Why don't agricultural prices always adjust towards parity?*

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Abstract: A prominent empirical regularity is the incomplete pass-through of exchange rate changes to domestic price changes, which reflects the failure of the purchasing power parity doctrine. We argue that such disconnection can be explained by the non-linear mean reversion dynamics of exchange rates: As a consequence of various trade barriers, there is a sizeable buffer region, a "band of inaction", within which exchange rates can move independently of prices, thus generating large and persistent deviations from parity. When examining panels of large numbers of disaggregated and tradable agricultural products with a non-linear exchange rate specification, we observe relatively fast adjustment speeds whenever deviations are sufficiently large so as to induce arbitrage. On the other hand, when deviations fall within the band of inaction, there is evidence that movements in rates follow a random walk. Additionally, the speed of adjustment is asymmetric, in the sense that positive deviations are adjusted faster than negative deviations.

JEL classification: F31, F41, F47

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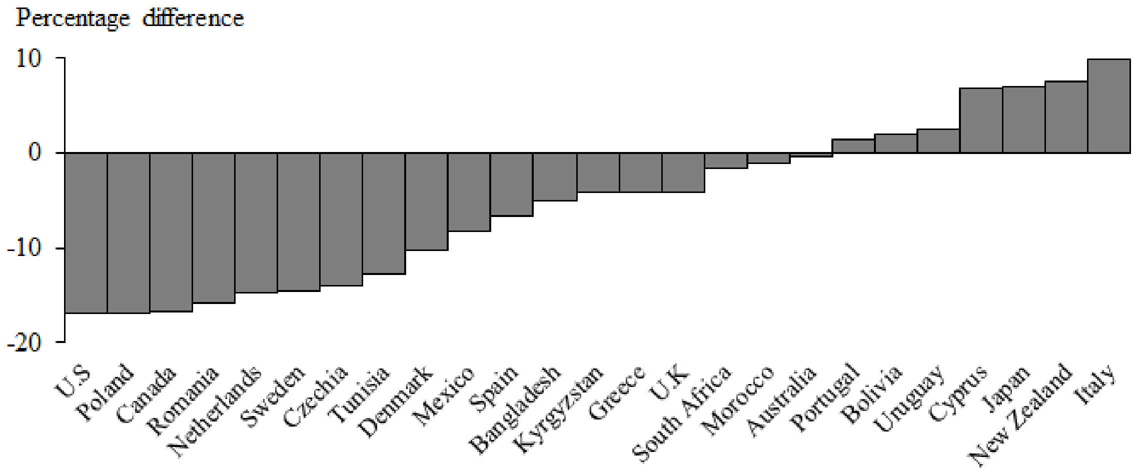
1. Introduction

For a highly traded agricultural product, changes in the domestic prices should reflect changes in the world price, once adjusted for currency changes. The underlying mechanism is a no-arbitrage condition that comes about by buying where the price is low and selling where it is high. But as can be clearly seen from the figure below, agricultural price differences across countries can be surprisingly large.[1]

Figure 1.1: Wheat price differentials, 2013, selected countries



Notes: This figure presents the percentage difference between domestic prices and the world price of a tonne of wheat, all expressed in USD, for 25 selected countries in 2013. The world price is measured as a weighted average of export prices (to be discussed). Data sources: FAO, 2017b and IMF, 2017.

The idea of international price equalization when prices are expressed in a common currency is encapsulated in the purchasing power parity (PPP) theory, which enjoys wide consensus as a long-run guidance of exchange rates. Price equalization depends crucially on the efficiency of market arbitrage, to which trade barriers (both natural and man-made) are an impediment, especially in sectors such as agriculture and clothing.[2] Recent estimates from World Bank indicate that liberalization of agricultural trade constitutes 63 percent of total world gains from free trade, compared with only 14 percent from clothing and 23 percent from other sectors (Anderson & Martin, 2005). Such large agricultural trade barriers is our

[1] It should be acknowledged that though efforts are made by the data provider, the FAO, to control for commodity grade differences and facilitate cross-country price comparisons, such differences might still exist.

[2] Despite the fall of global average tariff rate after 9 rounds of trade negotiations (even with the apparent failure of the last round at Doha) to approximately less than 6% (WTO, 2017), non-tariff distortions to agriculture trade remain substantial. Examples are the long-standing import restrictions of Japan leading to prices of rice, beef and other foods several times as high as world prices and Europe massive export subsidies under the Common Agricultural Policy (Krugman et al., 2018, Chapter 10).

motivation to study the reasons behind deviations from PPP. Specifically, we are interested in addressing the mechanism through which trade barriers cause a "disconnection" between economic fundamentals, in this case equalization of price levels, and currency values (Flood & Rose, 1999). This is related to the "PPP puzzle" – the difficulty in re-conciliating the high short-term variability of exchange rates and the slow rate of adjustment toward parity, as proposed by Rogoff (1996).

According to Manzur (2017), there are two prominent research streams seeking to address the PPP puzzle: One studies data spanning a long period of time (often more than a century) to augment the power of tests for the stationarity of PPP deviations (see e.g. Lothian & Taylor, 1996; Rapach & Wohar, 2002 and Taylor, 2002) and the other investigates possible non-linear dynamics of the adjustment process (Obstfeld & Taylor,1997; Taylor, 2001; Van Dijk et al., 2002). While the first is limited by the availability of long historical time series of prices and exchange rates, the second approach exhibits greater potential, as it relies mainly on the development of new non-linear econometric frameworks, which is documented to grow quickly (for a review, see Teräsvirta & Case, 2017).

In this paper, we focus on the second approach, and show that price deviations follow a non-linear autoregressive process. Specifically, when price deviations from parity fall within a no-arbitrage band, there is no incentive for arbitrage and the deviations follow a random walk. However, when price deviations become sufficiently large, arbitrage is profitable over time, and induce adjustments toward PPP. Our primary finding, similar to those of previous non-linear PPP studies, is that the speed of adjustment depends on the size of the deviation from PPP. However, an important innovation of our model is that it allows for different adjustment speeds for positive and negative deviations (outside of the band), instead of constraining them to be the same.[3] Indeed, the speed of adjustment is found to be faster than that reported in conventional PPP research, and positive deviations adjust faster than negative deviations.

Three distinct contributions are made in this study. First, we provide a unification of three foundations of exchange rate economics, namely, (i) conventional PPP theory (Cassel, 1918), (ii) the international trade cost models (Dornbusch, 1980 and Anderson & van Wincoop, 2003),

[3]A possible explanation for this behaviour is that the majority of currency interventions are implemented when currencies are overvalued (for instance, to maintain export competitiveness). Active exchange rate management with a strong bias towards preventing appreciation – a "fear of appreciation" – and its impact on growth, is documented in Levy-Yeyati et al. (2013).

and (iii) the more recent no-arbitrage band approach to modelling exchange rates (Taylor, 2001 and Obstfeld & Taylor,1997). Second, we examine the linearity (or otherwise) of exchange rate dynamics across a much larger number of countries and commodities than employed in previous PPP research.[4] Third, direct estimates of trade costs can be derived from this model.

The rest of the paper is organised as follows: Section 2 briefly reviews the recent developments in PPP research. A broad discussion on the interrelation between traditional PPP frameworks and the non-linear adjustment approach is the topic of section 3. Section 4 discusses our data and the related issues of measuring agricultural prices and provides a preliminary examination of the relative prices' stationarity. Section 5 describes the estimation procedures of our model, from which the empirical results are reported in section 6. Section 7 provides robustness checks with a bootstrap simulation analysis and section 8 concludes.

2. Literature review

To cover the vast literature on PPP is nothing short of an epic task. Nevertheless, Lothian (2016) provides a recent historical review documenting evidence for PPP throughout multiple exchange rate regimes, since as far back as the early 19th century.[5] But as Taylor (2006) points out, professional confidence in PPP has gone in and out of favour in quick succession during recent decades. Comprehensive surveys of this "mean-reverting" pattern of economic thought can be found in the collections of seminal articles compiled by Manzur (2008) and Taylor & Manzur (2013). For earlier surveys, see also Officer (1976), Frenkel & Johnson (1978) and Froot & Rogoff (1995).

If PPP holds in the long-run, relative prices (i.e. differences between domestic and world prices) should follow a stationary process. Therefore, the test for PPP's validity is to some extent linked with the development of stationary tests in time-series econometrics. Univariate and multivariate unit root tests (i.e., the ADF, PP and KPSS tests) in general yield mixed evidence regarding PPP. This is attributed to the low test power, particularly in small samples

[4] We study the producer prices for 130+ disaggregated agricultural commodities from 160+ countries. As we adopt the point of view that arbitrage is the driving force of price equalization, emphasis is placed on examining the actual transaction prices of goods, rather than price indices. The choice of prices to study PPP ultimately depends on the views on the nature of the mechanism governing PPP: Traded good prices should be used when commodity arbitrage is considered the primary factor, whereas if asset market equilibrium is the underlying factor, the use of price indices is more appropriate (Frenkel, 1978).

[5] A prominent early advocate of PPP is Cassel (1918), but according to Sarno & Taylor (2002), the foundation of PPP as a theory of exchange rates goes back to the 1500s, when scholarly activity took place at the Salamanca University of Spain.

(Abuaf & Jorion, 1990). The "first generation" of panel unit root tests developed in the 90s seek to enhance test power and yield stronger evidence of stationarity (Frankel & Rose, 1996; Jorion & Sweeney, 1996; Wu, 1996 and Levin et al., 2002). Yet, the support for PPP seems to disappear once serial correlation (Papell, 1997) and cross-sectional dependence (O'Connell, 1998) of error terms are controlled for. The "second generation" of panel unit root tests for heterogeneous panels deal with these issues, either by using orthogonalization procedures to asymptotically eliminate the cross-dependence of the series (Phillips & Sul, 2003; Bai & Ng, 2004; Moon & Perron, 2004), by employing a Fisher-type combination of individual tests (Choi, 2001; Breitung & Das, 2005; Demetrescu et al., 2006) or by augmenting the standard tests for individual series with current and lagged cross-section averages of all series (Pesaran, 2007). All these tests again yield mixed results regarding the long-run validity of PPP, though supporting evidence seems to be prevalent (Taylor & Manzur, 2013).

Possibly a new approach, a "third generation" of panel models, is needed to account for the documented large and persistent deviations from PPP. Obstfeld & Taylor (1997) made a first step toward that goal, by proposing a simple threshold specification to model the behaviour of relative prices, which is then modified by Parsley & Wei (2007). This approach emphasizes the role of arbitrage costs in determining a non-linear adjustment process. Specifically, these costs lead to a "band of no-arbitrage", within which the exchange rate could behave as a random walk with persistent PPP deviations. Once outside the no-arbitrage band, the force of arbitrage drives the rate back to the band a relatively fast convergence speed. Taylor (2001) shows that should a standard linear model is applied to such a non-linear process, estimates of convergence speed will be biased toward zero and half-life estimates biased upwards, hence the glacial adjustment speeds documented in previous research.

Alternative non-linear models have also been on the rise, involving more regimes as well as smooth/sharp transitions. Manzur (2017) shows that several variants of the threshold autoregressive (TAR) and smooth transition autoregressive (STAR) models yield adjustment speeds much higher than those derived from linear models. Balke & Fomby (1997), Lo & Zivot (2001), Wu & Chen (2008) and Nam (2011) all adopt a threshold vector error correction framework and find that the rate of convergence depends on whether the deviation is inside or outside a band. Sollis (2009)'s STAR model supports asymmetric adjustment speeds that are dependent on the sign and magnitude of deviations from parity. The Markov regime switching models by Frömmel et al. (2005), Kanas (2006) and Lee & Yoon (2013), among many others, document that in general, the strength of PPP is time-varying and regime-dependent, suggesting that the relationship between exchange rates and underlying fundamentals is non-linear. More recently, the application of quantile-autoregression-based unit root tests with both smooth and sharp breaks of Bahmani-Oskooee et al. (2016) and Bahmani-Oskooee & Wu (2018) support PPP in most OECD and African economies.[6]

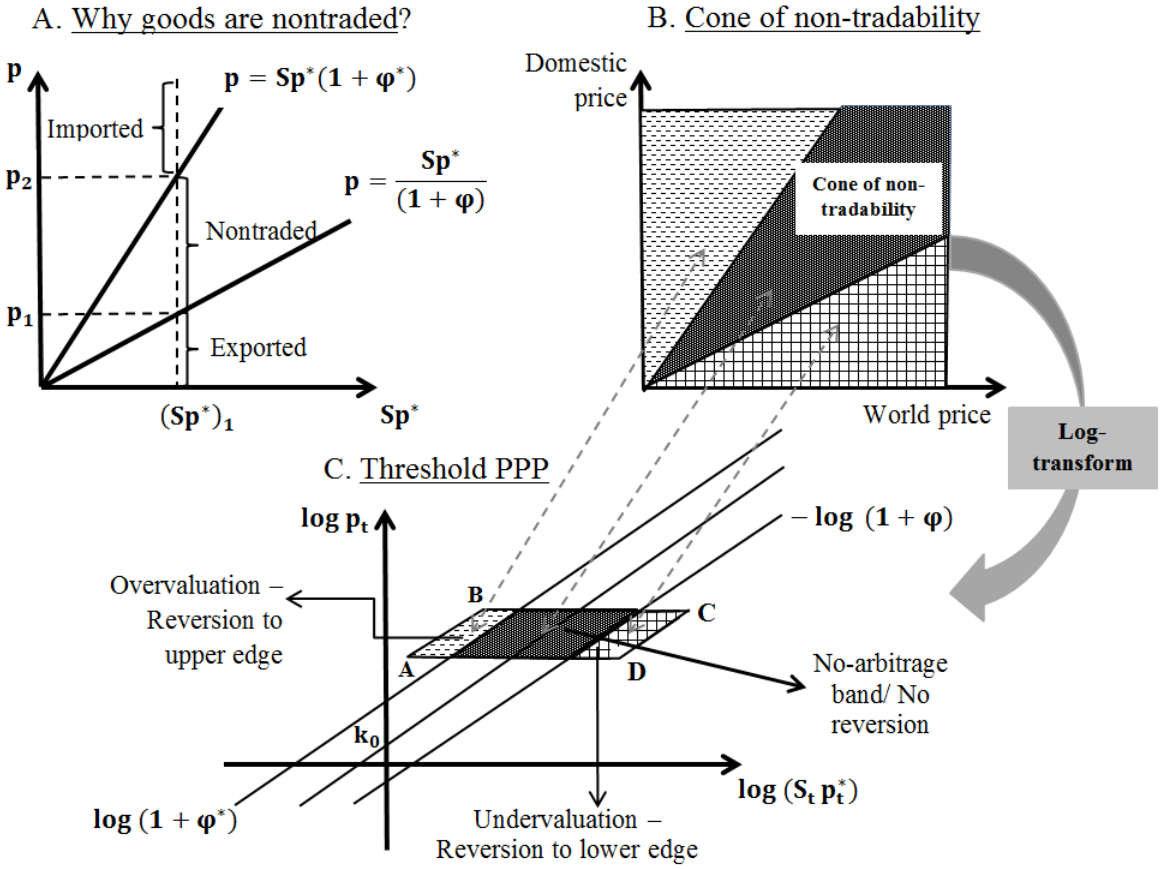
In this paper, we generalise the 3-regime threshold autoregressive models of Obstfeld & Taylor (1997) and Taylor (2001) in a panel context. Specifically, we relax the constraints of unified adjustment speeds in the outer regimes and equal sizes of the outer regimes. Our specification is empirically attractive, as it allows the speeds of adjustment in the outer regimes to be different. This model also extends Hansen (1999)'s threshold framework for non-dynamic panels. In section 6 we show evidence supporting our specification.

3. A neutral band of no-arbitrage

The absolute version of PPP posits that the purchasing power of a currency (S_t, the domestic cost of a unit of foreign currency) is determined by the ratio of the domestic price level (p_t) to the foreign price level (p_t^*). In natural logarithms we have: $\log S_t = \log p_t - \log p_t^*$, or equivalently $\log p_t = \log S_t + \log p_t^*$. This implies that higher (lower) domestic inflation relative to foreign inflation leads to an equi-proportional depreciation (appreciation) of the currency. Thus, when domestic price is greater than the world price, i.e. $\log p_t > \log S_t + \log p_t^*$, the domestic currency is considered overvalued, and vice versa, $\log p_t < \log S_t + \log p_t^*$ represents undervaluation. Absolute parity means that prices are completely equalized across countries, which would seem to be an unlikely situation when comparing the prices of different baskets of goods. A weaker version allowing for a constant "wedge" between prices is "relative PPP": $\log p_t = \log S_t + \log p_t^* + k_t$, with $k_t \neq 0$. This k_t can be considered as the "real" or "price-adjusted" exchange rate. For simplicity, we assume that $k_t = k_0$, a constant. Thus, relative PPP implies that $\Delta \log S = \Delta \log p - \Delta \log p^*$, so that the inflation differential between the two countries is offset by the corresponding movement of the exchange rate.

[6]For a recent survey on the application of non-linear econometric models to macroeconomic data, including generalizations of many of the mentioned models, see Teräsvirta & Case (2017).

Figure 3.1: The geometry of threshold PPP



Notes: p and p* refer to the domestic price (in local currency units) and foreign prices (in foreign currency units) of the same commodity. S denotes the exchange rate, measured as the local currency price of one foreign currency unit. Panel A is from Dornbusch (1980). The gray two-way dashed arrows connecting areas in panels B and C link analogous concepts.

In the traditional PPP frameworks described above, non-zero deviations k_t are only temporary and converge over time to either zero or the constant value k_0. In the presence of transaction costs, such an adjustment will occur only when deviations are sufficiently high to overcome these costs, so the adjustment process is non-linear. For example, financial theory predicts that even in highly liquid markets a so-called band of no arbitrage may exist where deviations are too small for arbitrage to be profitable. In macroeconomics, policies are often organized around targets, where intervention is activated only once the deviation from the target is significant, the most famous example being the Bretton Woods agreement, where many central banks pegged their exchange rate against a major currency, and allowed a narrow band of fluctuations. In addition, central bank interventions have been documented to lead to non-linear exchange rate adjustment processes (Leon & Najarian, 2005; Lin & Lee, 2016).

With respect to the traditional PPP models, when prices of the same goods are too different between countries (as a result of random, but temporary, shocks), *prima facie* there is a deadweight loss that can be eliminated by transferring the product from the low-cost location to where it is more highly valued. However, in reality there are a multitude of trade barriers (of both natural and man-made nature) between countries that hinder this process. Arbitrage only happens when the potential profit outweighs the costs to overcome those trade barriers. To formalize this simple idea, following Dornbusch (1980), we firstly suppose industries are competitive, and producer prices are driven down to costs. Then, let all trade barriers be represented by a non-negative fraction of the producer price (an ad-valorem term) and suppose these trade costs are incorporated into the seller's price, so a commodity is exported by the home country if $p(1 + \varphi) < Sp^*$ and is imported if $p > Sp^*(1 + \varphi^*)$, where φ and φ^* represent the degree of trade barriers encountered by domestic and foreign producers. These concepts are incorporated in panel A of Figure 3.1.[7] This implies a range of the domestic price in which the product is neither exported nor imported as: $Sp^*/(1 + \varphi) < p < Sp^*(1 + \varphi^*)$. Within this range, the good is non-traded, as illustrated by the dark shaded area in panel B of Figure 3.1. Accordingly, there is a "cone of non-tradability" as shown in panel B2. The width of the cone is related to the bilateral trade costs. It can easily be seen how successive increases in the price of a good can change its tradability status: When p is initially very low, the country will export this good; but as p rises, it becomes non-traded and finally imported.

From here, we can specify the trading conditions for the commodity:

$$\begin{cases} p/(Sp^*) < (1+\varphi)^{-1} : \text{Exported by the home country} \\ (1+\varphi)^{-1} \leq p/(Sp^*) \leq (1+\varphi^*) : \text{No international trade, only domestically traded in the home country} \\ 1 < (1+\varphi^*) < p/(Sp^*) : \text{Imported by the home country.} \end{cases}$$

Or, equivalently:

$$\begin{cases} \log\left[p/(Sp^*)\right] < -\log(1+\varphi) < 0 : \text{Profitable for home country to export} \\ -\log(1+\varphi) \leq \log\left[p/(Sp^*)\right] \leq \log\,(1+\varphi^*) : \text{No arbitrage oppoturnity} \\ 0 < \log\,(1+\varphi^*) < \log\left[p/(Sp^*)\right] : \text{Profitable for foreign country to export to home country.} \end{cases} \tag{3.1}$$

[7] It should be noted that, to be discussed later on, Dornbusch's original model assumes $\varphi = \varphi^*$, so that the width of the "cone of nontradability" (see panel B of Figure 3.1) is twice that of each of the bilateral trade costs. These fractions are also related to the so-called "Heckscher's (1916) commodity points".

Then, the relative price, log (p/Sp^*), is bounded by quantities related to trade costs faced by domestic and foreign producers. The interpretation of this simple model is straightforward. The quantity log $\left[p/(Sp^*)\right]$ is identical to our measure of deviation from absolute PPP (previously denoted as k), which represents the price differential. When trade costs are symmetric, these two entities face the same degree of trade barriers, i.e. $\varphi = \varphi^* \neq 0$, and log $\left[p/(Sp^*)\right]$ is bounded by two values that have the same magnitude but have opposite signs. In the absence of trade barriers for both sides, i.e. $\varphi = \varphi^* = 0$, we have log $\left[p/(Sp^*)\right] = 0$, there is no price differential and absolute parity holds. The logarithmic formulation (3.1) transforms the "cone of non-tradability" to a "band of no-arbitrage", defined by two rays that are now parallel, as shown in panel C of Figure 3.1.

4. Agricultural prices

In this section, we discuss the sources and construction of domestic and international traded agricultural prices used in our study. All data are annual.

4.1. Measuring prices

For domestic prices, we use local food prices of a wide array of food and agricultural items in a large number of countries from the Food and Agriculture Organization (hereafter FAO), who describe them as *"prices received by farmers . . . as collected at the point of initial sale (prices paid at the farm-gate)"* (FAO, 2017b). This is measured in local currency unit (LCU) and denoted as p_{ict}. We also collect the annual average exchange rates expressed in LCU per $US, from the IMF's International Financial Statistics database (IMF, 2017). This yields a database of 210 items in 165 countries over the period 1966 - 2015. Our panel data are unbalanced, that is, for each time period the number of producers vary across items and vice versa.

To compute the world price of each item, we adopt the approach of Mundlak & Larson (1992) and use a weighted average of export prices, with weights reflecting the relative importance of each export source.[8] Let there be C countries in the world market of item

[8]The export data are from the FAO detailed trade data matrix (FAO, 2017c). Using the export prices to construct world price has been the norm for FAO and in agriculture economics literature. This measure of foreign price is notably different and arguably more general than the conventional usage of the price of a numeraire country (i.e. the US). It could be argued that using an export-share weighted average of prices will introduce the so-called "Gershenkron" effect (Gerschenkron, 1947), that is, the world price is influenced by the price of large exporters. In the consumer theory context, this is problematic because countries whose price vectors are far from the world average price will have their GDP share upwardly biased (Diewert, 1999). However, since we are using producer prices rather than consumer prices, this effect is actually desirable because it accords with conventional trade

i, and let x_{ict} be the real value of exports of item i from country c in year t, measured in \$US, so that $X_{it} = \sum_{c=1}^{C} x_{ict}$ is the "world" trade in that commodity and $w_{ict} = x_{ict}/X_{it}$ is country c's export share. The \$US world price, in logarithmic form, of i in t is defined as: $\log p_{it}^{*} = \sum_{c=1}^{C} w_{ict} \log\left(p_{ict}^{x}/S_{ct}\right)$, where p_{ict}^{x} is the corresponding export price for c, in local currency units, and S_{ct} is country c's exchange rate vis-à-vis \$US. The items covered by the export database overlap with those covered by the production price database, thus further matching is required. This reduces the dimension of our data to 136 items in 165 countries in the 27-year period 1986 - 2013.[9] It should be acknowledged that though efforts are made by the FAO to facilitate price comparison across countries, potentially substantial heterogeneity remains due to different types of prices, item grades, methods of price collection etc. that will affect our measures.

4.2. Price differences

From the data described above we can construct our series of relative prices as: $K_{ict}^{*} = K'(p_{ict}/\left[S_{ct}p_{it}^{*}\right])$, where K' is a constant "wedge", to be discussed below. Using log-transform we have:

$$k_{ict}^{*} = k' + \log p_{ict} - \log p_{it}^{*} - \log S_{ct}. \tag{4.1}$$

To examine the degrees of relative price variation across different items, countries and years, we re-parametrise k' to include fixed effects as: $k' = \alpha + \text{fixed effects} + \text{residual}$. Then (4.1) can be re-written as:

$$k_{ict}^{*} = \alpha + \sum_{j=1}^{136} \omega_j DI_{ict}^{j} + \sum_{d=1}^{165} \gamma_d DC_{ict}^{d} + \sum_{y=1}^{27} \vartheta_y DY_{ict}^{y} + k_{ict}, \tag{4.2}$$

where DI_{ict}^{j} is a commodity dummy variable which equals 1 when $i = j$ and zero otherwise. Analogously, $DC_{ict}^{d} = 1$ when $c = d$ and $DY_{ict}^{y} = 1$ when $t = y$ are the country and year dummies. k_{ict} is now defined as the residual . The country effects could be related to country-specific factors such as the currency and trade policies. Item effects refer to the inherent characteristics that made the commodities more or less tradable (e.g. perishability, storage costs etc.). Fluctuations in the US dollar, the base currency, that affect all countries and items are captured by the time effects. The effects of other unobserved factors are summarily represented

theory, which posits that large exporters can influence world price. We thank Ranjan Ray for drawing our attention to this issue.

[9] For details of the data, see Appendix A1. We also show that our measures of the world prices agrees with major food indices published by the FAO.

by what is left over, k_{ict}, which will have a zero mean.

We estimate model (4.2) as a pooled regression and summarize the results by aggregating the country coefficients into income quartiles and the item coefficients into headings.[10] Figure 4.1 contains the results. Panel A1 shows that in the poorest group, local prices are more than 40% cheaper than the world average, about 30% cheaper in the second quartile, and 50% and 20% more expensive in the third and fourth quartiles. Large deviations localized to income groups is in broad agreement with the Harrod-Balassa-Samuelson hypothesis, in that rich countries generally exhibit higher prices. Interestingly, the third quartile prices are more than twice those of the richest countries. As can be seen from panel A2, both the estimates and standard errors of item heading effects vary widely across headings. Specifically, groups that are ready for consumption (e.g. fruits, vegetables or meat) yield significantly smaller confidence intervals relative to unprocessed and fibre items (for instance, industry materials, herbs, fibre crops and pulses). Although required careful investigation, this preliminary observation lends support for the argument that the estimated results reflect the wide range of trade costs imposed upon different items and item groups.

4.3. Outliers

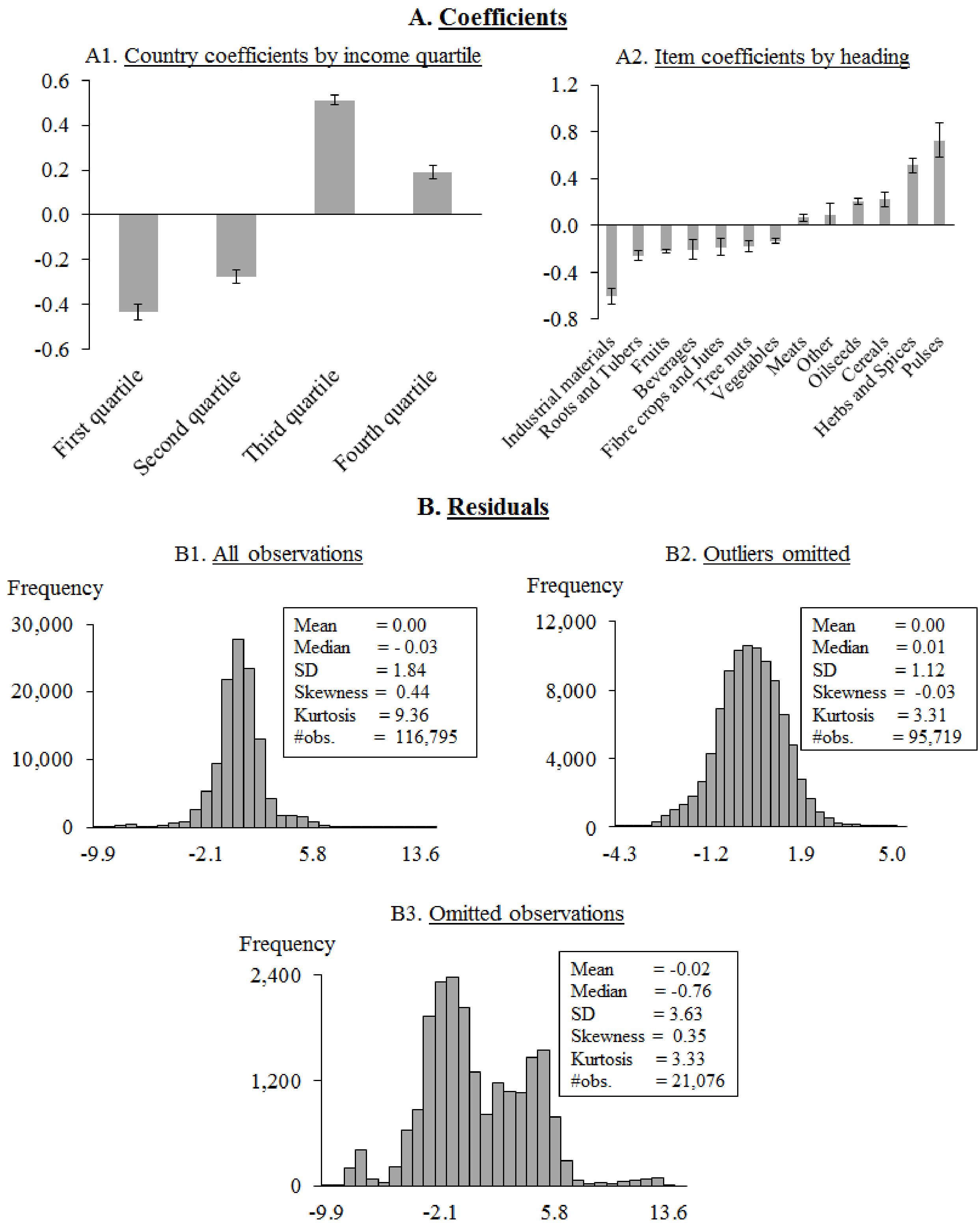
Panel B1 of Figure 4.1 is a histogram of the residuals from model (4.2). The standard deviation is large at 1.84[11], the tails are thick and there is a strong indication of outliers. As stated above, outliers can be thought of as a joint consequence of measurement errors in production prices and exchange rates. If at least 5% observations for a country-item pair falling in either of the 2.5% tails, then all observations for that pair shall be considered "outliers" and are omitted.[12] In Table 4.1, we present the list of countries and years to be omitted, together with their corresponding total numbers of item-specific omissions. The country list includes mostly African, South American and Eastern European countries, many of which are well-known for their substantial exchange rate arrangements in the 1990s. The cases of Italy and Turkey require

[10] For identification, we normalize each set of dummy variable coefficients so that they sum to zero. The detailed estimation procedure is described in Appendix A2.

[11] Which translates to $100\left(e^{1.84}-1\right) > 500\%$.

[12] In unreported results, we also check for the percentage of the number of "outliers" corresponding to each country across items. Relative to the cross-country distribution, the distribution among items is much more spread out, with the total number of "outlying items" reaches 123 (in a sample of 136 items). That is, outliers are not systematically confined in just a few items. This could be a result of lower data quality in some particular years, which affects all items. To check for this possibility, we also document the distribution of outliers throughout the years. However, there seem to be no systematic pattern of yearly outliers. In summary, country characteristic is the most important determinant of outliers. Outliers therefore may be an indicator of country-specific data quality.

Figure 4.1: Relative prices and fixed effects



Notes: This figure presents results of the dummy-variable regression for the relative prices of 165 countries, from 1986 to 2013. The model estimated is Equation (4.2). Estimated country coefficients are aggregated into income quartiles (with the first being the poorest), and item coefficients are aggregated into 13 item headings. Income quartiles are based on 2015 per capita GDP, in $US, with the first being the poorest, and the fourth being the richest. The vertical lines in panels A1 and A2 represent the ±2 standard-error intervals.

more investigation. Most of these countries also belong to the lowest two income quartiles, and tend to be subject to lower data quality. As a check for the validity of this approach, we observe that these countries indeed exhibit very high PPP deviation.

Panel B2 and B3 of Figure 4.3 present the distribution corresponding to the filtered residuals, and that of the "outlying" residuals, respectively. As can be seen, relative to the distribution of original residuals, the filtered one resembles a normal distribution more closely. Although dispersion is still large and standard tests still not support the normality of residual distribution, both skewness (-0.03) and kurtosis (3.31) values are now more in accord with a normal distribution. In subsequent analyses, we focus on the de-meaned relative prices with the outliers omitted. Following notations in model (4.2), hereafter these relative prices will be referred to as k_{ict}. The flow chart in Figure 4.2 summarises various data sample size changes under different analyses and treatments employed in this section and in the next.

4.4. Mean-reversion?

To conclude this section, we explore the possible mean reversion pattern of PPP deviations. Specifically we address the fundamental question: Can the current level of deviation help predict its future movements? This issue corresponds to the persistence of deviations from PPP, as well as the "mean-reversion" aspect of the deviation's data generating process, all of which can be related to the "beta-convergence" type extensively discussed in economics growth literature (see e.g. Sala-i-Martin, 1996 and Sokoloff & Engerman, 2000). To proceed, we need a general definition of deviation for each country. For simplicity, we use the un-weighted average deviation across all items: $\overline{k}_t = (1/I)\sum_{i=1}^{I} k_{it}$, where I denotes the number of items for that country. Due to data limitation, some countries do not have any observations for some years. As missing observations confound the interpretation of the mean-reversion dynamics, in the remaining analyses of this section, we limit our study to the sample of "survivors", i.e. countries will full 27 years of data.[13] Next, we look at the pattern of PPP deviation changes over time, with respect to the current deviation. This relationship can be estimated by the following simple "error correction" predictive regression: For each horizon h we have:

$$\Delta_{(h)}\overline{k}_{t+h} = \Phi^h + \Theta^h\overline{k}_t + u_t^h. \tag{4.3}$$

[13]For robustness checks, in unreported analyses we repeat the subsequent experiments with (i) the full sample (including countries with missing data) and (ii) using country-item deviations rather than country-average deviations. Both approaches give quantitatively similar conclusions to those reported. These results are available upon request.

Table 4.1: Distribution of outlying observations across countries and years

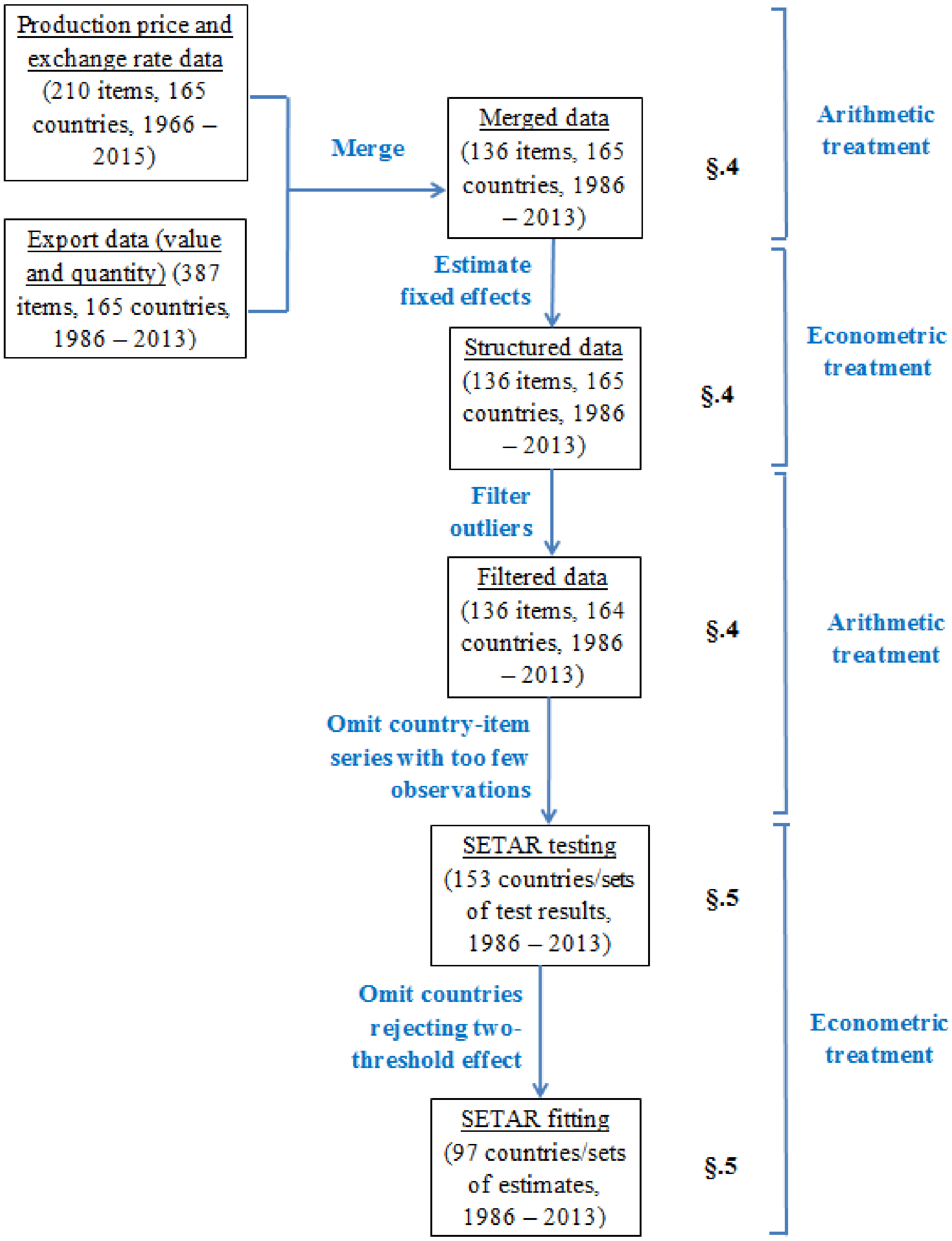
	Country (1)	Income ($ p.c) (2)	Obs.country (3)	Year (4)	Obs.year (5)
1	Bolivia	1,456	4,360	1986	677
2	Turkey	8,898	1,963	1987	674
3	Peru	4,274	1,457	1988	750
4	Romania	6,638	1,129	1989	759
5	FYR Macedonia	4,131	1,121	1990	873
6	Poland	11,622	1,040	1991	512
7	Argentina	6,328	1,030	1992	576
8	Azerbaijan	3,186	861	1993	629
9	Italy	29,536	839	1994	728
10	Ecuador	3,783	830	1995	759
11	Russia	6,717	820	1996	763
12	Brazil	5,441	703	1997	785
13	Uruguay	8,028	591	1998	797
14	Ukraine	1,863	574	1999	820
15	Suriname	5,534	558	2000	812
16	Bulgaria	5,234	495	2001	820
17	Belarus	4,792	439	2002	820
18	Zimbabwe	833	399	2003	832
19	Mozambique	557	335	2004	777
20	Ghana	1,221	319	2005	794
21	Greece	18,158	206	2006	807
22	Slovenia	19,578	189	2007	798
23	Sudan	977	171	2008	758
24	Nicaragua	1,513	112	2009	747
25	Afghanistan	409	103	2010	766
26	Zambia	1,007	65	2011	764
27	Portugal	18,768	64	2012	743
28	Lithuania	11,560	63	2013	736
29	Spain	26,141	56		
30	Slovakia	12,855	51		
31	Egypt	1,576	28		
32	Norway	67,315	22		
33	Croatia	10,701	21		
34	Bhutan	2,136	18		
35	Senegal	836	17		
36	Luxembourg	84,955	14		
37	Tanzania	647	8		
38	Lao	854	5		
	Total outlying obs.		**21,076**		**21,076**

Notes: This table presents the list of "outlying" countries and years. Income is measured as the 2015 US Dollar per capita (constant price, 2011 PPP). "Obs.country" and "Obs.year" denote the total number of outlying observations for each country and year, respectively. The countries are ranked by the number of outlying observations [column (3)].

Under PPP, we should expect a currently undervalued (overvalued) currency to appreciate (depreciate) in the future period. That is, the adjustment coefficient Θ^h is expected to have a negative sign. The larger the value of $|\Theta|$, the faster the adjustment speed. $|\Theta| = 1$ corresponds to full adjustment over the h-year horizon.

Figure 4.3 plots the scatterplot of $\Delta_{(h)}\overline{k}_{t+h}$ against $\overline{k}_t$ for 6 horizons: h = 1-, 5-, 10- and

Figure 4.2: Schematic of data treatments

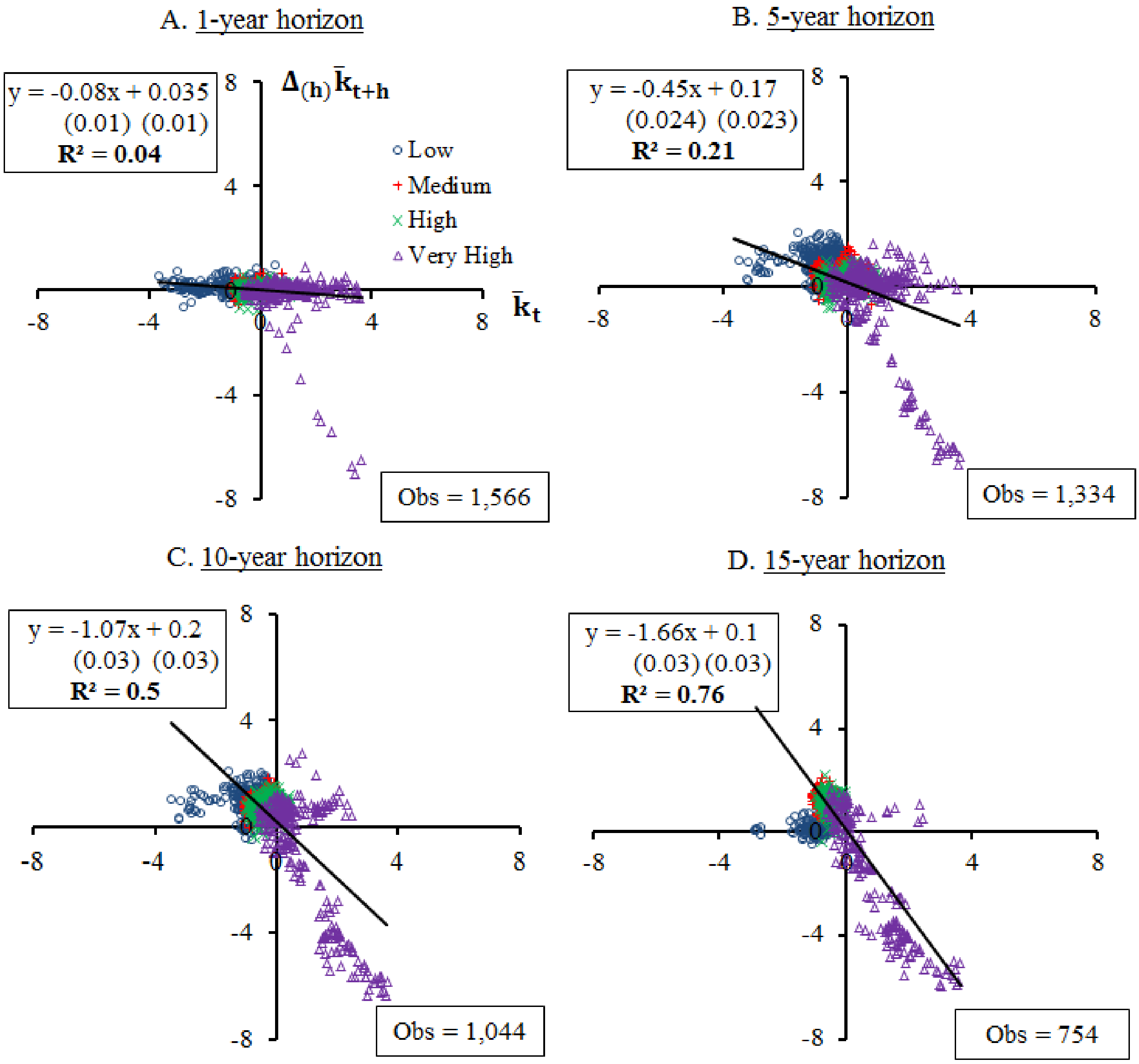


Notes: This figure presents a flow of data treatment throughout the paper. The section numbers indicate where corresponding data are used. Data treatment (how our data changes) is categorized as either arithmetic (pure numerical changes) or econometric (estimation involved).

15-year (with overlapping observations). We can see that the overall goodness-of-fit of the regression line improves when horizon increases. A similar conclusion along this line is made by Cumby (1996) and Clements et al. (2012).[14] As can be seen in panel C, at the 10-year horizon, the slope is very close to unity. It becomes more negative at longer horizons (about

[14]Though not mentioned in these papers, it can be shown by simple algebra that in this case, the intercept and slope coefficients of the h-year horizon regression ($h > 1$) is approximately h times that of the 1-year horizon regression. That is, $\Delta_{(h)}\bar{k}_{t+h} \approx (h \times \Phi^1) + (h \times \Theta^1)\bar{k}_t$. We derive this result in Appendix A3.

Figure 4.3: Scatterplot of future relative price and current deviation from parity



Notes: This figure presents the scatterplot, across all countries, of future relative price changes $\left(\Delta_{(h)}\bar{k}_{t+h}\right)$ against current deviation from parity $(\bar{k}_t)$. The predictive error correction model is: $\Delta_{(h)}\bar{k}_{t+h} = \Phi^h + \Theta^h\bar{k}_t + u_t^h$. In each plot, the OLS regression line, its fitted equation and R-squared are reported (with standard errors in parentheses). 'Obs.' denotes the total number of (country-year) observations used in each regression. The coloured data markers are based on the quartiles of deviations in the initial period $(\bar{k}_t)$. The sample includes only countries that have data in all years (i.e. the "survivors").

-1.67 after 15 years) but the estimates also become less precise due to a reduced sample size. In additional analysis, in each calendar year we divide our sample into 4 quartiles, based on the magnitude of current deviations $(\bar{k}_t)$, then track the evolution pattern of the countries in each quartile over the whole period. With these quartiles identified by different markers, Figure 4.3 shows that the majority of the mean-reversion is exhibited in the Low and Very High quartiles, but more frequently in the latter. This observation serves as a preliminary support for our argument that the mean-reversion speed tend to be higher with extreme deviations, but more so with positive deviations.

5. An asymmetric threshold autoregressive framework

This section presents the econometric model of prices and exchange rates that incorporates the above ideas of asymmetric trade costs and adjustment speeds.

5.1. The SETAR model

Consider the process of price differentials of an identical good in two countries, $\{k_t\}$. If PPP holds in the long-run, $\{k_t\}$ is stationary. For simplicity, we assume $\{k_t\}$ follows an AR(1) model, i.e. $k_t = \alpha + \beta k_{t-1} + \varepsilon_t$ with $0 < \beta < 1$. The process's equilibrium level (k_0) can be measured as the long run mean: $\alpha/(1-\beta)$ and the half life is $\omega = \log 0.5/\log \beta$. We can incorporate the above "no-arbitrage band" in a band-threshold autoregressive model (TAR), along the line of Obstfeld & Taylor (1997) and Taylor (2001):

$$k_t = \begin{cases} \alpha_L + \beta_L k_{t-1} + \varepsilon_t \text{ when } k_{t-1} < k_L; \\ \alpha_M + \beta_M k_{t-1} + \varepsilon_t \text{ when } k_L \leq k_{t-1} \leq k_H; \\ \alpha_H + \beta_H k_{t-1} + \varepsilon_t \text{ when } k_{t-1} > k_H. \end{cases} \tag{5.1}$$

We write this more compactly as:

$$k_t = \alpha' + \beta_L k_{t-1}\mathbf{I}(k_{t-1} < k_L) + \beta_M k_{t-1}\mathbf{I}(k_L \leq k_{t-1} \leq k_H) + \beta_H \mathbf{I}(k_{t-1} > k_H) + \varepsilon_t,$$

where the subscripts L,M,H represent the three regimes, each of which is characterized by a distinct set of AR (1) parameters; $\alpha' = \{\alpha_L, \alpha_M, \alpha_H\}$ is a vector of time-invariant intercepts; and $\mathbf{I}(.)$ is an indicator function that takes the value of 1 when the expression in parenthesis is true and zero otherwise. In this model, equilibrium is achieved whenever k_{t-1} is within the band, not just at its center (where $k_t = k_0$). Model (5.1) is known as the "self-exciting" threshold AR, or SETAR (self-exciting as the threshold variable used is the lag of the dependent variable).[15] The likelihood of obtaining more precise estimates increases with the time the process is outside the band, i.e. when true parameters are β_L and β_H. It can be shown that half-life estimates will be biased upwards.

[15] As pointed out in Section 3, in this context, the process mean-reverts towards the edges of the band, instead of towards the center. The version of the model where convergence is toward the center of the band is termed "Equilibrium TAR" (Balke & Fomby, 1997). This is essentially a 'single-threshold' special case of our "band TAR" model.

Typically, we can impose three constraints on model (5.1): (i) $\beta_L = \beta_H$, (ii) $\beta_M = 1$ and (iii) $k_H = -k_L$. The first constraint implies unified adjustment speeds in the lower and higher "outer" regimes. The second implies a random walk behaviour in the middle regime. The third implies equal distance from lower and higher bounds to the center of the band, i.e. domestic and foreign producers face the same degree of trade barriers. Although there is some intuition supporting these restrictions, we do not impose them, but rather opt for estimating the additional parameters. An important advantage of using a first-order TAR model is that its sufficient and necessary stationarity conditions (in case of i.i.d errors) are known (see e.g. Chan et al., 1985 and Kapetanios & Shin, 2006), while such conditions for higher-order processes are, to the best of our knowledge, still under development.

5.2. Specification and estimation

It is important to first determine whether the threshold effect is statistically significant and, in case of significant threshold effects, how many thresholds need to be specified. We begin by specifying that the true underlying process is a linear model, i.e. no threshold effect, so that $H_0 : \beta_L = \beta_H$ and $H_1 : \beta_L \neq \beta_H$. A likelihood ratio test of H_0 can be constructed using the SSRs under the null and the alternative. The test for threshold effects is sequential. For example, if the null hypothesis of linearity is rejected, then we can test for a single-threshold against a double-threshold model, with $H_0 : \beta_L \neq \beta_H\ ;\ \beta_H = \beta_M$ and $H_1 : \beta_L \neq \beta_H\ ;\ \beta_H \neq \beta_M$. This nested hypothesis test scheme can be extended to accommodate more thresholds (Lo & Zivot, 2001). The main complication here is that this type of test statistic has a non-standard asymptotic distribution because the threshold is an unidentified parameter under the null. This is the well-known "nuisance parameter" problem described by Davies (1987) and investigated by Andrews & Ploberger (1994) and Hansen (1996). Standard inferences are invalid and therefore we have to rely on a bootstrap procedure for the distribution of the test statistic. We described these procedures in detail and provide the bootstrapped p-value of the test statistics in Appendix A4.

After testing for non-linearity of the type we are interested in, i.e. two-thresholds, we proceed to formally estimate the SETAR(1) model. Suppose, for each country, we have $i = 1, \ldots, I$ commodities in $t = 2, \ldots, T$ years, with k_{it} the deviation from parity of i in t. To use these data in the context of (5.1) we require a panel specification. Here we essentially pool data over items (commodities) and assume a common speed-of-adjustment vector across items, for each regime. Following Hansen (1999), to account for the item fixed effects, we use deviation from means[16] and estimate:

$$k_{it} = \alpha' + \beta_L k_{i,t-1}\mathbf{I}(k_{i,t-1} < k_L) + \beta_M k_{i,t-1}\mathbf{I}(k_L \leq k_{i,t-1} \leq k_H) + \beta_H k_{i,t-1}\mathbf{I}(k_{i,t-1} > k_H) + \varepsilon_{it}, \tag{5.2}$$

where, for ease of notation, k_{it} is now interpreted as the de-meaned deviation; and $\alpha' = \{\alpha_L, \alpha_M, \alpha_H\}$ is a vector of country-specific regime-dependent intercepts. If (k_L, k_H) are known, equation (5.2) is linear in $(\beta_L, \beta_M, \beta_H)$ in their corresponding regimes, so OLS estimation is appropriate. Denote the sum of squared errors conditional on k_L and k_H as $S(k_L, k_H)$. The least-squares estimates of (k_L, k_H) minimize $S(k_L, k_H)$.

Next, given estimates of k_L and k_H, we can derive estimates of domestic and foreign trade barriers. Specifically, by combining the middle lines of models (3.1) and (5.1) we have:

$$-\log(1+\varphi) = k_L \text{ and } \log(1+\varphi^*) = k_H, \tag{5.3}$$

or equivalently, $\varphi = 1/\exp(k_L) - 1$ and $\varphi^* = \exp(k_H) - 1$. For small φ and φ^*, we have $\varphi \approx -k_L$ and $\varphi^* \approx k_H$. Following the conventional approach, our measure of the cost is derived from the geometric mean of the ad-valorem tax equivalences:

$$\tau_c = \sqrt{(1+\varphi)(1+\varphi^*)} - 1 = \sqrt{\left[1/\exp(k_L)\right] \times \exp(k_H)} - 1, \tag{5.4}$$

or equivalently, $\log(1+\tau_c) = (k_H - k_L)/2$, so that the cost is one-half the width of the "no-arbitrage band". Since we compare between a country and the world, this is a multilateral measure. Accordingly, the component φ can be considered as the cost when producers from home country export their goods to other countries, while φ^* is its counterpart for the other direction. In the special case when $k_H = -k_L = k^*$ we have a cost of k^* and the long-run mean of PPP deviations is the middle of the band, which is zero ($k_H + k_L = 0$). Much of the empirical applications of SETAR to PPP is limited to this special case. In our model, the simple average of the two thresholds can be different from zero.

6. Empirical results

We first test for the effect of one and two thresholds, following subsection 5.2. The test results allow us to detect 97 countries satisfying the two-threshold model specification.[17] We

[16] Additionally, the last annual observation for each item is omitted when constructing the lagged time series. This is to ensure that lagged values correspond to the correct items when pooling data across items.

[17] Appendix A4 presents the p-value of the corresponding F-statistics, which shows that 97/153 $\approx$ 64% of the countries exhibit behaviour in accordance with a two-threshold model. These cases reject both linearity and

then apply the estimation procedure outlined above. Panel A of Table 6.1 presents the estimated results for model (5.2). From panel B, we can see that on average, the Low regime exhibit an AR coefficient of 0.68, implying a half-life of 1.82 years while the High regime yields an average estimate of 0.25, implying a half-life of about 0.5 years. The average of the Middle regime's estimate is 0.62. It appears that mean reversion speed is generally greater for the High deviation regime than in the Low regime. Interestingly, the behaviour of the process in the middle regime can also be characterized by an AR(1) process, although with lower mean reversion speed and higher half-life (1.44 years).

However, not all of these coefficients are statically significant, and some imply random walk behaviour.[18] In addition, relative to the other two regimes, the High regime's coefficients are estimated less precisely, with much higher standard errors. This may be due to the fact that deviations falling in this regime are observed less frequently, since large positive deviations tend to be corrected more quickly.[19] When we restrict our sample to the countries with AR coefficient estimates that are both: (i) Significant at the 5% level for the outer two regimes and (ii) less than one in absolute value, we are left with 54 countries, yielding average estimates of 0.69, 0.61 and 0.4 for Low, Medium and High regimes, respectively. Corresponding half-lives of this sample are 1.85, 1.39 and 0.75 years. These results are summarized in panel C of Table 6.1. Panel A of Figure 6.1 presents the histograms of the regime-specific AR coefficient estimates for 97 countries. Based on these coefficient estimates, we can test for whether the Middle regime's coefficient is not different from unity, assuming that the test statistics follow a standard normal distribution. The corresponding two-tail t-stats (in absolute value) plotted in panel B1 of Figure 6.1 indicate that this null cannot be rejected for 23% of the countries. When we examine the smaller 54 countries sample, this proportion increases to 25%. This lends some support for the argument of a random walk behaviour of the relative prices in the Middle regime.

Another, weaker test for the existence of the "no-arbitrage band" is to see whether the Middle regime's coefficient is significantly larger than those of the outer regimes, that is, we

one-threshold non-linearity at the 5% level of significance. Very few countries exhibit more than two thresholds, the implication of which is not covered in this paper.

[18] A random walk process is associated with β not significantly different from unity, while β significantly larger than one corresponds to an explosive process.

[19] Intuitively, as Granger & Teräsvirta (1993) suggest, the precision of the threshold and AR estimates depends on the size of the regimes. That is, threshold searching will be difficult if there are only a few observations in the outer regimes.

Table 6.1: SETAR(1) model estimates

	Country (1)	$\widehat{\beta}_L$ (2)	$\widehat{\beta}_M$ (3)	$\widehat{\beta}_H$ (4)		Country (5)	$\widehat{\beta}_L$ (6)	$\widehat{\beta}_M$ (7)	$\widehat{\beta}_H$ (8)
				A. Full sample estimates					
1.	**Albania**	0.72 (0.07)	-0.24 (0.12)	0.44 (0.06)	53.	Lebanon	0.66 (0.06)	0.77 (0.04)	0.22 (0.14)
2.	**Algeria**	0.63 (0.05)	-0.12 (0.17)	0.74 (0.05)	54.	**Luxembourg**	0.84 (0.06)	0.98 (0.10)	0.52 (0.06)
3.	Ant. & Barb.	0.41 (0.15)	0.76 (0.15)	-2.21 (0.54)	55.	**Malta**	0.71 (0.06)	0.94 (0.10)	0.37 (0.10)
4.	Armenia	0.52 (0.11)	0.82 (0.07)	0.17 (0.10)	56.	**Mauritius**	0.89 (0.04)	-0.26 (0.20)	0.48 (0.13)
5.	Australia	0.88 (0.03)	0.74 (0.05)	0.03 (0.10)	57.	**Mexico**	0.74 (0.03)	0.71 (0.04)	0.24 (0.06)
6.	**Austria**	0.77 (0.06)	0.68 (0.03)	0.72 (0.05)	58.	**Moldova**	0.79 (0.07)	0.45 (0.13)	0.59 (0.23)
7.	**Bangladesh**	0.57 (0.08)	0.90 (0.05)	-0.17 (0.08)	59.	Morocco	0.51 (0.06)	0.64 (0.05)	0.29 (0.16)
8.	Belgium	0.58 (0.14)	0.27 (0.27)	-0.02 (0.06)	60.	**Myanmar**	0.71 (0.09)	0.66 (0.05)	0.51 (0.08)
9.	**Bolivia**	-0.19 (0.06)	-0.28 (0.05)	-0.54 (0.07)	61.	Namibia	0.52 (0.29)	0.80 (0.11)	0.09 (0.15)
10.	Brunei	0.38 (0.09)	0.64 (0.10)	0.14 (0.10)	62.	**Nepal**	0.91 (0.09)	1.00 (0.05)	0.67 (0.07)
11.	Bulgaria	0.75 (0.23)	0.40 (0.06)	0.81 (0.07)	63.	**Netherlands**	0.75 (0.04)	0.52 (0.09)	0.37 (0.09)
12.	**Burundi**	0.87 (0.04)	-0.16 (0.20)	0.67 (0.10)	64.	New Zealand	0.80 (0.04)	0.56 (0.07)	-0.28 (0.17)
13.	**Cabo Verde**	0.38 (0.17)	0.96 (0.09)	0.34 (0.11)	65.	**Niger**	0.96 (0.07)	0.99 (0.31)	1.15 (0.33)
14.	**Cambodia**	0.25 (0.08)	0.98 (0.11)	0.32 (0.16)	66.	Nigeria	0.28 (0.10)	0.74 (0.05)	0.02 (0.17)
15.	Canada	0.89 (0.03)	0.63 (0.06)	-0.18 (0.21)	67.	**Norway**	0.93 (0.03)	0.13 (0.17)	0.54 (0.10)
16.	**Chile**	0.67 (0.05)	0.76 (0.04)	-0.40 (0.12)	68.	Pakistan	0.74 (0.04)	0.86 (0.09)	0.10 (0.17)
17.	**China**	0.70 (0.05)	0.77 (0.03)	0.27 (0.10)	69.	**Palestine**	0.70 (0.05)	0.23 (0.11)	0.38 (0.13)
18.	**Colombia**	0.78 (0.04)	0.74 (0.07)	0.46 (0.08)	70.	Panama	0.86 (0.08)	0.72 (0.07)	0.15 (0.11)
19.	**Congo**	0.65 (0.13)	0.79 (0.11)	0.47 (0.05)	71.	**Paraguay**	0.83 (0.11)	0.56 (0.07)	0.49 (0.05)
20.	**Cook Islands**	0.59 (0.10)	0.94 (0.13)	-1.01 (0.19)	72.	**Philippines**	0.59 (0.07)	0.71 (0.07)	0.54 (0.04)
21.	**Costa Rica**	0.77 (0.10)	0.62 (0.08)	0.39 (0.10)	73.	Portugal	1.06 (0.09)	0.75 (0.05)	0.71 (0.04)
22.	**Croatia**	0.40 (0.09)	0.68 (0.08)	0.41 (0.05)	74.	**Puerto Rico**	0.72 (0.08)	0.56 (0.08)	0.30 (0.12)
23.	Cuba	0.90 (0.05)	-0.44 (0.39)	0.22 (0.17)	75.	Rwanda	0.75 (0.18)	0.59 (0.06)	0.10 (0.19)
24.	Cyprus	0.94 (0.03)	0.75 (0.07)	1.19 (0.08)	76.	Saint Lucia	0.84 (0.05)	1.59 (0.27)	0.05 (0.15)
25.	Czechia	0.90 (0.04)	0.33 (0.14)	0.07 (0.14)	77.	Senegal	0.55 (0.15)	0.81 (0.04)	0.25 (0.30)
26.	Ecuador	1.11 (0.13)	-0.09 (0.15)	0.56 (0.11)	78.	**Slovakia**	0.56 (0.03)	0.42 (0.04)	0.66 (0.06)
27.	**Egypt**	0.79 (0.06)	0.93 (0.08)	0.66 (0.03)	79.	**Slovenia**	0.86 (0.03)	0.66 (0.13)	0.54 (0.05)
28.	**El Salvador**	0.52 (0.17)	0.79 (0.03)	0.41 (0.16)	80.	**South Africa**	0.67 (0.05)	0.86 (0.02)	0.80 (0.10)
29.	Eritrea	0.03 (0.31)	0.98 (0.19)	-0.48 (0.23)	81.	**Spain**	0.91 (0.02)	0.86 (0.08)	0.73 (0.03)
30.	**Estonia**	0.48 (0.08)	0.91 (0.08)	0.76 (0.06)	82.	Sri Lanka	0.83 (0.04)	0.71 (0.05)	0.14 (0.13)
31.	**Ethiopia**	0.43 (0.08)	0.93 (0.03)	0.29 (0.09)	83.	Suriname	0.06 (1.07)	0.89 (0.07)	0.65 (0.09)
32.	Fiji	0.85 (0.08)	0.58 (0.17)	0.04 (0.16)	84.	Sweden	0.86 (0.04)	0.61 (0.10)	-0.34 (0.29)
33.	**Finland**	0.84 (0.04)	0.78 (0.08)	0.67 (0.10)	85.	**Syria**	0.70 (0.04)	0.92 (0.08)	0.37 (0.15)
34.	**France**	0.67 (0.04)	0.60 (0.04)	0.48 (0.04)	86.	Tajikistan	0.36 (0.14)	0.61 (0.05)	-0.14 (0.12)
35.	**Georgia**	0.91 (0.11)	0.25 (0.07)	0.24 (0.12)	87.	Thailand	0.78 (0.07)	0.75 (0.04)	0.08 (0.13)
36.	**Greece**	0.91 (0.02)	0.88 (0.07)	0.74 (0.04)	88.	Togo	0.76 (0.06)	0.81 (0.16)	-0.18 (0.26)
37.	Honduras	0.70 (0.05)	1.06 (0.13)	0.22 (0.17)	89.	**Tri. & Tob.**	0.37 (0.12)	0.81 (0.09)	0.60 (0.06)
38.	**Hong Kong**	0.25 (0.12)	0.52 (0.13)	-0.90 (0.22)	90.	Tunisia	0.76 (0.05)	0.75 (0.05)	0.12 (0.11)
39.	**Hungary**	0.73 (0.05)	0.84 (0.04)	0.25 (0.06)	91.	Turkmenistan	0.47 (0.13)	-1.70 (0.41)	-1.13 (0.29)
40.	Iceland	0.69 (0.17)	0.80 (0.05)	-0.15 (0.23)	92.	**U.K**	0.86 (0.04)	0.70 (0.09)	0.48 (0.12)
41.	India	0.42 (0.07)	0.40 (0.07)	0.03 (0.12)	93.	U.S	0.82 (0.03)	0.70 (0.03)	-0.12 (0.12)
42.	**Indonesia**	0.92 (0.09)	0.67 (0.05)	0.41 (0.08)	94.	**Ukraine**	0.88 (0.16)	0.63 (0.07)	0.90 (0.24)
43.	Iran	0.61 (0.04)	0.83 (0.04)	0.10 (0.10)	95.	Uruguay	0.75 (0.25)	1.02 (0.21)	0.75 (0.07)
44.	Iraq	0.63 (0.08)	0.65 (0.13)	-0.03 (0.19)	96.	**Viet Nam**	0.75 (0.05)	-0.70 (0.26)	0.46 (0.14)
45.	**Israel**	0.82 (0.03)	0.77 (0.06)	0.20 (0.08)	97.	Yemen	0.72 (0.07)	0.85 (0.07)	0.09 (0.15)
46.	**Jamaica**	0.46 (0.08)	0.86 (0.04)	0.83 (0.13)			B. 97 countries		
47.	Japan	0.81 (0.03)	0.86 (0.07)	1.17 (0.15)		Mean	**0.68** (0.09)	**0.62** (0.10)	**0.25** (0.13)
48.	Jordan	0.70 (0.04)	0.77 (0.05)	-0.09 (0.11)		SD	0.22 (0.11)	0.42 (0.07)	0.49 (0.08)
49.	**Kazakhstan**	0.93 (0.04)	0.21 (0.16)	-0.45 (0.19)		Half-life (in years)	**1.82**	**1.44**	**0.50**
50.	**Korea**	0.79 (0.05)	0.80 (0.06)	0.59 (0.09)			C. 54 countries		
51.	Kyrgyzstan	0.74 (0.05)	0.63 (0.21)	-0.09 (0.17)		Mean	**0.69** (0.07)	**0.61** (0.09)	**0.40** (0.10)
52.	**Latvia**	0.49 (0.10)	0.65 (0.06)	0.46 (0.09)		SD	0.21 (0.04)	0.38 (0.06)	0.40 (0.06)
						Half-life (in years)	**1.85**	**1.39**	**0.75**

Notes: This table presents the estimates of the two-threshold TAR model described in subsection 5.1. The countries listed in Panel A are those that simultaneously exhibit rejection of a linear null hypothesis and evidence of two-threshold effect. Panel B summaries the statistics for these estimates. Panel C provides statistics for a smaller sample that only includes countries yielding statistically significant estimates in both the Low and High regimes. The names of these countries are emboldened. Standard errors are in parentheses. Half-lives are measured in years. Country labels: "Ant. & Barb." = Antigua and Barbuda; "Tri. & Tob." = Trinidad and Tobago.

test for the null of $H_0 : \widehat{\beta}_M = \widehat{\beta}_R$ against $H_1 : \widehat{\beta}_M > \widehat{\beta}_R$ ($R = L, H$). Note that β is inversely related to the speed of adjustment towards PPP. The one-tail statistics plotted in panel B2 and

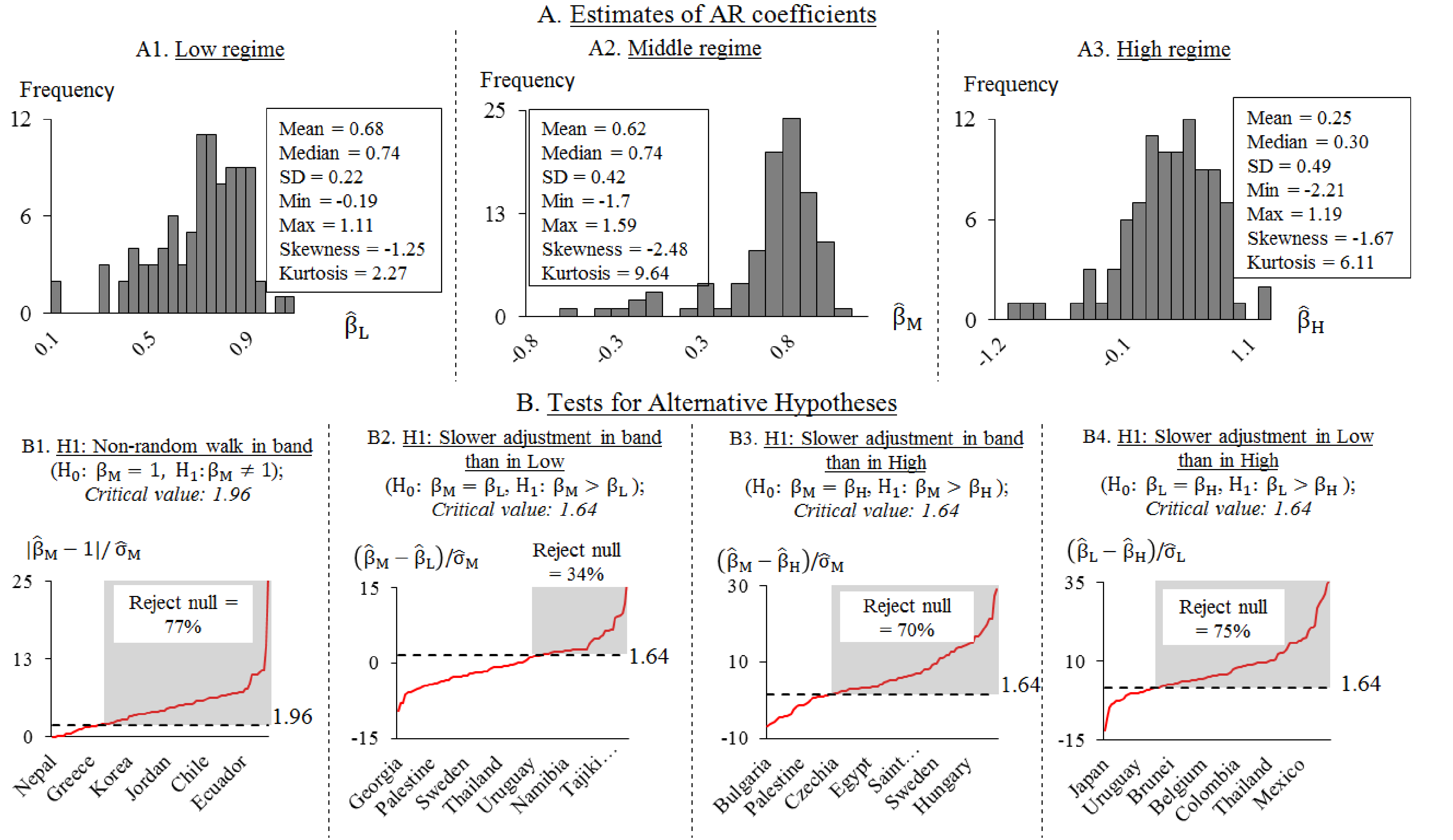
B3 show that the null of slower adjustment in the Middle than in the Low regime is rejected in 34% of the cases, while 70% reject the null of slower adjustment in the Middle than in the High regime. These observations pertain to the difference in and out of the band. Finally, in panel B4 we test whether the speed is higher in the High regime, and find that only 25% of the countries support this hypothesis.

Table 6.2: Trade cost measurements

Country (1)	Income ($ p.c) (2)	$1+\varphi$ (3)	$1+\varphi^*$ (4)	$1+\tau_c$ (5)	Country (6)	Income ($ p.c) (7)	$1+\varphi$ (8)	$1+\varphi^*$ (9)	$1+\tau_c$ (10)
1. Burundi	143	65.7	194.8	113.1	29. Costa Rica	6,233	178.6	136.6	156.2
2. Niger	291	66.6	438.2	170.8	30. Mauritius	7,602	69.3	189.4	114.6
3. Ethiopia	337	160.9	225.6	190.5	31. Mexico	8,607	119.1	179.9	146.4
4. Nepal	444	251.6	135.5	184.6	32. Chile	9,965	140.7	293.6	203.2
5. Myanmar	536	195.4	155.8	174.5	33. Latvia	10,007	167.8	142.6	154.7
6. Bangladesh	653	156.9	169.7	163.2	34. Cook Islands	10,136	94.1	153.0	120.0
7. Cambodia	789	120.6	208.7	158.6	35. Croatia	10,701	186.3	82.3	123.8
8. Syria	1,014	86.5	229.9	141.0	36. Hungary	12,410	152.6	168.6	160.4
9. Moldova	1,038	89.0	234.3	144.4	37. Estonia	12,436	149.1	224.0	182.8
10. Viet Nam	1,116	70.2	168.8	108.9	38. Slovakia	12,855	114.7	819.7	306.6
11. Bolivia	1,456	464.1	738.2	585.3	39. Tri. & Tob.	14,576	249.2	93.7	152.8
12. Egypt	1,576	271.1	66.3	134.1	40. Greece	18,158	16.3	907.9	121.7
13. Palestine	1,666	84.8	155.6	114.9	41. Slovenia	19,578	24.9	650.1	127.2
14. Philippines	1,734	196.2	106.1	144.3	42. Malta	20,279	107.4	169.5	134.9
15. Ukraine	1,863	189.7	269.8	226.2	43. Puerto Rico	20,837	131.9	173.0	151.1
16. Indonesia	2,043	213.5	167.2	188.9	44. Korea	25,280	112.9	214.3	155.5
17. Congo	2,044	196.8	91.8	134.4	45. Israel	25,986	99.2	207.0	143.3
18. Paraguay	2,130	191.3	94.9	134.7	46. Spain	26,141	20.2	620.3	111.9
19. Georgia	2,816	176.3	142.2	158.3	47. Hong Kong	34,900	119.8	193.6	152.3
20. Cabo Verde	2,973	179.7	116.5	144.7	48. France	36,026	100.8	178.0	133.9
21. El Salvador	3,300	341.4	294.2	316.9	49. Finland	38,625	74.4	175.3	114.2
22. Algeria	3,475	128.4	91.2	108.2	50. Austria	41,379	138.5	263.5	191.0
23. Albania	3,959	137.4	100.4	117.5	51. U.K	43,591	81.3	243.4	140.7
24. Jamaica	4,059	257.3	215.7	235.6	52. Netherlands	44,336	80.2	146.6	108.4
25. China	4,187	176.6	344.5	246.7	53. Norway	67,315	72.8	194.0	118.8
26. Colombia	4,747	102.8	231.5	154.3	54. Luxembourg	84,955	60.2	462.6	166.9
27. Kazakhstan	5,514	66.5	232.4	124.3	Mean	13,425	142.0	244.2	165.4
28. South Africa	6,126	170.8	281.9	219.4	SD	17,556	79.5	181.1	72.9

Notes: This table reports trade costs derived from a SETAR model. All numbers are expressed in percent, and are interpreted as a fraction of production cost. Columns (3) and (8) shows the costs encountered by domestic traders, while those of international traders are reported in columns (4) and (9). Columns (5) and (10) show the average comprehensive trade costs derived as: $1+\tau_c = \sqrt{(1+\varphi)(1+\varphi^*)}$. The countries listed are those with significant estimates from the SETAR(1) model, and are ranked by income, measured as the 2015 US Dollar per capita (constant price, 2011 PPP). Country labels: "Ant. & Barb." = Antigua and Barbuda; "Tri. & Tob." = Trinidad and Tobago.

Figure 6.1: SETAR(1) results



Notes:

1. Panel A: Histograms of the Low, Middle and High regime autoregressive coefficient estimates. Outliers are not shown.
2. Panel B: The t-statistics for four alternative hypotheses stated in the panels' titles. The gray areas represent support for these alternatives. $\hat{\beta}_L, \hat{\beta}_M, \hat{\beta}_H$ denote the regime-specific estimates. $\hat{\sigma}_M$ and $\hat{\sigma}_L$ are the standard errors of the Middle and Low coefficients, respectively. These numbers are extracted from Table 6.1.
3. In each panel, there are 97 observations.

In Table 6.2 we report the measure of comprehensive trade costs. We can see that costs are generally higher for low- and middle-income countries. The average "domestic" and "world" costs are 142% and 244%, respectively, implying that domestic and international exporters would induce an average cost of 42% and 144%, on top of their production prices. Taking average of domestic and foreign trade costs across all countries gives us 65%, not too different from the estimate of average comprehensive trade cost of 70% provided in Anderson & van Wincoop (2004). Note however that this result only applies to the set of country-specific agricultural products available to us.[20]

7. More on hypothesis testing

In this section, we conduct as robustness check a bootstrap simulation experiment for each country/panel in our sample independently. This exercise allows us to see whether our estimators have desirable asymptotic properties. For tractability, we shall focus on the set of 54 countries with statistically significant estimates of the regime-specific parameters.

- Step 1: Given the estimates in Table 6.1, for each country, we store the residuals from the fitted SETAR model (5.2) ($\widehat{\varepsilon}_{it}$), group them by items, and treat the pooled residuals as the empirical distribution.
- Step 2: We then adopt a non-parametric bootstrapping procedure: First, draw with replacement a sample of size $b + 99$ from the empirical distribution (where b is the number of item-years in each country-specific panel). Then, the b values of u_{it} are used as a bootstrap sample under the null hypothesis.
- Step 3: Generate a series of deviations:

  (7.1)
  $$k^s_{it} = \widehat{\alpha}' + \widehat{\beta}_L k^s_{i,t-1}\mathbf{I}(k^s_{t-1} < \widehat{k}_L) + \widehat{\beta}_M k^s_{i,t-1}\mathbf{I}(\widehat{k}_L < k^s_{t-1} < \widehat{k}_H) + \widehat{\beta}_H k^s_{i,t-1} I(k^s_{t-1} > \widehat{k}_H) + u_{it},$$

  where $\widehat{\alpha}', \widehat{\beta}_L, \widehat{\beta}_M, \widehat{\beta}_H, \widehat{k}_L, \widehat{k}_H$ are all estimates derived from actual data (note that $\widehat{k}_L$ and $\widehat{k}_H$

[20] To put these numbers into perspective, in unreported results (available upon request) we compare them with an alternative trade cost measure recently published by the United Nation's Economic and Social Commission for Asia and the Pacific (UNESCAP, 2016), denoted as τ_{UN}. This measure is derived on the basis of the trade model of Anderson & van Wincoop (2003), the model with heterogeneous firms of Melitz & Redding (2014), and the inverse gravity equations of Novy (2013). On average τ_{UN} is more than twice as large as τ_c. The discrepancy may be partly explained by the fact that the ESCAP database encompasses all agriculture, hunting, forestry and fishing related sub-sectors. A disadvantage of this latter method compared with ours is the somewhat arbitrary choice of the sector-specific elasticity of substitutions (Duval & Utoktham, 2011). Additionally, it could be argued that while τ_c is derived from data of actually traded agriculture products, τ_{UN} is an average tariff-equivalent for all goods, some of which may not be traded (or contain large non-tradable components) .

are not reported in Table 6.1). We set the initial value as $k^s_{i0} = 0$ then determine whether k^s_{i0} belongs to the Low, Middle or High regime. We then continue until generating $k^s_{i(b+100)}$. The first 100 simulations of the series $\{k^s_{it}\}$ are then discarded.[21]

- Step 4: Re-estimate the TAR model (5.2) for the simulated data. Store the set of simulated autoregressive coefficient estimates (denoted as $\widehat{\beta}^s_L, \widehat{\beta}^s_M, \widehat{\beta}^s_H$) and their corresponding standard errors (denoted as $\widehat{\sigma}^s_L, \widehat{\sigma}^s_M, \widehat{\sigma}^s_H$).
- Step 5: Repeat steps one to four 1,000 times.

Following this procedure, for each of the 54 countries, we obtain $n = 1,000$ simulated time series from which 1,000 sets of estimates are derived. It is then helpful to compute a measure of estimate precision. To do this, we compare the mean of the 1,000 coefficient estimates, denoted as $\overline{\beta}_R$ $R = L, M, H$, with the corresponding "true" values (estimates obtained using actual data ($\widehat{\beta}_R$). Similarly, we compare the standard deviation of the estimates, denoted as σ_R, with the average of the (asymptotic) standard errors: $\widehat{\sigma}_R = (1/n)\sum_{j=1}^{n} \widehat{\sigma}^s_{R_{(j)}}$ $(R = L, M, H)$. Table 7.1 documents the sets of values $\left\{\widehat{\beta}_R, \overline{\beta}_R, \sigma_R, \widehat{\sigma}_R\right\}$, in this order, for all regimes. The statistical properties of the estimators documented from our simulation generally supports the validity of our approach. Specifically, the average simulated coefficients are reasonably close to the estimates obtained from actual data.[22]

However, it can be seen that in all regimes, the dispersion of the estimated coefficients (as measured by σ) is larger than the asymptotic standard errors (measured by $\widehat{\sigma}$), implying that the actual estimated standard errors (reported in Table 6.1) understate the true sampling variability. The degree of understatement can be severe. From the second-to last-row and columns (9) and (10), this understatement is about $(1.32 - 0.38)/1.32 = 70\%$ for the Middle regime. The corresponding numbers for the Low and High regimes are both 40% . In agreement with the estimation results presented in Table 6.1, the simulation results indicate that relative to the Low regime, on average the High regime coefficient is smaller but are less precisely estimated.

These empirical observations can also be inferred from Figure 7.1, which shows boxplots

[21] This is to mitigate the effect of initial value. Note that in general, the two thresholds k_L and k_H have opposite signs, thus choosing $k^s_{i0} = 0$ would often place the initial observation in the Middle regime.

[22] In unreported results, instead of letting threshold parameters unrestricted, we alternatively keep them fixed (using actual threshold estimates) while re-estimating with the simulated samples. The least square estimators then give almost identical values of $\{\widehat{\beta}_R$ and $\overline{\beta}_R\}$. Similarly no substantial difference between $\{\sigma_R$ and $\widehat{\sigma}_R\}$. This shows that, for the SETAR model, when k_L and k_H are known, we are essentially estimating a linear model (with respect to the AR parameters). This property underlies the estimation procedure proposed by Hansen (1999) and discussed in Appendix A4.

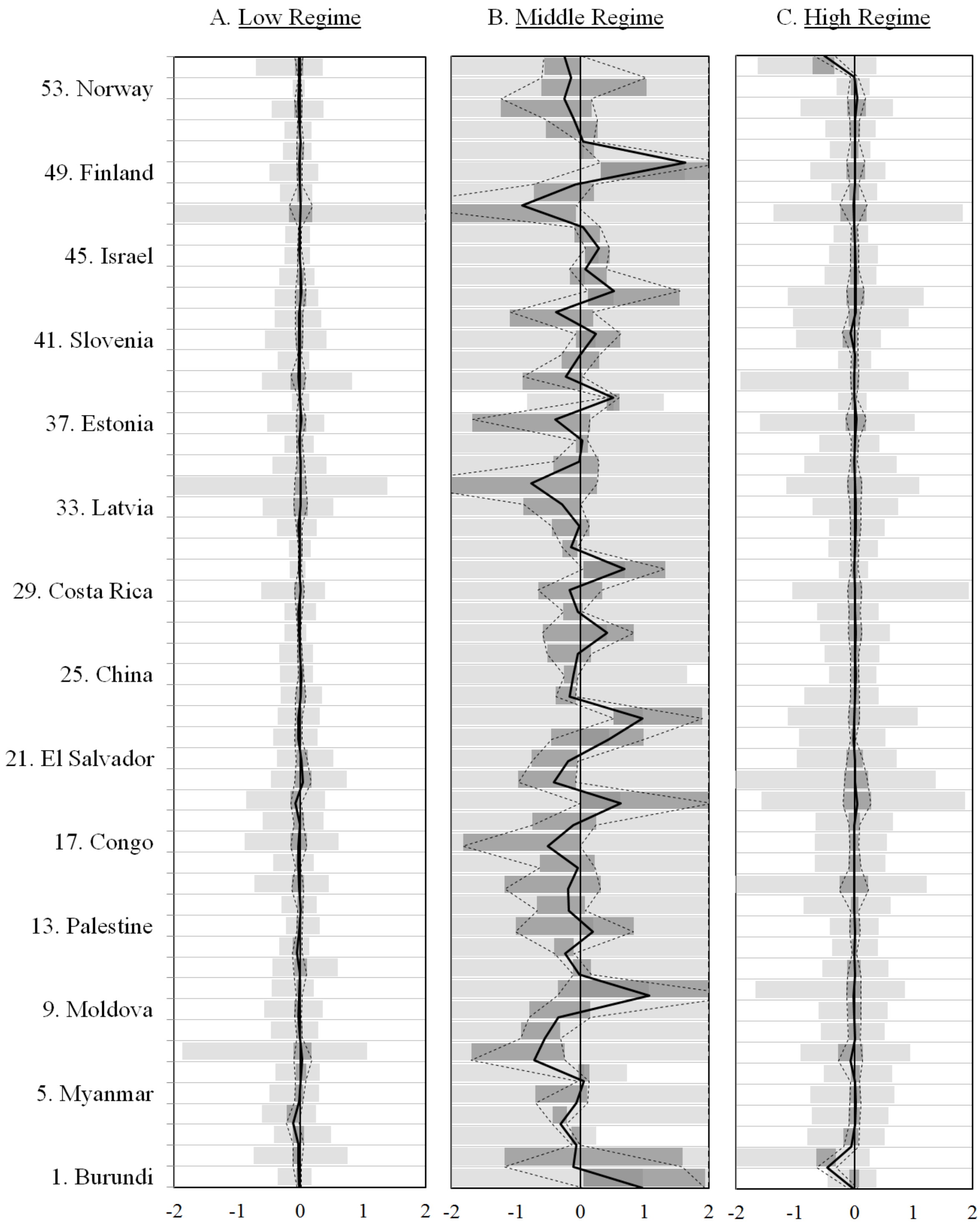
of the 1,000 estimation biases, which are computed as the differences between the estimated coefficients and their actual values, for each regime: $\widehat{\beta}^{s}_{R_{(j)}} - \widehat{\beta}_{R}$ (R = L, M, H; j = 1, . . . , 1, 000). As can be seen, the biases are much less dispersed in the Low and the High compared with the Middle regime. In all regimes there is no systematic change in the estimation precision across countries. These plots illustrates that on average, the regimes specific autoregressive coefficients are not significantly different from their "true" values. This again validates our statistical approach. Nevertheless, as pointed out above, because the asymptotic standard errors underestimate true sampling variability, the low probability of rejection of the random walk null using actual data estimates may be spurious.

Table 7.1: SETAR(1) model simulated coefficient estimates

Country	Income ($p.c)	**Low regime** True value $\widehat{\beta}_L$	Low regime Simulated Mean $\overline{\beta}_L$	Low regime Simulated SD σ_L	Low regime Simulated Mean SE $\widehat{\sigma}_L$	**Middle regime** True value $\widehat{\beta}_M$	Middle regime Simulated Mean $\overline{\beta}_M$	Middle regime Simulated SD σ_M	Middle regime Simulated Mean SE $\widehat{\sigma}_M$	**High regime** True value $\widehat{\beta}_H$	High regime Simulated Mean $\overline{\beta}_H$	High regime Simulated SD σ_H	High regime Simulated Mean SE $\widehat{\sigma}_H$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. Burundi	143	0.87	0.84	0.16	0.09	-0.16	0.93	2.05	0.6	0.67	0.56	0.23	0.16
2. Niger	291	0.96	0.82	0.24	0.14	0.99	1.24	3.54	0.91	1.15	0.76	0.37	0.21
3. Ethiopia	337	0.43	0.49	0.12	0.08	0.93	0.82	0.24	0.08	0.29	0.06	0.2	0.13
4. Nepal	444	0.91	0.26	0.21	0.13	1	0.59	0.6	0.15	0.67	0.49	0.2	0.12
5. Myanmar	536	0.71	0.71	0.14	0.08	0.66	0.33	1.1	0.31	0.51	0.32	0.2	0.13
6. Bangladesh	653	0.57	0.47	0.14	0.09	0.9	0.91	0.28	0.1	-0.17	-0.23	0.13	0.1
7. Cambodia	789	0.25	0.31	0.38	0.19	0.98	-0.14	1.77	0.56	0.32	-0.27	0.39	0.23
8. Syria	1,014	0.7	0.71	0.08	0.05	0.92	0.24	0.72	0.27	0.37	0.22	0.22	0.13
9. Moldova	1,038	0.79	0.82	0.13	0.08	0.45	0.04	1.5	0.45	0.59	-0.58	0.7	0.3
10. Viet Nam	1,116	0.75	0.74	0.15	0.1	-0.7	0.52	2.83	0.9	0.46	0.22	0.41	0.26
11. Bolivia	1,456	-0.19	0.12	0.34	0.18	-0.28	-0.09	0.69	0.19	-0.54	0.57	0.26	0.16
12. Egypt	1,576	0.79	0.57	0.09	0.07	0.93	0.69	0.51	0.15	0.66	0.67	0.11	0.06
13. Palestine	1,666	0.7	0.7	0.14	0.08	0.23	0.2	1.87	0.53	0.38	0.28	0.24	0.16
14. Philippines	1,734	0.59	0.61	0.1	0.06	0.71	0.37	0.82	0.26	0.54	0.58	0.17	0.09
15. Ukraine	1,863	0.88	0.64	0.24	0.15	0.63	0.26	2.67	0.72	0.9	-0.04	0.76	0.38
16. Indonesia	2,043	0.92	0.67	0.11	0.07	0.67	0.39	0.83	0.27	0.41	0.41	0.16	0.11
17. Congo	2,044	0.65	0.27	0.23	0.16	0.79	-0.16	1.81	0.56	0.47	0.47	0.2	0.11
18. Paraguay	2,130	0.83	0.36	0.23	0.14	0.56	0.3	1.13	0.37	0.49	0.52	0.2	0.11
19. Georgia	2,816	0.91	0.94	0.23	0.16	0.25	1.43	2.22	0.66	0.24	0.52	0.37	0.2
20. Cabo Verde	2,973	0.38	0.31	0.24	0.15	0.96	0.35	1.49	0.4	0.34	0.39	0.55	0.25
21. El Salvador	3,300	0.52	0.61	0.16	0.09	0.79	0.34	1.13	0.3	0.41	0.44	0.25	0.14
22. Algeria	3,475	0.63	0.52	0.11	0.08	-0.12	0.11	1.26	0.4	0.74	0.76	0.17	0.09
23. Albania	3,959	0.72	0.95	0.09	0.07	-0.24	1.02	1.35	0.4	0.44	0.56	0.28	0.14
24. Jamaica	4,059	0.46	0.41	0.13	0.09	0.86	0.55	0.51	0.16	0.83	0.58	0.19	0.1
25. China	4,187	0.7	0.64	0.08	0.05	0.77	0.5	0.52	0.13	0.27	0.25	0.14	0.09
26. Colombia	4,747	0.78	0.81	0.07	0.04	0.74	0.56	0.93	0.27	0.46	0.16	0.18	0.13
27. Kazakhstan	5,514	0.93	0.88	0.11	0.06	0.21	0.43	1.91	0.54	-0.45	-0.26	0.38	0.23
28. South Africa	6,126	0.67	0.78	0.07	0.04	0.86	0.68	0.56	0.14	0.8	0.63	0.28	0.13
29. Costa Rica	6,233	0.77	0.78	0.15	0.1	0.62	0.37	1.46	0.39	0.39	0.41	0.25	0.16
30. Mauritius	7,602	0.89	0.87	0.07	0.05	-0.26	0.5	1.25	0.37	0.48	0.64	0.34	0.2
31. Mexico	8,607	0.74	0.69	0.04	0.03	0.71	0.51	0.36	0.13	0.24	0.31	0.12	0.08
32. Chile	9,965	0.67	0.84	0.07	0.04	0.76	0.57	0.63	0.21	-0.4	-0.28	0.19	0.15
33. Latvia	10,007	0.49	0.37	0.18	0.12	0.65	0.11	1.22	0.35	0.46	0.39	0.19	0.12
34. Cook Islands	10,136	0.59	0.64	0.34	0.2	0.94	-0.46	4.32	1.17	-1.01	-1.49	0.59	0.36
35. Croatia	10,701	0.4	-0.01	0.15	0.11	0.68	0.59	0.62	0.29	0.41	0.51	0.14	0.08
36. Hungary	12,410	0.73	0.69	0.08	0.05	0.84	0.8	0.35	0.11	0.25	0.3	0.11	0.08
37. Estonia	12,436	0.48	0.64	0.14	0.09	0.91	-0.03	1.81	0.54	0.76	-0.15	0.33	0.21
38. Slovakia	12,855	0.56	0.66	0.05	0.04	0.42	0.91	0.19	0.11	0.66	-1.95	0.21	0.11
39. Tri. & Tob.	14,576	0.37	-0.32	0.31	0.18	0.81	0.31	1.02	0.34	0.6	0.7	0.25	0.13
40. Greece	18,158	0.91	0.91	0.06	0.03	0.88	0.76	1.3	0.34	0.74	0	0.09	0.07
41. Slovenia	19,578	0.86	0.85	0.14	0.07	0.66	0.85	1.34	0.37	0.54	-0.21	0.17	0.14
42. Malta	20,279	0.71	0.85	0.09	0.06	0.94	0.47	1.45	0.38	0.37	0.35	0.24	0.13
43. Puerto Rico	20,837	0.72	0.83	0.1	0.07	0.56	1.43	1.85	0.54	0.3	0.67	0.36	0.24
44. Korea	25,280	0.79	0.78	0.09	0.05	0.8	0.94	1.03	0.29	0.59	0.77	0.16	0.11
45. Israel	25,986	0.82	0.87	0.05	0.03	0.77	0.99	0.71	0.2	0.2	0.46	0.13	0.11
46. Spain	26,141	0.91	0.92	0.05	0.03	0.86	0.93	0.82	0.23	0.73	-0.33	0.09	0.08
47. Hong Kong	34,900	0.25	0.29	0.64	0.35	0.52	-1.33	4.35	1.19	-0.9	-0.93	0.77	0.37
48. France	36,026	0.67	0.69	0.07	0.04	0.6	0.33	1.3	0.35	0.48	0.02	0.17	0.12
49. Finland	38,625	0.84	0.85	0.08	0.05	0.78	2.09	1.7	0.62	0.67	0.83	0.22	0.15
50. Austria	41,379	0.77	0.73	0.08	0.05	0.68	0.86	0.58	0.15	0.72	0.96	0.15	0.1
51. U.K	43,591	0.86	0.83	0.07	0.04	0.7	0.56	1.07	0.28	0.48	0.46	0.2	0.12
52. Netherlands	44,336	0.75	0.67	0.13	0.07	0.52	0.11	1.28	0.41	0.37	0.2	0.31	0.17
53. Norway	67,315	0.93	0.93	0.04	0.03	0.13	0.39	1.32	0.34	0.54	0.47	0.26	0.16
54. Luxembourg	84,955	0.84	0.84	0.11	0.07	0.98	0.65	0.93	0.3	0.52	-0.91	0.33	0.19
Mean	13,425	0.69	0.64	0.15	0.09	0.61	0.51	1.32	0.38	0.40	0.21	0.27	0.16
SD	17,556	0.21	0.26	0.10	0.06	0.38	0.50	0.89	0.24	0.40	0.56	0.16	0.07

Notes: This table presents summary statistics of the two-threshold SETAR(1) model estimates from bootstrap simulations. The listed countries are those for which significant coefficient estimates are obtained using actual data. In each country/panel, $\widehat{\beta}_R$ is the estimates based on actual data; $\overline{\beta}_R = (1/n)\sum_{j=1}^{n}\widehat{\beta}^s_{R_{(j)}}$ and $\sigma_R = \sqrt{(1/n)\sum_{j=1}^{n}\left(\widehat{\beta}^s_{R_{(j)}} - \overline{\beta}_R\right)^2}$ $(j = 1, \ldots, 1,000)$ are the mean and standard deviation of the 1,000 estimates derived from simulated data; and $\widehat{\sigma}_R$ is the average standard errors corresponding to these estimates (R = L, M, H). Countries are ranked by income, which is measured by the 2015 US Dollar per capita, constant prices, 2011 PPP.

Figure 7.1: SETAR(1) estimate biases



Notes: This figure illustrate the performance of the estimators of the AR coefficients in the SETAR(1) model.
1. These are boxplots of 54 country-specific estimation biases obtained from 1,000 simulation trials, for each of the implied regimes. The underlying variable is the difference between simulated estimates and true values obtained from fitting actual data, that is, $\beta^{s}_{(j)} - \widehat{\beta}$ (j = 1, . . . , 1, 000). The countries are ordered from bottom to top by income.
2. In each panel, the dark shaded area indicates the inter-quartile range (IQR), which is bounded by the two dotted lines. The light shaded area indicates the range. The solid line indicates the median. Because of truncation at -2 and 2, the range is not shown fully for some countries.

To see if this concern is valid, in Figure 7.2, we re-plot the t-statistics described in Figure 6.1, but this time derived from bootstrapped samples. In panel A, when testing the null hypothesis of random walk, i.e. $H_0 : \overline{\beta}_M = 1$. We observe that the null cannot be rejected for 40% of the countries, compared with 77% when using actual estimates. Again, this implies that the movement of the relative prices in the Middle regime can be reasonably characterized by a random walk for some of the countries. However, these high standard errors also mean that it is harder to reject the nulls of slower adjustment in the band than in the Low and High regimes, as shown in panel C and D: The rejection rates drop to 12% and 22%, compared with the corresponding rates using actual data of 34% and 70%, respectively.[23] With respect to the null of slower adjustment in Low than in High regime, the rejection rate does not change much (from 75% to 70%). Overall, though we document non-spurious statistical evidence supporting random walk behaviour in the band, this result does not apply to all countries, and thus should be interpreted with caution.

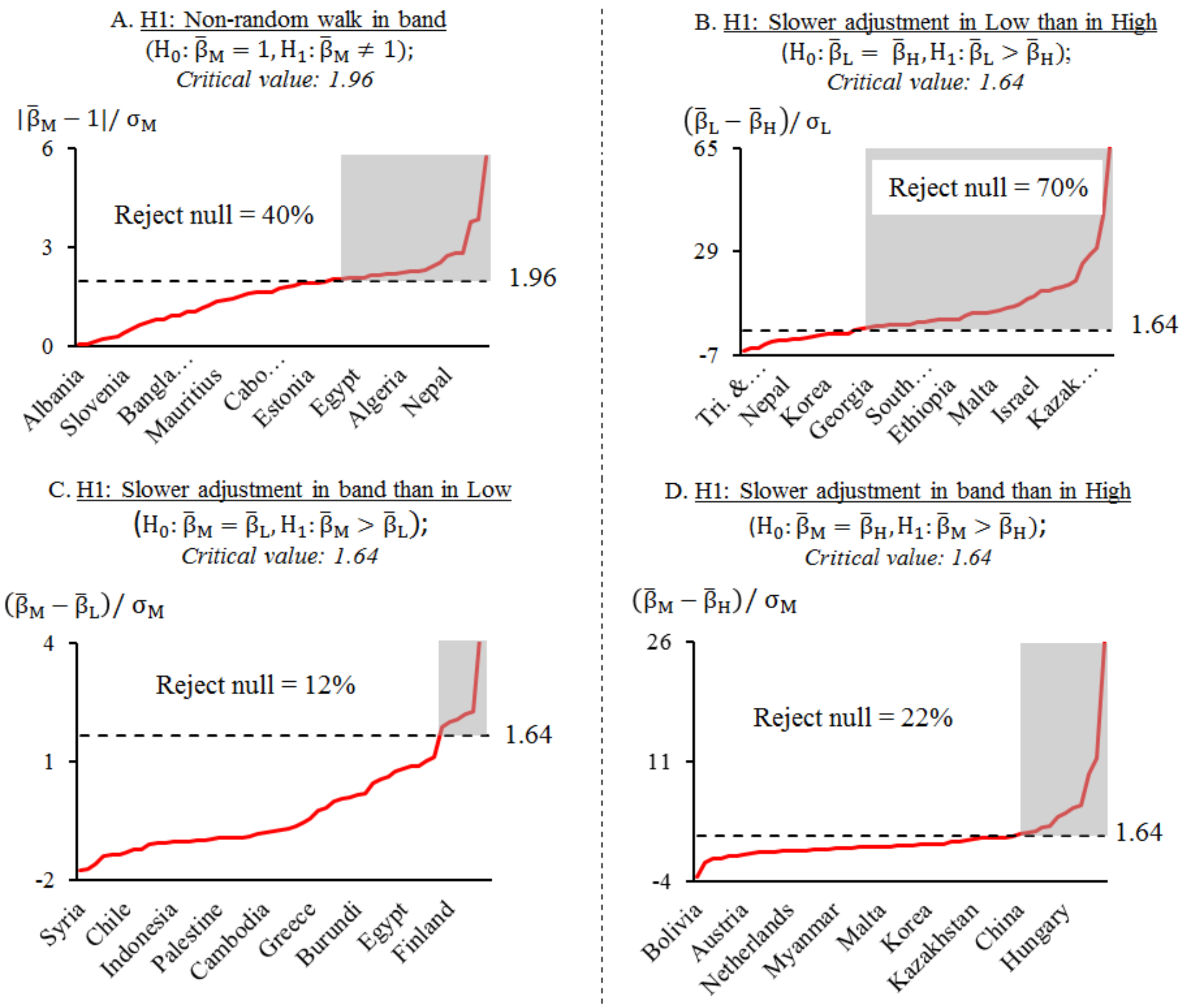
8. Summary and concluding comments

The first part of this paper integrates the traditional approaches to Purchasing Power Parity (PPP) with the recent notion of a "band of no-arbitrage". We show how the existence of trade costs can, in theory, create a sizeable buffer region within which exchange rates "wander" independently of prices and thus generate persistent deviations from parity. We then use FAO's agricultural production prices to apply an asymmetric non-linear threshold autoregressive model to test this "threshold PPP" theory. This large database has the attraction of referring to microeconomic transaction prices (and not price indexes), which more closely match price concept at the heart of international arbitrage.

Estimates of the model seem to imply that the behaviour of deviations from parity is at least partially in accordance with the theory; that is, the available evidence seems to suggest deviations follow a random walk once they enter the band. Even if we don't condition on this random walk behaviour, the speed of adjustment in the band is still significantly lower than that outside of the band. For the outer regimes, the implied half-life of PPP deviations is very short, generally less than one year. In light of the recently rising literature on non-linear adjustments toward PPP (Manzur, 2017; Bahmani-Oskooee & Wu, 2018), half-life estimates between one

[23]The comments from James Fogarty on this particular point is appreciated.

Figure 7.2: Tests based on SETAR(1)'s simulations



Notes: This figure presents the t-statistics for four hypotheses, based on the averages of the regime-specific estimate coefficients obtained from the simulated SETAR(1) process. The t-statistics are computed as $|\bar{\beta}_M - 1|/\sigma_M$ in panel A, and as $(\bar{\beta}_R - \bar{\beta}_r)/\sigma_R$ in other panels, where $\bar{\beta}_R$(or $\bar{\beta}_r$) and σ_R denote the mean and standard deviation of the estimates derived from the simulation samples. The grey areas represent support for the alternative hypotheses, which are stated in the panels' titles.

and two years is encouraging, and contrasts the glacial speeds highlighted by earlier studies (e.g. Rogoff, 1996). Additionally, we find that the speed of adjustment is asymmetric, in the sense that the reversion to parity tends to be faster when the deviations are positive (i.e. when local prices are relatively higher than the world counterparts). The size of the band also provides a measure of multilateral trade costs, which seems to be lower for more developed countries.

It should be acknowledged that there are important caveats in our study. Though effort is made to control for item fixed effects, there may be distinct features affecting their trade costs that our estimators are unable to capture. We could limit the study to specific items, such as the world's primary exports, to examine these features closer. The notion of asymmetric adjustment speed depending on the direction of the deviations also deserves careful investigation and could potentially offer insights into the underlying mechanisms of exchange rate regimes when the currencies are under/overvalued. In terms of the model employed, regime-switching, smooth-transition and time-varying specifications of autoregressive models are possible alternatives that may allow deeper insight into the dynamics of the adjustment process. Specifically, the notion of a time-varying size of "no-arbitrage band" could be of particular value. Finally, the decomposition of the general trade costs into more specific costs (related to distance, trade policies, culture, language etc.) offers another interesting venue for future research.

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Supplementary materials for "Why don't agricultural prices always adjust towards parity?"*

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Abstract: A prominent empirical regularity is the incomplete pass-through of exchange rate changes to domestic price changes, which reflects the failure of the purchasing power parity doctrine. We argue that such disconnection can be explained by the non-linear mean reversion dynamics of exchange rates: As a consequence of various trade barriers, there is a sizeable buffer region, a "band of inaction", within which exchange rates can move independently of prices, thus generating large and persistent deviations from parity. When examining panels of large numbers of disaggregated and tradable agricultural products with a non-linear exchange rate specification, we observe relatively fast adjustment speeds whenever deviations are sufficiently large so as to induce arbitrage. On the other hand, when deviations fall within the band of inaction, there is evidence that movements in rates follow a random walk. Additionally, the speed of adjustment is asymmetric, in the sense that positive deviations are adjusted faster than negative deviations.

JEL classification: F31, F41, F47

Keywords: Agricultural prices; Exchange rates; Purchasing power parity; Non-linear models; Threshold auto-regression

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A1. Data description

Data sources

The primary source is the FAO Statistic Division.

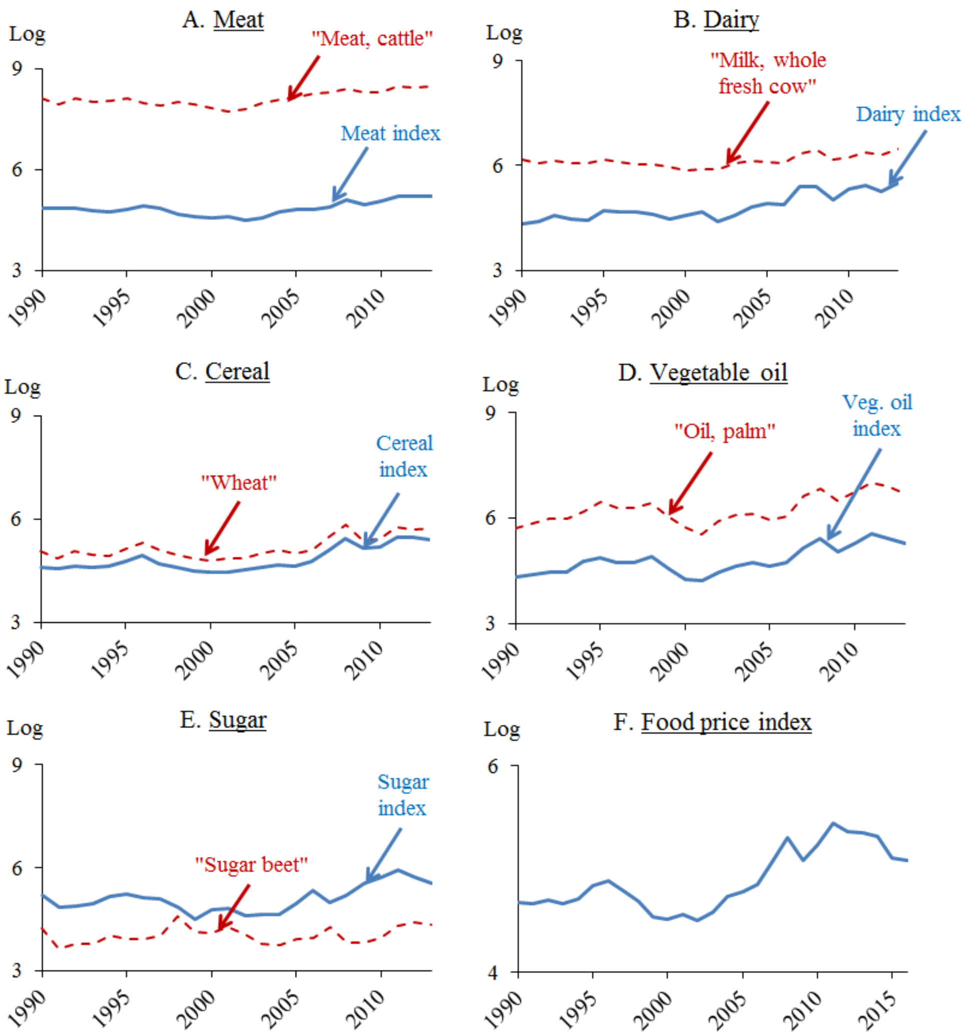
- The food and agricultural production price dataset (FAO, 2017c) are prices received by farmers for primary agricultural products as defined in the 1993 System of National Accounts (SNA-93) published by the International Monetary Fund. The producer's price is the amount receivable by the producer from the purchaser for a unit of a good or service produced as output minus any VAT, or similar deductible tax, invoiced to the purchaser. It excludes any transport charges invoiced separately by the producer. Time series refer to the national average prices of individual commodities comprising all grades, kinds and varieties, received by farmers when they participate in their capacity as sellers of their own products at the farm gate or first-point-of-sale. Due to data availability, for certain countries and products, the FAO uses consumer prices instead.[1]
- The food and agricultural trade dataset (FAO, 2017a) is collected, processed and disseminated by FAO according to the standard International Merchandise Trade Statistics methodology. The data is mainly provided by the United Nations Statistics Division (UNSD)[2], Eurostat, and other national authorities as needed. This source data is checked for outliers, trade partner data is used for non-reporting countries or missing cells, and data on food aid is added to take into account total cross-border trade flows. The trade database includes the following variables: export quantity, export value, import quantity and import value. The trade database includes all food and agricultural products imported/exported annually by all the countries in the world. Following Mundlak & Larson (1992), for each item, we compute the "world" price as export price, the logarithm of the ratio between export value and export quantity. We then weight these export prices by their corresponding export shares (values), as described in section 4.
- It should be noted that we also modified our data by (i) omitting all country-item entries

[1] The list of these countries and products is available at http://fenixservices.fao.org/faostat/static/documents/PP%5CCountryNotes_e.pdf.

[2] It is a widely accepted caveat that since the UNSD relies on the trade statistics reported by its member countries, trade data discrepancy due to misreporting is not uncommon, and could affect the quality of our export-weighted price data (Feenstra et al., 1999).

with missing annual exchange rate data and (ii) recoding countries in exchange rate data that were dissolved in recent periods (such as Czechoslovakia and Yugoslavia) so that they match with the production price data's country codes.

Figure A1.1: World food prices, 1990 - 2013



Note: This figure compares various food price indices (FAO, 2017d) with prices of selected disaggregated items. The time series of these items are represented by dashed lines, and are labelled by the items' original names (as shown in FAO production price data). All indices are weighted with the average export shares for 2002-2004. All disaggregated prices are weighted by current export shares. Since we are using log scale, multiplying the difference between any two time points by 100 gives us the annual percentage change during this period.

Why use export prices?

As a check for the validity of our world price construction using export data, in the first 5 panels of Figure A1.1, we plot the logarithm of the 5 food price indices provided by FAO side by side the "world price" (log p^*_{it}) of five selected comparable agricultural products. We take the annual average of the monthly data available at http://www.fao.org/worldfoodsituation/

foodpricesindex/en/. Even though they are different in scale due possibly to aggregation biases, the two sets of series track each other very closely.[3] Additionally it can be seen that in most cases the domestic prices exceed that of the world prices. The last panel of figure A1.1 present the average food price index for the period 1990 - 2016. The spikes at 2008-2009 and 2011-2012 corresponds to recent food crises.

Item headings

As the number of items in our dataset is well over 200, it is useful to first categorize them into groups. The original 21 aggregated groups (provided as a download option on FAO production price page) are constructed somewhat ambiguously and contains many duplications. Particularly, the most problematic group is under the “Crops Primary” heading, which contains some very broadly defined items that either (i) cannot be readily assigned to existing groups or (ii) be put into multiple groups (thus creating duplicated entries). For the former we create new “unique” headings, while for the later we determined the primary use of each items in order to re-classify them into existing groups. With categories having too few items, we sort them into a broad “Other” category. Table A1.1 presents our new heading system.

A2. A FIXED-EFFECT LEAST-SQUARED DUMMY-VARIABLE REGRESSION

We need to estimate model (4.2):

$$k^*_{ict} = \alpha + \sum_{j=1}^{136} \omega_j DI^j_{ict} + \sum_{d=1}^{165} \gamma_d DC^d_{ict} + \sum_{y=1}^{27} \vartheta_y DY^y_{ict} + k_{ict},$$

where DI^j_{ict} equals 1 when $i = j$ and zero otherwise. Analogously, $DC^d_{ict} = 1$ when $c = d$ and $DY^y_{ict} = 1$ when $t = y$ are the country and year dummies. k_{ict} is the residual real exchange rate. It is clear that no unique set of coefficients could minimize the sum of squared residual $\left(\sum \widehat{k}^2_{ict}\right)$. That is, equation (4.2) is not identified.[4] To circumvent this problem, a traditional approach is to constrain one of the ω_j, one of the γ_d and one of the ϑ_y to be zero (omitting one dummy variable for each category). The intercept coefficient estimated in such a model represents the relative price of a “base” type, corresponding to the omitted item, country and year. Each of the rest of the coefficients represents deviation from this “base” case, which does not yield particularly interesting interpretation regarding our purpose. Additionally, the choice

[3] This is also likely because our selected items are important components of these indices.

[4] To see this, we can add a constant to each dummy variable coefficients in (4.2) and subtract the sum of these constants from the intercept and all calculated values of $\widehat{k}_{ict}$ are unaffected. This is the familiar dummy variable trap problem.

Table A1.1: Basic headings for 210 items

	1. Fibre and Jutes	**2. Roots and Tubers**	**3. Beverages**	**4. Industrial materials**		**13. Fruits**
1	Flax fibre, tow	Cassava	Vanilla	Pyrethrum	1	Fruit, nes
2	Manila fibre	Roots	Tea	Wool	2	Grapefruits
3	Cotton lint	Sweet potatoes	Coffee, green	Silk-worm cocoons	3	Figs
4	Jute	Potatoes	Cocoa, beans	Tobacco	4	Persimmons
5			Kola nuts	Rubber	5	Avocados
	5. Tree nuts	**6. Pulses**	**7. Herbs and Spices**	**8. Other**	6	Kiwi fruit
1	Nuts, nes	Chick peas	Spices, nes	Eggs, other bird	7	Cherries
2	Chestnut	Beans, dry	Pepper	Sugar crops	8	Fruit, tropical nes
3	Cashew nuts	Lentils	Hops	Milk, cow	9	Cranberries
4	Walnuts	Broad beans	Ginger	Sugar beet	10	Grapes
5	Pistachios	Peas, dry	Chillies	Eggs, hen	11	Tangerines
6		Vetches	Cloves	Beeswax	12	Plums and sloes
7		Bambara beans	Cinnamon	Honey	13	Papayas
8			Anises		14	Mangoes, guavas
9			Peppermint		15	Oranges
	9. Cereals	**10. Meats**	**11. Oil seeds**	**12. Vegetables**	16	Apricots
1	Grain, mixed	Meat, nes	Olives	Pumpkins and gourds	17	Currants
2	Fonio	Meat, game	Nutmegs	Eggplants (aubergines)	18	Apples
3	Triticale	Meat, horse	Oilseeds, nes	Maize, green	19	Quinces
4	Oats	Meat, duck	Coconuts	Tomatoes	20	Pears
5	Buckwheat	Meat, cattle	Sunflowerseed	Cabbages and brassicas	21	Peaches, nectarines
6	Millet	Meat, goat	Cottonseed	Spinach	22	Lemons and limes
7	Canary seed	Meat, turkey	Rapeseed	Vegetables, fresh nes	23	Melons, other
8	Barley	Meat, pig	Sesame seed	Lettuce and chicory	24	Watermelons
9	Rye	Meat, sheep	Poppy seed	Mushrooms and truffles	25	Plantains
10	Wheat	Meat, rabbit	Soybeans	Cauliflowers and broccolis	26	Cherries, sour
11	Maize	Meat, goose	Mustard seed	Beans, green	27	Strawberries
12	Sorghum	Meat, chicken	Oil, palm	Chillies and peppers, green	28	Blueberries
13			Linseed	Artichokes	29	Pineapples
14				Cucumbers and gherkins	30	Bananas
15				Peas, green	31	Dates
16				Leeks, other alliaceous	32	Gooseberries
17				Carrots and turnips		
18				Asparagus		
19				Onions, shallots, green		
20				Onions, dry		
21				Garlic		

Note: This table lists the headings for 210 disaggregated items in the FAO annual production price database (FAO, 2017c). These headings are defined based on the original 21 headings of the FAO.

of the base type is somewhat arbitrary and clearly asymmetric. Instead, we adopt the approach of Suits (1984) and opt for a normalization of the dummy variable coefficients so they sum to zero.

First-round estimation

To begin, we estimate (4.2) using OLS method, by dropping the variables corresponding to the 136$^{\text{th}}$ item ("wools, greasy"), the 165$^{\text{th}}$ country ("Zimbabwe") and the 27$^{\text{th}}$ year ("2013"). This gives us an estimate of the intercept $\widehat{\alpha}$, in addition to three sets of slope estimates, denoted as $\{\widehat{\omega}_j\}$ (135 values), $\{\widehat{\gamma}_d\}$ (164 values) and $\{\widehat{\vartheta}_y\}$ (26 values), respectively. That is, we constrain that $\widehat{\omega}_{136} = \widehat{\gamma}_{165} = \widehat{\vartheta}_{27} = 0$.

Now we need to relax this constraint. Construct the means of rest of the coefficients as $\varkappa = \frac{\sum_{j=1}^{135} \widehat{\omega}_j}{136}$; $\eta = \frac{\sum_{d=1}^{164} \widehat{\gamma}_d}{165}$; $\psi = \frac{\sum_{y=1}^{26} \widehat{\vartheta}_y}{27}$ and deviate the original coefficients from their respective means: $\{\widehat{\omega}_j^*\} = \{\widehat{\omega}_j - \varkappa\}$, $\{\widehat{\gamma}_d^*\} = \{\widehat{\gamma}_d - \eta\}$ and $\{\widehat{\vartheta}_y^*\} = \{\widehat{\vartheta}_y - \psi\}$. This means that $\widehat{\omega}_{136}^* = -\varkappa$, $\widehat{\gamma}_{165}^* = -\eta$ and $\widehat{\vartheta}_{27}^* = -\psi$. By construction we have: $\sum_{i=1}^{136} \widehat{\omega}_j^* = \sum_{j=1}^{165} \widehat{\gamma}_d^* = \sum_{y=1}^{27} \widehat{\vartheta}_y^* = 0$.

Then, as the modified estimates are just linear combinations of the old estimates, their variance can be computed from the variance-covariance matrix of the old estimates. Define $\widehat{\alpha}^* = \widehat{\alpha} - \varkappa - \eta - \psi = \widehat{\alpha} + \widehat{\omega}_{136}^* + \widehat{\gamma}_{165}^* + \widehat{\vartheta}_{27}^*$. We refer to $\widehat{\alpha}^*$, $\{\widehat{\omega}_j^*\}$, $\{\widehat{\gamma}_d^*\}$ and $\{\widehat{\vartheta}_y^*\}$ as the "first-round" estimates. The modified intercept $\widehat{\alpha}^*$ can be interpreted as a "grand" average of PPP deviations (across all items, countries and years). Its value is about 0.6, which means the 'grand' average local price is 60% higher than the "grand" world price. It can be shown that the modified estimates have identical statistical properties to those given by (4.2). The new country dummy coefficients represent the extent to which behaviour of the respective countries (averaged over all items and years) differs from the grand average. Analogous interpretations of the other two sets of coefficients are straight-forward. In the analyses of Sections 5 and 5, we use the residuals derived from the first-round estimates, computed as: $k_{ict} = k_{ict}^* - \widehat{k}_{ict}^* = k_{ict}^* - (\widehat{\alpha}^* + \widehat{\omega}_i^* + \widehat{\gamma}_c^* + \widehat{\vartheta}_t^*)$.

Second-round estimation

As stated in Section A1, based on FAO's original 21 categories, we re-assign the items in our sample into 13 "headings" denoted as $\mathbf{S}_h$ ($h = 1, \ldots, 13$). Additionally, we sort countries into income quartiles, denoted as $\mathbf{S}_q$ ($q = 1, \ldots, 4$).[5] For simplicity, we refer to both headings and quartiles as "groups" in subsequent analyses. We can decompose the expressions in (4.2) into a group component and a within group component. Specifically, the group component is defined as the group mean of coefficients: $\lambda_q = (1/n^q) \sum_{d \in \mathbf{S}_q} \widehat{\gamma}_d^*$; $\Lambda_h = (1/n^h) \sum_{j \in \mathbf{S}_h} \widehat{\omega}_j^*$, where n^q denotes the number of countries in quartile $\mathbf{S}_q$ and n^h denotes the number of items under heading $\mathbf{S}_h$. Since our panels are unbalanced (n^q and n^h vary across quartiles and headings), these group means do not sum to zero. Nevertheless, the weighted group means do: $\sum_{q=1}^{4}(n^q/C)\lambda_q = \sum_{h=1}^{13}(n^h/I)\Lambda_h = 0$. That is, the weights are proportional to the number of individuals in a group.

[5] Per capita GDP data are obtained from FAO's macroeconomic indicators database (FAO, 2017a). These data are reported in terms of constant \$US prices (base year 2005). Using average per capita GDP over the full sample period result in little difference in the country ranking.

Next, define the within-group component as the difference between the first-round coefficients and the un-weighted group means:

$$\gamma_d^{**} = \gamma_d^{*} - \lambda_q \ (d \in \mathbf{S}_q); \ \omega_j^{**} = \omega_j^{*} - \Lambda_h \ (j \in \mathbf{S}_h).$$

It can be shown that our new within-group components are also constrained to sum to zero: $\sum_{d \in \mathbf{S}_q} \gamma_d^{**} = \sum_{j \in \mathbf{S}_h} \omega_j^{**} = 0$. Following these analyses, we extend our dummy variable regression as:

$$k_{ict}^{*} = \alpha + \sum_{q=1}^{4} \left[\lambda_q DC^g(d \in \mathbf{S}_q) + \sum_{d \in \mathbf{S}_q} \gamma_c^{**} DC^d(d = c)\right]$$

$$+ \sum_{h=1}^{13} \left[\Lambda_h DI^h(j \in \mathbf{S}_h) + \sum_{j \in \mathbf{S}_h} \omega_j^{**} DI^j(j = i)\right] \quad \text{(A2.1)}$$

$$+ \sum_{y=1}^{27} \vartheta_y DY^y(y = t) + k_{ict}.$$

As before, the dummy variables receive value of 1 when the expressions in parentheses are true and zero otherwise. Based on the above definitions, we can use the linear combinations of the first-round estimates (which are themselves combinations of the original estimates) to derive the "second-round" estimates as:

$$\widehat{\gamma}_d^{**} = \widehat{\gamma}_d^{*} - \frac{1}{n_q} \sum_{d \in \mathbf{S}_q} \widehat{\gamma}_d^{*} \ (d \in \mathbf{S}_q); \ \widehat{\omega}_j^{**} = \widehat{\omega}_j^{*} - \frac{1}{n_h} \sum_{j \in \mathbf{S}_h} \widehat{\omega}_j^{*} \ (j \in \mathbf{S}_h). \quad \text{(A2.2)}$$

Tables A2.1 and A2.2 present the second-round within- and between-group coefficients for countries and items, respectively.

Table A2.1: Deviation from PPP: Income quartile means and deviations from means

A. First quartile – 0.434 (0.037)																			
1	Burundi	-0.71	(0.10)	**143**	11	Togo	-0.69	(0.11)	**440**	21	Mozambique	5.38	(0.10)	**557**	31	Mauritania	-0.52	(0.55)	**868**
2	Central Africa	-0.37	(1.28)	**239**	12	Guinea	-0.91	(0.14)	**440**	22	Tanzania	-0.75	(0.15)	**647**	32	Mali	-0.31	(0.10)	**873**
3	Eritrea	-0.46	(0.17)	**266**	13	Gambia	-0.61	(0.14)	**442**	23	Kyrgyzstan	-0.52	(0.10)	**648**	33	Pakistan	-1.12	(0.08)	**904**
4	Madagascar	0.13	(0.09)	**272**	14	Nepal	-0.39	(0.08)	**444**	24	Bangladesh	-1.23	(0.08)	**653**	34	Sudan	3.86	(0.09)	**977**
5	Niger	-0.75	(0.12)	**291**	15	Rwanda	-0.46	(0.10)	**466**	25	Benin	0.12	(0.35)	**688**	35	Lesotho	-1.14	(0.47)	**1,004**
6	Ethiopia	-0.93	(0.07)	**337**	16	Haiti	-0.64	(0.81)	**476**	26	Kenya	-0.53	(0.08)	**777**	36	Zambia	6.38	(0.22)	**1,007**
7	Malawi	-0.60	(0.11)	**371**	17	Tajikistan	-0.19	(0.09)	**490**	27	Cambodia	-0.19	(0.10)	**789**	37	Syria	-0.82	(0.08)	**1,014**
8	Sierra Leone	1.20	(0.29)	**407**	18	Yemen	-0.04	(0.07)	**501**	28	Zimbabwe	2.01	(0.09)	**833**	38	Moldova	-0.97	(0.10)	**1,038**
9	Afghanistan	-0.59	(0.13)	**409**	19	Burkina Faso	-1.18	(0.12)	**514**	29	Senegal	-0.63	(0.11)	**836**	39	Chad	0.89	(0.20)	**1,047**
10	Guinea-Bissau	1.05	(0.24)	**432**	20	Myanmar	-1.02	(0.08)	**536**	30	Lao	-0.69	(0.12)	**854**	40	Cameroon	-0.98	(0.10)	**1,057**
															41	Viet Nam	-0.08	(0.10)	**1,116**
B. Second quartile – 0.276 (0.031)																			
1	Cote d'Ivoire	-1.23	(0.08)	**1,154**	11	Philippines	-0.87	(0.06)	**1,734**	21	Guatemala	-1.59	(0.90)	**2,404**	31	Azerbaijan	3.48	(0.07)	**3,186**
2	Ghana	6.99	(0.09)	**1,221**	12	Ukraine	-0.25	(0.07)	**1,863**	22	Sri Lanka	-0.79	(0.07)	**2,470**	32	El Salvador	1.14	(0.07)	**3,300**
3	India	-1.49	(0.08)	**1,279**	13	Timor-Leste	0.44	(0.29)	**1,908**	23	Samoa	-1.15	(0.64)	**2,527**	33	Algeria	-0.38	(0.07)	**3,475**
4	Bolivia	1.66	(0.04)	**1,456**	14	Iraq	-0.46	(0.10)	**2,007**	24	Jordan	-0.98	(0.07)	**2,564**	34	Iran	-0.74	(0.06)	**3,511**
5	Nicaragua	-0.83	(0.11)	**1,513**	15	Vanuatu	0.44	(0.18)	**2,024**	25	Armenia	-0.39	(0.08)	**2,587**	35	Bosn. & Herz.	-0.23	(0.09)	**3,614**
6	Comoros	0.41	(0.74)	**1,530**	16	Indonesia	-1.05	(0.07)	**2,043**	26	Guyana	0.49	(0.16)	**2,639**	36	Ecuador	2.81	(0.07)	**3,783**
7	Egypt	-1.22	(0.06)	**1,576**	17	Congo	-0.41	(0.09)	**2,044**	27	Angola	0.32	(0.23)	**2,779**	37	Tunisia	-0.91	(0.07)	**3,842**
8	Palestine	1.65	(0.08)	**1,666**	18	Paraguay	-1.45	(0.08)	**2,130**	28	Morocco	-0.68	(0.07)	**2,802**	38	Thailand	-0.89	(0.07)	**3,853**
9	Honduras	-1.16	(0.08)	**1,713**	19	Bhutan	0.00	(0.09)	**2,136**	29	Georgia	-0.20	(0.10)	**2,816**	39	Albania	-0.03	(0.08)	**3,959**
10	Nigeria	-0.55	(0.08)	**1,724**	20	Mongolia	-0.19	(0.12)	**2,197**	30	Cabo Verde	1.15	(0.10)	**2,973**	40	Belize	-0.95	(0.13)	**3,969**
															41	Jamaica	0.10	(0.07)	**4,059**
C. Third quartile 0.512 (0.022)																			
1	FYR Macedonia	1.52	(0.06)	**4,131**	11	Kazakhstan	-1.68	(0.08)	**5,514**	21	Argentina	1.11	(0.06)	**6,328**	31	Mexico	-1.67	(0.04)	**8,607**
2	Fiji	-0.74	(0.10)	**4,134**	12	Suriname	3.37	(0.07)	**5,534**	22	Romania	4.64	(0.05)	**6,638**	32	Turkey	7.84	(0.04)	**8,898**
3	China	-1.50	(0.05)	**4,187**	13	Cuba	-0.52	(0.08)	**5,589**	23	Russia	0.27	(0.06)	**6,717**	33	Chile	-1.79	(0.05)	**9,965**
4	Peru	-0.63	(0.05)	**4,274**	14	Grenadines	0.30	(0.18)	**5,686**	24	Botswana	-1.57	(0.27)	**6,873**	34	Latvia	-1.58	(0.07)	**10,007**
5	Serbia	-0.75	(0.11)	**4,298**	15	Saint Lucia	-0.24	(0.09)	**5,697**	25	Grenada	0.29	(0.15)	**6,931**	35	Cook Islands	-1.12	(0.13)	**10,136**
6	Namibia	-1.89	(0.13)	**4,665**	16	Dominican Rep.	-1.75	(0.06)	**5,795**	26	Turkmenistan	7.58	(0.18)	**7,130**	36	Croatia	-1.05	(0.06)	**10,701**
7	Colombia	-1.48	(0.06)	**4,747**	17	Lebanon	-1.53	(0.06)	**5,858**	27	Mauritius	-1.12	(0.07)	**7,602**	37	Oman	-0.59	(0.29)	**11,207**
8	Belarus	0.59	(0.08)	**4,792**	18	Maldives	0.50	(0.19)	**5,913**	28	Malaysia	-0.95	(0.08)	**7,622**	38	Lithuania	0.11	(0.08)	**11,560**
9	Bulgaria	0.60	(0.06)	**5,234**	19	South Africa	-1.58	(0.05)	**6,126**	29	Uruguay	0.71	(0.06)	**8,028**	39	Poland	0.55	(0.06)	**11,622**
10	Brazil	0.63	(0.07)	**5,441**	20	Costa Rica	-1.78	(0.09)	**6,233**	30	Panama	-1.20	(0.08)	**8,165**	40	Ant. & Barb.	0.02	(0.19)	**12,362**
															41	Hungary	-1.94	(0.05)	**12,410**
D. Fourth quartile 0.192 (0.03)																			
1	Estonia	1.52	(0.09)	**12,436**	11	Slovenia	2.94	(0.07)	**19,578**	21	New Zealand	-1.31	(0.07)	**31,127**	31	Australia	-1.00	(0.06)	**41,453**
2	Slovakia	0.37	(0.06)	**12,855**	12	Fr. Polynesia	-0.90	(1.28)	**20,246**	22	Hong Kong	-0.82	(0.13)	**34,900**	32	U.K	-0.92	(0.07)	**43,591**
3	Eq. Guinea	-1.85	(0.36)	**13,556**	13	Malta	-1.36	(0.08)	**20,279**	23	France	0.10	(0.06)	**36,026**	33	Netherlands	-0.55	(0.07)	**44,336**
4	Barbados	0.18	(0.10)	**14,563**	14	Puerto Rico	-0.29	(0.08)	**20,837**	24	Singapore	-0.06	(0.17)	**38,228**	34	U.S	-1.16	(0.05)	**46,876**
5	Tri. & Tob.	-0.86	(0.09)	**14,576**	15	Cyprus	-0.95	(0.06)	**21,722**	25	Canada	-1.28	(0.06)	**38,339**	35	Sweden	-1.10	(0.08)	**47,635**
6	Saudi Arabia	0.15	(0.15)	**15,146**	16	Korea	-0.48	(0.07)	**25,280**	26	Belgium	0.13	(0.10)	**38,607**	36	Denmark	-0.87	(0.07)	**49,929**
7	Seychelles	1.46	(0.22)	**15,366**	17	Brunei	0.30	(0.10)	**25,663**	27	Finland	0.40	(0.08)	**38,625**	37	Switzerland	-0.19	(0.06)	**59,038**
8	Czechia	-1.12	(0.07)	**15,727**	18	Israel	-0.61	(0.06)	**25,986**	28	Japan	0.40	(0.06)	**39,649**	38	Qatar	-0.97	(0.11)	**59,932**
9	Greece	2.51	(0.06)	**18,158**	19	Spain	1.89	(0.05)	**26,141**	29	Germany	-0.61	(0.07)	**40,789**	39	Iceland	-0.14	(0.11)	**60,655**
10	Portugal	2.17	(0.06)	**18,768**	20	Italy	4.61	(0.06)	**29,536**	30	Austria	0.69	(0.06)	**41,379**	40	Ireland	-1.24	(0.10)	**63,237**
															41	Norway	-0.35	(0.07)	**67,315**
															42	Luxembourg	1.16	(0.08)	**84,955**

Note: This table presents the second-round estimates of the country dummies in Equation A2.1 ($\widehat{\gamma}_d^{**}$; d = 1, . . . , 165). The bold numbers next to quartile headings represent the quartile effects ($\widehat{\lambda}_q$; q = 1, . . . , 4), with the first quartile being the poorest. Standard errors are in parentheses. In each quartile, the bold numbers denote the 2015 per capita GDP (in 2005 constant $US price). Within each quartile, countries are ranked by their income.

Table A2.2: Deviation from PPP: Item heading means and deviations from means

	1. Fibre and Jutes -0.184 (0.074)			**2. Roots and Tubers -0.259 (0.041)**			**3. Beverages -0.207 (0.084)**			**4. Industrial materials -0.6 (0.068)**				**13. Fruits -0.22 (0.018)**		
1	Flax fibre, tow	-0.629	(0.11)	Cassava	-0.63	(0.09)	Vanilla	-1.43	(0.20)	Pyrethrum	-0.37	(0.25)	1	Fruit, nes	-0.47	(0.07)
2	Manila fibre	0.141	(0.18)	Roots	-0.156	(0.07)	Tea	-0.93	(0.10)	Wool	-0.20	(0.08)	2	Grapefruits	-0.46	(0.06)
3	Cotton lint	0.244	(0.09)	Sweet potatoes	0.175	(0.05)	Coffee, green	0.18	(0.10)	Silk-worm cocoons	-0.03	(0.11)	3	Figs	-0.34	(0.07)
4	Jute	0.245	(0.13)	Potatoes	0.611	(0.05)	Cocoa, beans	0.33	(0.10)	Tobacco	0.22	(0.08)	4	Persimmons	-0.33	(0.15)
5							Kola nuts	1.85	(0.28)	Rubber	0.38	(0.11)	5	Avocados	-0.31	(0.07)
	5. Tree nuts -0.181 (0.048)			**6. Pulses 0.727 (0.148)**			**7. Herbs and Spices 0.514 (0.062)**			**8. Other 0.093 (0.094)**			6	Kiwi fruit	-0.30	(0.12)
1	Nuts, nes	-0.478	(0.09)	Chick peas	-0.305	(0.17)	Spices, nes	-0.82	(0.12)	Eggs, other bird	-1.53	(0.14)	7	Cherries	-0.29	(0.05)
2	Chestnut	-0.278	(0.10)	Beans, dry	-0.163	(0.16)	Pepper	-0.64	(0.11)	Sugar crops	-0.20	(0.56)	8	Fruit, tropical nes	-0.26	(0.12)
3	Cashew nuts	0.106	(0.10)	Lentils	-0.083	(0.17)	Hops	-0.47	(0.10)	Milk, cow	-0.10	(0.10)	9	Cranberries	-0.14	(0.21)
4	Walnuts	0.193	(0.07)	Broad beans	-0.011	(0.17)	Ginger	-0.13	(0.11)	Sugar beet	0.21	(0.11)	10	Grapes	-0.12	(0.05)
5	Pistachios	0.455	(0.11)	Peas, dry	0.017	(0.16)	Chillies	-0.12	(0.10)	Eggs, hen	0.22	(0.10)	11	Tangerines	-0.10	(0.06)
6				Vetches	0.124	(0.20)	Cloves	-0.04	(0.22)	Beeswax	0.63	(0.15)	12	Plums and sloes	-0.10	(0.05)
7				Bambara beans	0.421	(0.92)	Cinnamon	-0.01	(0.20)	Honey	0.76	(0.11)	13	Papayas	-0.09	(0.07)
8							Anises	0.30	(0.14)				14	Mangoes, guavas	-0.05	(0.06)
9							Peppermint	1.92	(0.37)				15	Oranges	-0.04	(0.05)
	9. Cereals 0.223 (0.063)			**10. Meats 0.068 (0.031)**			**11. Oil seeds 0.206 (0.029)**			**12. Vegetables -0.133 (0.018)**			16	Apricots	0.02	(0.06)
1	Grain, mixed	-0.978	(0.14)	Meat, nes	-0.748	(0.14)	Olives	-0.55	(0.07)	Pumpkins and gourds	-0.41	(0.05)	17	Currants	0.04	(0.09)
2	Fonio	-0.606	(0.69)	Meat, game	-0.454	(0.11)	Nutmegs	-0.54	(0.17)	Eggplants (aubergines)	-0.38	(0.06)	18	Apples	0.08	(0.05)
3	Triticale	-0.417	(0.10)	Meat, horse	-0.258	(0.12)	Oilseeds, nes	-0.48	(0.12)	Maize, green	-0.31	(0.09)	19	Quinces	0.08	(0.07)
4	Oats	0.021	(0.08)	Meat, duck	-0.025	(0.11)	Coconuts	-0.46	(0.07)	Tomatoes	-0.26	(0.04)	20	Pears	0.09	(0.05)
5	Buckwheat	0.05	(0.12)	Meat, cattle	-0.021	(0.06)	Sunflowerseed	-0.16	(0.06)	Cabbages and brassicas	-0.22	(0.04)	21	Peaches, nectarines	0.10	(0.05)
6	Millet	0.081	(0.09)	Meat, goat	0.088	(0.07)	Cottonseed	-0.08	(0.08)	Spinach	-0.15	(0.06)	22	Lemons and limes	0.11	(0.05)
7	Canary seed	0.171	(0.16)	Meat, turkey	0.148	(0.11)	Rapeseed	0.04	(0.06)	Vegetables, fresh nes	-0.14	(0.05)	23	Melons, other	0.12	(0.05)
8	Barley	0.192	(0.08)	Meat, pig	0.151	(0.06)	Sesame seed	0.13	(0.07)	Lettuce and chicory	-0.11	(0.05)	24	Watermelons	0.19	(0.05)
9	Rye	0.192	(0.09)	Meat, sheep	0.161	(0.06)	Poppy seed	0.15	(0.13)	Mushrooms and truffles	-0.10	(0.06)	25	Plantains	0.20	(0.07)
10	Wheat	0.262	(0.08)	Meat, rabbit	0.191	(0.12)	Soybeans	0.38	(0.05)	Cauliflowers and broccolis	-0.10	(0.05)	26	Cherries, sour	0.21	(0.08)
11	Maize	0.457	(0.07)	Meat, goose	0.221	(0.14)	Mustard seed	0.39	(0.11)	Beans, green	-0.07	(0.05)	27	Strawberries	0.25	(0.05)
12	Sorghum	0.575	(0.08)	Meat, chicken	0.545	(0.06)	Oil, palm	0.56	(0.11)	Chillies and peppers, green	-0.06	(0.05)	28	Blueberries	0.29	(0.18)
13							Linseed	0.62	(0.08)	Artichokes	-0.05	(0.09)	29	Pineapples	0.34	(0.06)
14										Cucumbers and gherkins	-0.03	(0.04)	30	Bananas	0.35	(0.05)
15										Peas, green	0.01	(0.05)	31	Dates	0.36	(0.09)
16										Leeks, other alliaceous	0.08	(0.09)	32	Gooseberries	0.55	(0.13)
17										Carrots and turnips	0.21	(0.04)				
18										Asparagus	0.29	(0.07)				
19										Onions, shallots, green	0.32	(0.06)				
20										Onions, dry	0.55	(0.04)				
21										Garlic	0.93	(0.05)				

Note: This table presents the second-round estimates of the item dummies in Equation A2.1 ($\widehat{\omega}_j^{**}$; j = 1, . . . , 136). The bold numbers next to item headings represent the group effects ($\widehat{\Lambda}_h$; h = 1, . . . , 13). Standard errors are in parentheses. The item groups are ranked by their numbers of items. Within a group, items are ranked by the magnitude of their estimates.

Outlier identification algorithm

As discussed in Section 4, our measure of PPP deviation is the residuals from first-round estimation: $k_{ict} = k^*_{ict} - \widehat{k}^*_{ict} = k^*_{ict} - (\widehat{\alpha}^* + \widehat{\omega}^*_i + \widehat{\gamma}^*_c + \widehat{\vartheta}^*_t)$. Here we outline the procedure to identify individual countries and items that yield extreme, or "outlying" observations of these residuals. To do this, we specify an indicator function for each country-item combination (ic):

$$\text{(A2.3)} \qquad \begin{aligned} &\mathbf{I}\left[r_{ic} \geq \pi\right]; \\ &\text{with } r_{ic} = \frac{N_{ic} - \sum_{t=1}^{T_{ic}} \mathbf{I}\left[\Phi^{-1}(\alpha/2) \leq k_{ict} \leq \Phi^{-1}(1-\alpha/2)\right]}{N_{ic}}, \end{aligned}$$

where $\mathbf{I}(.)$ denotes an indicator function, which receives value 1 if the corresponding condition in squared brackets holds and zero otherwise. r_{ic} is the share of outlying observations correspond to the country-item combination ic. π is the cut-off value, chosen to be 5%.[6] N_{ic} is the total number of annual observations while T_{ic} is the maximum number of years. $\Phi^{-1}(.)$ indicates the value of the inverse cumulative distribution function.

The tail size parameter is selected to be 0.025, so that outliers are confined in the most extreme 5% values. By construction, function $\mathbf{I}\left[\Phi^{-1}(0.025) \leq k_{ict} \leq \Phi^{-1}(1-0.025)\right] = 1$ indicates the "normal" residuals. Subtracting the number of normal observations from N_{ic} then gives us the number of "outlying" observations. Consequently, $\mathbf{I}\left[r_{ic} \geq 5\%\right] = 1$ signifies an "outlying" country-item pair ic, in which case all of the pair's annual observations shall be considered "outliers" and are omitted. How are the "outlying" residuals distributed among the omitted countries and years? Our results, reported in Table 4.1 of the main text, show that the countries identified as "outliers" composed mostly of African, South American and Eastern European countries, some of which are well-known for their substantial exchange rate rearrangements during the 1990s. In contrast, outliers are not systematically attribute to just a few items.

A3. β-TYPE CONVERGENCE ALGEBRA DERIVATION

Following the discussion in Section 5, in this Appendix we prove via simple algebra the proposition that the intercept and slope of the h-year predictive regression: $\Delta_{(h)}\overline{k}_{t+h} = \Phi^h + \Theta^h\overline{k}_t + u^h_t$ can be approximated by those of the 1-year regression. To see this, let the total

[6] Intuitively, the stricter the definition of "outliers" the more data will be filtered. When choosing this cut-off value, we need to take into account the trade-off between excluding to many observations (when π is too low) and excluding too few observations (when π is too high). Experimenting with different cut-off values give little difference in terms of the identification of outlying countries and items.

change in $\bar{k}$ over h years be the sum of the corresponding h annual change: $\Delta_{(h)}\bar{k}_{t+h} = \Delta_{(h)}k_{t+h} = \sum_{s=0}^{h-1} \Delta_{(1)}k_{t+h}$. For simplicity, assume the regression equation holds with no error at horizon 1, and suppress the horizon notation in the right-hand side, we have: $\Delta_{(1)}\bar{k}_{t+h} = \Phi + \Theta\bar{k}_{t+h-1}$ or $\bar{k}_{t+h} = \Phi + \Theta\bar{k}_{t+h-1} + \bar{k}_{t+h-1}$. Then by recursive substitution:

- When $h = 2$:

$$\begin{aligned}
\Delta_{(2)}k_{t+2} &= \Delta_{(1)}k_{t+2} + \Delta_{(1)}k_{t+1} \\
&= \left(\Phi + \Theta\bar{k}_{t+1}\right) + \left(\Phi + \Theta\bar{k}_t\right) \\
&= \left(\Phi + \Theta\left[\Phi + \Theta\bar{k}_t + \bar{k}_t\right]\right) + \left(\Phi + \Theta\bar{k}_t\right) \\
&= 2\Phi + \underbrace{\Theta\Phi + \Theta^2\bar{k}_t}_{=0,\text{ since } \Theta\Phi \approx 0 \text{ and } \Theta^2 \approx 0} + 2\Theta\bar{k}_t \\
&= 2\Phi + 2\Theta\bar{k}_t.
\end{aligned}$$

- When $h = 3$:

$$\begin{aligned}
\Delta_{(3)}k_{t+3} &= \Delta_{(1)}k_{t+3} + \Delta_{(1)}k_{t+2} + \Delta_{(1)}k_{t+1} \\
&= \left(\Phi + \Theta\bar{k}_{t+2}\right) + 2\Phi + 2\Theta\bar{k}_t \\
&= \left(\Phi + \Theta\left[\Phi + \Theta\bar{k}_{t+1} + \bar{k}_{t+1}\right]\right) + 2\Phi + 2\Theta\bar{k}_t \\
&= \Phi + \underbrace{\Theta\Phi + \Theta^2\bar{k}_{t+1}}_{=0} + \Theta\bar{k}_{t+1} + 2\Phi + 2\Theta\bar{k}_t \\
&= \Phi + \underbrace{\Theta\Phi + \Theta^2\bar{k}_t}_{=0} + \Theta\bar{k}_t + 2\Phi + 2\Theta\bar{k}_t \\
&= 3\Phi + 3\Theta\bar{k}_t.
\end{aligned}$$

- This property can be generalized to horizon $h \to \infty$: $\Delta_{(h)}k_{t+h} = h\Phi + h\Theta\bar{k}_t$. ■

A4. Estimating and testing for threshold effects

This section describes the estimation and testing procedure for the two-threshold SETAR(1) model, along the line of Hansen (1999). Recall that model (5.2) for a country (panel) c is:

$$k_{it} = \alpha' + \beta_L k_{i,t-1}\mathbf{I}(k_{i,t-1} < k_L) + \beta_M k_{i,t-1}\mathbf{I}(k_L \le k_{i,t-1} \le k_H) + \beta_H k_{i,t-1}\mathbf{I}(k_{i,t-1} > k_H) + \varepsilon_{it},$$

where $i = 1, \ldots, I$ and $t = 2, \ldots, T$ is the item and year for this country.

Estimation

- Step 1: In the first stage, we assume that model (5.2) only has one threshold, k_1, which we do not know corresponds to k_L or k_H yet:

(A4.1) $$k_{it} = \beta_1 k_{i,t-1}\mathbf{I}(k_{i,t-1} < k_1) + \beta_2 k_{i,t-1}\mathbf{I}(k_{i,t-1} \geq k_1) + \varepsilon_{it}.$$

Let $S_1(k_1)$ be the single-threshold sum of squared errors and let $\widehat{k}_1$ be the threshold estimate which minimizes $S_1(k_1)$. To implement the minimization, Hansen (1999) suggests the following steps: First, sort the distinct values of the observations into the two regimes, based on each of a potential threshold values $k_{i,t-1}$. Second, omit the values in the smallest and largest η% (here we choose $\eta = 10$) quantiles. This will ensure at least 10% of the observations fall within each regime. Third, for each of the remaining values of potential threshold, regression (A4.1) is estimated.[7]

- Step 2: Keeping the first-stage estimate ($\widehat{k}_1$) fixed, the second-stage minimizing criterion is:

(A4.2) $$S_2^r(k_2) = \begin{cases} S(\widehat{k}_1, k_2) \text{ if } \widehat{k}_1 < k_2 \\ S(k_2, \widehat{k}_1) \text{ if } \widehat{k}_1 \geq k_2, \end{cases}$$

and the second-stage threshold estimate is: $\widehat{k}_2^r = \operatorname{argmin}_{k_2}\left[S_2^r(k_2)\right]$.

- Step 3: Bai (1997) shows that while $\widehat{k}_2^r$ is asymptotically efficient, $\widehat{k}_1$ is not.[8] This is because the estimate of $\widehat{k}_1$ is obtained from a sum of squared errors function contaminated by the neglect of one regime. The asymptotic efficiency of $\widehat{k}_1$ can be improved by a third-stage estimation (see also Balke & Fomby, 1997), i.e. via fixing $\widehat{k}_2^r$ and defining a "refinement minimizing criterion" as:

(A4.3) $$S_1^r(k_1) = \begin{cases} S(k_1, \widehat{k}_2^r) \text{ if } k_1 < \widehat{k}_2^r \\ S(\widehat{k}_2^r, k_1) \text{ if } k_1 \geq \widehat{k}_2^r. \end{cases}$$

We can then have a refined estimate of k_1: $\widehat{k}_1^r = \operatorname{argmin}_{k_1}\left[S_1^r(k_1)\right]$. A few iterations

[7]For balanced panels, $S_1(k_1)$ is a step function with at most $N^2 = [I \times (T-1)]^2$ steps, since it depends on k_1 only through an indicator function. When the sample size N is very large, the above optimizing "grid-search" is numerically inefficient. According to Hansen (1999), a simplifying procedure can be performed: Instead of searching over all values of $k_{i,t-1}$ between the η and (1-η)% quantile, the search may be limited to specific quantiles.

[8]However the estimator in the first stage is still consistent for one of the thresholds (k_L or k_H), depending on which effect is stronger (see e.g. Bai, 1997 and Gonzalo & Pitarakis, 2002). This is because the single-threshold SSR function $S_1(k)$ asymptotically converges to a limit function with two local minima k_1 and k_2.

can be conducted, i.e. re-estimating the second threshold conditional on the first one and so on, until convergence is reached.[9] Finally, the smaller of the values $\widehat{k}_1^r$ and $\widehat{k}_2^r$ shall be our estimate of k_L, while the other is k_H. The parameters β_L, β_M and β_H are then estimated conditioned on these values. A major advantage of this iteration algorithm is that it provides a valuable short-cut by reducing the number of computations from N^2 to $j \times N$ (with j iterations) where N is the total number of item-year observations in the panel (Gonzalo & Pitarakis, 2002).

In practice, the minimization of $S(k_L, k_H)$ is quite cumbersome to implement, since it is a step function with at most N^2 steps (with N item-year observations). Since the dummy variable is a discontinuous function, an estimator based on either the minimization of SSR or maximizing the likehood function does not have a well-defined analytical form as the objective function is erratic. The minimization problem can be simplified by searching over values of k_L and k_H equal to the (at most N) distinct values of k_{it} in the sample (Hansen, 1999; Franses & van Dijk, 2000). It has been observed by Bai & Perron (1998) that this type of sequential procedure yields consistent estimates. Further details of our estimation procedure can be found in Appendix A4.

Testing for threshold effects

The above procedure assumes that the underlying data generating process is a double threshold model. In practice, we first carry out specification tests to detect significant threshold effects, given that they exist. As discussed in Section 5, this can be done via studying the F-statistics. But as Hansen (1999) points out, the distribution of these statistics is non-standard, thus necessitating the use of a bootstrap procedure.[10] We construct the bootstrap sample of F-statistics for the test for the existence of a single threshold (denoted as k_1) via 5 steps:

- Step 1: Using the first-stage estimation procedure outlined in subsection A4 we can estimate the following model:

$$k_{it} = \beta_L k_{i,t-1} \mathbf{I}(k_{i,t-1} < k_1) + \beta_H k_{i,t-1} \mathbf{I}(k_{i,t-1} \geq k_1) + \varepsilon_{it} \ (i = 1, \dots, I \text{ and } t = 1, \dots T)$$

  under $H_1 : \beta_L \neq \beta_H$ and obtain the residual $\widehat{\varepsilon}_{it}$.

- Step 2: Randomly draw a sample of $\widehat{\varepsilon}_{it}$ with replacement, and obtain bootstrap residuals

[9] We found that convergence is typically reached after a maximum of three iterations, and summarise the results in Table 6.1 of the main text.

[10] Hansen (1996) shows how this bootstrap method produces asymptotically valid p-values.

$\widehat{v}_{it}$.

- Step 3: Generate a new series under the null hypothesis $H_0 : \beta_L = \beta_H$ so that $k_{it} = \beta_L k_{i,t-1} + \widehat{v}_{it}$. Note that we treat $k_{i,t-1}$ and the threshold variable k_1 as given, holding their values fixed in repeated bootstrap samples.
- Step 4: With the bootstrap sample, estimate the model under H_0 and H_1 and calculate the F-statistic as: $F_1 = \dfrac{S_0 - S_1(\widehat{k}_1)}{S_1(\widehat{k}_1)/(I \times T)}$ where $S_1(\widehat{k}_1)$ is the sum of squared residuals (SSR) corresponding to $\widehat{k}_1$.
- Step 5: Repeat steps one to four 1,000 times, and the bootstrap p-value of F can be computed as the proportion of $F > F_1$. The null of no threshold effect is rejected if the p-value is smaller than a pre-determined significance level (i.e. 5%).

Similar to the estimation procedure, the test for threshold effect can be done in a sequential manner. That is, if the null hypothesis in a single-threshold (two regime) model is rejected, then we test for the double-threshold (three-regimes) model. Then, the null hypothesis becomes a single-threshold model, and the alternative hypothesis is a double-threshold model: $H_0 : \beta_L \neq \beta_H \; ; \; \beta_H = \beta_M$ and $H_1 : \beta_L \neq \beta_H \; ; \; \beta_H \neq \beta_M$. The corresponding bootstrap procedures can be constructed similarly as in the one-threshold case.[11]

The results for the sequential tests are presented in Table A4.1. As can be seen, 97/153 ≈ 64% of the countries exhibit behaviour in accordance with a two-threshold model, while some support either linear or more-than-two-threshold specifications. Based on these p-values, Table A4.1 also includes a column indicating the number of regimes associated with each model. Very few countries exhibit a three-threshold/four-regime behaviour - the implication of which is not covered in the scope of this paper. It should be noted that the power of these tests depends on the relative size of each regime, and it is difficult to detect certain types of threshold models, especially in small samples (Lo & Zivot, 2001). In the main text analyses, we limit our estimation to the sample of countries having at least three regimes. That is, those which reject both linearity and one-threshold non-linearity at the 5% level of significance. With respect to Table A4.1, these countries satisfy the joint condition that values in the columns named "0 vs.1" and "1 vs.2" must be both smaller than or equal to 0.05.

[11]The only difference is that the second-stage F-statistic: $F_2 = \dfrac{S_1(\widehat{k}_1) - S_2^r(\widehat{k}_2^r)}{S_2^r(\widehat{k}_2^r)/[n \times (T-1)]}$ (where $S_2^r(\widehat{k}_2^r)$ is the SSRs from the second-stage estimation) now also depends on β_L and β_H, which makes the bootstrap critical values not as accurate as those of F_1.

Table A4.1: Non-linearity test results

	Country (1)	0 vs. 1 (2)	1 vs. 2 (3)	2 vs. 3 (4)	#regime (5)		Country (6)	0 vs. 1 (7)	1 vs. 2 (8)	2 vs. 3 (9)	#regime (10)
1.	Afghanistan	0	0.12	0.22	two	77.	Kenya	0.26	0.5	0.64	one
2.	Albania	0	0	0.3	three	78.	Korea	0	0	0.98	three
3.	Algeria	0	0	0.04	four	79.	Kyrgyzstan	0	0	0.74	three
4.	Angola	0.06	0.08	0.06	one	80.	Lao	0.04	0.2	0.68	two
5.	Ant. & Barb.	0	0.04	0.46	three	81.	Latvia	0	0.02	0.28	three
6.	Armenia	0	0	0.26	three	82.	Lebanon	0	0	0	four
7.	Australia	0	0	0.76	three	83.	Lesotho	0.54	0.6	0.82	one
8.	Austria	0	0	0.12	three	84.	Lithuania	0.82	0.82	0.6	one
9.	Bangladesh	0	0	0	four	85.	Luxembourg	0	0	0.82	three
10.	Barbados	0.16	0.02	0.16	one	86.	Madagascar	0.26	0.28	0.34	one
11.	Belarus	0.04	0.06	0.12	two	87.	Malawi	0.58	0.88	0.54	one
12.	Belgium	0	0	0	four	88.	Malaysia	0.02	0.16	0.94	two
13.	Belize	0.04	0.28	1	two	89.	Maldives	0.98	0.82	0.54	one
14.	Benin	0.98	0.36	0.3	one	90.	Mali	0.6	0.34	0.32	one
15.	Bhutan	0.42	0.38	0.36	one	91.	Malta	0	0	0.02	four
16.	Bolivia	0	0	0.78	three	92.	Mauritania	0.34	0.38	0.68	one
17.	Bosn. & Herz.	0.04	0.16	0.78	two	93.	Mauritius	0	0	0.8	three
18.	Botswana	0.06	0.08	0.12	one	94.	Mexico	0	0	0.02	four
19.	Brazil	0.1	0.98	0.86	one	95.	Moldova	0	0	0	four
20.	Brunei	0	0	0.84	three	96.	Mongolia	0.32	0.22	0.34	one
21.	Bulgaria	0	0	0.28	three	97.	Morocco	0	0	0.12	three
22.	Burkina Faso	0.54	0.54	0.52	one	98.	Mozambique	0	1	0.98	two
23.	Burundi	0	0	1	three	99.	Myanmar	0	0	0.74	three
24.	Cabo Verde	0	0.02	0.36	three	100.	Namibia	0	0.04	1	three
25.	Cambodia	0	0	0.8	three	101.	Nepal	0	0.02	0.16	three
26.	Cameroon	0.1	0.1	0.2	one	102.	Netherlands	0	0	0.2	three
27.	Canada	0	0	0.7	three	103.	New Zealand	0	0	0.66	three
28.	Chad	0.04	0.2	0.76	two	104.	Nicaragua	0.32	0.14	0.06	one
29.	Chile	0	0	0.14	three	105.	Niger	0	0.02	0.12	three
30.	China	0	0	0	four	106.	Nigeria	0	0	0	four
31.	Colombia	0	0	0.28	three	107.	Norway	0	0	0.5	three
32.	Congo	0.02	0.02	0.18	three	108.	Pakistan	0	0	0.04	four
33.	Cook Islands	0	0	0.6	three	109.	Palestine	0	0	1	three
34.	Costa Rica	0	0.04	0.5	three	110.	Panama	0	0	0.56	three
35.	Cote d'Ivoire	0.5	0.74	0.72	one	111.	Paraguay	0	0	0.24	three
36.	Croatia	0	0	0.08	three	112.	Peru	0.84	0.94	0.86	one
37.	Cuba	0	0	0.1	three	113.	Philippines	0	0	0.06	three
38.	Cyprus	0	0	0.26	three	114.	Poland	0.52	0.3	0.24	one
39.	Czechia	0	0	0.7	three	115.	Portugal	0	0	0.36	three
40.	Denmark	0.02	0.14	0.9	two	116.	Puerto Rico	0	0	0.6	three
41.	Dominican Rep.	0.04	0.26	0.86	two	117.	Qatar	0	0.1	0.68	two
42.	Ecuador	0	0	0	four	118.	Romania	0.74	0.16	0.06	one
43.	Egypt	0.02	0.02	0.42	three	119.	Russia	0.02	0.38	0.7	two
44.	El Salvador	0.02	0.04	0.16	three	120.	Rwanda	0.04	0.04	0.18	three
45.	Eq. Guinea	0.66	0.26	0.26	one	121.	Saint Lucia	0	0.02	0.66	three
46.	Eritrea	0	0	0.02	four	122.	Saudi Arabia	0.2	0.24	0.38	one
47.	Estonia	0	0	0.2	three	123.	Senegal	0.02	0.04	0.2	three
48.	Ethiopia	0	0	0.36	three	124.	Serbia	0.86	0.56	0.34	one
49.	Fiji	0	0	0.96	three	125.	Seychelles	0.06	0.46	0.98	one
50.	Finland	0	0	0.12	three	126.	Sierra Leone	0.04	0.18	0.9	two
51.	France	0	0	0.02	four	127.	Singapore	0.08	0.18	0.46	one
52.	Gambia	0.34	0.82	0.48	one	128.	Slovakia	0	0	0	four
53.	Georgia	0	0	0.56	three	129.	Slovenia	0	0	0.5	three
54.	Germany	0.26	0.68	0.96	one	130.	South Africa	0	0	0.18	three
55.	Ghana	0.22	0.78	1	one	131.	Spain	0	0	0.8	three
56.	Greece	0	0	0.12	three	132.	Sri Lanka	0	0	0.02	four
57.	Grenada	0.24	0.72	0.98	one	133.	Sudan	0.16	0.02	0.02	one
58.	Grenadines	0.36	0.62	0.52	one	134.	Suriname	0	0	0.76	three
59.	Guinea	0.02	0.18	0.82	two	135.	Sweden	0	0	0.84	three
60.	Guinea-Bissau	0.02	0.06	0.46	two	136.	Switzerland	0	0.08	0.44	two
61.	Guyana	0.08	0.16	0.42	one	137.	Syria	0	0	0	four
62.	Honduras	0	0	0.02	four	138.	Tajikistan	0	0	0	four
63.	Hong Kong	0	0	0.76	three	139.	Tanzania	0.2	0.62	0.9	one
64.	Hungary	0	0	0.08	three	140.	Thailand	0	0	0.28	three
65.	Iceland	0	0	0.74	three	141.	Togo	0	0	0.06	three
66.	India	0	0	0.32	three	142.	Tri. & Tob.	0	0	0.64	three
67.	Indonesia	0	0	0.22	three	143.	Tunisia	0	0	0.3	three
68.	Iran	0	0	0.28	three	144.	Turkey	0.4	0.44	0.44	one
69.	Iraq	0.02	0.02	0.24	three	145.	Turkmenistan	0	0	0.64	three
70.	Ireland	0.02	0.08	0.36	two	146.	U.K	0	0	0.66	three
71.	Israel	0	0	0.52	three	147.	U.S	0	0	0.5	three
72.	Italy	0.26	0.28	0.42	one	148.	Ukraine	0.04	0.04	0.18	three
73.	Jamaica	0	0	0.16	three	149.	Uruguay	0	0	0	four
74.	Japan	0	0	0.08	three	150.	Vanuatu	0.02	0.38	0.98	two
75.	Jordan	0	0	0.08	three	151.	Viet Nam	0	0	0	four
76.	Kazakhstan	0	0	0.38	three	152.	Yemen	0	0	0.08	three
						153.	Zimbabwe	0.3	0.76	1	one

Note: this Table presents the bootstrap p-values of the F-statistics when testing for linearity against one threshold (column "0 vs. 1"); one against two thresholds (column "1 vs. 2") and two against three thresholds (column "2 vs. 3"). "#regime" denotes the number of regimes specified for each country. Note that "one regime" is equivalent to a linear model.

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