043]	[0.012]	[0.628]	[0.000]	[0.000]
Δp	δ_2	-0.229**	-0.0990*	-0.0353	-0.0759	0.0126	-0.196**	-0.126**
		(0.0442)	(0.0402)	(0.0403)	(0.0501)	(0.0493)	(0.0483)	(0.0424)
		[0.000]	[0.014]	[0.381]	[0.129]	[0.799]	[0.000]	[0.003]

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 17: Estimates of error-correction model with only the standard regressors, USD, omitting 4 worst-fitting countries*

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
		PMG	PMG	PMG	MG	MG	DFE	DFE
		No trend	Homo-genous trend	Hetero-geneous trends	No trend	(Hetero–geneous) trends	No trend	(Homo-genous) trend
t			-0.0530**	-0.00486**		0.0331		-0.0551
			(0.00501)	(0.00106)		(0.0539)		(0.0393)
			[0.000]	[0.000]		[0.540]		[0.161]
Long run								
y	θ_1	0.710**	0.769**	1.020**	-0.270	-0.929	-0.143	0.936+
		(0.0695)	(0.148)	(0.0871)	(0.410)	(0.983)	(1.097)	(0.538)
		[0.000]	[0.000]	[0.000]	[0.509]	[0.344]	[0.896]	[0.082]
p	θ_2	-0.866**	-1.046**	-0.982**	-0.0222	0.197	-1.283	-1.080*
		(0.0632)	(0.122)	(0.0681)	(0.324)	(0.416)	(1.494)	(0.550)
		[0.000]	[0.000]	[0.000]	[0.945]	[0.635]	[0.390]	[0.050]
Short run								
EC term	ϕ	-0.0645+	-0.0845**	-0.177**	-0.238**	-0.427**	-0.0336	-0.0600
		(0.0387)	(0.0209)	(0.0285)	(0.0616)	(0.0758)	(0.0630)	(0.0540)
		[0.095]	[0.000]	[0.000]	[0.000]	[0.000]	[0.593]	[0.267]
Δy	δ_1	0.243**	0.184**	0.109**	0.168**	0.0586	0.224**	0.173**
		(0.0497)	(0.0346)	(0.0395)	(0.0586)	(0.0589)	(0.0424)	(0.0312)
		[0.000]	[0.000]	[0.006]	[0.004]	[0.320]	[0.000]	[0.000]
Δp	δ_2	-0.237**	-0.136**	-0.107**	-0.124**	-0.0458	-0.200**	-0.133**
		(0.0491)	(0.0298)	(0.0316)	(0.0462)	(0.0470)	(0.0528)	(0.0434)
		[0.000]	[0.000]	[0.001]	[0.008]	[0.329]	[0.000]	[0.002]

Standard errors in parentheses; p-values in brackets.

** p<0.01, * p<0.05, + p<0.1

* *Czech Republic, Poland, Slovakia, and Turkey*

arises from low tax rates will still dampen consumption. Either way, however, the use of before-tax volatility actually *decreases* the coefficient on the interaction term, so it does not seem as if tax-driven price volatility is masking the effect of "true" price volatility. The models based on total-price volatility therefore remain my preferred specifications.

If, as the version of the preferred model *with* trend suggests, people's responsiveness to prices is immune to the volatility of prices, then θ_2 is a perfectly serviceable measure of price elasticity. On the other hand, if price elasticity does vary with price uncertainty—as the model *without* trend implies—then total long-run price elasticity is not θ_2, but $\theta_2 + \theta_4\widehat{\sigma}_{it}$. This is analogous to the total price elasticities derived for the ADL:

$$\text{Short run price elasticity:} \qquad \frac{\partial g_{it}}{\partial p_{it}} = \delta_2 + \delta_4\widehat{\sigma}_{it}$$

$$\text{Long run price elasticity:} \qquad \frac{\delta_2 + \delta_4\widehat{\sigma}_{it}}{1-\lambda}$$

The model without trend implies, therefore, that the "total" long-run elasticity with respect to price is

$$\widehat{\theta}_2 + \widehat{\theta}_4\overline{\widehat{\sigma}} = -0.918 \tag{17}$$

where $\overline{\widehat{\sigma}}$ is the mean rolling price standard deviation across all countries and time periods. This total elasticity is, of course, smaller in magnitude than $\widehat{\theta}_2$, but still on the relatively high end of price elasticity estimates when compared to the literature.

Although the PMG estimator constrains long-run coefficients to be homogenous, we can substitute country-specific averages $\overline{\widehat{\sigma}}_i$ into (17) to interpolate the variation in "total" price elasticity due to volatility differences. These country-specific total price elasticities are plotted in Figure 7. Over time, volatility levels within a country evolve and may thereby alter total price elasticities; and so Figure 7 also depicts the range of total price elasticities implied by each country's range of price volatilities $\widehat{\sigma}_{it}$. (Some of these ranges extend into positive price elasticities, but the worst offenders, the Czech Republic and Slovakia, are actually omitted from the regression, and so their implied wrong-sign elasticities should not cast doubt on the model as a whole.) It should be observed that the United States, whose price responsiveness is generally found to be low in comparison to other countries', has the highest average price volatility in the sample, and so by construction its total elasticity is of comparatively low magnitude. Although this does not establish that rational habits are responsible for the United States' low price responsiveness, the model does at least correctly predict this phenomenon.

The remaining long-term parameter, the time trend, is about -0.05 and statistically significantly. All other things equal, this implies, per-capita gasoline consumption has been declining about 5% per year. This negative trend seems to have been widespread: in the version of the ECM with heterogeneous trends, the majority of country-specific trends are negative (as are nearly all the country-specific trends estimated using 2SLS on the ADL). There are variety of potential explanations for these downward trends. Demographic shifts, for instance, might have reduced the number of drivers in ageing populations or pushed populations towards locations that demanded less driving. The more probable explanation is that technological innovations, tightening fuel-economy standards, and individual investments in fuel efficiency have dampened gasoline demand.

The short-run coefficients reported in Table 15, which are the averages of the country-specific short-run coefficients, are (like MG estimates) not as reliable as the long-run estimates, since each country's short-run coefficients have been estimated using relatively little data. Nonetheless, estimates of δ_1 and δ_2 appear to be very reasonable: the short-run income elasticity of around 0.2 is approximately a quarter the long-run income elasticity; the short-run price elasticity (non-"total") of -0.15 to -0.21 is roughly

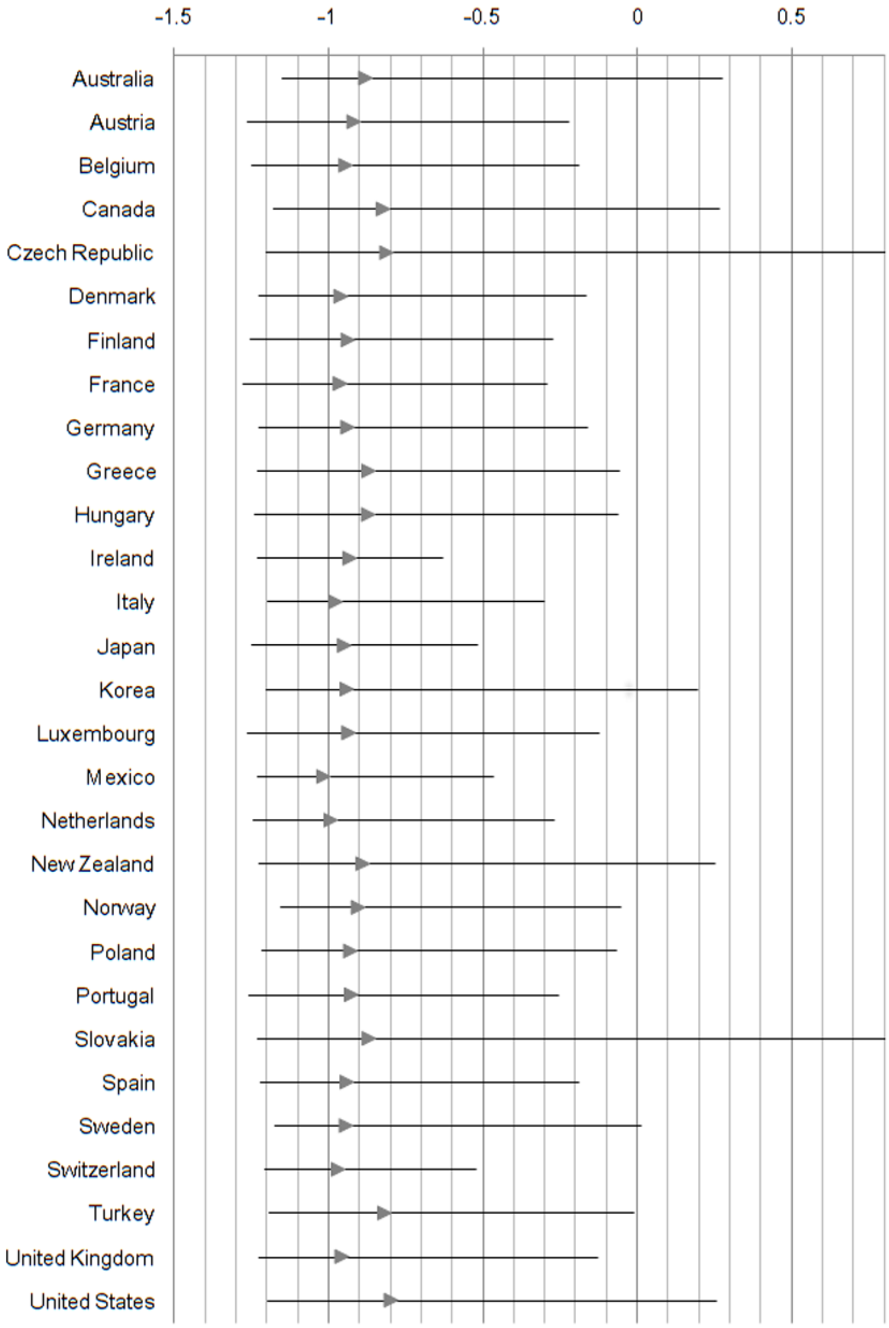
Table 18: Estimates of error-correction model with before-tax volatilities, USD

		(1) PMG Homogenous trend	(2) PMG Heterogeneous trends	(3) PMG Homogeneous trend, $\widehat{\sigma}_{BT}$ only in interaction	(4) PMG Heterogeneous trends, $\widehat{\sigma}_{BT}$ only in interaction
t		-0.0660**	-0.00316**	-0.0506**	-0.00346*
		(0.00995)	(0.00122)	(0.00408)	(0.00164)
		[0.000]	[0.009]	[0.000]	[0.035]
Long run					
y	θ_1	0.623**	0.460**	0.707**	0.220**
		(0.193)	(0.0377)	(0.121)	(0.0225)
		[0.001]	[0.000]	[0.000]	[0.000]
p	θ_2	-0.428+	-0.188**	-0.834**	-0.0738**
		(0.260)	(0.0591)	(0.155)	(0.0247)
		[0.100]	[0.001]	[0.000]	[0.003]
$\widehat{\sigma}_{BT}$	θ_3	0.200	-0.298**		
		(0.413)	(0.101)		
		[0.629]	[0.003]		
$\widehat{\sigma}$	θ_3			-1.367**	0.181**
				(0.422)	(0.0380)
				[0.001]	[0.000]
$\widehat{\sigma}_{BT}\widetilde{p}$	θ_4	-5.018*	-3.609**	-1.309	-1.160**
		(2.031)	(0.521)	(1.198)	(0.237)
		[0.013]	[0.000]	[0.274]	[0.000]
Short run					
EC term	ϕ	-0.0567**	-0.275**	-0.102**	-0.317**
		(0.0207)	(0.0429)	(0.0276)	(0.0622)
		[0.006]	[0.000]	[0.000]	[0.000]
Δy	δ_1	0.195**	0.108**	0.187**	0.171**
		(0.0296)	(0.0370)	(0.0320)	(0.0379)
		[0.000]	[0.004]	[0.000]	[0.000]
Δp	δ_2	-0.155**	-0.178**	-0.138**	-0.176**
		(0.0340)	(0.0362)	(0.0390)	(0.0476)
		[0.000]	[0.000]	[0.000]	[0.000]
$\Delta\widehat{\sigma}_{BT}$	δ_3	0.0421	0.0923*		
		(0.0365)	(0.0362)		
		[0.249]	[0.011]		
$\Delta\widehat{\sigma}$	δ_3			0.125*	-0.0185
				(0.0509)	(0.0528)
				[0.014]	[0.726]
$\Delta\left(\widehat{\sigma}_{BT}p\right)$	δ_4	0.0224	0.647**	0.181	0.157
		(0.257)	(0.202)	(0.184)	(0.188)
		[0.931]	[0.001]	[0.324]	[0.404]

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Figure 7: Country-specific "total" long-run price elasticities.

Triangle indicates country-specific price elasticity implied by mean volatility $\overline{\widehat{\sigma}}_i$; line indicates range of elasticities implied by country's range of price volatilities $[\widehat{\sigma}_{i,\min}, \widehat{\sigma}_{i,\max}]$.



fifteen to twenty percent of the long-run price elasticity.

The unreliability of the short-run estimates does show up in the remaining coefficients, however: in the short run, the effect of price volatility is estimated to be negative if a trend is excluded and *positive* if it is included; the effect of the price-volatility interaction term is statistically insignificant in either case. The relative unreliability of the short-run estimates seems to be a worthwhile trade-off, however, for the heterogeneity that improves the long-run estimates of primary interest.

6 Conclusion

Consumers' gasoline consumption is decided by a multitude of choices—some large, some small; some in the form of investment decisions, others in the form of everyday routines. All of these choices can be swept into a habits framework, which highlights the importance of price uncertainty and volatility in shaping the demand of forward-looking consumers.

The rational habits framework suggests two major implications for consumer behavior. This paper has tested for both: first, that price uncertainty will depress demand; and second, that price uncertainty will dampen the price *responsiveness* of demand. Evidence for the first implication is strong. In the long run, price volatility *does* depress gasoline demand; the effect of the rolling-standard-deviation measure on demand is not only statistically significant but of a similar magnitude to price elasticity itself.

Evidence for the second implication is not as unequivocal. In some of my preferred specifications, it does indeed appear that total price responsiveness is greater when prices are less volatile. The estimated effect of price volatility on price elasticity, however, is quite sensitive to the model specification and estimation method. Future work on consumer habits should keep this sensitivity in mind and give careful thought to choosing an appropriate estimator.

It should be noted again—particularly in light of the fragile estimates of price volatility's effect on price elasticity—that this paper has based all its tests for rational habits on a price-uncertainty measure that uses the rolling standard deviation of prices as a proxy for anticipated future price volatility. The appropriateness of this proxy is therefore key to the results. Imperfections in this proxy, even imperfections that amount to well-behaved measurement error, introduce a downward bias (in magnitude) to estimates of uncertainty's effects, and may therefore disguise habits' influence on price elasticity. Future work on consumer habits should keep this in mind as well: thoughtful, explicit modelling of consumers' expectations may bring evidence of rational habits into starker relief.

Altogether, there is compelling evidence that consumers around the world exhibit at least some of the behaviors associated with rational gasoline habits. In light of these habits, policymakers should heed the role of price uncertainty in shaping gasoline demand. Policies to stabilize gasoline prices may have the undesired effect of increasing demand, and to offset this increase there may be a need for further intervention. This intervention may be made easier, however, by the increased effectiveness of price instruments when price volatility is low. Given rational habits, in fact, stable price increases are a longer policy lever than traditionally-measured price elasticity suggests. Not only may gasoline taxes explain some of the variation in price elasticity around the world, but their influence on price volatility may allow them to re-shape one country's demand to look like another's.

7 Further Data Exposition

7.1 Geographic Scope

The twenty-nine countries in my sample are Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States.

7.2 Grades and Prices

The IEA reports price and tax data by product, i.e. by petrol type and grade. The availability of data on any product naturally depends on the product's availability to consumers, which in turn depends upon local regulations. For a number of countries—including Finland, France, Ireland, Italy, Luxembourg, and the U.K.—data on unleaded gasoline is not available until 1990. To avoid the problems associated with switching from a measure of price based solely on leaded gasoline to a measure based on unleaded gasoline (or some average of leaded and unleaded), I concentrate on the period 1990 onwards.

Even in this later period, however, data availability varies by product and country, with this variation driven by differences in regulation and definition. In Australia, for example, "95 RON" is considered premium, and regular unleaded gasoline is 91 RON (MotorMouth 2010); in the UK, "95 RON" is regular unleaded (Boulter and Latham 2009). Such differences in reported octane ratings may exaggerate differences in the actual content of the fuels, as the definition of the Research Octane Number (RON) varies by country, and its definition tends to be lower-skewing in countries that define "regular unleaded" by a lower RON. Whatever the differences in definition across countries, I need a price series for each country that is measured by a constant definition, since varying the definition over time would introduce false price variation (unless, of course, such variations reflected actual changes in the type of gasoline in use). Where annual data for "regular unleaded" is available from 1990 on—however "regular unleaded" may be defined locally—I use this as the product. Where annual data on regular unleaded is not available contiguously from 1990 but data on 95 RON is, I use 95 RON. Where data on neither regular unleaded nor 95 RON is available contiguously from 1990, I use whichever product has the longer contiguous availability. After determining which product to use for annual data, I use the same product for quarterly data. Table 19 shows the product for which each country's price measures are taken.

Table 19: Gasoline product used for price and tax data

Regular Unleaded	95 RON	
Australia	Belgium	Norway
Austria	Czech Republic	Poland
Canada	Finland	Portugal
Denmark	France	Slovak Republic
Germany	Greece	Spain
Japan	Hungary	Sweden
Korea	Ireland	Switzerland
Mexico	Italy	Turkey
New Zealand	Luxembourg	United Kingdom
United States	Netherlands	

8 Local-currency Estimates

This appendix reports local-currency results corresponding to the common-currency results presented in the main text. As noted in Section 3.3, not all the estimators applied to the common-currency data can be sensibly applied to the local-currency data: in particular, the random-effects estimator of Table 20 and the pooled 2SLS estimator of Table 22 are both biased because of their comparison of non-differenced log prices and log income across different currencies.

That said, the remaining results should not be subject to the currency-generated bias. The within-groups (fixed-effects) 2SLS results (Table 21), in fact, make a little bit more sense than their common-currency counterparts, with negative and statistically-significant price effects no matter the specification of the trend. The results with respect to income and the rational-habits variables, however, show a pattern similar to the common-currency results, with income's effect becoming more pronounced as a homogenous and then a heterogeneous trend is introduced, and the rational-habits variables never showing a statistically-significant effect.

Turning to system GMM (Table 24), the estimators are just as uninformative when applied to local-currency data as they were when applied to common-currency data.

Moving on to the preferred estimator, namely the pooled mean group estimator applied to the ECM, there are some interesting contrasts to the common-currency results. Generally speaking, I find lower-magnitude long-run income and price elasticities in the local-currency data. In the "standard" model without rational-habits variables, the long-run income elasticity is about 0.3, which is considerably below both the literature's averages and most of the common-currency estimates. Similarly, the long-run price elasticities from the "standard" model with no trend or heterogeneous trends (-0.65 and -0.14, respectively) are smaller than the corresponding common-currency results.

There is a confounding blip in the homogenous-trend versions of the local-currency estimates, with price elasticity in the "standard" model shooting to -1.28 and "total" price elasticity in the rational-habits model shooting to -1.08. The latter is driven almost entirely by an implausibly-sized and incorrectly-signed coefficient on $\widehat{\sigma}\widetilde{p}$, and so I am inclined to be suspicious of these homogenous-trend results.

With respect to the rational habits variables, the local-currency results are less conclusive than their common-currency counterparts. Whereas the coefficient on $\widehat{\sigma}$ was negative and highly statistically significant in all common-currency estimates of the ECM, when using local currencies the coefficient on $\widehat{\sigma}$ is nowhere near statistically significant unless heterogeneous trends are included—and even then the p-value is 0.065. With respect to the interaction term $\widehat{\sigma}\widetilde{p}$, the local-currency data produces the expected positive coefficient ($p = 0.07$) only when heterogeneous trends are included. Without a trend, the coefficient on $\widehat{\sigma}\widetilde{p}$ is indistinguishable from 0; and with a homogenous trend, as has been noted, the coefficient on $\widehat{\sigma}\widetilde{p}$ is hugely *negative*.

Overall, it seems that in practice the local-currency approach may be less reliable than the common-currency approach.

Table 20: Random- vs. fixed-effects estimator, static model, local currencies

		(1) Static Random effects	(2) Static Fixed effects	(3) Dynamic Random effects	(4) Dynamic Fixed effects
g_{t-1}	λ			0.992**	0.905**
				(0.00660)	(0.0160)
				[0.000]	[0.000]
y	δ_1	0.298**	0.265**	0.00672	-0.0178
		(0.0413)	(0.0429)	(0.00609)	(0.0160)
		[0.000]	[0.000]	[0.270]	[0.267]
p	δ_2	-0.494**	-0.586**	-0.00261	-0.169**
		(0.0508)	(0.0635)	(0.00601)	(0.0282)
		[0.000]	[0.000]	[0.664]	[0.000]
$\widehat{\sigma}$	δ_3	-0.216	-0.169	-0.185*	-0.0772
		(0.267)	(0.266)	(0.0937)	(0.0944)
		[0.419]	[0.527]	[0.048]	[0.414]
$\widehat{\sigma}\widetilde{p}$	δ_4	-0.410	0.335	-1.469**	0.331
		(0.693)	(0.752)	(0.275)	(0.407)
		[0.554]	[0.656]	[0.000]	[0.417]
R^2		0.2892	0.2274	0.9951	0.8288
Hausman test[a]		11.21 [0.024]		74.79 [0.000]	

Standard errors in parentheses; P-values in brackets.
** p<0.01, * p<0.05, + p<0.1
[a]Under H_0 that random- and fixed-effects estimates equivalent, $\chi^2(4)$ for static model, $\chi^2(4)$ for dynamic.

Table 21: Within-groups (fixed effects) estimates with 2SLS instrumenting for price, local currencies

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}		0.906** (0.0287) [0.000]	0.908** (0.0279) [0.000]	0.697** (0.0418) [0.000]
y		-0.00128 (0.0217) [0.953]	0.0566* (0.0272) [0.038]	0.235** (0.0595) [0.000]
p		-0.203** (0.0459) [0.000]	-0.158** (0.0524) [0.003]	-0.210** (0.0482) [0.000]
$\widehat{\sigma}$		-0.0667 (0.125) [0.595]	-0.0322 (0.127) [0.800]	-0.000603 (0.125) [0.996]
$\widehat{\sigma}\widetilde{p}$		0.419 (0.513) [0.415]	0.305 (0.513) [0.552]	-0.454 (0.523) [0.386]
t			-0.00245* (0.00103) [0.017]	[country-specific trends]
R^2		0.899	0.902	0.935
Implied long-run elasticities				
y	$\frac{\delta_1}{1-\lambda}$	-.0136 (0.232) [0.953]	.616 (0.292) [0.036]	.776 (0.186) [0.000]
p	$\frac{\delta_2}{1-\lambda}$	-2.165 (0.656) [0.001]	-1.715 (0.653) [0.009]	-0.695 (0.161) [0.000]
Tests				
Endogeneity: price[a]		9.769 [0.0018]	4.228 [0.0398]	6.198 [0.0128]
Endogeneity: price & interaction[b]		11.735 [0.0028]	6.557 [0.0377]	8.041 [0.0179]
Underidentification[c]		125.510 [0.000]	92.181 [0.0000]	98.878 [0.000]
Exogeneity[d]		5.653 [0.0592]	8.344 [0.0154]	4.362 [0.113]

Robust standard errors in parentheses; p-values in brackets.
** $p<0.01$, * $p<0.05$, + $p<0.1$

[a] Difference-in-Sargan/Hansen $\chi^2(1)$ under H_0.
[b] Difference-in-Sargan/Hansen $\chi^2(2)$ under H_0.
[c] Kleibergen-Paap (2006) rk statistic; $\chi^2(3)$ under H_0.
[d] Overidentifying restrictions test (Hansen J statistic); $\chi^2(2)$ under H_0.

Table 22: Pooled estimates with 2SLS instrumenting for prices, local currencies

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}	λ	1.002**	1.001**	0.959**
		(0.00662)	(0.00675)	(0.0168)
		[0.000]	[0.000]	[0.000]
y	δ_1	0.00454	0.00443	0.00922
		(0.00675)	(0.00676)	(0.0156)
		[0.501]	[0.513]	[0.555]
p	δ_2	-0.00118	-0.000166	-0.0142
		(0.00673)	(0.00670)	(0.0166)
		[0.861]	[0.980]	[0.393]
$\widehat{\sigma}$	δ_3	-0.0981	-0.0139	-0.194
		(0.117)	(0.117)	(0.124)
		[0.401]	[0.906]	[0.119]
$\widehat{\sigma}\widetilde{p}$	δ_4	-1.800**	-0.929*	-0.866*
		(0.469)	(0.434)	(0.390)
		[0.000]	[0.033]	[0.027]
t			-0.00216**	[country-specific trends]
			(0.000620)	
			[0.001]	
R^2		0.996	0.996	0.997

Robust standard errors in parentheses;
p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 23: Within-groups (fixed-effects) estimates, local currencies

		(1) No trend	(2) Common trend	(3) Individual trends
g_{t-1}	λ	0.905**	0.893**	0.729**
		(0.0218)	(0.0231)	(0.0358)
		[0.000]	[0.000]	[0.000]
y	δ_1	-0.0178	0.0559+	0.255**
		(0.0215)	(0.0287)	(0.0606)
		[0.408]	[0.052]	[0.000]
p	δ_2	-0.169**	-0.156**	-0.168**
		(0.0377)	(0.0397)	(0.0392)
		[0.000]	[0.000]	[0.000]
$\widehat{\sigma}$	δ_3	-0.0772	-0.00558	-0.0446
		(0.117)	(0.119)	(0.114)
		[0.510]	[0.963]	[0.695]
$\widehat{\sigma}\widetilde{p}$	δ_4	0.331	0.386	-0.348
		(0.422)	(0.402)	(0.432)
		[0.433]	[0.337]	[0.420]
t			-0.00280**	
			(0.00103)	
			[0.007]	
R^2		0.903	0.905	0.938

Robust standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 24: System GMM, local currencies

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		No trend	With trend	No trend Collapsed IV matrix	With trend Collapsed IV matrix	No trend Reduced IV count	With trend Reduced IV count	No trend No outside IVs	With trend No outside IVs
g_{t-1}	λ	1.005**	0.991**	1.035**	0.928**	1.006**	0.724	1.002**	0.977**
		(0.00733)	(0.0143)	(0.0271)	(0.136)	(0.149)	(0.575)	(0.0180)	(0.0410)
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.218]	[0.000]	[0.000]
y	δ_1	0.0100	0.0569	0.0311	0.234	0.167	0.602	0.0151+	0.0423
		(0.00814)	(0.0364)	(0.0378)	(0.189)	(0.297)	(0.981)	(0.00863)	(0.0349)
		[0.228]	[0.129]	[0.417]	[0.227]	[0.579]	[0.545]	[0.091]	[0.236]
p	δ_2	-0.00597	-0.0451	-0.0184	-0.201	-0.133	-0.535	-0.0157	-0.0298
		(0.00701)	(0.0319)	(0.0320)	(0.170)	(0.259)	(0.892)	(0.0206)	(0.0312)
		[0.402]	[0.168]	[0.571]	[0.248]	[0.610]	[0.554]	[0.454]	[0.348]
$\widehat{\sigma}$	δ_3	-0.146	0.0971	-0.191	0.0145	-1.463	-1.224	-0.106	0.160
		(0.191)	(0.203)	(0.257)	(0.232)	(2.323)	(2.302)	(0.240)	(0.252)
		[0.451]	[0.636]	[0.464]	[0.951]	[0.534]	[0.599]	[0.660]	[0.530]
$\widehat{\sigma}\widetilde{p}$	δ_4	-1.649*	-0.421	-1.995*	-0.00918	-0.455	3.255	-2.904*	-1.773+
		(0.655)	(0.678)	(0.955)	(1.367)	(4.162)	(7.916)	(1.144)	(0.881)
		[0.018]	[0.540]	[0.046]	[0.995]	[0.914]	[0.684]	[0.017]	[0.054]
t			-0.00399**		-0.00640		-0.0125		-0.00352*
			(0.00139)		(0.00479)		(0.0190)		(0.00135)
			[0.008]		[0.192]		[0.514]		[0.014]
Sargan		420.4	380.5	90.69	59.02	10.38	10.65	411.6	378.2
Sargan df		169	168	17	16	3	2	165	164
Sargan P		0	0	0	7.65e-07	0.0156	0.00487	0	0
Hansen		26.77	23.08	20.45	22.96	7.894	5.770	25.96	23.87
Hansen df		169	168	17	16	3	2	165	164
Hansen P		1	1	0.252	0.115	0.0482	0.0558	1	1
AR(2) test		-0.415	-0.503	-0.371	-0.311	0.399	0.436	-0.297	-0.419
AR(2) P		0.678	0.615	0.711	0.756	0.690	0.663	0.767	0.675

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 25: Estimates of the error-correction model, all countries, local currencies

		(1) PMG No trend	(2) PMG (Homogenous) trend	(3) PMG (Heterogenous) trends	(4) MG No trend	(5) MG (Heterogeneous) trends	(6) DFE No trend	(7) DFE (Homogeneous) trend
t			-0.0499**	-0.00140		-0.0126		-0.0376+
			(0.00648)	(0.00136)		(0.00872)		(0.0212)
			[0.000]	[0.302]		[0.149]		[0.076]
Long run								
y	θ_1	0.258**	0.560*	0.0594	-0.286	0.190	-0.815	0.300
		(0.0343)	(0.268)	(0.0746)	(0.402)	(0.483)	(0.646)	(0.545)
		[0.000]	[0.037]	[0.426]	[0.476]	[0.694]	[0.207]	[0.582]
p	θ_2	-0.501**	-0.0955	-0.440**	-0.0252	0.111	-1.666	-1.112
		(0.0809)	(0.231)	(0.0640)	(0.433)	(0.549)	(1.013)	(0.728)
		[0.000]	[0.679]	[0.000]	[0.954]	[0.839]	[0.100]	[0.126]
$\widehat{\sigma}$	θ_3	-0.359	-0.376	-0.354+	-0.0753	1.458	1.214	1.791
		(0.279)	(0.841)	(0.192)	(1.978)	(1.111)	(2.166)	(1.687)
		[0.199]	[0.655]	[0.065]	[0.970]	[0.189]	[0.575]	[0.288]
$\widehat{\sigma}\widetilde{p}$	θ_4	-1.457	-27.64**	2.258+	-35.85+	-15.25	4.331	3.088
		(2.102)	(5.587)	(1.244)	(19.67)	(21.12)	(9.114)	(7.007)
		[0.488]	[0.000]	[0.070]	[0.068]	[0.470]	[0.635]	[0.659]
Short run								
EC term	ϕ	-0.130**	-0.0890**	-0.252**	-0.452**	-0.515**	-0.0663+	-0.0820*
		(0.0479)	(0.0215)	(0.0483)	(0.0726)	(0.0938)	(0.0342)	(0.0359)
		[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.052]	[0.022]
Δy	δ_1	0.267**	0.407**	0.272**	0.272+	0.271	0.379**	0.379**
		(0.0625)	(0.0711)	(0.0836)	(0.154)	(0.169)	(0.0794)	(0.0822)
		[0.000]	[0.000]	[0.001]	[0.077]	[0.110]	[0.000]	[0.000]
Δp	δ_2	-0.139**	-0.147**	-0.0670+	-0.111+	-0.102	-0.117*	-0.105*
		(0.0515)	(0.0316)	(0.0394)	(0.0643)	(0.0698)	(0.0498)	(0.0477)
		[0.007]	[0.000]	[0.089]	[0.085]	[0.143]	[0.019]	[0.028]
$\Delta\widehat{\sigma}$	δ_3	-0.00355	0.0783	0.103*	-0.110	-0.0395	-0.000811	0.00461
		(0.0599)	(0.0759)	(0.0520)	(0.123)	(0.135)	(0.111)	(0.115)
		[0.953]	[0.303]	[0.047]	[0.371]	[0.769]	[0.994]	[0.968]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	δ_4	-1.045*	0.720	-0.739+	1.655	1.784	-0.144	-0.00948
		(0.501)	(0.644)	(0.419)	(1.843)	(2.013)	(0.347)	(0.352)
		[0.037]	[0.264]	[0.078]	[0.369]	[0.375]	[0.679]	[0.979]

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

Table 26: Estimates of error-correction model with only the standard regressors, local currencies

		(1) PMG No trend	(2) PMG Homogenous trend	(3) PMG Heterogeneous trends	(4) MG No trend	(5) MG (Heterogeneous) trends	(6) DFE No trend	(7) DFE (Homogenous) trend
t			-0.0463**	-0.00383*		0.0620		-0.0342
			(0.00817)	(0.00163)		(0.0968)		(0.0212)
			[0.000]	[0.019]		[0.522]		[0.106]
Long run								
y	θ_1	0.301**	0.283	0.275**	-0.246	-1.565	-0.741	0.307
		(0.0321)	(0.320)	(0.0436)	(0.625)	(1.815)	(0.637)	(0.543)
		[0.000]	[0.375]	[0.000]	[0.694]	[0.388]	[0.245]	[0.571]
p	θ_2	-0.648**	-1.283**	-0.139**	-0.660**	-1.569	-1.435*	-0.981*
		(0.0389)	(0.165)	(0.0237)	(0.217)	(1.311)	(0.662)	(0.468)
		[0.000]	[0.000]	[0.000]	[0.002]	[0.231]	[0.030]	[0.036]
Short run								
EC term	ϕ	-0.142**	-0.0803**	-0.295**	-0.376**	-0.507**	-0.0681+	-0.0820*
		(0.0508)	(0.0175)	(0.0642)	(0.0638)	(0.0713)	(0.0362)	(0.0377)
		[0.005]	[0.000]	[0.000]	[0.000]	[0.000]	[0.060]	[0.030]
Δy	δ_1	0.273**	0.384**	0.286**	0.330**	0.239**	0.350**	0.358**
		(0.0600)	(0.0575)	(0.0726)	(0.0659)	(0.0880)	(0.0518)	(0.0578)
		[0.000]	[0.000]	[0.000]	[0.000]	[0.007]	[0.000]	[0.000]
Δp	δ_2	-0.138*	-0.0992**	-0.0875*	-0.0109	-0.00316	-0.109**	-0.0880*
		(0.0569)	(0.0371)	(0.0425)	(0.0456)	(0.0422)	(0.0411)	(0.0385)
		[0.016]	[0.007]	[0.039]	[0.812]	[0.940]	[0.008]	[0.022]

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

9 Implementation of Estimation and Tests

All estimation has been performed in Stata 11 (2009). The panel unit root tests reported in Tables 4 and 5 are implemented using the Stata (2009) program *xtunitroot*. The cointegration tests reported in Tables 6 and 7 are implemented using Persyn and Westerlund's program *xtwest*, detailed in Persyn and Westerlund (2008). The PMG, MG, and DFE estimators of the error-correction models are implemented using Blackburne and Frank's *xtpmg* (2007b), detailed in Blackburne and Frank (2007a). GMM estimates of the ADL are computed using Roodman's (2011) *xtabond2*, and least-squares estimates are computed using Schaffer's *xtivreg2*.

10 PMG Estimates with Individual Country-Specific Short-Run Coefficients

Table 27 (pp. 50-64) reports the *country-specific* short-run ECM coefficients estimated by PMG, averages of which are reported in Tables 14 and 25.

Table 27: Pooled mean group estimates of error-correction model with reporting of individual short-run parameters

	(1) USD No trend	(2) USD Homogenous trend	(3) USD Heterogeneous trends	(4) Local currency No trend	(5) Local currency Homogenous trend	(6) Local currency Heterogeneous trends
Long Run						
y	0.555**	0.774**	0.388**	0.258**	0.560*	0.0594
	(0.0306)	(0.0905)	(0.0412)	(0.0343)	(0.268)	(0.0746)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.037]	[0.426]
p	-0.693**	-0.981**	-0.626**	-0.501**	-0.0955	-0.440**
	(0.0755)	(0.122)	(0.0398)	(0.0809)	(0.231)	(0.0640)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.679]	[0.000]
$\widehat{\sigma}$	-1.249**	-1.464**	-0.881**	-0.359	-0.376	-0.354+
	(0.249)	(0.353)	(0.100)	(0.279)	(0.841)	(0.192)
	[0.000]	[0.000]	[0.000]	[0.199]	[0.655]	[0.065]
$\widehat{\sigma}\widetilde{p}$	0.816	-0.307	-0.0718	-1.457	-27.64**	2.258+
	(1.205)	(1.872)	(0.520)	(2.102)	(5.587)	(1.244)
	[0.498]	[0.870]	[0.890]	[0.488]	[0.000]	[0.070]
t		-0.0473**			-0.0499**	
		(0.00303)			(0.00648)	
		[0.000]			[0.000]	
Individual Short-Run Estimates						
Australia						
EC term	-0.220*	-0.0444+	-0.175**	-0.384**	-0.0367+	-0.636**
	(0.0903)	(0.0227)	(0.0645)	(0.101)	(0.0212)	(0.136)
	[0.015]	[0.051]	[0.007]	[0.000]	[0.083]	[0.000]
Δy	0.0463	0.0671	0.0842	0.0927	0.578	-0.00186
	(0.0814)	(0.0854)	(0.0767)	(0.309)	(0.471)	(0.341)
	[0.570]	[0.432]	[0.272]	[0.764]	[0.220]	[0.996]
Δp	0.0162	0.00870	0.0151	0.129	0.0933	0.241*
	(0.0745)	(0.0777)	(0.0690)	(0.102)	(0.127)	(0.0988)
	[0.828]	[0.911]	[0.827]	[0.206]	[0.464]	[0.015]
$\Delta\widehat{\sigma}$	-0.292	-0.368	-0.256	-0.325+	-0.336	-0.219
	(0.222)	(0.224)	(0.207)	(0.185)	(0.230)	(0.173)
	[0.189]	[0.100]	[0.218]	[0.079]	[0.144]	[0.205]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.942+	1.048*	1.123*	1.571	1.032	-0.0404
	(0.514)	(0.501)	(0.452)	(1.391)	(1.785)	(1.238)
	[0.067]	[0.036]	[0.013]	[0.259]	[0.563]	[0.974]
t			-0.00148			0.00101
			(0.000985)			(0.00151)
			[0.134]			[0.504]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Austria						
EC term	-0.0802	-0.0468	-0.202*	-0.106	-0.00346	-0.202
	(0.0574)	(0.0675)	(0.0963)	(0.0708)	(0.0634)	(0.158)
	[0.162]	[0.488]	[0.036]	[0.136]	[0.956]	[0.199]
Δy	0.640**	0.624**	0.579**	0.522	0.625	0.544
	(0.176)	(0.188)	(0.169)	(0.607)	(0.645)	(0.603)
	[0.000]	[0.001]	[0.001]	[0.389]	[0.332]	[0.366]
Δp	-0.458*	-0.446*	-0.362*	-0.443+	-0.512*	-0.422+
	(0.178)	(0.194)	(0.178)	(0.227)	(0.245)	(0.227)
	[0.010]	[0.021]	[0.043]	[0.050]	[0.037]	[0.063]
$\Delta\widehat{\sigma}$	-0.0487	0.0784	0.0216	-0.310	-0.208	-0.242
	(0.280)	(0.308)	(0.272)	(0.414)	(0.450)	(0.421)
	[0.862]	[0.799]	[0.937]	[0.454]	[0.644]	[0.566]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-1.349	-0.743	-0.514	-3.304	-1.122	-1.937
	(1.316)	(1.515)	(1.337)	(5.616)	(8.261)	(6.326)
	[0.306]	[0.624]	[0.701]	[0.556]	[0.892]	[0.759]
t			-0.00426			-0.00264
			(0.00308)			(0.00390)
			[0.167]			[0.497]
Belgium						
EC term	0.202**	-0.486**	-0.270+	0.151**	-0.373**	-0.122
	(0.0624)	(0.117)	(0.160)	(0.0513)	(0.0803)	(0.124)
	[0.001]	[0.000]	[0.091]	[0.003]	[0.000]	[0.326]
Δy	0.497**	-0.0812	0.153	-0.380	-0.412	-0.210
	(0.162)	(0.159)	(0.179)	(0.828)	(0.506)	(0.717)
	[0.002]	[0.610]	[0.393]	[0.646]	[0.416]	[0.769]
Δp	-0.390*	0.163	0.0120	-0.524**	-0.117	-0.208
	(0.165)	(0.180)	(0.196)	(0.194)	(0.140)	(0.216)
	[0.018]	[0.367]	[0.951]	[0.007]	[0.401]	[0.336]
$\Delta\widehat{\sigma}$	-0.319	0.161	-0.00887	0.0339	0.826*	0.464
	(0.477)	(0.419)	(0.421)	(0.485)	(0.343)	(0.456)
	[0.504]	[0.701]	[0.983]	[0.944]	[0.016]	[0.309]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	2.305	1.726	1.072	2.536	5.328*	-0.426
	(1.417)	(1.512)	(1.218)	(3.846)	(2.711)	(3.676)
	[0.104]	[0.254]	[0.379]	[0.510]	[0.049]	[0.908]
t			-0.0170**			-0.0108*
			(0.00564)			(0.00458)
			[0.002]			[0.019]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Canada						
EC term	-0.0606 (0.0585) [0.301]	0.0251 (0.0163) [0.123]	-0.101** (0.0375) [0.007]	0.0719 (0.0635) [0.258]	0.0244** (0.00845) [0.004]	-0.365** (0.0843) [0.000]
Δy	0.0939 (0.158) [0.553]	0.121 (0.145) [0.404]	-0.141 (0.124) [0.256]	0.431* (0.172) [0.013]	0.423** (0.114) [0.000]	-0.0604 (0.117) [0.606]
Δp	-0.0606 (0.102) [0.552]	-0.117 (0.0910) [0.198]	-0.00868 (0.0717) [0.904]	-0.122 (0.0757) [0.107]	-0.120* (0.0526) [0.022]	0.0478 (0.0547) [0.382]
$\Delta\widehat{\sigma}$	0.0399 (0.120) [0.740]	-0.132 (0.109) [0.226]	-0.0586 (0.0810) [0.469]	-0.0929 (0.0990) [0.348]	-0.114 (0.0827) [0.167]	-0.0130 (0.0721) [0.857]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.0155 (0.358) [0.966]	-0.419 (0.348) [0.228]	-0.116 (0.263) [0.658]	-0.926+ (0.558) [0.097]	-1.462** (0.489) [0.003]	-0.797+ (0.470) [0.090]
t			0.00339** (0.000785) [0.000]			0.00502** (0.000941) [0.000]
Czech Republic						
EC term	-1.225** (0.148) [0.000]	-0.338** (0.0622) [0.000]	-1.092** (0.211) [0.000]	-0.888** (0.0921) [0.000]	-0.269** (0.0530) [0.000]	-0.847** (0.0790) [0.000]
Δy	-0.358** (0.127) [0.005]	0.177 (0.145) [0.223]	-0.227 (0.150) [0.130]	0.732** (0.211) [0.001]	1.351** (0.413) [0.001]	0.763** (0.165) [0.000]
Δp	0.635** (0.193) [0.001]	0.353 (0.251) [0.160]	0.454** (0.158) [0.004]	0.300** (0.0924) [0.001]	-0.00226 (0.159) [0.989]	0.255** (0.0691) [0.000]
$\Delta\widehat{\sigma}$	0.825** (0.155) [0.000]	0.308 (0.219) [0.159]	0.776** (0.164) [0.000]	-0.110 (0.195) [0.572]	-0.755* (0.329) [0.022]	0.254+ (0.143) [0.077]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.528 (1.733) [0.761]	0.698 (1.454) [0.631]	1.371 (1.061) [0.196]	-0.508 (0.647) [0.433]	-1.172 (1.310) [0.371]	-0.703 (0.489) [0.150]
t			0.00975+ (0.00580) [0.093]			0.00692** (0.00256) [0.007]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Denmark						
EC term	-0.292** (0.0573) [0.000]	-0.0722** (0.00847) [0.000]	-0.117+ (0.0670) [0.081]	-0.247** (0.0403) [0.000]	-0.0617** (0.00622) [0.000]	-0.0891** (0.0298) [0.003]
Δy	-0.00514 (0.0760) [0.946]	0.150** (0.0423) [0.000]	0.126* (0.0618) [0.041]	0.0107 (0.177) [0.952]	0.0316 (0.1000) [0.752]	0.0812 (0.0919) [0.376]
Δp	-0.0439 (0.0764) [0.566]	-0.135** (0.0414) [0.001]	-0.111* (0.0550) [0.044]	0.00923 (0.0664) [0.890]	-0.155** (0.0330) [0.000]	-0.103** (0.0385) [0.007]
$\Delta\widehat{\sigma}$	-0.0448 (0.190) [0.814]	0.0979 (0.120) [0.414]	0.0550 (0.115) [0.633]	-0.0526 (0.197) [0.789]	-0.223* (0.108) [0.040]	-0.143 (0.105) [0.175]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.249 (0.677) [0.713]	0.119 (0.410) [0.772]	0.128 (0.386) [0.741]	-3.058+ (1.675) [0.068]	1.348 (0.976) [0.167]	-1.064 (0.955) [0.265]
t			-0.00308** (0.000782) [0.000]			-0.00281** (0.000417) [0.000]
Finland						
EC term	-0.0424 (0.0603) [0.482]	-0.0163 (0.0242) [0.500]	-0.0364 (0.0919) [0.692]	-0.425** (0.154) [0.006]	-0.00120 (0.0107) [0.911]	-0.477* (0.197) [0.015]
Δy	0.229** (0.0590) [0.000]	0.258** (0.0461) [0.000]	0.244** (0.0630) [0.000]	0.0924 (0.0658) [0.160]	0.152* (0.0709) [0.032]	0.0637 (0.0731) [0.384]
Δp	-0.179* (0.0754) [0.017]	-0.191** (0.0715) [0.008]	-0.183* (0.0810) [0.024]	-0.152+ (0.0853) [0.075]	-0.345** (0.0497) [0.000]	-0.156+ (0.0914) [0.088]
$\Delta\widehat{\sigma}$	0.0557 (0.106) [0.598]	0.108 (0.141) [0.444]	0.0884 (0.144) [0.539]	-0.146 (0.133) [0.270]	-0.270* (0.135) [0.046]	-0.223+ (0.129) [0.083]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.877+ (0.528) [0.097]	-0.731 (0.588) [0.214]	-0.726 (0.666) [0.276]	1.192 (0.870) [0.171]	0.792 (0.931) [0.395]	0.305 (0.862) [0.724]
t			-0.000520 (0.00119) [0.663]			0.00115 (0.00131) [0.379]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
France						
EC term	0.0308+	-0.142*	-0.190	0.0763**	-0.184**	-0.0171
	(0.0160)	(0.0592)	(0.122)	(0.0140)	(0.0590)	(0.0660)
	[0.054]	[0.016]	[0.119]	[0.000]	[0.002]	[0.796]
Δy	0.174**	0.111+	0.112+	0.784**	0.821**	0.864**
	(0.0594)	(0.0595)	(0.0648)	(0.196)	(0.222)	(0.195)
	[0.003]	[0.061]	[0.085]	[0.000]	[0.000]	[0.000]
Δp	-0.253**	-0.211**	-0.185**	-0.158**	-0.153*	-0.133*
	(0.0623)	(0.0623)	(0.0682)	(0.0602)	(0.0690)	(0.0600)
	[0.000]	[0.001]	[0.007]	[0.009]	[0.027]	[0.027]
$\Delta\widehat{\sigma}$	-0.0110	0.170	0.143	0.205	0.249	0.231+
	(0.0952)	(0.123)	(0.117)	(0.133)	(0.164)	(0.128)
	[0.908]	[0.167]	[0.222]	[0.123]	[0.129]	[0.071]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.585	-0.192	-0.278	-1.630	1.784	-1.781
	(0.423)	(0.501)	(0.428)	(1.355)	(2.105)	(1.339)
	[0.167]	[0.701]	[0.516]	[0.229]	[0.397]	[0.184]
t			-0.00884+			-0.00347
			(0.00479)			(0.00237)
			[0.065]			[0.143]
Germany						
EC term	0.136+	-0.0553**	-1.005**	0.215**	-0.0499**	-0.0106
	(0.0782)	(0.0185)	(0.330)	(0.0824)	(0.0132)	(0.105)
	[0.081]	[0.003]	[0.002]	[0.009]	[0.000]	[0.920]
Δy	0.297**	0.196**	-0.147	0.564	0.112	0.202
	(0.0907)	(0.0726)	(0.133)	(0.374)	(0.322)	(0.345)
	[0.001]	[0.007]	[0.268]	[0.132]	[0.729]	[0.558]
Δp	-0.490**	-0.331**	0.104	-0.405**	-0.270**	-0.256*
	(0.0952)	(0.0874)	(0.171)	(0.105)	(0.0828)	(0.109)
	[0.000]	[0.000]	[0.543]	[0.000]	[0.001]	[0.019]
$\Delta\widehat{\sigma}$	-0.375*	-0.120	0.214	0.147	0.175	0.156
	(0.176)	(0.182)	(0.207)	(0.143)	(0.121)	(0.119)
	[0.033]	[0.510]	[0.300]	[0.306]	[0.148]	[0.192]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.971	0.964+	1.649*	-0.0582	0.673	-0.206
	(0.601)	(0.524)	(0.760)	(0.983)	(0.860)	(0.906)
	[0.106]	[0.066]	[0.030]	[0.953]	[0.434]	[0.820]
t			-0.0128**			-0.00297+
			(0.00378)			(0.00155)
			[0.001]			[0.055]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Greece						
EC term	-0.0373	0.0110	-0.0536	0.0120	0.0114	-0.232**
	(0.0496)	(0.0170)	(0.0485)	(0.0369)	(0.0128)	(0.0877)
	[0.453]	[0.518]	[0.269]	[0.744]	[0.374]	[0.008]
Δy	0.0741	0.0927*	0.0576	0.156	0.0927	-0.263
	(0.0467)	(0.0425)	(0.0448)	(0.159)	(0.171)	(0.184)
	[0.113]	[0.029]	[0.199]	[0.329]	[0.587]	[0.153]
Δp	0.0198	-0.0193	-0.000402	0.1000	0.115	0.157*
	(0.0577)	(0.0573)	(0.0551)	(0.0740)	(0.0750)	(0.0623)
	[0.731]	[0.737]	[0.994]	[0.177]	[0.124]	[0.012]
$\Delta\widehat{\sigma}$	0.00219	-0.0914	-0.0867	-0.0539	-0.0626	-0.0281
	(0.108)	(0.118)	(0.109)	(0.0979)	(0.0957)	(0.0836)
	[0.984]	[0.438]	[0.424]	[0.582]	[0.513]	[0.736]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.819+	-1.039**	-0.705	-4.121**	-4.807**	-4.518**
	(0.425)	(0.401)	(0.431)	(1.563)	(1.683)	(1.199)
	[0.054]	[0.009]	[0.102]	[0.008]	[0.004]	[0.000]
t			0.00159+			0.00736**
			(0.000905)			(0.00239)
			[0.078]			[0.002]
Hungary						
EC term	-0.330**	0.0995	-0.184*	-0.372**	0.104*	-0.263**
	(0.0640)	(0.0684)	(0.0788)	(0.0958)	(0.0448)	(0.0926)
	[0.000]	[0.146]	[0.020]	[0.000]	[0.020]	[0.004]
Δy	0.0910	0.239*	0.135+	0.187	0.486*	0.280+
	(0.0699)	(0.108)	(0.0700)	(0.193)	(0.225)	(0.166)
	[0.193]	[0.027]	[0.054]	[0.331]	[0.031]	[0.093]
Δp	-0.179*	-0.148	-0.223*	-0.0187	-0.274+	-0.174
	(0.0886)	(0.144)	(0.0928)	(0.116)	(0.148)	(0.110)
	[0.043]	[0.306]	[0.016]	[0.872]	[0.064]	[0.113]
$\Delta\widehat{\sigma}$	0.335**	-0.0608	0.132	0.508**	0.503*	0.459**
	(0.121)	(0.208)	(0.128)	(0.195)	(0.230)	(0.156)
	[0.006]	[0.770]	[0.302]	[0.009]	[0.029]	[0.003]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.240	-1.359	-0.233	-4.514	0.138	-0.478
	(0.618)	(1.020)	(0.679)	(4.393)	(5.460)	(4.016)
	[0.698]	[0.183]	[0.731]	[0.304]	[0.980]	[0.905]
t			0.00519**			0.00496**
			(0.00147)			(0.00124)
			[0.000]			[0.000]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Ireland						
EC term	-0.407** (0.107) [0.000]	-0.110+ (0.0630) [0.080]	-0.385** (0.118) [0.001]	-0.0739 (0.0823) [0.369]	-0.0327 (0.0360) [0.364]	-0.0219 (0.147) [0.882]
Δy	-0.0688 (0.139) [0.620]	0.00939 (0.182) [0.959]	-0.0484 (0.154) [0.753]	0.634** (0.208) [0.002]	0.621** (0.214) [0.004]	0.657** (0.195) [0.001]
Δp	0.116 (0.137) [0.395]	0.0914 (0.192) [0.634]	0.0895 (0.162) [0.580]	0.134 (0.210) [0.524]	0.127 (0.208) [0.543]	0.125 (0.209) [0.548]
$\Delta\widehat{\sigma}$	-0.350 (0.319) [0.273]	-0.123 (0.480) [0.798]	-0.551 (0.433) [0.203]	0.00360 (0.324) [0.991]	0.000763 (0.323) [0.998]	0.00220 (0.324) [0.995]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-3.333* (1.375) [0.015]	-1.547 (1.805) [0.391]	-3.303* (1.655) [0.046]	-2.308 (5.267) [0.661]	-1.633 (5.404) [0.763]	-2.008 (5.453) [0.713]
t			0.00472 (0.00298) [0.114]			-0.000825 (0.00508) [0.871]
Italy						
EC term	0.176+ (0.0910) [0.054]	-0.302** (0.0460) [0.000]	-0.117* (0.0559) [0.037]	0.149 (0.0912) [0.102]	-0.222** (0.0342) [0.000]	-0.0801+ (0.0416) [0.055]
Δy	0.587** (0.198) [0.003]	0.160 (0.121) [0.188]	0.239* (0.0965) [0.013]	-0.0250 (0.918) [0.978]	0.847* (0.432) [0.050]	0.407 (0.372) [0.274]
Δp	-0.718** (0.223) [0.001]	-0.198 (0.142) [0.164]	-0.227* (0.114) [0.046]	-0.775* (0.354) [0.028]	-0.383* (0.176) [0.029]	-0.379* (0.149) [0.011]
$\Delta\widehat{\sigma}$	-0.200 (0.358) [0.576]	0.311 (0.229) [0.175]	0.181 (0.165) [0.272]	-0.728 (0.742) [0.326]	0.296 (0.397) [0.457]	0.0596 (0.310) [0.848]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.715 (1.627) [0.660]	1.162 (1.004) [0.247]	0.932 (0.709) [0.189]	3.215 (10.24) [0.753]	6.720 (5.062) [0.184]	4.213 (4.197) [0.315]
t			-0.0114** (0.00135) [0.000]			-0.00953** (0.000960) [0.000]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Japan						
EC term	-0.125**	-0.0384**	-0.132**	-0.126**	-0.0291**	-0.340**
	(0.0234)	(0.00934)	(0.0408)	(0.0266)	(0.00785)	(0.120)
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.005]
Δy	0.0723	0.0523	0.110	0.0529	-0.0450	0.168
	(0.0517)	(0.0659)	(0.0686)	(0.130)	(0.142)	(0.146)
	[0.162]	[0.427]	[0.109]	[0.685]	[0.752]	[0.249]
Δp	-0.0138	-0.0207	-0.0567	0.0162	-0.0330	0.0796
	(0.0525)	(0.0629)	(0.0611)	(0.0524)	(0.0530)	(0.0599)
	[0.793]	[0.742]	[0.354]	[0.758]	[0.534]	[0.184]
$\Delta\widehat{\sigma}$	0.0889	0.0528	0.0538	0.111	0.110	0.0798
	(0.0594)	(0.0642)	(0.0618)	(0.113)	(0.125)	(0.112)
	[0.135]	[0.411]	[0.384]	[0.330]	[0.379]	[0.476]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.435	-0.327	-0.204	-0.505	-0.428	-1.206
	(0.348)	(0.386)	(0.371)	(0.725)	(0.809)	(0.757)
	[0.212]	[0.396]	[0.581]	[0.486]	[0.597]	[0.111]
t			0.000127			0.00389+
			(0.000905)			(0.00215)
			[0.888]			[0.071]
Korea						
EC term	-0.265**	-0.173**	-0.136**	-0.196**	-0.125**	-0.156**
	(0.0448)	(0.0186)	(0.0457)	(0.0390)	(0.0256)	(0.0460)
	[0.000]	[0.000]	[0.003]	[0.000]	[0.000]	[0.001]
Δy	0.165	0.232**	0.318**	0.935**	0.802*	0.841*
	(0.123)	(0.0828)	(0.0912)	(0.360)	(0.357)	(0.379)
	[0.180]	[0.005]	[0.000]	[0.009]	[0.025]	[0.026]
Δp	-0.192	-0.196	-0.218	-0.0285	-0.261	-0.171
	(0.212)	(0.147)	(0.155)	(0.162)	(0.175)	(0.199)
	[0.365]	[0.183]	[0.159]	[0.860]	[0.135]	[0.389]
$\Delta\widehat{\sigma}$	0.175	0.409*	0.487*	0.577	0.993*	0.731
	(0.291)	(0.202)	(0.224)	(0.497)	(0.464)	(0.505)
	[0.548]	[0.043]	[0.030]	[0.245]	[0.032]	[0.148]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.971	2.484*	2.343*	1.900	5.086**	2.209
	(1.388)	(1.026)	(1.060)	(1.854)	(1.829)	(1.911)
	[0.484]	[0.015]	[0.027]	[0.305]	[0.005]	[0.248]
t			-0.00981**			-0.00384
			(0.00264)			(0.00330)
			[0.000]			[0.245]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Luxembourg						
EC term	0.103 (0.155) [0.505]	-0.250** (0.0485) [0.000]	-0.504** (0.137) [0.000]	0.00355 (0.160) [0.982]	-0.177** (0.0403) [0.000]	-0.167 (0.106) [0.117]
Δy	0.276 (0.237) [0.245]	0.0307 (0.134) [0.820]	-0.114 (0.153) [0.454]	0.522 (0.486) [0.283]	0.346 (0.285) [0.226]	0.392 (0.317) [0.217]
Δp	-0.535* (0.209) [0.010]	-0.144 (0.132) [0.275]	0.0589 (0.158) [0.709]	-0.440 (0.268) [0.101]	-0.297* (0.144) [0.039]	-0.191 (0.185) [0.303]
$\Delta\widehat{\sigma}$	-0.225 (0.342) [0.511]	0.378 (0.248) [0.128]	0.309 (0.216) [0.153]	-0.258 (0.478) [0.589]	0.0763 (0.309) [0.805]	-0.0114 (0.320) [0.972]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.637 (1.476) [0.666]	0.975 (0.916) [0.287]	-0.126 (0.843) [0.881]	0.388 (3.924) [0.921]	5.536* (2.459) [0.024]	0.971 (2.733) [0.722]
t			-0.0121** (0.00194) [0.000]			-0.00825** (0.00177) [0.000]
Mexico						
EC term	-0.319** (0.0792) [0.000]	0.0943** (0.0334) [0.005]	-0.102 (0.0782) [0.191]	-0.0364 (0.116) [0.755]	0.0853** (0.0293) [0.004]	-0.0792 (0.0717) [0.269]
Δy	0.228+ (0.123) [0.065]	0.445** (0.112) [0.000]	0.336** (0.0980) [0.001]	0.488** (0.188) [0.009]	0.381** (0.141) [0.007]	0.210 (0.149) [0.159]
Δp	-0.133 (0.109) [0.219]	-0.272* (0.113) [0.017]	-0.175+ (0.0983) [0.074]	-0.243 (0.284) [0.393]	-0.291 (0.226) [0.198]	-0.387+ (0.209) [0.063]
$\Delta\widehat{\sigma}$	0.473* (0.204) [0.020]	0.0422 (0.260) [0.871]	0.195 (0.224) [0.384]	0.561 (0.554) [0.312]	0.530 (0.443) [0.231]	0.481 (0.398) [0.226]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-1.005 (0.874) [0.250]	-1.928* (0.979) [0.049]	-1.673* (0.812) [0.039]	-9.593 (11.63) [0.409]	-7.624 (9.268) [0.411]	-7.228 (8.368) [0.388]
t			0.00395** (0.00106) [0.000]			0.00469** (0.00120) [0.000]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Netherlands						
EC term	-0.0308	-0.0205	0.0739	-0.108	-0.00854	-0.499**
	(0.171)	(0.0180)	(0.117)	(0.0794)	(0.0108)	(0.166)
	[0.857]	[0.255]	[0.526]	[0.174]	[0.428]	[0.003]
Δy	0.364**	0.361**	0.407**	0.0638	-0.0502	0.520+
	(0.119)	(0.0978)	(0.108)	(0.253)	(0.243)	(0.276)
	[0.002]	[0.000]	[0.000]	[0.801]	[0.836]	[0.060]
Δp	-0.322**	-0.291**	-0.329**	-0.251**	-0.273**	-0.186*
	(0.113)	(0.0980)	(0.106)	(0.0870)	(0.0876)	(0.0794)
	[0.005]	[0.003]	[0.002]	[0.004]	[0.002]	[0.019]
$\Delta\widehat{\sigma}$	-0.0572	0.0410	-0.0279	-0.152	-0.186	-0.0388
	(0.276)	(0.217)	(0.221)	(0.174)	(0.176)	(0.158)
	[0.836]	[0.850]	[0.900]	[0.382]	[0.291]	[0.807]
$\Delta(\widehat{\sigma}\widetilde{p})$	-0.472	-0.426	-0.849	-0.678	-1.019	-1.541
	(0.784)	(0.653)	(0.794)	(1.620)	(1.670)	(1.379)
	[0.548]	[0.514]	[0.285]	[0.676]	[0.542]	[0.264]
t			-0.00130			0.00385*
			(0.000846)			(0.00179)
			[0.126]			[0.031]
New Zealand						
EC term	-0.0779	-0.00966	-0.0642	-0.126*	-0.00385	-0.231**
	(0.0546)	(0.0236)	(0.0500)	(0.0578)	(0.0129)	(0.0848)
	[0.154]	[0.682]	[0.199]	[0.030]	[0.765]	[0.007]
Δy	0.0755	0.103+	0.0833	0.261	0.358+	0.191
	(0.0526)	(0.0532)	(0.0526)	(0.169)	(0.185)	(0.166)
	[0.151]	[0.054]	[0.113]	[0.122]	[0.053]	[0.250]
Δp	-0.0194	-0.0181	-0.0183	-0.0264	-0.0542	0.00947
	(0.0597)	(0.0708)	(0.0687)	(0.0794)	(0.0874)	(0.0799)
	[0.746]	[0.798]	[0.790]	[0.739]	[0.535]	[0.906]
$\Delta\widehat{\sigma}$	0.00488	-0.0185	-0.0130	-0.489**	-0.442*	-0.493**
	(0.141)	(0.170)	(0.160)	(0.178)	(0.198)	(0.166)
	[0.972]	[0.914]	[0.936]	[0.006]	[0.025]	[0.003]
$\Delta(\widehat{\sigma}\widetilde{p})$	-0.186	-0.307	-0.173	0.858	0.307	0.0701
	(0.391)	(0.401)	(0.397)	(1.068)	(1.257)	(0.971)
	[0.634]	[0.444]	[0.663]	[0.422]	[0.807]	[0.942]
t			0.000182			0.00146
			(0.00110)			(0.000900)
			[0.869]			[0.104]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Norway						
EC term	0.0901**	-0.277**	-0.424*	0.170**	-0.133**	0.371**
	(0.0318)	(0.0827)	(0.173)	(0.0342)	(0.0500)	(0.120)
	[0.005]	[0.001]	[0.014]	[0.000]	[0.008]	[0.002]
Δy	0.464**	0.480**	0.388**	0.111	0.203	0.00589
	(0.127)	(0.108)	(0.115)	(0.111)	(0.140)	(0.122)
	[0.000]	[0.000]	[0.001]	[0.319]	[0.147]	[0.962]
Δp	-0.504**	-0.486**	-0.352**	-0.257*	-0.241+	-0.235*
	(0.134)	(0.110)	(0.130)	(0.119)	(0.134)	(0.109)
	[0.000]	[0.000]	[0.007]	[0.030]	[0.073]	[0.032]
$\Delta\widehat{\sigma}$	-0.392**	-0.104	-0.110	0.289*	0.330*	0.344**
	(0.149)	(0.166)	(0.163)	(0.138)	(0.156)	(0.127)
	[0.008]	[0.530]	[0.501]	[0.036]	[0.034]	[0.007]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.131	0.532	0.0883	-2.880	-2.949	-2.015
	(0.663)	(0.762)	(0.585)	(2.110)	(2.412)	(2.026)
	[0.843]	[0.485]	[0.880]	[0.172]	[0.222]	[0.320]
t			-0.0127**			0.00153
			(0.00402)			(0.00189)
			[0.002]			[0.420]
Poland						
EC term	-0.416**	-0.133*	-0.429**	-0.342**	-0.0370	-0.312*
	(0.118)	(0.0600)	(0.136)	(0.114)	(0.0358)	(0.131)
	[0.000]	[0.026]	[0.002]	[0.003]	[0.301]	[0.017]
Δy	-0.289*	-0.108	-0.256*	0.339	0.650*	0.358
	(0.130)	(0.131)	(0.130)	(0.274)	(0.308)	(0.302)
	[0.026]	[0.407]	[0.050]	[0.216]	[0.035]	[0.235]
Δp	0.306	0.192	0.344	0.399**	0.181	0.406**
	(0.200)	(0.232)	(0.214)	(0.138)	(0.151)	(0.157)
	[0.127]	[0.409]	[0.109]	[0.004]	[0.232]	[0.010]
$\Delta\widehat{\sigma}$	0.988**	1.140**	1.052**	0.587+	0.849*	0.643+
	(0.208)	(0.253)	(0.221)	(0.309)	(0.372)	(0.337)
	[0.000]	[0.000]	[0.000]	[0.057]	[0.022]	[0.056]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.774	0.0465	0.215	-3.091	-2.628	-3.598
	(0.783)	(0.923)	(0.822)	(2.469)	(3.249)	(2.674)
	[0.323]	[0.960]	[0.793]	[0.210]	[0.419]	[0.178]
t			-0.00127			-0.00145
			(0.00339)			(0.00239)
			[0.709]			[0.544]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Portugal						
EC term	-0.0402	-0.209**	-0.254*	-0.0706	-0.175**	-0.0600
	(0.172)	(0.0487)	(0.114)	(0.135)	(0.0272)	(0.0590)
	[0.815]	[0.000]	[0.026]	[0.600]	[0.000]	[0.309]
Δy	0.713**	0.223	0.245+	0.539	0.215	0.0249
	(0.157)	(0.150)	(0.137)	(0.404)	(0.210)	(0.246)
	[0.000]	[0.137]	[0.075]	[0.182]	[0.307]	[0.919]
Δp	-0.803**	-0.145	-0.204	-0.832**	-0.218	-0.323+
	(0.158)	(0.185)	(0.159)	(0.266)	(0.138)	(0.170)
	[0.000]	[0.435]	[0.198]	[0.002]	[0.115]	[0.058]
$\Delta\widehat{\sigma}$	-0.512**	0.283	0.0209	-0.184	0.260	0.147
	(0.188)	(0.235)	(0.172)	(0.299)	(0.175)	(0.183)
	[0.007]	[0.229]	[0.903]	[0.539]	[0.138]	[0.421]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.523	0.295	-0.229	0.0261	2.656+	-0.646
	(0.717)	(0.604)	(0.465)	(2.971)	(1.553)	(1.777)
	[0.465]	[0.625]	[0.623]	[0.993]	[0.087]	[0.716]
t			-0.00728**			-0.00735**
			(0.00165)			(0.00127)
			[0.000]			[0.000]
Slovakia						
EC term	-0.575**	-0.147	-0.917**	-0.669**	-0.189+	-0.887**
	(0.197)	(0.106)	(0.217)	(0.214)	(0.0985)	(0.280)
	[0.004]	[0.166]	[0.000]	[0.002]	[0.055]	[0.002]
Δy	-0.0991	0.155	-0.260	-0.538	0.590	-1.205
	(0.233)	(0.243)	(0.210)	(0.645)	(0.647)	(0.925)
	[0.671]	[0.525]	[0.216]	[0.404]	[0.361]	[0.193]
Δp	-0.156	-0.468	0.0658	-0.0584	-0.146	-0.155
	(0.302)	(0.327)	(0.280)	(0.270)	(0.315)	(0.284)
	[0.605]	[0.153]	[0.814]	[0.829]	[0.643]	[0.584]
$\Delta\widehat{\sigma}$	0.577+	0.404	0.495+	-0.181	-0.477	-0.0233
	(0.328)	(0.369)	(0.277)	(0.480)	(0.537)	(0.480)
	[0.079]	[0.272]	[0.074]	[0.707]	[0.374]	[0.961]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.236	2.592	1.035	2.791	0.186	4.486
	(2.080)	(2.430)	(1.921)	(2.131)	(2.359)	(2.762)
	[0.910]	[0.286]	[0.590]	[0.190]	[0.937]	[0.104]
t			0.0115*			0.0151+
			(0.00523)			(0.00783)
			[0.029]			[0.054]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Spain						
EC term	0.0182 (0.0766) [0.812]	-0.643** (0.219) [0.003]	-1.720** (0.200) [0.000]	0.102 (0.0631) [0.105]	-0.300* (0.134) [0.025]	-0.386* (0.194) [0.046]
Δy	0.169 (0.160) [0.288]	-0.137 (0.159) [0.388]	-0.302** (0.0897) [0.001]	0.0863 (0.543) [0.874]	0.623 (0.518) [0.229]	1.089+ (0.604) [0.071]
Δp	-0.311 (0.214) [0.147]	0.0458 (0.199) [0.818]	0.204+ (0.113) [0.071]	-0.157 (0.312) [0.613]	-0.303 (0.281) [0.280]	-0.0451 (0.267) [0.866]
$\Delta\widehat{\sigma}$	-0.331 (0.320) [0.302]	0.820+ (0.447) [0.067]	1.069** (0.242) [0.000]	-0.0823 (0.443) [0.853]	-0.0307 (0.410) [0.940]	0.0330 (0.378) [0.930]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.0726 (1.207) [0.952]	2.363 (1.701) [0.165]	2.587* (1.101) [0.019]	-1.094 (6.998) [0.876]	9.539 (7.807) [0.222]	0.601 (6.003) [0.920]
t			-0.0558** (0.00646) [0.000]			-0.0137** (0.00523) [0.009]
Sweden						
EC term	0.0105 (0.0921) [0.909]	-0.0518* (0.0230) [0.024]	-0.203** (0.0710) [0.004]	-0.332+ (0.169) [0.050]	-0.0323+ (0.0182) [0.076]	-0.466* (0.210) [0.026]
Δy	0.185+ (0.102) [0.068]	0.141 (0.0865) [0.102]	0.0914 (0.0776) [0.239]	0.00603 (0.248) [0.981]	-0.223 (0.267) [0.405]	-0.216 (0.249) [0.384]
Δp	-0.106 (0.0922) [0.252]	-0.0316 (0.0860) [0.714]	0.0177 (0.0768) [0.817]	-0.0587 (0.107) [0.582]	-0.0968 (0.100) [0.334]	0.0772 (0.121) [0.524]
$\Delta\widehat{\sigma}$	0.0889 (0.216) [0.681]	0.256 (0.201) [0.203]	0.265 (0.170) [0.120]	-0.0162 (0.183) [0.930]	-0.0551 (0.179) [0.758]	-0.0289 (0.171) [0.866]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.466 (0.794) [0.557]	-0.236 (0.665) [0.723]	0.153 (0.607) [0.801]	0.385 (1.761) [0.827]	0.455 (1.733) [0.793]	-1.142 (1.585) [0.471]
t			-0.00309** (0.000945) [0.001]			-0.000878 (0.00136) [0.518]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
Switzerland						
EC term	-0.338**	-0.00812	-0.589**	-0.316+	-0.0652*	-0.267+
	(0.123)	(0.0239)	(0.160)	(0.177)	(0.0313)	(0.153)
	[0.006]	[0.734]	[0.000]	[0.074]	[0.037]	[0.081]
Δy	-0.0475	0.0874	-0.0963	0.0168	0.904+	0.741
	(0.0921)	(0.0924)	(0.0866)	(0.385)	(0.516)	(0.504)
	[0.606]	[0.345]	[0.266]	[0.965]	[0.080]	[0.142]
Δp	-0.186	-0.375**	-0.0702	-0.0467	-0.257+	-0.121
	(0.117)	(0.111)	(0.119)	(0.153)	(0.134)	(0.143)
	[0.113]	[0.001]	[0.555]	[0.759]	[0.054]	[0.399]
$\Delta\widehat{\sigma}$	-0.107	-0.296+	0.0892	-0.235	0.0279	-0.00775
	(0.150)	(0.177)	(0.170)	(0.252)	(0.278)	(0.259)
	[0.474]	[0.096]	[0.600]	[0.352]	[0.920]	[0.976]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	0.909	1.621	2.073*	-0.298	3.189	0.606
	(0.882)	(1.062)	(0.844)	(2.444)	(2.756)	(2.452)
	[0.303]	[0.127]	[0.014]	[0.903]	[0.247]	[0.805]
t			-0.00265*			-0.00391*
			(0.00118)			(0.00176)
			[0.024]			[0.026]
Turkey						
EC term	-0.0712	-0.441**	-0.345**	0.0170	-0.221*	-0.333**
	(0.0936)	(0.138)	(0.129)	(0.0986)	(0.0878)	(0.115)
	[0.447]	[0.001]	[0.008]	[0.863]	[0.012]	[0.004]
Δy	0.246+	0.0189	0.119	0.0535	0.0720	0.341
	(0.128)	(0.128)	(0.114)	(0.323)	(0.266)	(0.250)
	[0.054]	[0.882]	[0.297]	[0.868]	[0.787]	[0.174]
Δp	-0.183	0.212	0.104	-0.0538	0.0464	0.295
	(0.159)	(0.176)	(0.164)	(0.283)	(0.237)	(0.230)
	[0.249]	[0.227]	[0.523]	[0.849]	[0.845]	[0.199]
$\Delta\widehat{\sigma}$	0.124	0.427	0.265	-0.197	-0.233	-0.0379
	(0.358)	(0.315)	(0.298)	(0.446)	(0.375)	(0.335)
	[0.730]	[0.176]	[0.375]	[0.658]	[0.534]	[0.910]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-4.037**	-1.636	-1.535	-4.459	0.623	-1.650
	(1.427)	(1.562)	(1.381)	(3.419)	(3.361)	(2.657)
	[0.005]	[0.295]	[0.267]	[0.192]	[0.853]	[0.535]
t			-0.0193**			-0.0228**
			(0.00658)			(0.00619)
			[0.003]			[0.000]

	(1) USD No t	(2) USD Homogenous t	(3) USD Heterogeneous trends	(4) Local currency No t	(5) Local currency With t	(6) Local currency Heterogeneous trends
United Kingdom						
EC term	0.0921	-0.0638+	-0.0655	0.112+	-0.0711**	-0.0634
	(0.0637)	(0.0335)	(0.153)	(0.0587)	(0.0233)	(0.122)
	[0.148]	[0.057]	[0.669]	[0.056]	[0.002]	[0.605]
Δy	0.0532	-0.0441	-0.0272	0.515	0.707+	0.665
	(0.145)	(0.124)	(0.156)	(0.464)	(0.400)	(0.433)
	[0.713]	[0.723]	[0.862]	[0.266]	[0.077]	[0.125]
Δp	0.00828	0.0698	0.0653	-0.0459	-0.00489	0.00366
	(0.140)	(0.134)	(0.147)	(0.138)	(0.118)	(0.129)
	[0.953]	[0.601]	[0.657]	[0.739]	[0.967]	[0.977]
$\Delta\widehat{\sigma}$	-0.00265	0.107	0.0853	0.480	0.424	0.426
	(0.124)	(0.142)	(0.136)	(0.328)	(0.277)	(0.302)
	[0.983]	[0.451]	[0.531]	[0.144]	[0.126]	[0.158]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-1.158	-1.031	-1.087	-1.867	0.512	-1.430
	(0.773)	(0.749)	(0.735)	(3.101)	(2.827)	(2.847)
	[0.134]	[0.169]	[0.139]	[0.547]	[0.856]	[0.616]
t			-0.00301			-0.00322+
			(0.00228)			(0.00184)
			[0.186]			[0.080]
United States						
EC term	-0.0211	-0.00496	-0.0354+	-0.0235	-0.00488	-0.0756
	(0.0148)	(0.00519)	(0.0201)	(0.0153)	(0.00309)	(0.0532)
	[0.155]	[0.339]	[0.079]	[0.124]	[0.114]	[0.155]
Δy	0.466**	0.530**	0.405**	0.499**	0.534**	0.422*
	(0.145)	(0.139)	(0.155)	(0.140)	(0.136)	(0.166)
	[0.001]	[0.000]	[0.009]	[0.000]	[0.000]	[0.011]
Δp	-0.0108	-0.0171	-0.0126	-0.0129	-0.0226	0.00303
	(0.0227)	(0.0225)	(0.0216)	(0.0215)	(0.0198)	(0.0298)
	[0.634]	[0.447]	[0.560]	[0.547]	[0.255]	[0.919]
$\Delta\widehat{\sigma}$	0.0119	0.00159	0.00873	0.00738	0.0116	-0.00607
	(0.0376)	(0.0373)	(0.0355)	(0.0351)	(0.0358)	(0.0364)
	[0.751]	[0.966]	[0.806]	[0.833]	[0.745]	[0.868]
$\Delta\left(\widehat{\sigma}\widetilde{p}\right)$	-0.320*	-0.330*	-0.300*	-0.266+	-0.174	-0.485*
	(0.133)	(0.137)	(0.131)	(0.146)	(0.176)	(0.193)
	[0.016]	[0.016]	[0.022]	[0.069]	[0.324]	[0.012]
t			0.000553			0.000910
			(0.000555)			(0.000786)
			[0.319]			[0.247]

Standard errors in parentheses; p-values in brackets.
** p<0.01, * p<0.05, + p<0.1

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