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# ‘On the Road Again’: A 118 country panel analysis of gasoline and diesel demand☆

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ABSTRACT

The current paper contributes to the literature on the relationship between economic growth, fuel prices, and the demand for gasoline and diesel within the transportation sector by assembling a wide panel dataset of fuel consumption and prices for 35 OECD and 83 Non-OECD countries. The unbalanced data spans 1978–2016, with the full 39 years of data for 36 countries. In addition, our dynamic panel estimates address nonstationarity, heterogeneity, and cross-sectional dependence. The OECD panel price elasticity for gasoline is around −0.7 or about three times that for the non-OECD panel; whereas, the OECD price elasticity for diesel is only modestly larger (in absolute terms) than the non-OECD elasticity (−0.3 and −0.2, respectively). For gasoline, the non-OECD GDP elasticity is around 1.0 or about twice that for OECD countries. For the OECD panel, the diesel GDP elasticity is about three times that of the OECD GDP elasticity for gasoline; whereas, for the non-OECD panel, the two GDP elasticities (for gasoline and diesel) are about the same. For non-OECD countries, subpanels based on geography and income produced mostly similar results. We found no evidence of GDP or price asymmetric effects for the 1978–2016 period. Lastly, the large (at least for the OECD panel) and statistically significant transportation price elasticities reported here provide stark contrast to the economy-wide energy price elasticities calculated in Liddle and Huntington (2020a).

## 1. Introduction

Transportation plays a critical role in shaping both world demand for petroleum and global greenhouse gas emissions. The growth in transportation energy demand most likely will be considerably faster in the lower-income economies than in mature developed regions. As incomes rise in less developed, lower income countries, more households will be able to afford private automobiles and motorcycles, will want to be more mobile, and will drive greater distances. Meanwhile, OECD trends over the next few decades are expected to be relatively flat due to shifting mobility trends caused by demographics and telecommuting as well as slower growth rates of vehicle ownership. Evaluating future trends will require an improved understanding of how transportation energy demand will respond to a range of different factors across countries at varying stages of development.

The current paper contributes to the literature on gasoline and diesel demand estimation by assembling an unusually wide panel

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**Table 1**
Mean Elasticity Estimates for Gasoline from Surveys and Meta-Analyses.

| | | Short Run | Long Run |
|---|---|---|---|
| **Price Elasticity:** | | | |
| | Dahl-Sterner (1991) | −0.26 | −0.86 |
| | Graham and Glaister (2004) | −0.25 | −0.77 |
| | Brons et al (2008) | −0.36 | −0.81 |
| | Havranek et al (2012): | | |
| | Unadjusted^ | −0.23 | −0.69 |
| | adjusted for bias^^ | −0.09 | −0.31 |
| | Labandeira et al (2017) | −0.29 | −0.77 |
| | Huntington et al (2019)[1] | −0.33 | −0.61 |
| | **-Average of Studies** | −0.26 | −0.69 |
| | Minimum Response | −0.09 | −0.31 |
| | Maximum Response | −0.36 | −0.86 |
| **Income Elasticity:** | | | |
| | Dahl and Sterner 1991 | 0.48 | 1.21 |
| | Graham and Glaister (2004) | 0.47 | 0.93 |
| | Havranek and Kokes (2015) | | |
| | Unadjusted^ | 0.28 | 0.66 |
| | adjusted for bias^^ | 0.1 | 0.23 |
| | Huntington et al (2019)[1] | 0.64 | 0.94 |
| | **-Average of Studies** | 0.38 | 0.79 |
| | Minimum Response | 0.1 | 0.23 |
| | Maximum Response | 0.64 | 1.21 |

^ Unadjusted = all estimates; comparable to the other studies.
^^ Adjusted = estimates have been adjusted for insignificance or having wrong sign.
[1] Study covered major developing countries only.

dataset that covers not only consumption for these fuels and economic growth but also end-use fuel prices for 35 OECD and 83 Non-OECD countries. The analysis expands coverage to include diesel fuel because it is an important transportation fuel in a number of countries. It also uses relatively long (time) panels covering the 1978–2016 period for many countries when data is available for all years. Moreover, the approach also employs estimation methods that address nonstationarity of the key economic data, heterogeneity in the responses for each country, and cross-sectional dependence between countries. We seek to determine (i) whether gasoline and diesel demand grows as rapidly as economic growth in both mature and developing countries as a general rule, and (ii) whether higher gasoline and diesel prices significantly reduce fuel demand (and if so, by how much) within these same country groups.

Long-panel studies like the current analysis are useful for extracting long-run trends from the available data. A potential disadvantage is that long-panel studies do not necessarily incorporate recent trends/phenomena that may be very important for a comprehensive understanding of transportation energy demand over the next few decades. For example, both autonomous vehicles and electric cars represent two very important new developments that are expected to reshape this sector. The modern electric car has become much more common in the last few years and now represents about 2% of total global vehicles. It plays an extremely important role in Norway and China. Despite the importance of electric vehicles, long panel studies are not ideal for evaluating this recent trend because such data covers only the last few years. In addition, the growth of electric cars depends upon many factors other than inexpensive power, including: range anxiety, recharge time, the availability of charging infrastructure, and country-specific public policy that phases out vehicles using fossil fuels. For all these reasons, our analysis focuses upon the demand for gasoline and diesel fuel.

The next section reviews the range of estimates in previous studies as reported by several surveys and meta-analyses covering previous empirical studies. Section 3 describes the data set and explains the development of the energy price data in greater detail. Section 4 discusses the empirical methods used to derive estimates that adjust for nonstationarity, heterogeneity and cross-sectional dependence. This section also describes our approach for testing whether the responses to price increases and decreases are symmetric. Section 5 presents the empirical results and discusses their implications for understanding energy market trends. Section 6 concludes by summarizing the key findings.

## 2. Previous elasticity estimates

There have been many econometric studies that estimate key elasticities for the road transportation sector. Elasticities can determine how economic, demographic and price variables shape the response of vehicle trips, vehicles miles driven, car ownership and final fuels used for mobility.

We estimate price and income responses for as many different countries and over as long a time period as available data allows in order to derive a comprehensive evaluation for policy developers. Moreover, we derive consumption responses to economic growth that control for local gasoline and diesel fuel prices. By focusing the analysis on these three variables—price, income, and fuel consumption—we are able to maximize our coverage to as many countries for which these three indicators are available for 20 years or

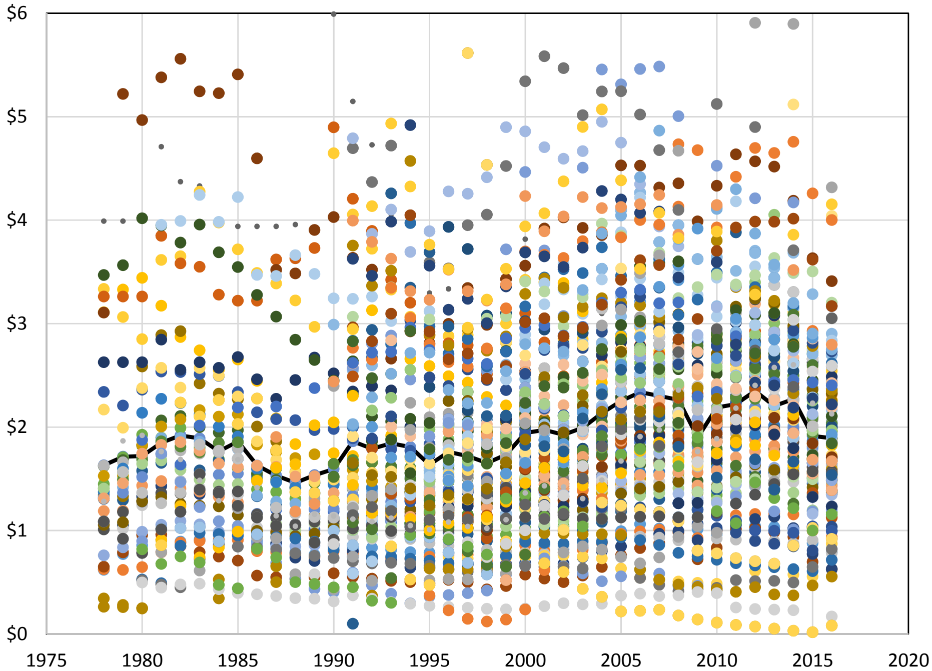


**Fig. 1a.** Country premium gasoline prices (in 2015 USD at PPP per liter), 1978–2016. Solid line indicates average price for all countries in each year.

more. Our research design is motivated more by the comprehensive coverage of a range of different country experiences for a few critical variables than by representing the many important decisions, like car purchases and number of trips, that may govern this response. Due to data constraints, an important excluded cost is the value of time spent on travel, which will depend upon the value of time as well as the average road speed while traveling. However, the value of time escalates approximately with disposable income (Schafer and Victor, 2000; Graham and Glaister, 2004), and hence will be incorporated indirectly through our income variable to a large extent.

Surveys of earlier econometric estimates (Dahl and Sterner, 1991; Graham and Glaister, 2004; Huntington et al., 2019) and meta-analyses seeking to explain the range of results across different studies (Brons et al., 2008; Havranek et al., 2012; Havranek and Kokes, 2015; Labandeira et al., 2017) have played important roles in assessing/summarizing previous work and informing policy developers. Collectively, they have revealed reasonable estimates of the mean and range of responses to prices and income. They study the final estimates reported by previous studies, making their best effort to control for a range of possible differences that include econometric methods, control variables, regions, time horizons, and data sources such as annual statistical reports or consumer surveys.

Meta-type analyses can contribute insights, such as: (i) for price elasticities, studies that employed dynamic models tend to produce lower (in absolute terms) results, while studies based on cross-sectional data tend to produce higher (in absolute terms) results (Brons et al. 2008); and (ii) for income elasticities, studies that consider cross-sectional data report larger elasticities than do studies that employ dynamic models (Havranek and Kokes 2015). However, some questions are more challenging to address via meta-analysis, such as: (i) whether the price and income elasticities estimates differ among OECD and developing countries; and (ii) whether those elasticities differ between gasoline and diesel. For example, Havranek and Kokes (2015) found on average higher income elasticities for OECD countries than for developing ones, but there was so much imprecision surrounding their estimates that the differences they uncovered were not all statistically significant. Similarly, the data considered by Dahl (2012) distinguished between gasoline and diesel; however, the diesel-based data points were insufficient to draw significant conclusions regarding their differences compared to gasoline.

For the readers' reference, Table 1 indicates the average gasoline elasticities reported by the above surveys and meta-analyses. The long-run income elasticity has ranged from 0.7 to 1.2, and the long-run price elasticity has ranged from −0.6 to −0.9. The present paper differentiates between gasoline and diesel results, too. In a meta-type-analysis, Dahl (2012) developed suggested price elasticities from a database of previous (often country-specific) estimates of between −0.1 and −0.3 for gasoline and between −0.1 and 0.4 for diesel. Our results presented in Section 5 generally fall within these broad ranges, and key differences are discussed.

Meta-type studies are even more challenged in determining significant differences between subjects (e.g., end-use fuels/development levels) after controlling for important modeling and statistical concerns like employing a dynamic model and/or addressing nonstationarity, heterogeneity, and cross-sectional dependence. Indeed, we have seen no meta-studies that have been able to control for the concern regarding cross-sectional dependence even though this issue is of growing importance in both theoretical and applied

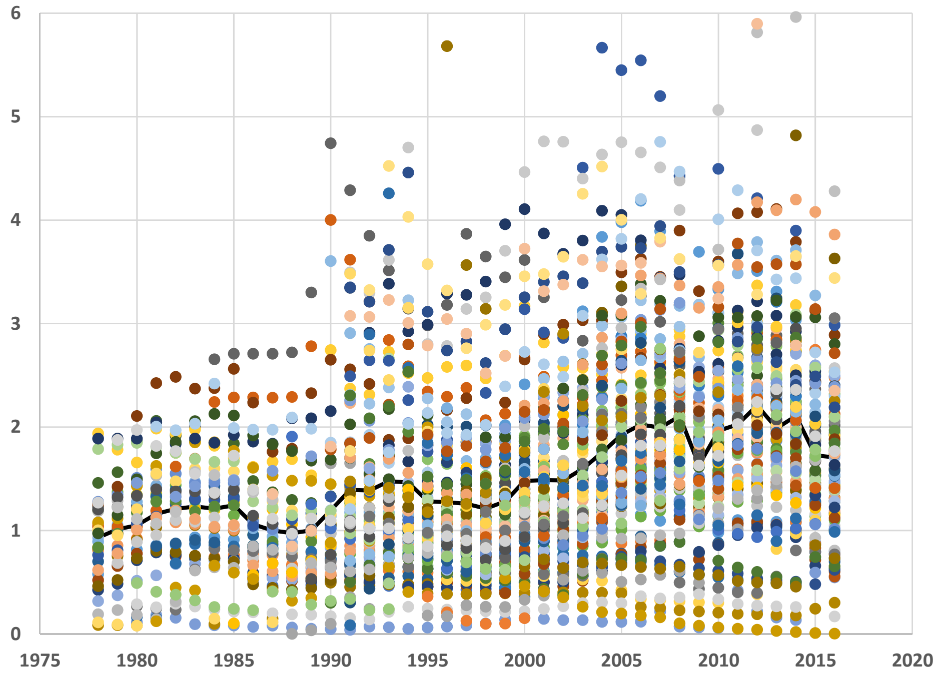


**Fig. 1b.** Country diesel prices (in 2015 USD at PPP per liter), 1978–2016. Solid line indicates average price for all countries in each year.

panel econometrics. In other words, Havranek and Kokes (2015) and Havranek et al. (2012) are certainly correct in pointing out and trying to adjust for publication bias, but the bias works in the opposite direction, too (not all published studies are of the highest quality, at least, not at the highest *current* quality standards). So, one of our most important contributions is to control for several crucial factors: (i) employing the current state-of-the-art-models and methods; and (ii) the same time, considering the largest panel—in terms of time and countries—to date.

In other words, our comprehensive evaluation should be viewed as both a complement to and an extension of these above efforts. We assemble a large data set as key inputs and directly derive the key estimates for responses to price and per-capita GDP rather than use the estimates done by other researchers. This approach allows us to standardize the data sample, the covered time horizon, and the econometric approach applied to every country's experience. At the same time, this approach allows us to assess the statistical difference among those price and income responses in regards to both (i) gasoline and diesel end-use and (ii) OECD/high-income and non-OECED countries.

## 3. Data

When estimating demand elasticities, price data typically are what constrain datasets. Real prices (in 2015 USD at PPP per liter) of premium gasoline and diesel are from Enerdata.[1] Premium gasoline prices are highly correlated with unleaded gasoline prices, as are diesel prices with commercial diesel prices. The prices for premium gasoline and diesel had by far the greatest degree of coverage. This data, while unbalanced, covers 1978–2016. Any country with at least 20 (yearly) price observations was included.

In any given year, countries can experience very different prices from the global average. Country prices by year for gasoline and diesel fuel can vary from well below $1 per liter to about $6 per liter, as shown by Figs. 1a and 1b, respectively. (For clarity, Figs. 1a and 1b show the wide dispersion of transport fuel prices without identifying all 118 countries individually.) This cross-country range is very large relative to the variation in the average prices for all countries over time, as indicated by the solid line in each figure.

Final consumption (in Mtoe) of diesel and motor gasoline for road transport was sourced from Enerdata as well. Real GDP per capita (in 2010 USD using PPPs) and population (to convert fuel consumption to per capita) are from the World Development Indicators database.[2]

The dataset comprises 118 countries, of which 35 are relatively rich and usually fully integrated with each other through international trade (which will be referenced as OECD or high income), and 83 are generally less wealthy countries (which will be referenced as non-OECD).[3] Of the non-OECD countries, according to the World Bank circa 2018, 58 are classified as middle-income

[1] Enerdata Global Energy & $CO_2$ database. https://www.enerdata.net/research/energy-market-data-co2-emissions-database.html

[2] For a few countries—Kuwait, Libya, Niger, Qatar, and Taiwan—GDP and population data were taken from Enerdata, too.

[3] Each country is classified to one country grouping for the full sample. See Appendix A for further discussion on the income/development classifications.

**Table 2**
Summary statistics for OECD and Non-OECD panels, 1978–2016.

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | All 118 Countries | | | | |
| GDP pc | 4394 | 16,327 | 19,730 | 288 | 192,428 |
| Price gas | 3460 | 2.03 | 1.09 | 0.017 | 8.67 |
| Price diesel | 3442 | 1.59 | 0.92 | 0.0002 | 5.96 |
| Gas pc | 4448 | 0.18 | 0.24 | 0.0004 | 1.52 |
| Diesel pc | 4323 | 0.16 | 0.27 | 0.0003 | 3.92 |
| | OECD (35 countries) | | | | |
| GDP pc | 1317 | 29,678 | 12,667 | 4914 | 91,500 |
| Price gas | 1276 | 1.76 | 0.77 | 0.43 | 7.21 |
| Price diesel | 1256 | 1.40 | 0.65 | 0.32 | 4.74 |
| Gas pc | 1317 | 0.35 | 0.29 | 0.014 | 1.52 |
| Diesel pc | 1317 | 0.31 | 0.37 | 0.035 | 3.92 |
| | Non-OECD (83 countries) | | | | |
| GDP pc | 3077 | 10,612 | 19,449 | 288 | 192,428 |
| Price gas | 2184 | 2.20 | 1.21 | 0.017 | 8.67 |
| Price diesel | 2186 | 1.70 | 1.03 | 0.0002 | 5.96 |
| Gas pc | 3131 | 0.11 | 0.17 | 0.0004 | 1.02 |
| Diesel pc | 3006 | 0.094 | 0.17 | 0.0003 | 1.72 |

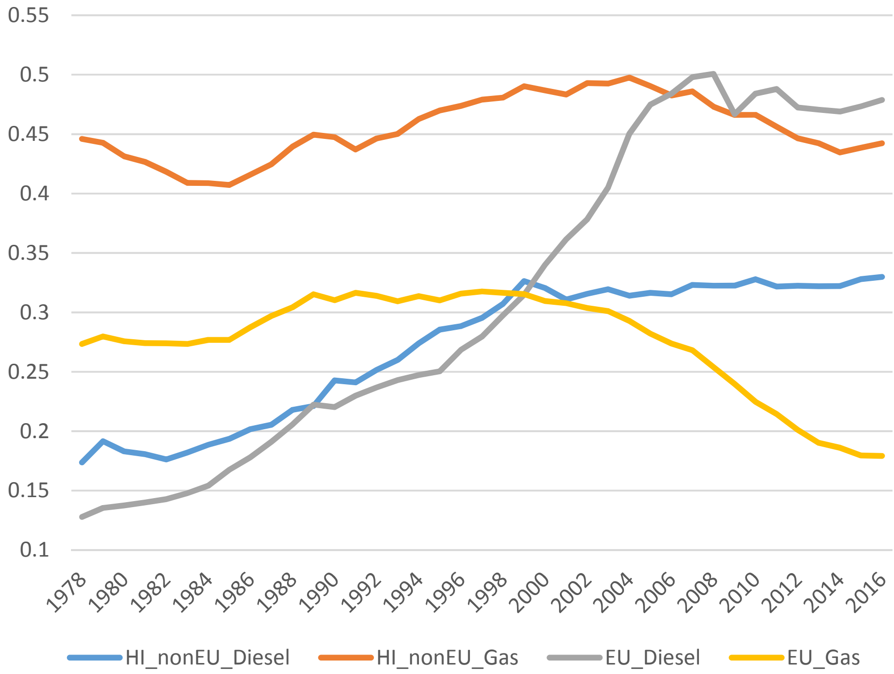


**Fig. 2a.** Average per capita diesel and gasoline consumption (in Mtoe/person) for nine high-income, non-European countries plus Greece and Slovakia (HI-nonEU) and 27 European countries (EU) that have substantial penetration of diesel vehicles in their passenger car fleets. Data are Mtoe/person for road transport and run from 1978 to 2016.

(which can be further separated into 32 upper-middle-income and 26 lower-middle-income), 20 as low-income (of which 18 are from Sub-Saharan Africa), and five are high-income, Gulf states (Bahrain, Kuwait, Qatar, Saudi Arabia, and United Arab Emirates).

Summary statistics are displayed in Table 2. The country-by-country coverage of the price variables is reported in Appendix Table A.1. Figs. 2a and 2b display per capita fuel consumption for various income/geographic groupings.

Diesel passenger cars have long been more popular in Europe than in North America; yet, after the Kyoto Protocol in 1997, many European governments instituted policies (both lowering the price of buying diesel cars as well as making the fuel cheaper compared to gasoline) to make diesel even more popular. For example, the share of diesel cars in the passenger car fleet for the EU28 increased from 27% in 2005 to over 42% in 2017, and for 10 countries diesel cars represented the majority of their fleet in 2017 (data from European Environment Agency). So, in displaying the average fuel consumption, we separate 27 European countries from nine high-income, non-European countries plus Greece and Slovakia, which still have relatively low penetration rates for passenger diesel cars. For

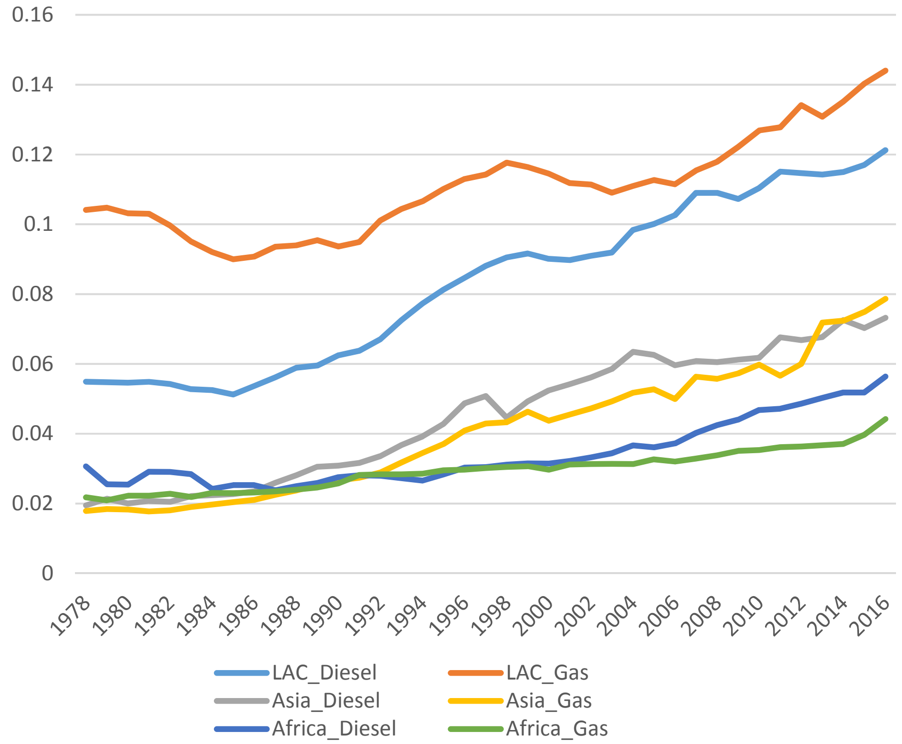


**Fig. 2b.** Average per capita diesel and gasoline consumption (in Mtoe/person) for 20 Latin America and Caribbean countries (LAC), 12 (middle- and low-income) Asian countries (Asia), and 34 African countries (Africa). Data are Mtoe/person for road transport and run from 1978 to 2016.

**Table 3**
Pesaran (2015) CD test and Correlation Coefficients, 118 Countries, 1978–2016, unbalanced.

| Variables | CD-test | Corr. coeff. | Abs. corr. coeff. |
|---|---|---|---|
| GDP pc | 271* | 0.55 | 0.73 |
| Price gas | 133* | 0.33 | 0.50 |
| Price diesel | 200* | 0.50 | 0.62 |
| Gas pc | 19* | 0.04 | 0.48 |
| Diesel pc | 191* | 0.38 | 0.59 |

[*] p-value < 0.001. Null hypothesis is weak cross-sectional dependence. Corr. coeff. = mean correlation coefficient; Abs. corr. coeff. = mean absolute value correlation coefficient All variables in natural logs.

the non-European group, gasoline consumption has fluctuated some but is roughly the same in 2016 as it was in 1978; diesel consumption increased until about 1999 but has been mostly steady since then (and is substantially smaller than gasoline consumption). For Europe, diesel consumption steadily increased until around 2007 and passed gasoline consumption in 1999, which has declined since then.

Fig. 2b shows average consumption for three other geographical groups. For each of Latin America and Caribbean, (non-high-income) Asia, and Africa, diesel and gasoline mostly move (upwards) together. For some groups, gasoline dominates; for others diesel does. The high share of diesel cars in the passenger fleet, however, is mostly a European phenomenon, so for most of the rest of the world, diesel predominately represents freight consumption.

### *3.1. Statistical characteristics of data*

When analyzing datasets like ours that have many cross-sections and at least 20 years of observations per cross-section—often referred to as long-panel (or at least moderately-long-panel) data, several important statistical and modeling issues are common regardless of the specific model used or research questions investigated. For example, statistical, data-based issues, like cross-sectional dependence and nonstationarity, and modeling issues, like dynamics and heterogeneity, need to be considered/addressed when working with long-panel data. Recently, Liddle and Huntington (2020a) and Liddle et al. (2020) worked on similarly structured datasets and used similar methods—but focused on economy-wide analysis, rather than transport; so, we draw on those papers for the

**Table 4**
Pesaran (2007) Panel Unit Root Test Results. 118 Countries, 1978–2016, unbalanced.

| Variables | Constant without trend | | | Constant with trend | | |
|---|---|---|---|---|---|---|
| | Number of lags | | | | | |
| | 0 | 1 | 2 | 0 | 1 | 2 |
| GDP pc | 1.000 | 1.000 | 1.000 | 0.244 | 0.000 | 0.001 |
| Price gas | 0.000 | 0.000 | 0.057 | 0.297 | 0.106 | 0.996 |
| Price diesel | 0.000 | 0.000 | 0.000 | 0.239 | 0.006 | 0.760 |
| Gas pc | 1.000 | 0.975 | 0.965 | 1.000 | 1.000 | 1.000 |
| Diesel pc | 0.000 | 0.000 | 0.024 | 0.624 | 0.909 | 1.000 |
| ΔGDP pc | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ΔPrice gas | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ΔPrice diesel | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ΔGas pc | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ΔDiesel pc | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Notes: P-values shown. Null hypothesis is the series is I(1). All variables in natural logs. Δ = first difference operator.

following discussions of statistical/data issues and modeling/estimation approaches.

For the variables we consider, cross-sectional correlation/dependence is expected because of, for example, macroeconomic linkages that manifest themselves through (i) global shocks (income/oil prices); (ii) institutional memberships like OECD and World Trade Organization; and (iii) technology transfer. The results of the Pesaran (2015) cross-sectional dependence (CD) test,[4] which employs the correlation coefficients between the time-series for each panel member, are shown in Table 3. For all five variables, the test rejected the null hypothesis of weak cross-sectional dependence at the highest level of significance. For each variable considered, the absolute value mean correlation coefficients ranged from 0.48 to 0.73 (see Table 3). For most variables, the absolute value mean correlation coefficient and the mean correlation coefficient are similar, suggesting nearly all countries are positively correlated. For gasoline consumption, however, the relatively small value for the mean correlation coefficient suggests that the correlations are a mix of negative and positive.

When the errors of panel regressions are cross-sectionally correlated, standard estimation methods can produce both inconsistent parameter estimates and incorrect inferences (Kapetanios et al. 2011). Thus, because cross-sectional dependence can impart bias problems as well as inefficiency, only making adjustments to the standard errors (e.g., via Driscoll and Kraay 1998) may not be sufficient.

The variables analyzed are also highly trending, stock-based variables, and thus, may be nonstationary—in other words, their mean, variance, and/or covariance with other variables change over time. The Pesaran (2007) panel unit root test for heterogeneous panels, which allows for cross-sectional dependence to be caused by a single (unobserved) common factor,[5] suggests that the variables are likely nonstationary in levels, but stationary in first differences (see Table 4). When ordinary least squares (OLS) regressions are performed on time-series (or on time-series cross-sectional) variables that are not stationary, then measures like R-squared and t-statistics are unreliable, and there is a serious risk of the estimated relationships being spurious if these non-stationary variables are not cointegrated (Kao, 1999; Beck et al., 2008).

## 4. Model and methods

Following previous transport analyses, we model per capita road fuel consumption as a function of the real price and real per-capita income. Since the same vehicles cannot run on both diesel and gasoline, we analyze the two fuel types separately. While ideally one would want vehicle stock data, restricting coverage to the few countries with such data severely limits the analysis to only a small subset of interesting country experiences. Indeed, the most complete data on vehicles-in-use we could find was from International Organization of Motor Vehicle Manufacturers. They have data for most countries; however, much of the data for non-OECD countries is of questionable quality, and the time-span is only 2005–2015—too short to employ our preferred methods. Furthermore, their data are for passenger cars only and do not distinguish between gasoline and diesel vehicles (which, at the least, is important for Europe); whereas, our consumption and price data are comprised from all road vehicles (i.e., passenger cars and trucks). Hence, we leave analyzing models that include vehicle stocks for future work.

Transport fuel use incorporates decisions both to purchase new vehicles and to use all owned vehicles. To incorporate the gradual adjustments imposed by new vehicles gradually replacing older vintages, we consider a dynamic, adjustment model whereby the lag of the dependent variable (fuel consumption per capita) is included on the right-hand-side along with income/GDP per capita, fuel price, and their one period lags:

$$ln\ Fuel_{it} = \alpha_i + \gamma_t + \beta_i^1 ln\ Fuel_{it-1} + \beta_i^2 ln\ GDP_{it} + \beta_i^3 ln\ price_{it} + \beta_i^4 ln\ GDP_{it-1} + \beta_i^5 ln\ price_{it-1} + \varepsilon_{it} \quad (1)$$

[4] This test is implemented via the Stata command xtcd, which was developed by Markus Eberhardt.
[5] This test is implemented via the Stata command pescadf, which was developed by Piotr Lewandowski.

where subscripts *it* denote the *i*th cross-section and *t*th time period, *Fuel* is either road gasoline or diesel consumption per capita, *GDP* is GDP per capita, and *price* is either premium gasoline or diesel price, $\alpha$ is a cross-sectional specific constant, $\gamma$ are common time effects, the $\beta$s are (potentially) cross-sectional specific coefficients to be estimated, and $\varepsilon$ is the error term.[6] So, the long-run GDP and price elasticities, respectively, are:

$$\frac{\beta^2 + \beta^4}{(1 - \beta^1)} \text{ and } \frac{\beta^3 + \beta^5}{(1 - \beta^1)} \tag{2}$$

We test at the *panel* level for the joint statistical significance of the two lagged independent variable terms (i.e., $\beta^4$ and $\beta^5$). Regardless of the outcome from that test, for robustness/completeness, we run the partial adjustment or ADL (1,0,0) model, which includes a lag of only the dependent variable, since the software routines we use do not allow for lag structure to vary across countries; yet, the ADL (1,0,0) model may fit (some) individual countries better than the ADL (1,1,1) model.

We think it is likely, however, that the relationships (i.e., elasticities) will not be the same for each country—i.e., there should be a substantial degree of heterogeneity. And if one mistakenly assumes that parameters are homogeneous (when the true coefficients of a dynamic panel in fact are heterogeneous), then all parameter estimates of the panel will be inconsistent, and inferences based on those coefficients could be very misleading (Pesaran and Smith 1995). Hence, we use a mean group-type estimator (MG) that first estimates cross-section specific regressions and then averages those estimated individual-country coefficients to arrive at panel coefficients (standard errors are constructed nonparametrically as described in Pesaran and Smith 1995).[7]

When using MG methods, there are two ways to calculate panel long-run parameters from a dynamic model.[8] First, one applies to Equation (2) the panel short-run estimates (which themselves are the average of the individual country short-run coefficients). Such an approach is referred to as the long-run average (LRA) and is the most common approach in the literature (standard errors are then computed via the Delta method). The second approach first computes the long-run coefficient for each country (again applying Equation (2)), and then computes the average (of country-long-run coefficients) to arrive at the panel coefficient. This average long-run (ALR) method is closer to the spirt of MG estimations since the panel long-run coefficient is directly based on the average of the individual country long-run coefficients.

The Pesaran (2006) Common Correlated Effects mean group (CCE) estimator accounts for the presence of unobserved common factors—i.e., cross-sectional dependence—by including in the regression cross-sectional averages of the dependent and independent variables, and it is robust to nonstationarity, cointegration, breaks, and serial correlation. The cross-sectional average terms can capture omitted variables, and like time dummies, they can account for temporary, global shocks. However, cross-sectional averages represent an improvement over time dummies in several ways. For example, cross-sectional averages can more easily capture multiple global shocks (e.g., shocks to GDP and shocks to oil prices) and are more likely to capture pervasive features of cross-sectional dependence (e.g., the phenomenon that OECD countries have very similar GDP *growth rates*).

The CCE estimator is not consistent in dynamic panels, however, since the lagged dependent variable is no longer strictly exogenous. Chudik and Pesaran (2015) demonstrated that the estimator becomes consistent again when additional $\sqrt[3]{T}$ lags (in our case, 2, for series with at least 20 years) of the cross-sectional means are included. Hence, we employ the Dynamic Common Correlated Effects (DCCE) estimator of Chudik and Pesaran (2015).[9] As diagnostic tests, we run on the regression residuals and report (i) the Pesaran CD test to determine the extent of cross-sectional dependence and (ii) the Pesaran CIPS test to confirm stationarity. As a final diagnostic, we consider a test based on Pesaran and Yamagata (2008), which compares the difference between coefficients obtained from a pooled, fixed effects regression with the coefficients obtained from the DCCE regression,[10] to confirm that the country-specific slopes/coefficients are not homogenous.[11]

Dynamic models estimated with panel data are subject to a downward bias, called the dynamic panel or Nickell bias. In the literature this bias is often addressed using the general methods of moments (GMM) estimator (e.g., Cialani and Mortazavi 2018), but GMM was designed for short T panels, and thus, does not necessarily handle nonstationarity. In addition, GMM was not intended to manage heterogeneity and cross-sectional dependence. Moreover, since the instrument count increases rapidly with time observations, Roodman (2009) warns that the risk of over-parameterization for GMM is great when T exceeds 10. Since this bias is on the order of 1/T (Nickell 1981), it can be mitigated by having many time observations.

Bruno (2005) determined that in unbalanced panels (like ours), the bias declines with average group (cross-section) size (i.e., the bias is not determined entirely by the shortest series). Beck and Katz (2009) claimed that with at least 20 time observations, applying bias correction (e.g., Kiviet 1995) is counter-productive; whereas, Judson and Owen (1999) were more conservative, recommending

[6] In supplemental Appendix D, we consider a model that includes cross-price elasticities for a Europe-only panel (i.e., countries for which there is high penetration of diesel vehicles in their passenger car fleets).

[7] Again, we draw on Liddle and Huntington (2020a) and Liddle et al. (2020) for the following discussion of long-panel data estimators.

[8] In both cases, we follow the standard practice of robust regressions (see Hamilton 1992), where outliers are weighted down in the calculation of averages.

[9] The Dynamic Common Correlated Effects estimator of Chudik and Pesaran (2015) is implemented via Stata command xtmg, which was developed by Markus Eberhardt.

[10] That test is implemented via Stata command xthst, which was written by Tore Bersvendsen and Jan Ditzen.

[11] Supplemental Appendix B analyzes a composite index of diesel and gasoline as a means to discuss the limitations of alternative estimators. The road fuel real price index is available via: https://ssrn.com/abstract=3552662.

**Table 5**
Road Gasoline, OECD and Non-OECD panels, Dynamic models, DCCE estimator.

| | OECD | | Non-OECD | |
|---|---|---|---|---|
| | ADL (1,0,0) | ADL(1,1,1) | ADL (1,0,0) | ADL(1,1,1) |
| GDP | 0.157*** | 0.329**** | 0.604**** | 0.607*** |
| | (0.048) | (0.068) | (0.13) | (0.18) |
| Price | −0.157**** | −0.199**** | −0.134**** | −0.114*** |
| | (0.020) | (0.030) | (0.031) | (0.035) |
| Fuel t-1 | 0.729**** | 0.751**** | 0.368**** | 0.340**** |
| | (0.024) | (0.036) | (0.059) | (0.066) |
| GDP t-1 | | −0.224*** | | 0.181 |
| | | (0.074) | | (0.13) |
| Price t-1 | | 0.055 | | −0.046 |
| | | (0.039) | | (0.038) |
| | Long Run | | | |
| GDP | 0.577*** | 0.420 | 0.956**** | 1.194*** |
| LRA | [0.214 0.939] | [−0.365 1.205] | [0.509 1.404] | [0.495 1.894] |
| ALR | 0.700**** | 0.560*** | 1.000**** | 1.153**** |
| | [0.358 1.042] | [0.179 0.941] | [0.566 1.434] | [0.603 1.703] |
| Price | −0.580**** | −0.580*** | −0.213**** | −0.243*** |
| LRA | [−0.755–0.405] | [−1.003–0.158] | [−0.316–0.110] | [−0.401–0.0837] |
| ALR | −0.730**** | −0.738**** | −0.247**** | −0.273*** |
| | [−0.921–0.538] | [−0.935–0.540] | [−0.356–0.138] | [−0.459–0.0869] |
| Obs (N) | 1206 (35) | 1206 (35) | 1887 (83) | 1798 (77) |
| RMSE | 0.030 | 0.028 | 0.053 | 0.047 |
| CIPS | I(0) | I(0) | I(0) | I(0) |
| CD;$\overline{\rho}$ | 8.0****; 0.057 | 4.6****; 0.032 | −0.2; −0.002 | −0.2; −0.002 |
| P-Y (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
LRA = long-run average, calculated directly from mean group panel results (standard errors computed via the Delta method).
ARL = average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).
Obs (N) = observations (cross-sections).
**Diagnostics**: RMSE = root mean squared error. CD; $\overline{\rho}$= Pesaran (2015) CD test statistic; corresponding mean correlation coefficient of the residuals. The null hypothesis is weak cross-sectional dependence. CIPS= Pesaran (2007) CIPS test on residuals; I(0) = stationary. P-Y= Pesaran and Yamagata (2008) p-value of adj. delta test statistic for slope homogeneity. The null hypothesis is slope coefficients are the same.

bias correction unless there are 30 time observations.[12] In addition to our shortest cross-sections having 20 years of data, our average OECD/high income country has 35 observations, and our average non-OECD country has 29. (Again, panel coverage is displayed in Appendix Table A.1.)

### 4.1. Modeling asymmetry

There has been interest in the idea that energy demand may react differently to price increases than to price decreases—i.e., price asymmetry—for some time, and that interest has particularly focused on transport (e.g., Gately 1992). One of the first papers to consider both income and price asymmetric effects on energy demand was Gately and Huntington (2002). Yet, the decomposition method taken by Gately and Huntington is problematic for our analysis that begins tracking price changes in 1979 from a data sample that begins in 1978. Price changes after 1978 largely ignore the historic price shocks of the 1970 s that were featured prominently in the Gately-Huntington discussion of structural changes that began in 1973. There is no reason to use the Gately-Huntington decomposition method when the data set covers price changes that start in 1979 rather than in the beginning of that decade. Their method was developed primarily to differentiate the response of price shocks during the 1970 s from other price movements. It is inappropriate to apply the same decomposition method to a different starting point, as argued by some researchers (Ryan and Plourde, 2002; Griffin and Schulman, 2005), unless there are convincing arguments that there were major structural transformations before and after the years when prices were peaking in their samples.

When covering years without major transformations, it is more straightforward and direct to follow the decomposition approach of Huntington (2010) and Frondel and Vance (2013) that decomposes, for example, fuel prices into *price*$^+$ and *price*$^-$, where

$$price^{+}_{it} = price_{it}, \text{if } \ price_{it} => price_{i(t-1),} \text{and } \ price^{+}_{it} = 0 \ \text{ otherwise.} \tag{3}$$

When *price*$^-$ is defined accordingly, then

[12] However, Pesaran et al. (1999) cautioned that bias correction to the short-run coefficients, because of the nonlinear transformation involved, can exacerbate the bias of the (transformed) long-run coefficients.

**Table 6**
Road Diesel, OECD and Non-OECD panels, Dynamic models, DCCE estimator.

| | OECD | | Non-OECD | |
|---|---|---|---|---|
| | ADL (1,0,0) | ADL(1,1,1) | ADL (1,0,0) | ADL(1,1,1) |
| GDP | 0.658**** | 1.061**** | 0.617*** | 0.744*** |
| | (0.10) | (0.15) | (0.22) | (0.25) |
| Price | −0.0887**** | −0.113*** | −0.107*** | −0.0845*** |
| | (0.022) | (0.040) | (0.035) | (0.031) |
| Fuel t-1 | 0.551**** | 0.542**** | 0.266**** | 0.191*** |
| | (0.055) | (0.058) | (0.055) | (0.058) |
| GDP t-1 | | −0.443*** | | −0.283 |
| | | (0.15) | | (0.17) |
| Price t-1 | | 0.011 | | −0.0684 |
| | | (0.035) | | (0.044) |
| | Long Run | | | |
| GDP | 1.465**** | 1.349*** | 0.841*** | 0.570 |
| LRA | [0.903 2.028] | [0.379 2.319] | [0.249 1.433] | [-0.171 1.311] |
| ALR | 1.696**** | 1.671**** | 1.034**** | 1.169**** |
| | [1.298 2.094] | [1.238 2.103] | [0.561 1.500] | [0.597 1.741] |
| Price | −0.197**** | −0.225* | −0.143*** | −0.189*** |
| LRA | [-0.305–0.0899] | [-0.458 0.0077] | [-0.241–0.0461] | [-0.321–0.0565] |
| ALR | −0.319*** | −0.349** | −0.139*** | −0.239*** |
| | [-0.519–0.119] | [-0.615–0.0841] | [-0.235–0.0422] | [-0.386–0.0914] |
| Obs (N) | 1186 (35) | 1186 (35) | 1839 (80) | 1779 (76) |
| RMSE | 0.051 | 0.047 | 0.090 | 0.078 |
| CIPS | I(0) | I(0) | I(0) | I(0) |
| CD;$\overline{\rho}$ | 0.9; 0.004 | 0.7; 0.003 | −0.7; −0.004 | −1.3; −0.006 |
| P-Y (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
LRA = long-run average, calculated directly from mean group panel results (standard errors computed via the Delta method).
ARL = average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).
Obs (N) = observations (cross-sections).
**Diagnostics**: RMSE = root mean squared error. CD; $\overline{\rho}$= Pesaran (2015) CD test statistic; corresponding mean correlation coefficient of the residuals. The null hypothesis is weak cross-sectional dependence. CIPS= Pesaran (2007) CIPS test on residuals; I(0) = stationary. P-Y= Pesaran and Yamagata (2008) p-value of adj. delta test statistic for slope homogeneity. The null hypothesis is slope coefficients are the same.

$$price_{it} = price_{it}^{+} + price_{it}^{-} \tag{4}$$

And when *GDP* is similarly decomposed, the ADL (1,0,0)/partial adjustment version Equation (1) is transformed to

$$ln\ Fuel_{it} = \alpha_i + \gamma_t + \beta_i^1 ln\ Fuel_{it-1} + \beta_i^2 ln\ GDP_{it}^{+} + \beta_i^3 ln\ GDP_{it}^{-} + \beta_i^4 lnprice_{it}^{+} + \beta_i^5 ln\ price_{it}^{-} + \varepsilon_{it} \tag{5}$$

This specification (Equation (5)) allows short-run asymmetry but ignores any lagged adjustment to price and income changes. Degrees of freedom become a problem with the CCE approach if we allow for both short and long run asymmetry in both price and income. We justify this specification because asymmetric price or quantity movements usually reflect short-run adjustment costs as consumers move to a new long-run equilibrium rather than different long-run conditions. Moreover, our estimates presented in the next section do not find any short-run asymmetry. It seems unlikely to have long-run asymmetry coincide with short-run symmetry.

## 5. Results and discussion

Table 5 displays the results for gasoline and the OECD and non-OECD country panels. For robustness/completeness both the ADL (1,1,1) and the partial adjustment, ADL (1,0,0) model results are shown. At the panel level, the joint test on the significance of the lagged GDP and price terms suggests that the ADL (1,1,1) specification is preferred for the OECD panel, whereas, the ADL (1,0,0) specification is preferred for the non-OECD panel. In all cases, the residuals are stationary; equal coefficients across countries is rejected at the highest level of significance, and for the non-OECD panel, weak cross-sectional dependence cannot be rejected. While weak cross-sectional dependence is rejected for the OECD panel,[13] the cross-sectional average terms appear to have mitigated

[13] In practice, OECD countries are so connected that it is very hard to remove evidence of strong cross-sectional dependence even when using CCE-type estimators (e.g., Eberhardt and Presbitero 2015; Liddle and Huntington 2020a).

**Table 7**
Road Gasoline and Diesel, OECD subpanels, Dynamic models, DCCE estimator.

| | Non-Europe OECD/high income | | | | High income Europe | | | |
|---|---|---|---|---|---|---|---|---|
| | Gas | | Diesel | | Gas | | Diesel | |
| | ADL (1 0 0) | ADL(1 1 1) | ADL (1 0 0) | ADL(1 1 1) | ADL (1 0 0) | ADL(1 1 1) | ADL (1 0 0) | ADL(1 1 1) |
| GDP | 0.161** | 0.307*** | 0.496** | 0.763* | 0.160** | 0.353**** | 0.700**** | 1.037**** |
| | (0.063) | (0.088) | (0.02072) | (0.46) | (0.076) | (0.082) | (0.117) | (0.128) |
| Price | −0.161**** | −0.128*** | −0.054 | 0.0073 | −0.154**** | −0.235**** | −0.108**** | −0.150*** |
| | (0.037) | (0.047) | (0.048) | (0.058) | (0.025) | (0.034) | (0.023) | (0.045) |
| Fuel t-1 | 0.737**** | 0.699**** | 0.447**** | 0.499**** | 0.726**** | 0.806**** | 0.621**** | 0.573**** |
| | | (0.064) | (0.10) | (0.109) | (0.030) | (0.041) | (0.055) | (0.071) |
| | (0.043) | | | | | | | |
| GDP t-1 | | −0.281** | | −0.360 | | −0.195** | | −0.391** |
| | | (0.117) | | (0.44) | | (0.098) | | (0.156) |
| Price t-1 | | −0.117** | | 0.019 | | 0.151**** | | 0.00903 |
| | | (0.052) | | (0.079) | | (0.037) | | (0.039) |
| GDP | 0.612** | 0.078 | 0.897** | 0.803 | 0.582** | 0.816 | 1.846**** | 1.511*** |
| LRA | (0.261) | (0.443) | (0.397) | (1.29) | (0.285) | (0.681) | (0.408) | (0.535) |
| ALR | 0.585** | 0.314 | 0.903* | 0.937** | 0.784*** | 0.720** | 1.984**** | 2.122**** |
| | (0.229) | (0.244) | (0.482) | (0.355) | (0.261) | (0.267) | (0.184) | (0.201) |
| Price | −0.612**** | −0.741*** | −0.097 | 0.052 | −0.560**** | −0.434 | −0.286**** | −0.329** |
| LRA | (0.173) | (0.255) | (0.089) | (0.196) | (0.110) | (0.278) | (0.0731) | (0.150) |
| ALR | −0.801**** | −0.871**** | −0.154 | −0.248 | −0.711**** | −0.659**** | −0.369*** | −0.384** |
| | (0.123) | (0.162) | (0.107) | (0.299) | (0.136) | (0.127) | (0.126) | (0.154) |
| RMSE | 0.035 | 0.033 | 0.060 | 0.056 | 0.28 | 0.026 | 0.045 | 0.042 |
| Obs (N) | 387 (11) | 387 (11) | 387 (11) | 387 (11) | 819 (24) | 819 (24) | 799 (24) | 799 (24) |

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses.
LRA = long-run average, calculated directly from mean group panel results (standard errors computed via the Delta method).
ARL = average long-run, individual country long-run coefficients are computed from mean group results; panel mean and standard errors are drawn from robust regression (on that series of country results).
RMSE = root mean squared error.
Obs (N) = observations (cross-sections).

dependence since the resulting mean correlation coefficients are relatively small (less than 0.1).[14]

Focusing on the long-run coefficients, the long-run average and average long-run calculations are mostly similar; however, for the OECD panel, the average long-run coefficients are larger than the long-run average coefficients, and for the ADL (1,1,1) model, the GDP elasticity is insignificant when the long-run average is considered, but highly significant when the average long-run is used. The GDP elasticities are all near one for the non-OECD panel, but are substantially smaller for the OECD panel—such a finding may be expected since the OECD countries are more likely to be near saturation in terms of vehicle ownership (indeed, Fig. 1a suggested saturation in terms of gasoline consumption). While the price elasticities are significant and negative for the non-OECD panel, the price elasticities are considerably larger, in absolute terms, for OECD countries—over −0.7 for the average long-run.

Table 6 displays the results for diesel. In this case, the chi-squared test on lagged GDP and prices suggested that the ADL (1,1,1) model was preferred for both panels; yet, for robustness/completeness both models are again shown. (The p-value of the chi-squared test for the non-OECD panel was 0.08.) For all four regressions, the residuals are stationary; weak cross-sectional dependence cannot be rejected, but equal coefficients are rejected. Again, like the results for gasoline, the long-run average and average long-run calculations are mostly similar, but, likewise, the average long-run produces larger absolute coefficients than the long-run average.

For the OECD diesel panel, the GDP elasticity is large (particularly compared to that for gasoline) and greater than unity; for the non-OECD diesel panel, the GDP elasticity is (typically) near unity (as it was for gasoline). For both OECD and non-OECD panels, the diesel price elasticity is negative and significant, but relatively smaller than it was for gasoline (-0.35 or less). In the case of diesel, the GDP elasticity is larger for OECD countries. In so far as the diesel consumption represents freight, the smaller price but larger (at least nearer to unity) GDP elasticities than gasoline makes intuitive sense. The freight industry would have costs beyond fuel (labor, capital), and so may not be overly sensitive to just fuel costs; whereas, the demand for freight would be highly correlated with the overall health/size of the economy.

Because of the importance of diesel vehicles in the passenger fleets of many/most European countries, we divide the 35 OECD countries into (1) the nine non-European countries plus Greece and Slovakia, and (2) the 24 European countries that have a high degree of diesel penetration in their passenger fleets (Appendix Fig. D.1 displays some data on the share of diesel in European countries' passenger car fleets). These results (for both gasoline and diesel) are shown in Table 7.

For gasoline, the average long-run elasticities reported previously in Table 5 (ADL(1,1,1) model) are effectively in between the

[14] In addition, supplemental Appendix C contains an analysis of a balanced panel that includes an additional residual cross-sectional dependence test. The results of that test reject strong cross-sectional dependence (in favor of semi-weak dependence).

elasticities for the two new groups in Table 7. The non-Europe group has the lower GDP elasticity and the higher (in absolute terms) price elasticity, thus, making the Table 5 gasoline results seem very much like a weighted average between OECD non-Europe and OECD Europe. However, the diesel results lead to different conclusions. The larger than unity income elasticity and relatively large, negative price elasticity for diesel reported in Table 6 are derived from the European countries (where diesel is used both for passenger vehicles and freight). For the non-European countries (Table 7), diesel's income elasticity is around unity, and the price elasticity is small (and insignificant)—results that suggest that diesel is primarily used for freight there. In other words, since European households represent a substantial share of road diesel consumers, the price elasticity is higher there than where diesel consumers are largely the freight industry, and the usually high (and typically growing) share of diesel vehicles in the European passenger fleet led to the unusually high income elasticity of greater than unity there.

The next two tables display regressions on several sub-panels of non-OECD countries. For simplicity/ease of presentation, only the ADL (1,0,0) model is shown, and the long-run average calculation is applied.[15]

The first column of Table 8 shows middle-income countries; in the next two columns, those countries are split into upper-middle and lower-middle income. The elasticities are mostly similar, except that the GDP elasticity is lower (and only marginally statistically significant) for the lower-middle income panel. The table displays further groupings that primarily are based on geography. For the panels of non-OECD Asia, Latin America and Caribbean (LAC), and Sub Saharan Africa (SSA), the results are similar for those of the middle-income panels—the GDP elasticity is near unity, and the price elasticity is in the range of −0.2 to −0.45. The model does not fit well at all for the former Soviet Union (FSU) and Middle East/North Africa (MENA) panels. Incidentally, those two groups contain the largest number of countries where oil revenues represent a substantial portion of the economy/exports. When countries with oil revenues of over 10% GDP (in 2014) are removed from the subpanels (other than FSU and MENA), the results are not appreciably different.

Table 9 displays mostly similar results for subpanels and road diesel. Exceptions for the GDP elasticity are: (1) the elasticity for the Asia panel is larger than that for gasoline, whereas, the elasticity for LAC is smaller; and (2) the elasticity is significant for FSU but insignificant for SSA. The price elasticities are very similar across subpanels, but are mostly insignificant; exceptions are significant coefficients for lower-middle income and SSA (but only marginally).

### 5.1. *Asymmetry analysis results*

Lastly, we present the results of the asymmetry analysis. We perform this analysis on the OECD and non-OECD panels. Since we analyze both income and price asymmetries at the same time, the number of cross-sectional average terms increases, and this reduction in degrees of freedom means cross-sections with fewer than 24 observations are dropped from a dynamic model. This loss of cross-sections is particularly acute for the non-OECD panel. Hence, the only dynamic model we consider is the ADL (1,0,0), and we run a static model (i.e., no lagged dependent variable and using the CCE estimator) as well.

Table 10 displays the difference between the increase and decrease series (for both GDP and price) as well as the p-value of that difference. The results indicate that the impact of changes in GDP and price since 1979 are highly symmetric for both OECD and non-OECD panels,[16] for both gasoline and diesel, and for both the ADL (1,0,0) and static models—indeed, the lowest p-value is around 0.5. This result of no asymmetries is mostly similar to Liddle and Sadorsky (2020), who focused on economy-wide energy consumption and OECD and non-OECD panels. Liddle and Sadorsky found some evidence of long-run price asymmetry for OECD countries (but found no other evidence of long-run asymmetries for either GDP or price).

## 6. Summary and conclusions

We analyzed road gasoline and diesel demand elasticities for particularly large panels of OECD and non-OECD countries—probably the largest such panels to date—and employed methods that address nonstationarity, heterogeneity, and cross-sectional dependence. While the mean group approach first analyzes each country separately, taking (weighted) panel averages of those 118 individual coefficients provides a relatively robust perspective on the responses to price and income since those ultimate panel estimates are based upon a wide range of fuel price and GDP experiences.

What can public policy learn from the conclusions emanating from the above analysis? We might summarize our preferred results with Table 11 below (this table excludes the subpanel results, i.e., Tables 7–9). For gasoline, the OECD price elasticity is around −0.7 or about twice that for non-OECD; whereas for diesel, the OECD price elasticity is only modestly larger (in absolute terms) than the non-OECD elasticity (but is around half what it is for gasoline). Also, for gasoline, the non-OECD GDP elasticity is around 1.0 or about twice that for OECD. For the OECD panel, the diesel GDP elasticity is about three times that of the GDP elasticity for gasoline—but this likely reflects the rapid increase of passenger diesel vehicles in Europe, which is unlikely to continue indefinitely (indeed, there is evidence of

[15] For each subpanel, the chi-squared test on the GDP and price lag terms suggested that the ADL (1,0,0) model was preferred at the panel level; however, in most cases, the results were not appreciably different if the ADL (1,1,1) model was run.

[16] Data availability for fuel consumption and price changes limited our analysis to periods beginning in 1979. Gately and Huntington (2002) found larger gasoline consumption responses in the OECD to price changes during the 1970s than during later periods. Hughes et al (2008) report similar findings for the United States. In contrast, asymmetries are seldom found for countries outside the OECD regardless of the sample period. See, e.g., Gately and Huntington (2002). In the current analysis, highly *symmetric* (price and income) elasticities were found for UMI and LMI panels (and for both gasoline and diesel) as well. These results are shown in supplemental Appendix Table E.1.

**Table 8**
Road Gasoline, ADL(1,0,0) model, DCCE estimator, Non-OECD subpanels.

| | MI | UMI | LMI | Asia | LAC | FSU | MENA | SSA |
|---|---|---|---|---|---|---|---|---|
| GDP | 0.615**** | 0.773**** | 0.450* | 0.554*** | 0.977*** | 0.194 | 0.104 | 0.757*** |
| | (0.16) | (0.21) | (0.241) | (0.21) | (0.28) | (0.403) | (0.101) | (0.27) |
| Price | −0.130**** | −0.112** | −0.156*** | −0.199**** | −0.109** | −0.184 | −0.036 | −0.216*** |
| | (0.037) | (0.054) | (0.052) | (0.043) | (0.046) | (0.15) | (0.061) | (0.072) |
| Fuel t-1 | 0.404**** | 0.411**** | 0.378*** | 0.562**** | 0.350**** | 0.228 | 0.715**** | 0.282** |
| | (0.062) | (0.076) | (0.11) | (0.11) | (0.090) | (0.225) | (0.097) | (0.11) |
| | Long Run | | | | | | | |
| GDP | 1.033**** | 1.312*** | 0.722* | 1.266** | 1.502*** | 0.252 | 0.366 | 1.056** |
| | [0.480 1.585] | [0.542 2.081] | [−0.0781 1.521] | [0.149 2.382] | [0.532 2.472] | [−0.782 1.285] | [−0.373 1.105] | [0.249 1.862] |
| price | −0.218*** | −0.191** | −0.251*** | −0.454*** | −0.167** | −0.239 | −0.126 | −0.301*** |
| | [−0.349–0.088] | [−0.378–0.0035] | [−0.435–0.067] | [−0.740–0.168] | [−0.314–0.020] | [−0.648 0.171] | [−0.554 0.303] | [−0.519–0.0839] |
| RMSE | 0.051 | 0.037 | 0.064 | 0.040 | 0.033 | 0.069 | 0.046 | 0.066 |
| Obs (N) | 1374 (58) | 747(32) | 627 (26) | 345 (12) | 430 (20) | 192 (10) | 361 (14) | 619 (30) |

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
Long-run calculated directly from mean group panel results (standard errors computed via the Delta method).
MI = middle-income; UMI = upper middle-income; LMI = lower middle-income; LAC = Latin America & Caribbean; FSU = former Soviet Union; MENA = Middle East/North Africa; SSA = sub-Saharan Africa.
RMSE = root mean squared error.
Obs (N) = observations (cross-sections).

**Table 9**
Road Diesel, ADL(1,0,0) model, DCCE estimator, Non-OECD subpanels.

| | MI | UMI | LMI | Asia | LAC | FSU | MENA | SSA |
|---|---|---|---|---|---|---|---|---|
| GDP | 0.751**** | 0.786**** | 0.747* | 0.920**** | 0.608*** | 0.932** | 0.314 | 0.206 |
| | (0.16) | (0.15) | (0.39) | (0.21) | (0.19) | (0.42) | (0.29) | (0.52) |
| Price | −0.0966*** | −0.043 | −0.133** | −0.0767 | −0.076 | −0.297 | −0.051 | −0.134* |
| | | (0.034) | (0.055) | (0.068) | (0.089) | (0.20) | (0.040) | (0.070) |
| Fuel t-1 | 0.267**** | 0.219*** | 0.349**** | 0.477**** | 0.214*** | 0.180 | 0.608**** | 0.098 |
| | (0.052) | (0.065) | (0.086) | (0.094) | (0.080) | (0.16) | (0.082) | (0.11) |
| | Long Run | | | | | | | |
| GDP | 1.024**** | 1.006**** | 1.147* | 1.761*** | 0.774*** | 1.136** | 0.801 | 0.228 |
| | [0.567 1.480] | [0.590 1.421] | [−0.060 2.354] | [0.762 2.760] | [0.264 1.284] | [0.0317 2.241] | [−0.693 2.295] | [−0.911 1.367] |
| price | −0.132*** | −0.055 | −0.204** | −0.147 | −0.097 | −0.362 | −0.129 | −0.149* |
| | [−0.229–0.0350] | [−0.142 0.032] | [−0.379–0.0302] | [−0.408 0.114] | [−0.320 0.126] | [−0.859 0.135] | [−0.335 0.076] | [−0.304 0.0064] |
| RMSE | 0.078 | 0.078 | 0.078 | 0.076 | 0.041 | 0.062 | 0.14 | 0.090 |
| Obs (N) | 1371 (57) | 749 (31) | 622 (26) | 351(12) | 433 (20) | 192 (10) | 358 (14) | 565 (27) |

Notes: ****, ***, **, * indicate statistical significance at the 0.001, 0.01, 0.05, and 0.1 levels, respectively. Standard errors in parentheses. 95% confidence intervals shown in brackets for the long-run coefficients.
Long-run calculated directly from mean group panel results (standard errors computed via the Delta method).
MI = middle-income; UMI = upper middle-income; LMI = lower middle-income; LAC = Latin America & Caribbean; FSU = former Soviet Union; MENA = Middle East/North Africa; SSA = sub-Saharan Africa.
RMSE = root mean squared error.
Obs (N) = observations (cross-sections).

**Table 10**
Tests for asymmetric income and price responses. Road gasoline and road diesel, partial adjustment and static models, OECD and non-OECD panels.

| | Gasoline | | Diesel | |
|---|---|---|---|---|
| | ADL (1,0,0) | Static | ADL (1,0,0) | Static |
| | OECD countries | | | |
| $GDP^{+} – GDP^{-}$ | 0.0005 (0.99) | −0.002 (0.99) | −0.001 (0.99) | −0.002 (0.99) |
| $Price^{+} – Price^{-}$ | 0.002 (0.96) | 0.05 (0.56) | −0.03 (0.50) | −0.002 (0.98) |
| Obs (N) | 1062 (30) | 1229 (35) | 1062 (30) | 1229 (35) |
| | Non-OECD countries | | | |
| $GDP^{+} – GDP^{-}$ | 0.06 (0.76) | 0.08 (0.60) | 0.05 (0.84) | 0.1 (0.54) |
| $Price^{+} – Price^{-}$ | −0.03 (0.60) | 0.006 (0.91) | −0.002 (0.98) | 0.05 (0.45) |
| Obs (N) | 943 (32) | 2094 (82) | 943 (32) | 2094 (82) |

Notes: Difference in up and down coefficient shown. P-value of difference in parentheses.
Obs (N) = Observations (cross-sections).
ADL (1,0,0) model run with DCCE estimator. Static model run with CCE estimator.

**Table 11**
Summary of preferred long-run elasticity results, OECD and non-OECD panels.

| | GDP | Price | Model Type |
|---|---|---|---|
| OECD gasoline | 0.56** | −0.74** | ADL(1,1,1) |
| Non-OECD gasoline | 1.00** | −0.25** | ADL(1,0,0) |
| OECD diesel | 1.67** | −0.35* | ADL(1,1,1) |
| Non-OECD diesel | 1.17** | −0.24** | ADL(1,1,1) |

Notes: ** and * indicate statistical significance at the 0.01 and 0.05 or higher levels, respectively.

a policy shift that will favor electric vehicles in the future). On the other hand, for the non-OECD panel, the two (gasoline and diesel) GDP elasticities are about the same (i.e., near unity). Similarly, the two price elasticities—gasoline and diesel—are nearly the same for the non-OECD panel.

To further summarize results: for non-OECD countries, subpanels based on geography and income produced mostly similar coefficients. Also, we found no evidence of GDP or price asymmetric effects for either OECD or non-OECD panels, although our sample excludes much of the world oil price shocks of the 1970s.

Our approach emphasizes the value of considering price and income responses simultaneously rather separately as done in several surveys and meta analyses covered in Section 2. Again, from the summary provided by Table 11, the average long-run price elasticities for gasoline within the OECD is quite high, suggesting that gasoline taxes or other policies that raise gasoline prices in these countries should be more effective in curtailing this demand than elsewhere. A tax that raised gasoline prices by 0.76% would be needed to offset each 1% growth in real OECD GDP in order to keep demand from growing.[17] The other fuels—diesel in OECD and both fuels in non-OECD—would require much larger taxes to accomplish the same goal. Taxes would need to increase fuel prices by 4.00% to 4.88% for each 1% growth in real GDP.

We hypothesized that the difference between gasoline and diesel results for the non-Europe, high-income panel might reflect that diesel is used there more for freight than for personal transport. Yet, the gasoline and diesel results did not differ much for the non-OECD panel. Whether that non-OECD result suggests that for those countries a similar difference between freight and personal transport does not exist or that passenger fuel consumption is far from saturation will require more data/time. Similarly, the analysis could be improved if/when time-series data for diesel and gasoline vehicle stocks could be included.

Lastly, the price elasticities reported here—statistically significant for non-OECD countries and significant and large in the case of gasoline for OECD countries—provide stark contrast to (i) two recent *economy-wide energy* price elasticity estimates and (ii) two recent *sectorial electricity* price elasticity estimates. Considering those economy-wide energy estimates, price elasticities for non-OECD panels were highly insignificant (Liddle and Huntington, 2020a; Liddle et al., 2020), and price elasticities for OECD panels were only around −0.2 (Liddle and Huntington 2020a). As for the sectorial estimates, price elasticities for residential electricity demand were −0.22 for high-income panels and −0.08 for middle-income panels (Liddle and Huntington, 2020b); whereas, price elasticities for industry electricity demand were −0.25 for high-income panels and highly insignificant for middle-income panels (Liddle and Hasanov 2020).

## CRediT authorship contribution statement

**Brantley Liddle:** Conceptualization, Methodology, Formal analysis, Data curation, Writing - original draft, Writing - review &

[17] Holding constant all other factors, each one percent growth in real GDP would raise gasoline consumption by 0.56%, which could be eliminated by a price increase of 0.76% (=. 0.56/0.74).

editing. **Hillard Huntington:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Income/development classification and price data coverage

In classifying countries (as either OECD/High-income or non-OECD), we believe that both income-level achieved and institutional membership(s) are important. So, for example, we list OECD, middle-income Mexico and Turkey as non-OECD. Yet, some additional judgements had to be made. For example, Chile, an OECD member since 2010 and classified as high-income by the World Bank since 2012, is listed as non-OECD; whereas, Estonia, Latvia, and Lithuania, all of whom achieved those two distinctions at more or less similar times as Chile, are listed as OECD/High-income because those Baltic countries have been European Union members since 2004. The following Appendix Table A.1 displays the price data coverage grouped by our preferred OECD/non-OECD classification.

**Table A1**
Dataset Coverage for Road Gasoline and Diesel.

| Country | Obs | Coverage | Country | Obs | Coverage | Country | Obs | Coverage |
|---|---|---|---|---|---|---|---|---|
| | | | OECD/High-income | | | | | |
| Australia | 39 | 1978–2016 | Hong-Kong | 27 | 1990–2016 | Poland | 39 | 1978–2016 |
| Austria | 39 | 1978–2016 | Hungary | 39 | 1978–2016 | Portugal | 39 | 1978–2016 |
| Belgium | 39 | 1978–2016 | Ireland | 39 | 1978–2016 | Slovakia | 39 | 1978–2016 |
| Canada | 39 | 1978–2016 | Israel | 31 | 1986–2016 | Slovenia | 22 | 1995–2016 |
| Cyprus | 39 | 1978–2016[1] | Italy | 39 | 1978–2016 | South Korea | 39 | 1978–2016 |
| Czech Rep. | 39 | 1978–2016 | Japan | 39 | 1978–2016 | Spain | 39 | 1978–2016 |
| Denmark | 39 | 1978–2016 | Latvia | 22 | 1995–2016 | Sweden | 39 | 1978–2016 |
| Estonia | 22 | 1995–2016 | Lithuania | 22 | 1995–2016 | Switzerland | 39 | 1978–2016 |
| Finland | 39 | 1978–2016 | Luxembourg | 38 | 1979–2016 | Taiwan | 39 | 1978–2016 |
| France | 39 | 1978–2016 | Netherlands | 39 | 1978–2016 | United Kingdom | 39 | 1978–2016 |
| Germany | 39 | 1978–2016 | New Zealand | 39 | 1978–2016 | United States | 39 | 1978–2016 |
| Greece | 39 | 1978–2016 | Norway | 39 | 1978–2016 | | | |
| | | | Non-OECD (includes some high-income Gulf states) | | | | | |
| Algeria | 21 | 1996–2016 | Guatemala | 21 | 1996–2016 | Pakistan | 39 | 1978–2016 |
| Argentina | 33 | 1981–2016ˆ | Haiti | 20 | 1996–2016ˆ | Panama | 21 | 1996–2016 |
| Armenia | 21 | 1995–2016ˆ | Honduras | 21 | 1996–2016 | Paraguay | 21 | 1996–2016 |
| Bahrain | 20 | 1996–2016ˆ | India | 39 | 1978–2016 | Peru | 26 | 1991–2016 |
| Bangladesh | 22 | 1995–2016 | Indonesia | 39 | 1978–2016 | Philippines | 39 | 1978–2016 |
| Benin | 21 | 1992–2016ˆ | Iran | 37 | 1980–2016 | Qatar | 37 | 1980–2016 |
| Bolivia | 33 | 1981–2016ˆ | Ivory Coast | 31 | 1978–2016ˆ | Romania | 27 | 1990–2016 |
| Botswana | 22 | 1991–2016ˆ | Jamaica | 21 | 1996–2016 | Russia | 24 | 1993–2016 |
| Brazil | 29 | 1988–2016 | Jordan | 21 | 1995–2015 | Saudi Arabia | 28 | 1978–2016ˆ |
| Burkina Faso | 23 | 1991–2016ˆ | Kazakhstan | 21 | 1996–2016 | Senegal | 26 | 1991–2016 |
| Burundi | 22 | 1991–2016ˆ | Kenya | 26 | 1991–2016 | Sierra Leone | 21 | 1991–2014ˆ |
| Cameroon | 26 | 1991–2016 | Kuwait | 37 | 1980–2016 | South Africa | 39 | 1978–2016 |
| Central African Rep. | 22 | 1991–2016ˆ | Lao PDR | 20 | 1990–2016ˆ | Sri-lanka | 38 | 1978–2016ˆ |
| Chad | 25 | 1991–2016ˆ | Lebanon | 21 | 1990–2016ˆ | Sudan | 24 | 1991–2016ˆ |
| Chile | 23 | 1994–2016 | Libya | 35 | 1980–2014 | Swaziland[2] | 22 | 1991–2016ˆ |
| China | 23 | 1994–2016 | Malawi | 21 | 1991–2014 | Tanzania | 25 | 1991–2016ˆ |
| Colombia | 31 | 1981–2016ˆ | Malaysia | 39 | 1978–2016 | Thailand | 39 | 1978–2016 |
| Congo DR | 26 | 1991–2016 | Mali | 22 | 1991–2016ˆ | Togo | 22 | 1991–2016ˆ |
| Costa Rica | 21 | 1996–2016 | Mauritania | 26 | 1991–2016 | Tunisia | 24 | 1993–2016 |
| Croatia | 22 | 1995–2016 | Mexico | 39 | 1978–2016 | Turkey | 39 | 1978–2016 |
| Dominican Rep. | 20 | 1996–2015 | Mongolia | 20 | 1996–2016ˆ | Uganda | 26 | 1987–2016ˆ |
| Ecuador | 21 | 1996–2016 | Morocco | 31 | 1981–2015ˆ | United Arab Emirates | 38 | 1979–2016 |
| Egypt | 26 | 1990–2016ˆ | Mozambique | 25 | 1991–2016ˆ | Uruguay | 21 | 1996–2016 |
| El Salvador | 21 | 1996–2016 | Namibia | 22 | 1991–2016ˆ | Uzbekistan | 21 | 1995–2016ˆ |
| Ethiopia | 26 | 1991–2016 | Nepal | 22 | 1991–2016ˆ | Venezuela | 36 | 1981–2016 |
| Gabon | 21 | 1991–2016ˆ | Nicaragua | 21 | 1996–2016 | Vietnam | 22 | 1995–2016 |
| Gambia | 20 | 1991–2016ˆ | Niger | 31 | 1980–2015ˆ | Zambia | 21 | 1991–2014ˆ |
| Ghana | 28 | 1989–2016 | Nigeria | 37 | 1980–2016 | | | |

Notes: ˆ observations for some years missing. Obs = observations.
[1] Diesel price data for Cyprus run from 1998 to 2016.
[2] Name changed to eSwatini in 2018.

## Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2020.10.015.

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