



Using Apple Products to Evaluate the Law of One Price and Exchange Rate Passthrough

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ERSA working paper 901

March 2025

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January 29, 2025

Abstract

We construct a novel dataset on Apple product prices to assess the adherence of different price measures to the law of one price (LOP) and purchasing power parity (PPP), along with their convergence properties following deviation. Using panel and Bayesian methods, we evaluate overall conformity to LOP/PPP, then apply dynamic models to measure price and exchange rate convergence. We estimate the half-lives of deviations and quantify the adjustment process by examining how the adjustment parameters evolve over time. Our findings show that Apple products adhere more closely to LOP/PPP than traditional price measures, such as the Big Mac Index and the Consumer Price Index, with deviations lasting only a few months. Importantly, transaction costs are identified as a primary driver of persistent deviations from LOP, providing new empirical support for its theoretical predictions. These results underscore the advantages of using homogeneous, globally traded goods like Apple products in studying real exchange rate dynamics.

JEL Codes: C22, C23, E31, F31, F41

Keywords: Real Exchange Rate (RER), Law of One Price (LOP), Purchasing Power Parity (PPP), Arbitrage, Apple Products

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1 Introduction

The real exchange rate (RER) is central to understanding open economies, underpinning theories such as the law of one price (LOP) and the purchasing power parity (PPP) hypothesis. According to the LOP, after taking the nominal exchange rate into account and in the absence of market frictions, arbitrage should ensure that prices of identical goods in different countries converge. If the LOP holds for all goods, it implies a strict version of PPP, suggesting a real exchange rate of unity, where a unit of currency in one country has the same purchasing power as the same unit in another.

Even in more flexible forms of PPP that account for certain frictions, RERs should exhibit stationarity. However, statistical tests often reject RER stationarity. Empirical studies reveal that RERs tend to show persistence, with deviations from PPP often lasting much longer than anticipated. Seminal research by Rogoff (1996) and Obstfeld and Rogoff (2000) found that the half-lives of these deviations range from 3 to 5 years.

This persistent deviation, known as the *PPP puzzle* (Rogoff, 1996), raises key challenges. Trade frictions, such as transportation costs, might explain why PPP holds only in the long run. However, the prolonged deviations observed are difficult to reconcile, especially given the relatively minor frictions in modern economies. For example, recent findings by Vo and Vo (2023) suggest that arbitrage forces and efficient resource allocation can resolve measurable frictions faster than previous studies suggest, thus challenging the robustness of previous aggregate studies.

One of the main limitations in testing the PPP hypothesis lies in the limitations of the data. As Parsley and Wei (2007) points out, many aggregate PPP assessments face significant issues such as differences in price indices, time aggregation bias (Taylor, 2001), and product aggregation bias (Imbs et al., 2005). Moreover, non-tradable goods are often included in price indices despite the fact that PPP only applies to tradable goods (Balassa, 1964; Samuelson, 1964).

This article advances the literature by exploiting a novel data set focused on Apple products, which addresses several of these data limitations. We explore the strength and speed of arbitrage forces in reducing transaction costs and driving the LOP in the context of Apple products, a unique, globally traded product line. Apple products offer a consistent basis for this type of analysis because they (i) possess uniform attributes, allowing prices of individual models to be compared directly, (ii) involve physical exchange, enabling the direct measurement of trade barriers like taxes and transport costs, and (iii) are sold worldwide, providing a broad platform for analysing global price variation.

The data set used in this article consists of annual prices for iPods, iPads, and iPhones in nearly 50 countries covering a 14-year period. Compared to other price measures used in LOP and PPP studies, Apple product prices offer several advantages: global availability, homogeneity, and high tradability. Additionally, Apple products originate from a single

point, allowing for better control over transaction costs such as tariffs, shipping, and local taxes. Controlling for these factors reveals much stronger adherence to the LOP and demonstrates that deviations are less persistent compared to other products.¹

2 Literature Review and the Problem with PPP

The evidence on the law of one price (LOP) and purchasing power parity (PPP) studies appears to have generally evolved alongside improved and expanded datasets, as well as increasingly sophisticated econometric techniques on which to test these hypotheses. In the 1990s, a consensus was finally reached within the literature that even though RERs were found to converge to parity in the long-run, *deviations* from the LOP or PPP were still extremely persistent (Rogoff, 1996). Although obvious frictions such as transport costs mean that the PPP hypothesis is expected to hold only in the “long run”, the extant evidence on measurable trade frictions are insufficient to explain the estimated half-lives of the deviations — unless arbitrage forces are unreasonably weak. Put differently, even if PPP should only hold in the long run, the length of the implied long run does not seem reasonable in a modern digital economy.

According to a well-cited publication by Rogoff (1996), after evaluating numerous publications on the topic, he found that the estimated half-lives of deviations from PPP were in the vicinity of three to five years. Rogoff (1996, p. 647) defined this as ‘the PPP puzzle’.² Thus, even though more economists may have reached some semblance of a consensus on the topic of whether RERs are mean reverting, the second PPP puzzle of Rogoff remained: the exceptionally long half-lives of deviations from PPP.

One of the limitations and causes of several disputes surrounding the LOP and PPP studies has been the datasets themselves used to test these theories: whether parity held and what the speed of adjustment toward parity was when deviations occurred. Due to data availability, the vast majority of research has been dedicated to studying these parity concepts on broad baskets of prices. Consequently, most of what we know about RERs

¹Prior studies that have tested PPP/LOP using Apple product prices use only cross-sectional data and have not been published in a full length peer-reviewed journal (Mazumder, 2016; Jošić and Barišić, 2017). Our study uses a longitudinal panel that allows us to examine the price convergence and the dynamics of the pass-through of the exchange rate over time. Additionally, we expand the scope of analysis beyond iPads to include multiple categories of Apple products, enhancing robustness and generalisability. A key methodological improvement is our explicit control for transaction costs—including VAT, import duties, and shipping fees—which previous studies did not account for, thus providing a more precise evaluation of LOP adherence.

²The half-life is defined as the time period it takes for a RER deviation to permanently subside below one half in response to a unit shock. Half-life measurements are seen as the benchmark in this field for measuring the speed of convergence toward parity. That said, Chortareas and Kapetanios (2013) suggest that the measure of half-life used in the literature might be problematic. Instead, the authors propose alternative measures that focus on the cumulative effects of shocks. These alternative measures also appear to produce results that suggest that the PPP puzzle may be less pronounced than traditionally found in the literature.

originates from studies that use some variant of aggregate price indices (most commonly, the consumer price index).

The remaining literature utilises other broad price measures such as producer, retail, wholesale, export or terms-of-trade price indices, wage rate indicators, and even components or subcomponents of the mentioned price indices (see, for example, Taylor (2002), Taylor (2006), Officer (2012) and Vo and Vo (2023)). Despite the considerable attention general price indices have received in PPP studies, their use entails several obstacles and biases that researchers need to attempt to overcome.

The first obstacle studies that use price index measures encounter is that the price baskets and products in these aggregate indices are not directly comparable. These aggregate measures embed heterogeneous *weights* and *goods* which are generally calculated based on the consumption behaviour of individual countries. Complicating matters further is that the weights and even the products included in these baskets are dynamic over time as consumption preferences change, and products are introduced or dropped and/or experience a change in quantity or quality.

In addition, these price indices often devote a significant weight to non-tradable goods and services — whereas LOP or PPP can only hold for tradables. Even the supposedly tradable products in these composite indices often incorporate a notable non-tradable component. For example, the products sold at a local retailer also embed the input costs of local wages, rent, electricity, etc. The study of, and controlling for, the impact of such ‘non-tradables’ — which was first formulated as a productivity bias hypothesis by Balassa (1964) and Samuelson (1964) — has consequently received a notable amount of attention from researchers. As a result, much of the debate surrounding the validity of PPP has often been about the choice of an appropriate basket or by using other statistical techniques to extract information for making PPP comparisons.

In addition to the noteworthy obstacles outlined above, there are also the issues of *time-* and *product-aggregation* arising from the use of composite indices in analyses. Regarding the first, Taylor (2001) showed that when price data are averages and collected at discrete points in time — i.e. the way aggregate price indices are generally constructed — the persistence of the RER may be overestimated.

Due to the underlying components having ‘heterogeneous dynamics’ that vary with the characteristics of goods, there also exists an *aggregation bias* that causes positive persistence in RERs (Imbs et al., 2005, p. 4). According to the authors, it is difficult to foresee why various products in price indices should all converge to parity at a similar speed. Failing to account for this phenomenon causes price indices to have an upward persistence bias relative to their sub-components. Furthermore, price indices also preclude any price level comparisons (i.e. comparing relative price indices is not the same as using relative price levels — the latter of which actually yields an implied exchange rate). Finally, the problem of calculating the RER from indices is further magnified with the

choice of a specific base period where PPP is assumed to hold (Marsh, Passari and Sarno, 2012).

It is therefore perhaps not all that surprising that most research indicate that large and persistent deviations from PPP do occur; especially when considering that these various price baskets are compiled by assigning differential weights when trying to compare apples with oranges while simultaneously including a large non-tradable component — which are assured to have very weak forces of arbitrage — while also succumbing to time and product aggregation biases. As a result of all these issues surrounding composite price indices, researchers have also been investigating alternative price data sources on which to perform their analyses.³

The LOP on a relevant tradable product, despite facing its own set of challenges, can control for most of the biases and limitations outlined above. However, because of the lack of price data on comparable goods across locations, the literature on LOP is notably less voluminous than that of PPP.

It thus remains difficult to find a large current dataset of similar products that are simultaneously sold in a large cross-section of countries. As a result, most of the literature on both LOP and PPP has also focused on monthly (or longer) time frequencies due to data limitations.⁴ Research on the topic also generally suffers from low statistical power. Studies have tried to overcome this by either using longer timespans (for example Froot, Kim and Rogoff (2019)) or by utilising multiple country panel datasets (for example Chortareas and Kapetanios (2009)). However, both of these options introduce their own obstacles: for time series this includes behavioural changes over historical periods and varying exchange rate regimes which causes structural breaks in data; while panel datasets test *all* of the time series simultaneously, so the probability of *Type II* statistical inferencing errors is high (Taylor and Taylor, 2004).

3 Potential Solutions to the PPP Problem: Apple Products

The LOP, despite facing its own set of challenges, can control for most of the biases and limitations outlined above. However, because of the lack of price data on comparable goods across locations, the literature on the topic is notably less voluminous than that of PPP. What’s more, several products in LOP analyses still embed a large non-tradable

³See, for example, Cavallo and Rigobon (2016), Cavallo, Neiman and Rigobon (2019), Crucini and Telmer (2020) and Vo and Vo (2023)

⁴Other LOP databases include: The World Bank’s International Comparison Program (ICP), The Economist Intelligence Unit’s Worldwide Cost of Living (WCOL) Survey, The Economist Magazine’s Big Mac Index (BMI) and Eurostat’s Harmonised Index of Consumer Prices (HICP).

component (Engel, 1999).⁵

The benefits of using Apple Product Prices (APPs) in the LOP analyses will circumvent some of the notable issues that other researchers have encountered on the topic.⁶ In particular, the first reason why using APPs are such a good tool for in-depth LOP analyses is that these products are widely available internationally. According to Apple’s website, it currently has online iStores in more than 100 countries (Apple, 2023).⁷ Second, each Apple product is a perfectly homogeneous good. Third, the price ratios and real exchange rates calculated from these products can be measured in price levels (compared to CPI or other index-based measures which are all dependent on choosing an appropriate base period). Fourth, the products are entirely tradable, and have a relatively ‘high value-to-weight-ratio’ which makes them ideal — at least compared to most products — for arbitraging. Fifth, because the Apple products are produced in China and Taiwan and subsequently shipped from there, the most significant non-tradable component of their price is attributable to these specific countries. The non-tradable input is therefore the same for all the products. Sixth, since it is a specific technological product that is imported by each country and sold by the countries’ respective online iStores, taxes, tariffs and even shipping costs can be measured, or at least estimated, and controlled for. This allow one to estimate how much these transaction costs expand the ‘band of no arbitrage’ embedded in theories on nonlinear real exchange rate adjustments. Finally, the APPs data does not suffer from any *product aggregation bias* nor *time aggregation bias*.

4 Issues surrounding Apple Products in a study on LOP

Apple products exhibit stronger adherence to the Law of One Price than the Big Mac Index due to their inherent characteristics. Unlike Big Macs, which are subject to variations in local sourcing, labour costs, and rent, Apple products are globally standardised with minimal price differentiation in production costs. Furthermore, Apple products are highly tradable, whereas Big Macs are perishable and largely non-tradable. Our analysis controls for transaction costs such as tariffs and VAT, factors that significantly impact price deviations, reinforcing Apple products as a more reliable measure for LOP studies.

Although there are clear advantages to using Apple products in LOP research, there

⁵Despite its inclusion of non-tradable goods, CPI remains the standard benchmark for PPP studies. Accordingly, we compare our findings to both CPI and BMI to provide consistency with previous literature and to allow meaningful comparisons across methodologies (see, e.g., Cumby, 1996; Click, 1996; Ong, 1997; Lutz, 2002; Parsley and Wei, 2007; Chen, Wang and Shen, 2007; Clements, Lan and Seah, 2012).

⁶In 2007, an Australian bank, Commonwealth Securities (CommSec) conducted a comparison of iPod Nano prices in USD in a similar fashion to *The Economist* magazine’s Big Mac Index (CommSec, 2007). Since then, CommSec has also published several ‘*Economic Insights*’ newsletters on the topic of iPad and iPhone PPP comparisons for several countries.

⁷Refer to apple.com/choose-country-region/ (Apple, 2023).

are also some difficulties that need to be addressed. One of the biggest hurdles using a time series dataset on Apple products is the technological leap each new product version introduces. More specifically, the new features and specifications mean that each new device does not exactly replicate the one it replaced. However, this can potentially be controlled for in the annual panel dataset via 'time effects'. Furthermore, telecommunication operators' bargaining power might significantly influence the price of iPhones in the various domestic markets. Thus, the annual dataset will instead focus on other Apple products such as iPods in the earlier years and subsequently on iPads. Another disadvantage is that Apple products represent only a small portion of the consumer electronics market and therefore cannot serve as a representative sample of all tradable products. The dataset is therefore limited in terms of product span. Finally, due to the significant brand-power and status of Apple, the product might also be prone to being priced for each market.

5 Dataset

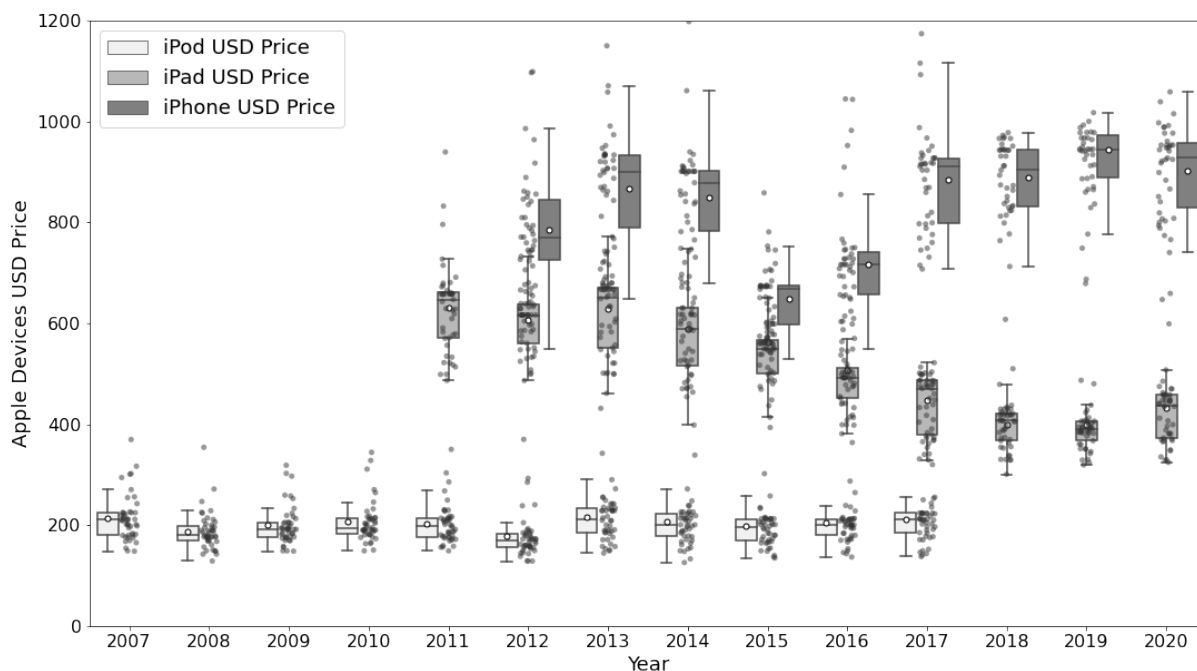
The Internet Archive's *The Wayback Machine*, was the primary price source that was used to compile a database on the historical prices from Apple's online retail stores. *The Wayback Machine* is an easily navigable digital archive of the world wide web. This archive allows users to both browse and retrieve historical website snapshots. One of the main benefits of using *The Wayback Machine* as the data source on APPs, is that it is a fairly simple process of programming a scraper to navigate the historical archives.

Figure 1 uses box plots to summarise the distributions of the scraped annual price data.⁸ The average exchange rate value for the month the data was retrieved (extracted and calculated from Bloomberg) in order to convert the domestic prices to USD. From these box plots, one can visualise some of the summary statistics of USD prices for the three Apple devices in the annual price dataset between the years 2007 to 2020. For iPod Nanos, their dollar prices averaged around USD200 over the 2007 to 2017 period. The inter-quartile range was also fairly tight around the means (dots) and medians (horizontal lines) for the music players. Meanwhile, for iPads, the average prices appear to have steadily declined since the tablet's introduction in 2010 (at least for the base model). For the higher-end models, they have become costlier, as will be seen in the following section. In addition, the price dispersion for these devices appears to be more varied for these devices than for iPod Nanos. Finally, the iPhone prices tended to be the most expensive out of the three Apple products analysed and their prices have also appeared to become higher over time (with 2015 and 2016 appearing to be exceptions).

Figures 8 (a) to (c) in Appendix A utilises box plots to show the distributions of

⁸The shaded area of the box plot shows the inter-quartile range (i.e. middle 50% of data) separated by the median. The whiskers represent the outer quartiles and the dots indicate outliers.

Figure 1: Box Plots Showing the USD Price of the Three Apple Products on the *Annual Dataset* from 2007 to 2020

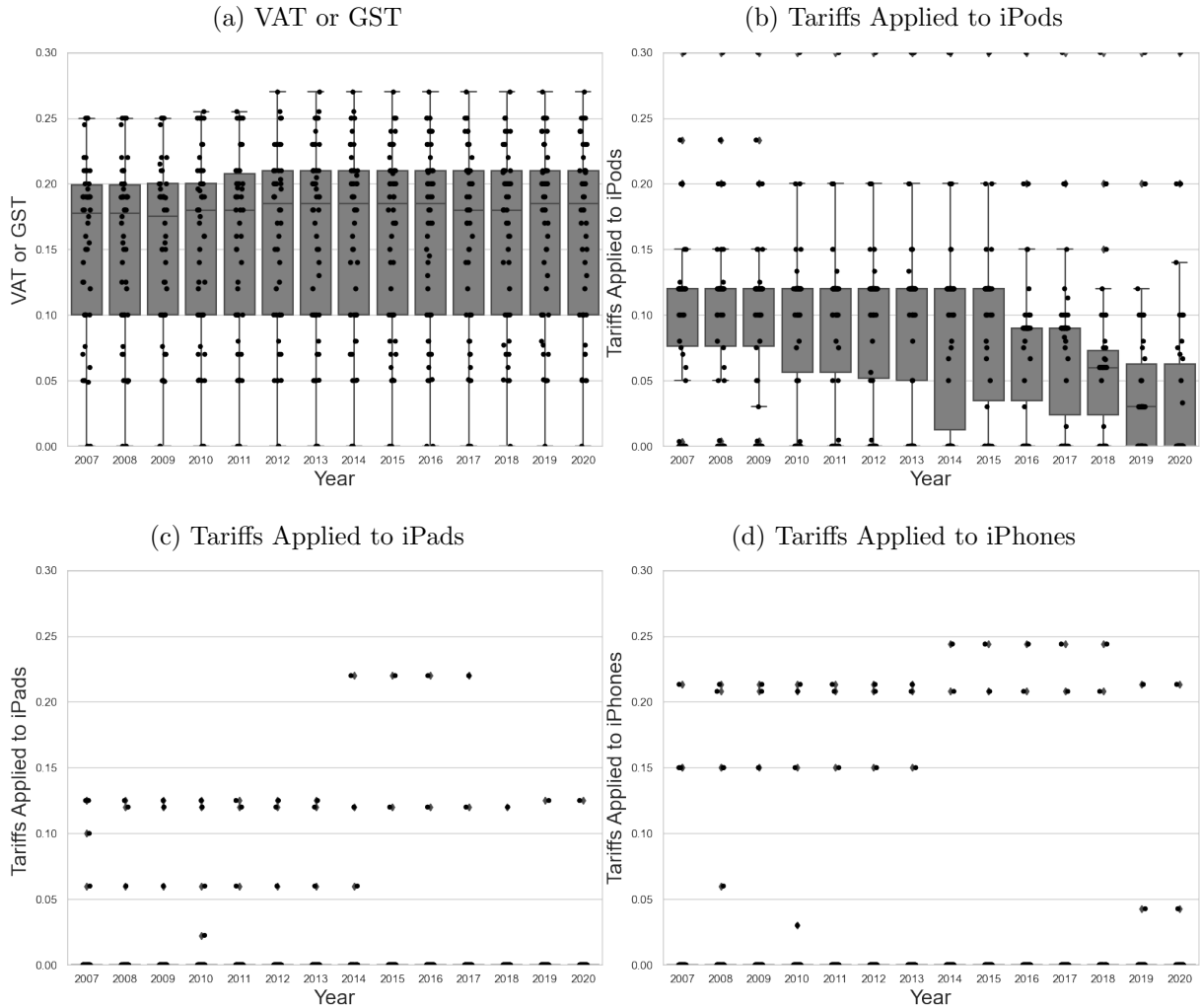


the converted USD prices for each country for the different products. The average USD price for each device across the different countries and time periods are illustrated as dotted vertical blue lines. From these charts it is clear that the country prices converted into USD are quite dispersed across the different countries. Interestingly, and completely contrary to USD prices of the Big Mac index, the developed countries tend to be the ones with lowest Apple product prices (for example Australia, Canada, US, etc.), while the developing nations (for example Argentina, Brazil, Turkey and South Africa) tend to record the highest prices. Meanwhile, for Big Macs, where services are a significant portion of the burger’s price tag, we tend to observe cheaper prices in emerging markets compared to developed ones. The price variation for iPhones is also wider than for the other devices. This feature could be due to the various deals that have existed with different telecommunications operators.

As mentioned, one of the main benefits of using Apple devices in LOP analyses is that one is able to control for most of the price heterogeneity, specifically regarding the transaction costs embedded in the prices of these devices. The first of these ‘input costs’ we control for is the local taxes imposed on the prices of these devices. Using various years of KPMG’s *Indirect Tax Rate Survey* publications, the applicable value added tax (VAT) or general sales tax (GST) rate was extracted for each of the various countries evaluated. This is done for every year covered in this analysis from 2007 to 2020 (refer to KPMG (2016-2022)). For the United States, the average tax rate on all the states are used (excluding Puerto Rico). A box plot of the VAT or GST tax rates is shown in Figure

5 subplot (a). Interestingly, the average tax rate in the sample increased from 15.1% in 2007 to 16.5% in 2020 (seemingly post the 2008 global financial crisis as government revenue streams suffered). In addition the tax rates are widely dispersed across countries ranging from 0% (for Hong Kong) up to 27% in Hungary.

Figure 2: Various Transaction Costs Embedded in Apple Devices (y-axis limited to 30%)



Second, since all Apple devices are shipped from China to the various importing countries, it is important to account for the different import tariffs that each country levies on these products. Using the applicable harmonised system (HS) of tariff codes that’s applicable to each of the devices for each of the importing countries, we can also control for any import duties embedded in these products’ prices. All applied tariff rates were sourced from the International Trade Centre’s Market Access Map (International Trade Centre, 2022).⁹ Figure 5, subplots (b) to (d), illustrate with box plots the tariff rates that

⁹For iPods, the HS tariff code 852713 was used, which applies to “radio broadcast receivers capable of operating without an external source of power, combined with sound recording or reproducing apparatus (excluding pocket-size radio cassette players).” iPads were associated with the HS code 847130 which applies to all “data-processing machines, automatic, portable, weighing less than 10kg, consisting of

were applied to imported iPods, iPads and iPhones. On aggregate, the tariff rates levied on iPods have generally declined from an average of about 11% in 2007 to just over 4% in 2020. Meanwhile, for iPads and iPhones, only a small number of countries impose (fairly high) import levies on these devices for the sample of 51 countries evaluated. As such, countries which impose import tariffs on these two products show up as outliers in the box plots.

For shipping costs, container freight market rates were used from the United Nations Conference on Trade and Development (UNCTAD) Review of Marine Transport (UNCTAD, 2022). Currently the only freight rates that are tracked are on some of the main global shipping routes.¹⁰ All of these shipping rates are standardised to USD per (either 20 or 40) foot equivalent units (FEU) rates. For the countries in the sample that are on the main routes (for example US, Japan, Singapore, Brazil, South Africa, etc), the ‘main shipping route’ rates are directly extracted from the UNCTAD reports and used as the respective shipping costs. For the remaining countries the shipping rates are *estimated* by taking the distance of that specific country i to Shanghai as a proportion of the distance from the closest port which is also a main shipping route to Shanghai. This distance is multiplied by the UNCTAD’s standard shipping rate on that main route. For example, this calculation for Argentina entailed taking the distance of Buenos Aires to Shanghai as a ratio of the distance of Santos (Brazil) to Shanghai (that is, the main shipping route) times the standardised shipping rate from Santos to Shanghai. This calculation methodology was followed for all 51 countries in the sample. Figure 3 illustrates the evolution of shipping rates for the countries included in the analyses. Finally, the exchange rate data for the Apple device dataset is sourced directly from Bloomberg. The average exchange rate price for the month that the device’s sticker price was scraped is applied in this analysis.

6 Static Exchange Rate Passthrough

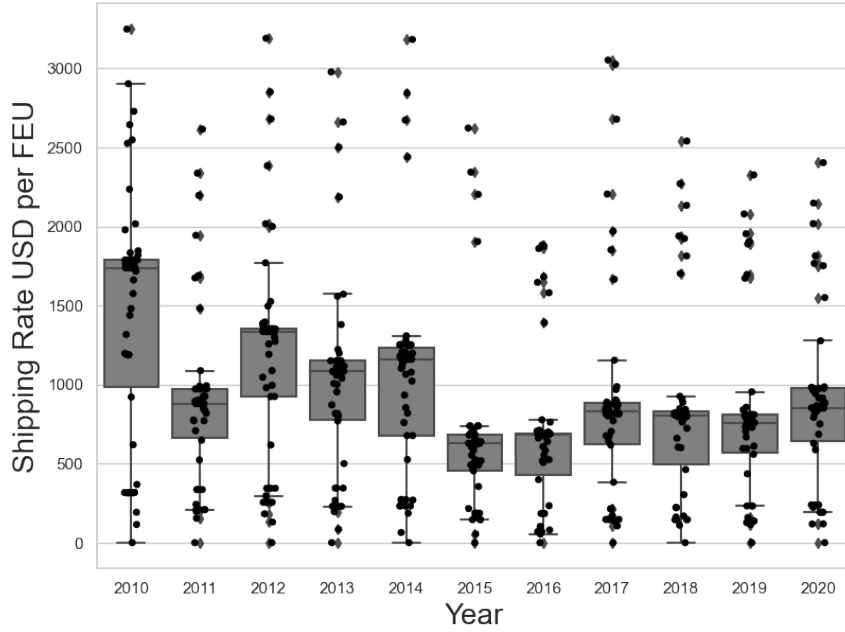
6.1 Panel Regressions Specifications

We can now evaluate the degree of exchange rate pass-through on the various relative price measures by comparing the derived $\hat{\alpha}_x$ and $\hat{\beta}_x$ parameters (associated with the price basket or product x) from each of the price ratios by estimating a modified version of the

a central processing unit, a keyboard and a display (excluding peripheral units).” On iPhones, the applicable HS code is 851712 which applies to “telephones for cellular networks for other wireless networks, other than line telephone sets with cordless handsets.” Refer to [trade.gov/harmonized-system-hs-codes](https://www.trade.gov/harmonized-system-hs-codes) for more information on the HS codes (International Trade Administration, 2023).

¹⁰These shipping routes include: the Shanghai-United States East & West Coast routes, Shanghai-Northern Europe, Shanghai-Mediterranean, Shanghai-South America (Santos), Shanghai-Australia/New Zealand, Shanghai-South Africa (Durban), Shanghai-Persian Gulf, Shanghai-South East Asia (Singapore) etc.

Figure 3: Shipping Rate, USD per 20 or 40 Foot Equivalent Units (FEU) from 2010 to 2020



equation specified in Section 5:¹¹

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \epsilon_t^{i\text{US},x} \quad (1)$$

The estimates can be derived from the panel dataset, where each country i in the panel's relative price ratio and respective nominal exchange rate is expressed relative to the United States (US) as country j in the subsequent evaluations, for each good x . The α_x and $\hat{\beta}_x$ parameters in Equation 1 will however still embed transaction costs. For the APPs datasets, these can be partially controlled for by re-specifying the equation to incorporate the data on the three transaction cost measures outlined in Section 5 to restate Equation 1 as:

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \delta_{x1} \ln \left(\frac{1 + \tau_t^{i,x}}{1 + \tau_t^{\text{US},x}} \right) + \delta_{x2} \ln \left(\frac{1 + \iota_t^{i,x}}{1 + \iota_t^{\text{US},x}} \right) + \delta_{x3} \ln \left(\frac{\lambda_t^{i,x}}{\lambda_t^{\text{US},x}} \right) + \epsilon_t^{i\text{US},x} \quad (2)$$

Where $\tau_t^{i,x}$ is the associated VAT or GST rate that country i levies on product x at time t , while $\iota_t^{i,x}$ represents the import tariff rate country i imposes on good x at time t on imports originating from China; and, $\lambda_t^{i,x}$ represents the estimated shipping rate from China to the respective importing country i . By including these various transaction cost measures on the APPs relative price ratio analyses, one is able to control for a notable amount of good price heterogeneity across the respective markets.

¹¹Where product $x = [\text{CPI}, \text{Big Macs}, \text{iPods}, \text{iPads}, \text{iPhones}]$.

6.2 Results: Panel Regressions

Panel unit root and cointegration tests are first applied on all of the relative price and exchange rate measures. According to the Levin-Lin-Chu, Harris-Tzavalis, Breitung as well as Fisher-type unit-root tests, it was generally found that that we *cannot* reject the null hypothesis at a 90% confidence level that either the various logarithmic price ratios (i.e. $p_t^{i,x} - p_t^{\text{US},x}$) or associated logarithmic exchange rate variables (i.e. $e_t^{i\text{US}}$) each contained a unit root. Subsequently, both the Kao and Westerlund panel cointegration tests were performed, and the null hypothesis of ‘no cointegration’ is strongly rejected for all of the price measures and exchange rates.

Tables 8 to 16 in Appendix F reports some of the various panel regression specifications for Equation 1, on the relative price ratios: CPI, Big Macs and APPs.¹² For each price ratio measure, five different panel regression models were estimated: simple pooling, country-specific fixed effects, time period fixed effects, combined country and time fixed effects and random effects. When simply evaluating the estimated coefficients from the pooled OLS method across the various price ratios, it initially appears that *all* of the price ratios generally adhere to the notion of LOP or PPP, i.e. the α_x s (though statistically significant) are generally small, while the β_x s are fairly close to parity. However, once country specific fixed effects are included, LOP or PPP adherence suffers for the CPI, BMI and iPhone price ratios. The iPod and iPad price measures however are fairly robust across the various panel regression specifications. A summary of the most appropriate panel regression methods (i.e. testing whether fixed effects are redundant and subsequently using the Hausman Test to decide between the fixed and random effects models) is provided in Table 1:

As noted in Click (1996), one of the typical reasons for the failure of LOP or PPP is that local prices are established without regard to exchange rates. This could mean that prices are set at different base levels (i.e. $\alpha_x \neq 0$), or that prices do not change as exchange rates move (i.e. $\beta_x \neq 1$), or possibly both. Despite the prominent (i.e. > 0) estimates for $\hat{\alpha}_{\text{iPod}}$ and $\hat{\alpha}_{\text{iPad}}$ (i.e. 0.3131 and 0.2152 respectively), the *relative* LOP appears to hold fairly well for these two products with both $\hat{\beta}_{\text{iPod}}$ and $\hat{\beta}_{\text{iPad}}$ ‘close’ to parity. Although iPhone price ratios perform well in the pooled and random effects model in Table 16 (indicating LOP potentially holds), this price ratio performs significantly worse once country-fixed effects are included. The regressions in Tables 8 to 12 also shows one of the pitfalls with PPP studies, how sensitive the $\hat{\alpha}_{\text{CPI}}$ coefficients are when it comes to choosing the correct base period. For example, the $\hat{\alpha}_{\text{CPI}}$ estimate fluctuates from -0.1191 to 0.1473 in the pooled OLS regressions and from 0.7720 to 0.9630 in the fixed country and time effects regressions. Overall, the CPI ratios and Big Mac prices do not appear to adhere to PPP

¹²For the CPI relative price ratios we included all the various base years to conduct the analyses. The base period chosen only affects the intercept (i.e. the $\hat{\alpha}_{\text{CPI}s}$) and not the slope. For the various panel regressions Python was used with the `statsmodels` package by Seabold and Perktold (2010).

Table 1: Summary of panel regressions showing the adherence of different product price ratios to the Law of One Price (LOP).

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \epsilon_t^{i\text{US},x}$$

Coefficient	Price Ratio (x)				
	CPI	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.7220 to 0.9630 (0.0379)***	0.6097 (0.0640)***	0.3131 (0.0336)***	0.2152 (0.0265)***	0.5500 (0.0411)***
$\hat{\beta}_x$	0.5724 (0.0193)***	0.6293 (0.0269)***	0.9903 (0.0110)***	0.9922 (0.0097)***	0.7647 (0.0333)***
R ² Overall	0.8079 to 0.8217	0.8680	0.9919	0.9929	0.9340
Countries	49C	31C	46C	45C	39C
Years	14Y	14Y	11Y	10Y	9Y
Panel Effects	Entity, Time	Entity, Time	Random	Random	Entity, Time

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 2: Panel Regressions Summary on Balanced Panel Dataset: Same 25 Countries Over 2012 to 2017

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \epsilon_t^{i\text{US},x}$$

Coefficient	Price Ratio (x)				
	CPI	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.9271 to 1.1269 (0.0501)***	0.9997 (0.0973)***	0.5530 (0.0996)***	0.1536 (0.0410)***	0.8254 (0.1115)***
$\hat{\beta}_x$	0.3998 (0.0293)***	0.2555 (0.0581)***	0.8270 (0.0581)***	1.0036 (0.0176)***	0.6620 (0.0652)***
R ² Overall	0.6348 to 0.6431	0.8680	0.9476	0.9883	0.8716
Countries	25C	25C	25C	25C	25C
Years	6Y	6Y	6Y	6Y	6Y
Panel Effects	Entity, Time	Entity, Time	Entity, Time	Random	Entity, Time

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

except in the basic pooled panel regressions.

Table 2 summarises the most relevant balanced regression results from tables 21 to 29 in Appendix H that utilise the same set of 25 countries over 2012 to 2017. Overall, the iPad coefficients again hold up well. However, the PPP-adherence of the CPI and BMI price ratios have deteriorated even further when using this perfectly balanced dataset

(i.e. more prominent $\hat{\alpha}$ s and smaller $\hat{\beta}$ s). Though this deterioration in performance is also true for the coefficients derived from the iPod price ratios, the main reason for this is because the most appropriate panel estimation method has switched from random effects to fixed effects as determined by the Hausman test.¹³ The deterioration in the $\hat{\alpha}$ and $\hat{\beta}$ coefficients for some of the price ratios could be due to some of the ‘higher inflation’ or outlier countries driving some of the results in Table 1. Also, since *The Economist* only started tracking Big Mac prices for Eurozone countries in the more recent publications, none of these countries were included in the balanced panel.

Following the initial evaluations, one can now also evaluate how the estimates in Table 1 change once transaction costs are introduced. Table 3 summarises the most appropriate regression specifications from Appendix G (i.e. Tables 17 to 20) when also including the various transaction cost measures (as specified in Equation 2). Table 4 similarly summarises the balanced panel regressions. Neither the $\hat{\alpha}_{\text{Big Mac}}$ intercept nor the $\hat{\beta}_{\text{Big Mac}}$ slope saw a noticeable impact after including local VAT or GST rates. Meanwhile, for the iPod relative price ratio, a noticeable decrease is observed in $\hat{\alpha}_{\text{iPod}}$. Specifically, after accounting for transaction costs, $\hat{\alpha}_{\text{iPod}}$ is now noticeably less statistically significant. Also, $\hat{\beta}_{\text{iPod}}$ gets even closer to unity after including the logarithmic relative rates on taxes and tariffs. Both VAT or GST rates as well as iPod import tariff rates were found to be statistically significant contributors to countries’ price ratios.

For the iPad price ratios, adding transaction costs to the specification did not noticeably decrease $\hat{\alpha}_{\text{iPad}}$ in the fixed entity and time effects model. Specifically, once fixed effects were added, $\hat{\alpha}_{\text{iPad}}$ remained fairly large and $\hat{\beta}_{\text{iPad}}$ also slightly less than parity. That said, for the pooled and random effects specifications (refer to Table 19), the intercept dropped significantly once transaction costs were accounted for and the coefficient estimates were also in line with those obtained from the iPod price ratio.¹⁴ In addition, the estimation method in Table 3 changes for iPads from random effects in the previous estimation that excluded transaction costs, to a panel regression that includes fixed country and time effects. This potentially indicates that the tax or tariff ratios contain cross sectional information that interacts in the regressions in the iPad dataset.

Finally, for iPhone prices, VAT or GST tax rates were found to be a statistically significant contributor to the relative price ratio and by adding the transaction costs it did decrease the $\hat{\alpha}_{\text{iPhone}}$ coefficient from 0.55 to 0.4177 in the (most appropriate) country and time fixed effects model. Again, similar to the iPad data, the pooled OLS and random effects specifications were more supportive of LOP adherence for the phones. Nevertheless, iPhones are still notably more suited than Big Macs or CPI in terms of adhering to LOP (PPP), at least from the panel data regression analyses performed. Overall, some of

¹³When comparing the fixed country and time effects as well as the random effects regressions for both the balanced and unbalanced panels of the iPod datasets, they actually yield fairly similar results.

¹⁴What’s more, in the balanced panel iPad regression in Table 4, though the $\hat{\alpha}_{\text{iPad}}$ still appears fairly large, it has become statistically less significant.

the specifications appear to be quite sensitive regarding the effects (for example fixed or random) used.

Table 3: Panel Regressions Summary Including Transaction Costs

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \delta_{x1} \ln \left(\frac{1+\tau_t^{i,x}}{1+\tau_t^{\text{US},x}} \right) + \delta_{x2} \ln \left(\frac{1+\iota_t^{i,x}}{1+\iota_t^{\text{US},x}} \right) + \delta_{x3} \ln \left(\frac{\lambda_t^{i,x}}{\lambda_t^{\text{US},x}} \right) + \epsilon_t^{i\text{US},x}$$

Coefficient(x)	Price Ratio (x)			
	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.5868 (0.1031)***	0.0791 (0.0377)**	0.3443 (0.0827)***	0.4177 (0.0859)***
$\hat{\beta}_x$	0.6931 (0.0215)***	1.0017 (0.0080)***	0.9506 (0.0264)***	0.7746 (0.0349)***
$\hat{\delta}_{x1}$	-1.5499 (0.7704)**	1.7418 (0.2780)***	-0.2263 (0.5929)	0.12189 (0.6055)**
$\hat{\delta}_{x2}$		0.5696 (0.1827)***	0.1790 (0.3467)	0.2141 (0.3917)
$\hat{\delta}_{x3}$			0.0305 (0.0237)	0.0043 (0.0246)
R ² Overall	0.9008	0.9953	0.9907	0.9407
Countries	31C	46C	45C	39C
Years	14Y	11Y	10Y	9Y
Panel Effects	Entity, Time	Random	Entity, Time	Entity, Time

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

The results in this study appear to be in contrast to Click (1996) that conducted a similar analysis on Big Macs from 1986 to 1995. His finding was that the “failure of PPP is due exclusively to time-invariant country effects.” (Click, 1996, p. 211). However, in this study, when including these fixed effects for countries, the Big Mac index does not appear to come close to adhering to the LOP over the time period (2007-2020). In fact, for most of the price datasets, my findings are exactly the opposite to that of Click (1996). More specifically, after including fixed country effects, the panels regressions performed notably worse (particularly for CPI and BMI) in these price measures’ adherence to LOP or PPP. As Froot and Rogoff (1996) indicated, the results by Click (1996) could be attributable to several countries in the study having officially fixed their nominal exchange rate within their evaluation period and some countries during that period also experienced hyperinflation. Regarding the latter, such ‘outliers’ may well have been driving the results.¹⁵ Similar to the technique employed by Fujiki and Kitamura (2004), we have

¹⁵Our balanced panel regressions, which exclude a large number of these outliers, also seem to indicate that outliers can easily drive some of the results.

Table 4: Panel Regressions Summary Including Transaction Costs on Balanced Panel Dataset: Same 25 Countries Over 2012 to 2017

$$p_t^{i_x} - p_t^{US_x} = \alpha_x + \beta_x e_t^{iUS} + \delta_{x1} \ln \left(\frac{1+\tau_{i_x t}}{1+\tau_{US_x t}} \right) + \delta_{x2} \ln \left(\frac{1+\iota_{i_x t}}{1+\iota_{US_x t}} \right) + \delta_{x3} \ln \left(\frac{\lambda_{i_x t}}{\lambda_{US_x t}} \right) + \epsilon_t^{iUS_x}$$

Coefficient(x)	Price Ratio (x)			
	Big Mac	iPods	iPads	IPhones
$\hat{\alpha}_x$	0.8694 (0.1673)***	0.1299 (0.0534)**	0.5275 (0.2143)**	0.7853 (0.2005)***
$\hat{\beta}_x$	0.2590 (0.0570)***	0.9916 (0.0164)***	0.9614 (0.0762)***	0.6575 (0.0743)***
$\hat{\delta}_{x1}$	1.4341 (1.4972)	1.6411 (0.4179)***	-1.0465 (1.6772)	0.5050 (1.4693)
$\hat{\delta}_{x2}$		1.0640 (0.3622)**		-0.1034 (0.4719)
$\hat{\delta}_{x3}$		0.0505 (0.0142)***	0.1394 (0.0348)***	-0.0033 (0.0303)
R ² Overall	0.5038	0.9923	0.9678	0.8737
Countries	25C	25C	25C	25C
Years	6Y	6Y	6Y	6Y
Panel Effects	Entity, Time	Random	Entity, Time	Entity, Time

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

evaluated *various* panel models before including the most appropriate one (shown in the summaries: Table 1 to Table 4). Also, none of the ‘outlier’ countries are included that experienced either hyperinflation or currency rebasing.¹⁶ Overall, the findings in this subsection appear to be supportive of Fujiki and Kitamura (2004, p. 4)’s claim that studies on PPP (or LOP) are “sensitive to the choice of statistical models, and thus it might be desirable to employ *various* statistical techniques” [emphasis added]. Thus, having conducted numerous panel regression models, it appears as though iPods, and to some extent iPads, adhere fairly well to the LOP.

6.3 Bayesian Generalised Linear Model Estimations

PyMC is a powerful library package that’s available in the Python programming language (Salvatier, Wiecki and Fonnesbeck, 2016). By utilising this package, it’s possible to run Markov chain Monte Carlo (MCMC) algorithms to construct a Bayesian Generalised

¹⁶This is the reason why Estonia and Slovakia were excluded from the iPod dataset with their currencies being rebased to euros over the analyses. For example, simply including Estonia and Slovakia in the iPod price panel (which originally consisted of 48 countries) can move the panel regression’s $\hat{\beta}_{iPod}$ with fixed country and time effects in Table 14 from 0.9594 to 1.0063.

Linear Model (BGLM) to evaluate some of the relationships specified in Equations 1 and 2. To date, other research papers have not yet employed Bayesian reformulations in order to analyse the LOP and PPP. By using this alternative statistical approach, it would be possible to re-specify the Equation 1 to evaluate exchange rate passthrough in terms of a probability distribution function to yield:

$$p_t^{i,x} - p_t^{\text{US},x} \sim \mathcal{N} \left(\alpha_x + \beta_x e_t^{i\text{US}}, \sigma_t^{i\text{US},x^2} \right) \quad (3)$$

According to this specification, $p_t^{i,x} - p_t^{\text{US},x}$ is now formulated as a random vector of which each element is distributed according to a specified statistical distribution (in this case a normal distribution). The mean of this normal distribution is simply the linear predictor (i.e. $\alpha_x + \beta_x e_t^{i\text{US}}$) with a variance of $\sigma_t^{i\text{US},x^2}$. According to Davidson-Pilon (2015), there are numerous advantages to the Bayesian approach outlined in Equation 3. First of all, one is now able to quantify any prior information or knowledge that you may have regarding the parameters (i.e. α_x , β_x and σ_x). For example, after having conducted some of the panel regressions in Equations 1 and 2, we can potentially infer that the means for α_x , β_x (i.e. μ_{α_x} and μ_{β_x}) are 0 and 1 respectively, but with a fairly high degree of uncertainty, so that we also assign a fairly high value for the standard deviations of these parameters (i.e. σ_{α_x} and σ_{β_x}) as well as a fairly high level of uncertainty for the overall model (i.e. a large value for $\sigma_t^{i\text{US},x^2}$).

By deploying the MCMC algorithms on these prior distributions we are better equipped to *quantify* uncertainty by obtaining posterior distributions of how likely different values for the parameters are. The narrower the posterior distributions, the more certain we are that the model we have defined fits the actual data. What's more, by using these BGLM models we can also evaluate the evolution of the parameter distributions when accounting for transaction costs (as outlined for the cost variables in Section 5). The narrower the posterior distributions of the α_x and β_x parameters around 'zero' and 'one' respectively, and the more we can reduce uncertainty (i.e. the σ_x parameter), the greater confidence we'll have that the utilised price ratio potentially adheres to the LOP or PPP.

6.4 Results: Bayesian Generalised Linear Model Estimations

By employing a BGLM model with the linear specification defined in Equation 3 and by having specified the priors as follow:¹⁷

$$\sigma_t^{i\text{US},x} \sim HN \left(\sigma_{\sigma_t^{i\text{US},x}} = 10 \right) \quad (4)$$

¹⁷The robustness of this Bayesian analyses was checked by including a large array of various prior specifications, for example 1) informative priors, 2) weak priors and 3) diffuse priors. However, there's almost no noticeable change in the resulting posterior distributions, which implies the data is robust and not sensitive to specific prior specifications.

$$\alpha_x \sim \mathcal{N}(\mu_{\alpha_x} = 0, \sigma_{\alpha_x} = 1) \quad (5)$$

$$\beta_x \sim \mathcal{N}(\mu_{\beta_x} = 1, \sigma_{\beta_x} = 1) \quad (6)$$

and employing the BGLM specification:

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \sigma_t^{i\text{US},x} \quad (7)$$

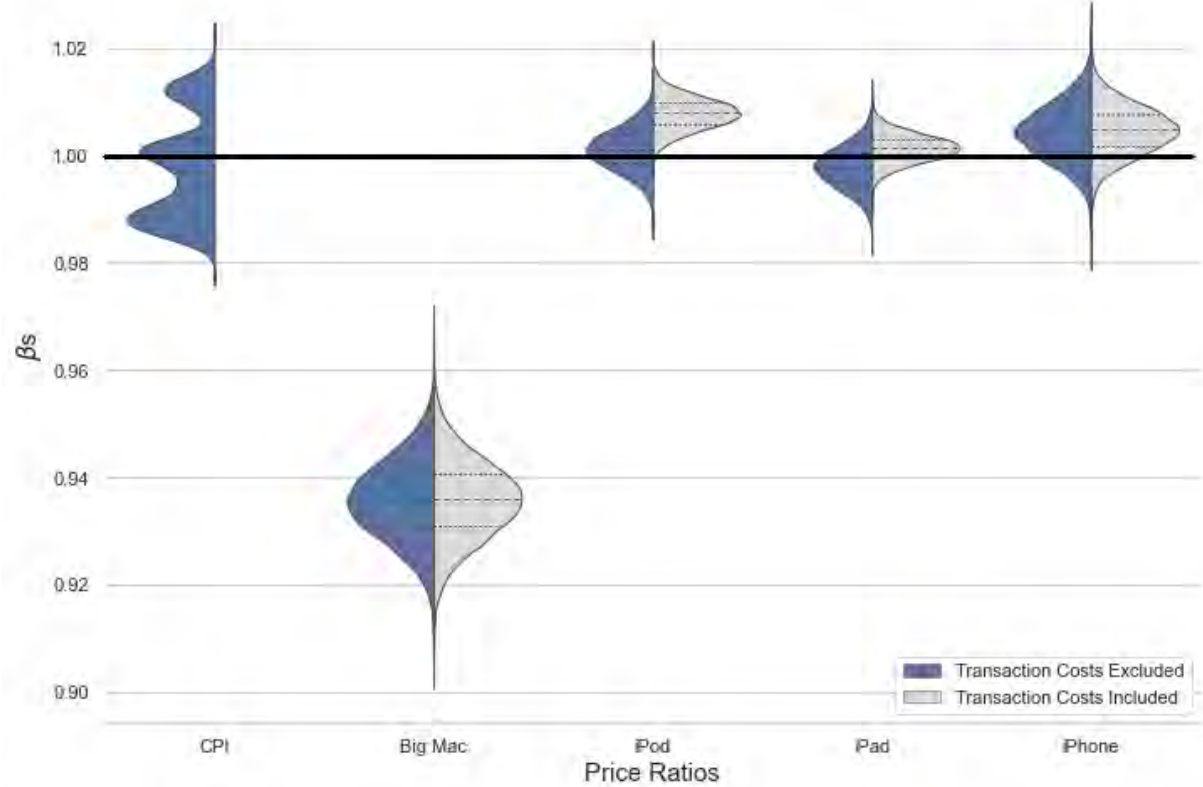
we subsequently draw 4,000 posterior samples from four chains for this model and plot the resultant marginal posterior distributions of the parameters for CPI, Big Macs, iPods, iPads and iPhones (Appendix A Figures 9 to 22 for the various CPI bases and 23, 25, 27 and 29 respectively). First, for all the models, the sampling chains for the individual parameters appear to be well converged and stationary. Second, it is noteworthy that for the Apple products' relative price ratios, the distribution around the linear BGLM specification (i.e. $\sigma_t^{i\text{US},x}$) is noticeably smaller than for the Big Mac price ratios. Specifically, the maximum posterior estimate of $\sigma_t^{i\text{US},\text{Big Macs}}$ is 0.362. This indicates a fairly wide distribution around the specified BGLM model for the BMI price ratios. For the CPI models, the intercepts (i.e. α_{CPI}) vary with each respective base period chosen. As such, even though each σ_t^{CPI} for any specific base does not appear to be all that large (i.e. only varying between 0.1269 to 0.165), when the total deviations of all the BGLM CPI models are taken into account (i.e. across all the various bases) the width over all these posterior distributions are notable. Meanwhile for iPods, iPads and iPhones these values are: 0.2019, 0.1682 and 0.1616 respectively, which is roughly *half* of the deviation from the BGLM compared to these derived from the BMI price measures. Third, in general, the coefficients for the maximum posterior estimates generally correspond with the coefficients from the regressions in Appendix E Tables F and G. Finally, it again seems as though, the APPs adhere better to the notion of relative LOP; with their respective β_x s, closer to, and more narrowly distributed around parity. This stands in contrast to the BMI price basket that doesn't even include unity in its posterior distribution. For CPI, this again depends on the base period chosen (i.e. some posterior betas include '1' while others don't). In order to evaluate the effect of transaction costs, we can also modify Equation 7 to account for these input costs by re-specifying the BGLM as:

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \delta_{x1} \ln \left(\frac{1 + \tau_t^{i,x}}{1 + \tau_t^{\text{US},x}} \right) + \delta_{x2} \ln \left(\frac{1 + \iota_t^{i,x}}{1 + \iota_t^{\text{US},x}} \right) + \delta_{x3} \ln \left(\frac{\lambda_t^{i,x}}{\lambda_t^{\text{US},x}} \right) + \sigma_t^{i\text{US},x} \quad (8)$$

Once including for the effect of transaction costs in the various BGLM models (refer to Figures 24, 26, 28, 30), the posterior deviation for Big Macs (i.e. $\sigma_t^{i\text{US},\text{Big Mac}}$) declines only

slightly to 0.35, while the comparable values for $\sigma_t^{iUS,iPod}$, $\sigma_t^{iUS,iPad}$ and $\sigma_t^{iUS,iPhone}$ drops noticeably to 0.1502, 0.1087 and 0.1369 respectively. In other words, when also including the transaction costs in the BGLM model, it reduces the amount of uncertainty observed. We can also evaluate the impact the inclusion of taxes, tariffs and shipping costs have had on the α_x and β_x parameter distributions (see Figure 4 which illustrates — via the use of violin plots — the distributions of the MCMC generated β_x s for each of the price ratios). Overall, the β_x s have not been noticeably impacted by the inclusion of transaction costs. Specifically, when evaluating the pre- and post transaction cost inclusion effect on the distributions of the parameters themselves, the $\beta_{Big\ MacS}$ does not include ‘unity’ in their distributions. Again, for the β_{CPIs} , it depends on the base period chosen. That said, several of the Bayesian derived betas are close to ‘one’. Meanwhile, for *all* the APPs price measures, their respective β_x distributions include ‘one’ within their posterior likelihood distributions.

Figure 4: Violin Plots of MCMC Generated β s



Even more interesting and noteworthy from this analysis is that the α_x parameter distributions for the APPs measures have shifted significantly closer to ‘zero’ following the inclusion of transaction costs in the BGLM specifications. This finding supports the notion that after controlling for the impact of transaction costs, the APPs measures adhere notably better to the LOP. In fact, for the APPs datasets, the α_{iPod} distribution now includes ‘zero’ when input costs are accounted for. It must also be added however that all

of the α_x parameter distributions have widened somewhat (indicating more uncertainty) after these cost measures have been included. For Big Macs meanwhile, the $\alpha_{\text{Big Mac}}$ parameter has both widened and shifted further away from ‘zero’. From the BGLM analyses above, we are again more confident that the notion of the LOP appears to be better supported by APPs products, while it seems less likely that Big Macs and CPI adhere to LOP or PPP.

Figures 31 and 32 in Appendix A illustrates the β and α distributions for the balanced panels. Overall, the results are fairly comparable to those derived above. It is however noteworthy that for the balanced panel the α_{CPI} and β_{CPI} parameter distributions appear to be more stable over the various base periods. This could also be because the balanced panel contains fewer years, and accordingly, bases. What’s more, the LOP for both iPods and iPads appears to hold within the balanced panel dataset with both α_{iPod} and α_{iPad} distributions including ‘zero’ while both these product’s β s still include ‘one’.

Figure 5: Violin Plots of MCMC Generated α s

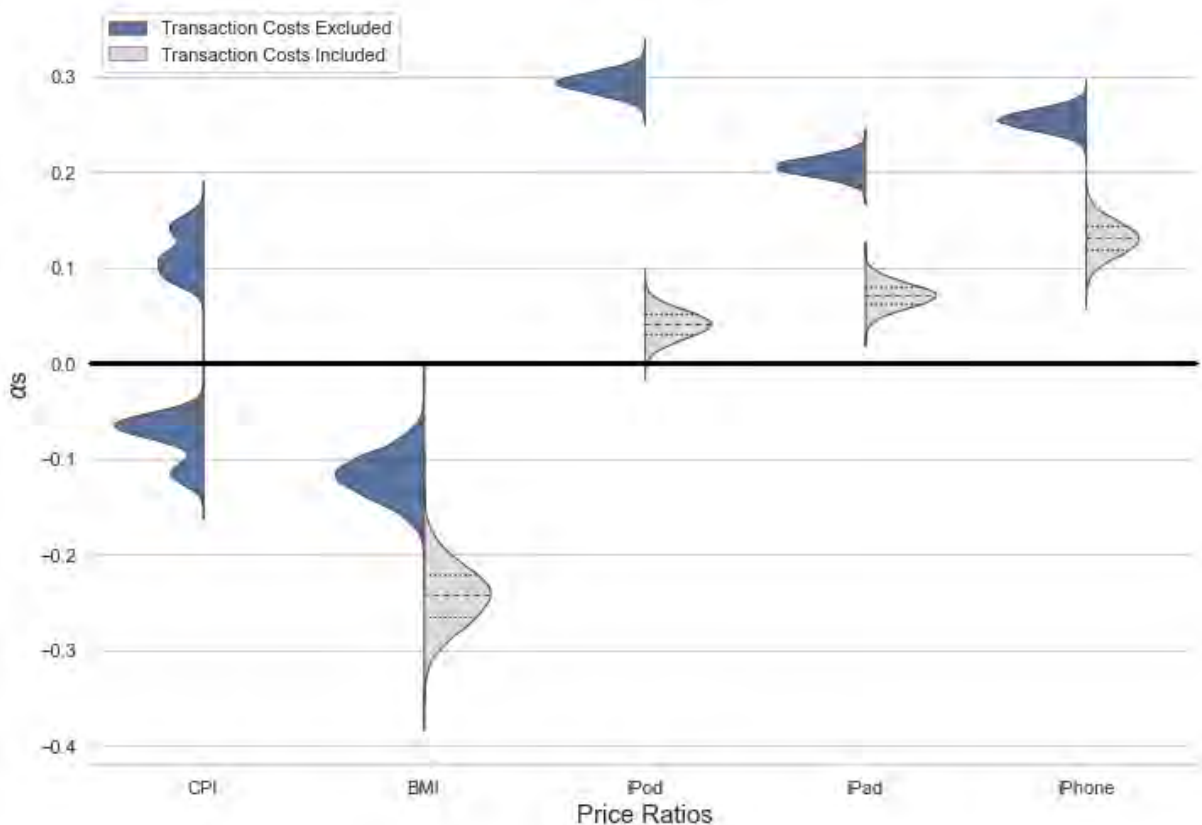
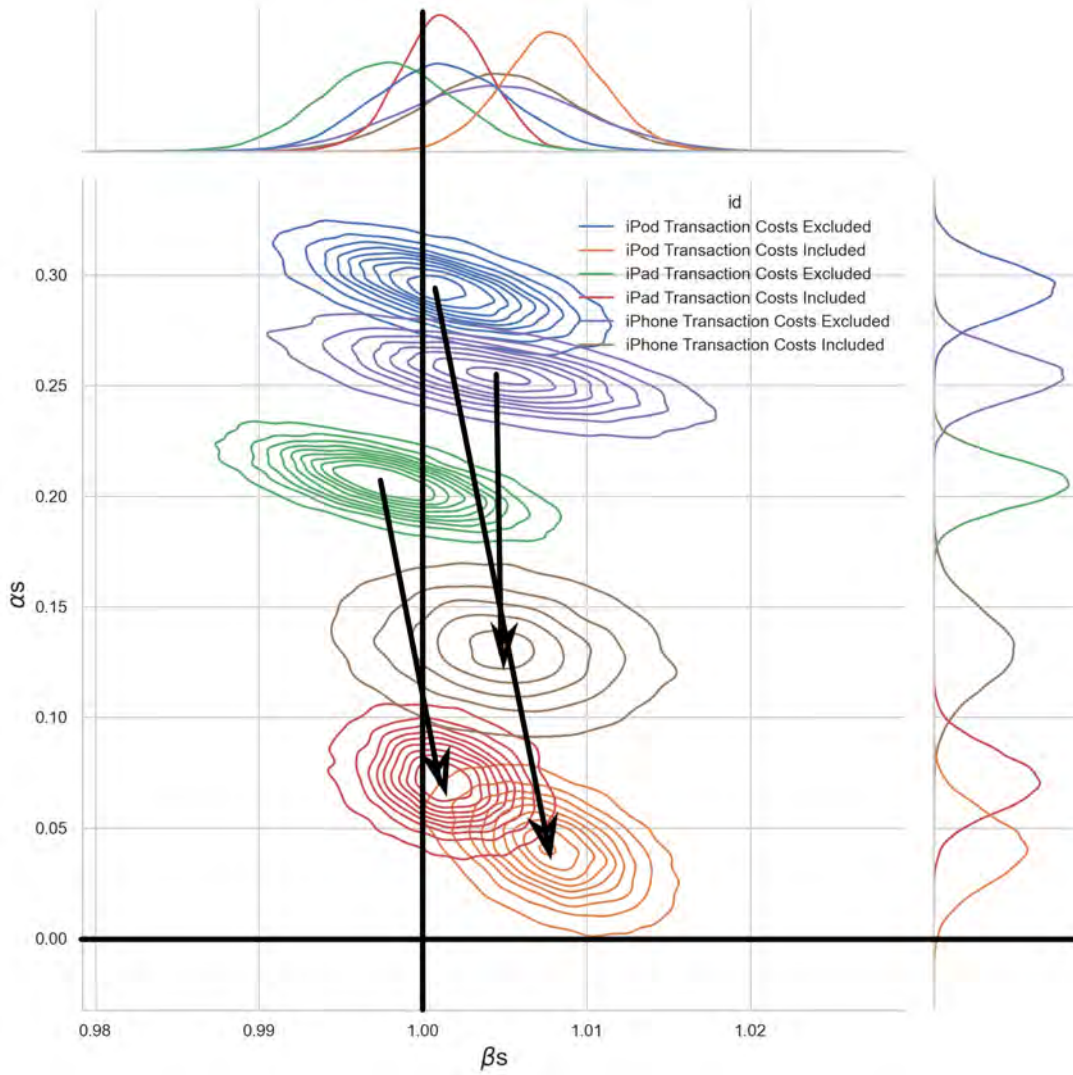


Figure 6 illustrates a joint kernel density plot of the MCMC generated α_x s and β_x s for the APPs. Again, this chart clearly illustrates how the β_x s are distributed around ‘1’ both before and after including transaction costs, though the α_x s have shifted noticeably lower after transaction costs were accounted for.

Figure 6: Kernel Density Joint Plots of MCMC Generated α_s and β_s Prior- and Post-Transaction Costs



7 Dynamic Estimations and the Speed of Adjustment

7.1 h Period Analyses

In addition to the ‘absolute’ LOP and PPP specifications defined in the previous section, we can also control for the heterogeneity of the α_x parameter by estimating the following difference equation:

$$\Delta p_t^{i,x} - \Delta p_t^{\text{US},x} = \beta_x \Delta e_t^{i\text{US}} + \epsilon_t^{i\text{US},x} \quad (9)$$

Equation 9 thus eliminates the bias emanating from the intercept, α_x . Even though

we'll lose some power from the dataset when conducting this analysis by removing the long-term relationship between the price levels amongst variables, we can continue differencing over subsequent time periods (of length h) to evaluate over what time-frame convergence between exchange rates and relative prices take place (as per the analyses conducted by Clements, Lan and Seah (2012) on Big Macs). More specifically, we can formulate:

$$\Delta^{(h)} p_t^{i,x} - \Delta^{(h)} p_t^{\text{US},x} = \beta_{h,x} \Delta^{(h)} e_t^{i\text{US}} + \epsilon_t^{i\text{US},x} \quad (10)$$

Where $\Delta^{(h)} p_t^{i,x} = p_t^{i,x} - p_{t-h}^{i,x}$ is the h period logarithmic change in the price level, and similarly for the exchange rate $\Delta^{(h)} e_t^{i\text{US}} = e_t^{i\text{US}} - e_{t-h}^{i\text{US}}$. Equation 9 is thus simply Equation 10 with the specific case of $h = 1$. This evaluation is an informal method of testing whether the derived RERs are stationary (or at least converge to some constant over time) since the movement in the nominal exchange rate should approximate the change in relative prices. By estimating each $\hat{\beta}_{h,x}$ over each extended time-frame (i.e. $h + 1$), one would be able to assess how much of the dispersion between the various relative price measures and exchange rates decrease over time.

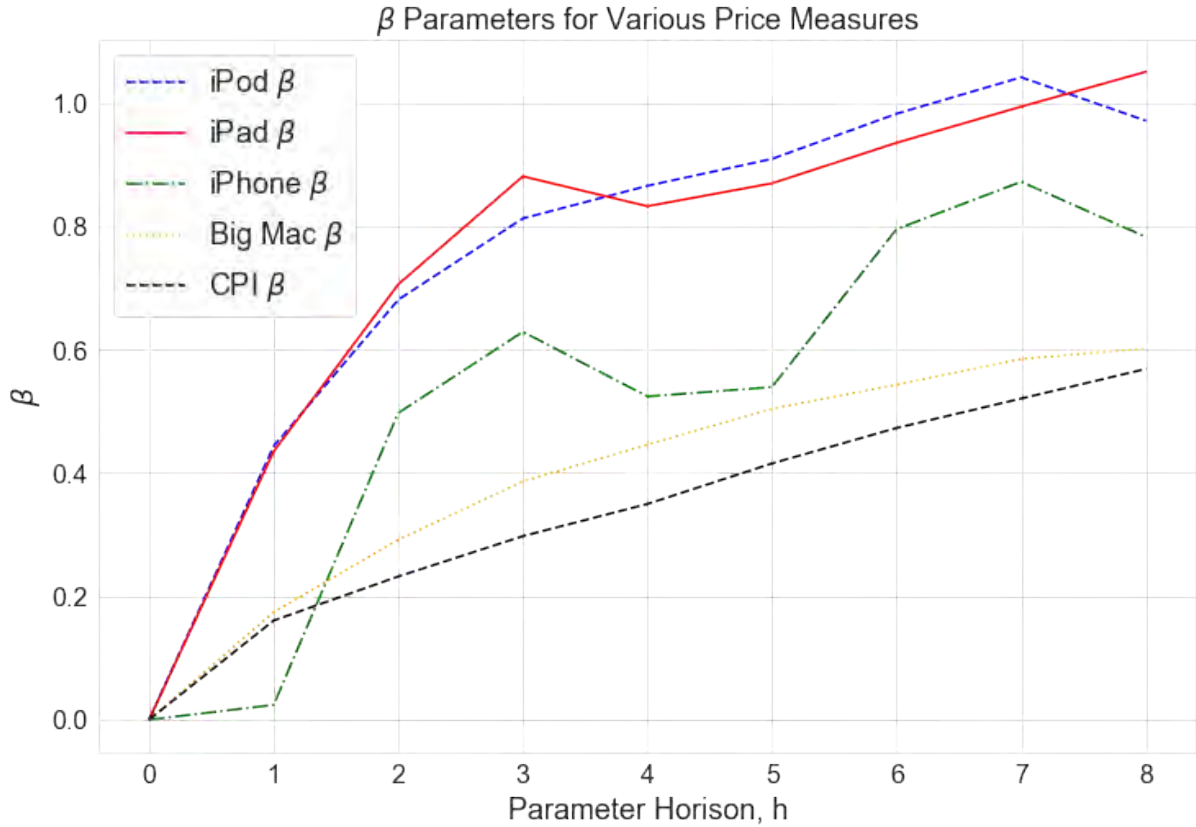
7.2 Results: h Period Analyses

Figures 33 through 37 in Appendix A illustrates with regression plots how the $\hat{\beta}_{h,x}$ parameters evolve for each relative price ratio when the timeframe is extended by one year at a time from $h = 1$ to $h = 9$. Again, and supporting the previous analyses, the APPs relative price ratios' $\hat{\beta}_{h,x}$ s — particularly for iPods and iPads — appear to converge to '1' noticeably quicker than for CPI and Big Macs. Figure 7 summarises all of these estimated $\hat{\beta}_{h,x}$ parameters from $h = 1$ to $h = 8$ time periods for the different price ratios. This chart illustrates how much quicker the Apple product relative price ratios and exchange rates converge to unity over time. In fact, for $h = 6$, the $\hat{\beta}_{h,x}$ for iPods and iPads have reached 0.9825 and 0.9354 respectively, while the comparable estimates for Big Macs and CPI do not even reach 0.66 over the $h = 9$ year period. Though the relative prices on iPhones converge slower to unity than iPads or iPods, it is nevertheless noticeably quicker than for both CPI and Big Macs.

7.3 Testing for Real Exchange Rate Stationarity

Following the analyses above, we can proceed to formally test for RER stationarity in order to assess LOP and PPP adherence. Intuitively, if cross country price differences on goods are eliminated, the RER (which is simply the price ratio expressed in a common currency) should be stationary over time (Fujiki and Kitamura, 2004). The RER between country i and the US for good x at time t can be expressed as:

Figure 7: APPs, Big Mac and CPI β s over h Period Changes



$$q_t^{iUS,x} \equiv p_t^{i,x} - p_t^{US,x} - e_t^{iUS} = \epsilon_t^{iUS,x} \quad (11)$$

By calculating $q_t^{iUS,x}$ for each of the relative price ratios in the study, we can subsequently test whether each of the derived RERs are indeed stationary. According to Rogoff (1996) most of the investigations on the time series properties of RERs have not been able to reject the null of a unit root (i.e. no mean reversion) - unless it is tested on a very long time series or large panels. Also, where the null has been rejected, most of the analyses have only been able to observe very slow convergence rates.

7.4 Results: Real Exchange Rate Stationarity Panel Tests

Table 5 summarises the test statistics and p -values for a number of panel data unit root tests which is performed on each of the RERs calculated from the five relative price ratios. For tests (1) to (8), the null hypothesis tested is whether all panels contain unit roots. For test (9) however, the Handri-LM test actually entails the null hypothesis whether all the panels are stationary. As a summary measure of LOP or PPP adherence, the proportion of tests (out of a total of nine) that's supportive of RER stationarity (at a 99% confidence level) is shown in the last row of the table.

The results from Table 5 indicate that the RER deviations calculated from the APPs

Table 5: Real Exchange Rate Unit Root Tests

Unit Root Test Statistic:	$q_t^{iUS,x}$				
	CPI	Big Mac	iPods	iPads	IPhones
(1) Levin-Lin-Chu: adjusted t -stat	-1.9552 (0.0253)**	-1.0721 (0.1418)	-7.7501 (0.0000)***	-14.3304 (0.0000)***	-0.7762 (0.2188)
(2) Harris-Tzavalis: ρ	0.8408 (0.9183)	0.7371 (0.0437)**	0.1483 (0.0000)***	0.1109 (0.0000)***	0.0431 (0.000)***
(3) Breitung: λ	0.3088 (0.6213)	-1.3482 (0.0888)*	-6.6184 (0.0000)***	-8.9388 (0.0000)***	-6.7749 (0.000)***
(4) Im-Pesaran-Shin: Z-t-tilde-bar	-0.4484 (0.3269)	-2.9275 (0.0017)***	-5.9792 (0.0000)***	-7.5400 (0.0000)***	-7.2250 (0.000)***
(5) Fisher-type (ADF): Inv - χ^2	(106.0696) (0.2714)	49.1651 (0.8815)	357.8382 (0.0000)***	256.5966 (0.0000)***	135.3290 (0.000)***
(6) Fisher-type (ADF): Inv - \mathcal{N}	1.8160 (0.9653)	1.2696 (0.8979)	-10.6310 (0.0000)***	-9.6133 (0.0000)***	-4.5894 (0.000)***
(7) Fisher-type (ADF): Inverse logit t	1.1809 (0.8806)	1.0053 (0.8418)	-13.7823 (0.0000)***	-10.0489 (0.0000)***	-4.6623 (0.000)***
(8) Fisher-type (ADF): Modified Inv - χ^2	0.5764 (0.2822)	-1.1526 (0.8755)	19.5979 (0.0000)***	12.4174 (0.0000)***	4.5900 (0.000)***
(9) Hadri LM: z	35.9598 (0.0000)***	28.8122 (0.0000)***	5.5488 (0.0000)***	1.0287 (0.1518)	0.5405 (0.2944)
% of Panel Tests Stationarity Supportive:					
	0%	11%	89%	100%	89%

Note: p -values in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

are transitory (i.e. the RERs are stationary). Specifically, from these specified stationarity tests, it again appears as though the Apple price ratios adhere to the LOP notably better than do Big Macs; and especially compared to CPI's ability to hold to PPP. This finding is in contrast to Chen, Wang and Shen (2007) that covered a sample of 16 countries over 1992 to 1999 and using (fewer) cointegration tests than this dissertation found that "PPP is overwhelmingly not rejected when the Big Mac price is used." Additionally, it was found that *none* of the unit root tests indicated that the RERs derived from the CPI ratios were stationary, while only *one* out of the nine tests were supportive of the LOP for the Big Mac as a price ratio measure. Meanwhile, for Apple product derived RERs, at least eight out of the nine tests were indicating that these product derived real exchange rates are stationary.

7.5 Linear Specifications: Half-life Analyses

We can also proceed with additional convergence tests by estimating the *speed* of the RER adjustments. According to Taylor and Taylor (2004, p. 146), “[o]ne way to get a feel for how fast the real exchange rate mean reverts is by asking how long it would take for the effect of a shock to die out by 50 percent — in other words, we can compute the half-life of shocks to the real exchange rate.” According to Rogoff (1996), the PPP literature generally indicates a half-life speed of around three- to five years. To calculate the speed of convergence, one estimates $\hat{\rho}_x$ in Equation 12 in the following AR(1) process:

$$\Delta q_t^{iUS,x} = \rho_x q_{t-1}^{iUS,x} + \epsilon_t^{iUS,x} \quad (12)$$

The respective price ratios’ half-lives can then be derived by calculating: $\log(0.5)/\log(1+\hat{\rho}_x)$. As is evident from this formula, the closer $\hat{\rho}_x$ gets to -1, the shorter the estimated period half-life will be. Meanwhile, should $\hat{\rho}_x$ be found to be closer to 0, the RER will appear to follow a random walk since the equation above will approximate $\Delta q_t^{iUS,x} = \epsilon_t^{iUS,x}$.

7.6 Half-life Analyses Results

Table 6 shows the $\hat{\rho}_x$ estimates (as formulated in Equation 12) as well as their associated half-lives (in years) for the various price ratio measures. When controlling for fixed country and time effects, all of the half-lives decline significantly. The adjustment speeds for the APP derived price ratios — when including fixed effects — range from just under six months for iPods to just over four months for iPads to ‘zero’ (i.e. the full real exchange rate adjustment occurred within a year) for iPhones. Overall, the adjustment speeds for the APPs are noticeably shorter than for CPI (attaining a half-lives ranging from 2.91 to 10.57 years, depending on the base year chosen). Note that for the fixed country and time effects, the $\hat{\rho}_{CPIs}$ do not vary with the base periods. Overall, the CPI derived half-lives also supports the literature finding of three- to five years. The Big Mac RERs also adjust fairly quickly with a derived half-life of just over 1.14 years.

We can again account for the transaction costs on Big Macs (again only VAT or GST) and on the APPs, by stripping out their impact on each domestic price for each product x , i.e. $P_t^{i,x}$. More specifically, we can calculate a ‘net’ domestic price (i.e. $P_t^{i,x_{net}}$) for each product x by deflating these prices by their associated VAT or GST tax rate (i.e. $\tau_t^{i,x}$) as well as applied import tariff levy (i.e. $\iota_t^{i,x}$) for each year t . That is, by calculating:

$$P_t^{i,x_{net}} = \frac{P_t^{i,x}}{(1 + \tau_t^{i,x})(1 + \iota_t^{i,x})} \quad (13)$$

From these *net* domestic prices, we can subsequently derive their associated *net* RERs, i.e. $\Delta q_t^{iUS,x_{net}}$. The half-lives estimated from these *net* relative price ratios are shown in

Table 6: Panel Half-Life Estimates

	$\Delta q_t^{iUS,x} = \rho_x q_{t-1}^{iUS,x} + \epsilon_t^{iUS,x}$				
$\hat{\rho}_x$:	CPI	Big Mac	iPods	iPads	iPhones
Pooled OLS	-0.0635 to -0.2117	-0.0771	-0.1649	-0.2984	-0.6040
<i>Standard Error</i>	(0.0181)*** to (0.0211)***	(0.0192)***	(0.0253)***	(0.0334)***	(0.0513)***
<i>Half-life (Years)</i>	2.91 to 10.57	8.64	3.85	1.96	0.75
Fixed Effects	-0.2221	-0.4568	-0.7648	-0.8701	-1.1185
<i>Standard Error</i>	(0.0270)***	(0.0447)***	(0.0505)***	(0.0528)***	(0.0649)***
<i>Half-life (Years)</i>	2.76	1.14	0.48	0.34	0.00

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 7. Interestingly, we did not observe as noticeable a reduction in the *net* derived half-lives when fixed country and time effects were included as we did in Table 6. However, for the pooled panel regressions, the half-lives for the Apple RERs did decline by 1.7 years (or 44%) for iPods, 1 year (or 51%) for iPads and 0.38 years (or 50%) for iPhones. Big Mac RERs only witnessed a decline of 1.06 years (or down 12%) after including VAT or GST. As such, it seems as though the fixed country effects also managed to pick up part of the impact attributable to transaction costs. Overall, and contrary to the meta study of Rogoff (1996), the RERs that are derived from Apple products appear to be stationary over various tests despite the time series component of the panel being fairly short. What's more, the convergence rates or half-lives of these deviations are also notably shorter than the 'three to five' years which is generally the literature consensus. Overall, the various tests and analyses conducted in this chapter indicates that certain products (like APPs) do indeed conform to and support the law of one price, particularly after one is able to control for transaction costs.

Table 7: Panel Half-Life Estimates on *Net* Price Ratios

	$\Delta q_t^{iUS,x_{net}} = \rho_x q_{t-1}^{iUS,x_{net}} + \epsilon_t^{iUS,x_{net}}$			
$\hat{\rho}_{x_{net}}$	Big Mac	iPods	iPads	iPhones
Pooled OLS	-0.0874	-0.2754	-0.5148	-0.8426
<i>Standard Error</i>	(0.0197)***	(0.0323)***	(0.0411)***	(0.0539)***
<i>Half-life (Years)</i>	7.58	2.15	0.96	0.37
Fixed Country and Time Effects	-0.4500	-0.7873	-0.8860	-1.1363
<i>Standard Error</i>	(0.0445)***	(0.0497)***	(0.0526)***	(0.0643)***
<i>Half-life (Years)</i>	1.16	0.45	0.32	0.00

Note: Standard Errors in Parenthesis

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

8 Conclusion

The central topic explored in this paper has been to evaluate what new panel datasets consisting of Apple product prices (APPs) could potentially reveal about some of the dynamics pertaining to the LOP as well as deviations away from it. The literature on the LOP subject matter is not as extensive as that on PPP. This is mainly due to the limited datasets on which to explore the topic. As such, we have constructed a new dataset, consisting of APPs, as well as their associated transaction or input costs, to evaluate what relationships and dynamics (that have not been explored in existing publications) can be revealed.

In conclusion, our analyses strongly support the hypothesis that Apple products adhere to the Law of One Price (LOP) under various estimation methods. Particularly after controlling for transaction costs, Apple prices demonstrate greater conformity to LOP than other traditional price measures like the Big Mac Index or CPI. Future research could explore similar analyses using other globally traded homogeneous goods to further validate these findings.

In addition, we were also better equipped with the new datasets to assess the impact transaction costs play in driving LOP deviations. In other words, by using a homogeneous product in the form of APPs and by controlling for some of the various input costs that drive wedges between local and international prices — i.e. countries' tax and tariff rates as well as shipping costs — we have been able to eliminate a notable amount of price heterogeneity across the respective markets. This has helped to tease out some of the underlying dynamics driving LOP relationships. Specifically, even though Apple products generally adhere to the relative LOP fairly well, after incorporating transaction costs, the absolute LOP is also often supported. This means that transaction costs are one of the main factors driving non-adherence to the LOP. At least for homogeneous, highly tradable goods like Apple products.

However, there are also disadvantages to using Apple products. One of the primary hurdles using a time series dataset on APPs is the technological leap each new product version introduces. More specifically, the new features and specifications mean that each new device is not exactly the same as the one it replaced. Next, Apple products cannot serve as a representative sample of all tradable products. This means that the findings and results from the dissertation cannot be extrapolated to all tradable products. Finally, there appears to be some pricing to the market, at least for iPhone devices.

Some of the new estimation techniques, including Bayesian formulations and piecewise linear regression estimations, to date do not appear to have been used in the real exchange rate literature. One of the several advantages of these techniques are that they require almost no parameter tuning in order to derive the results. In summary, the data supports the finding that the LOP hold for certain products after accounting for transaction costs

and that RER deviations from the LOP last only a few months. Some of the paper’s results help solve, at least in terms of product-derived real exchange rates, the duality problem of lengthy half-lives as well as the concept of LOP as only being a long-run phenomenon.

References

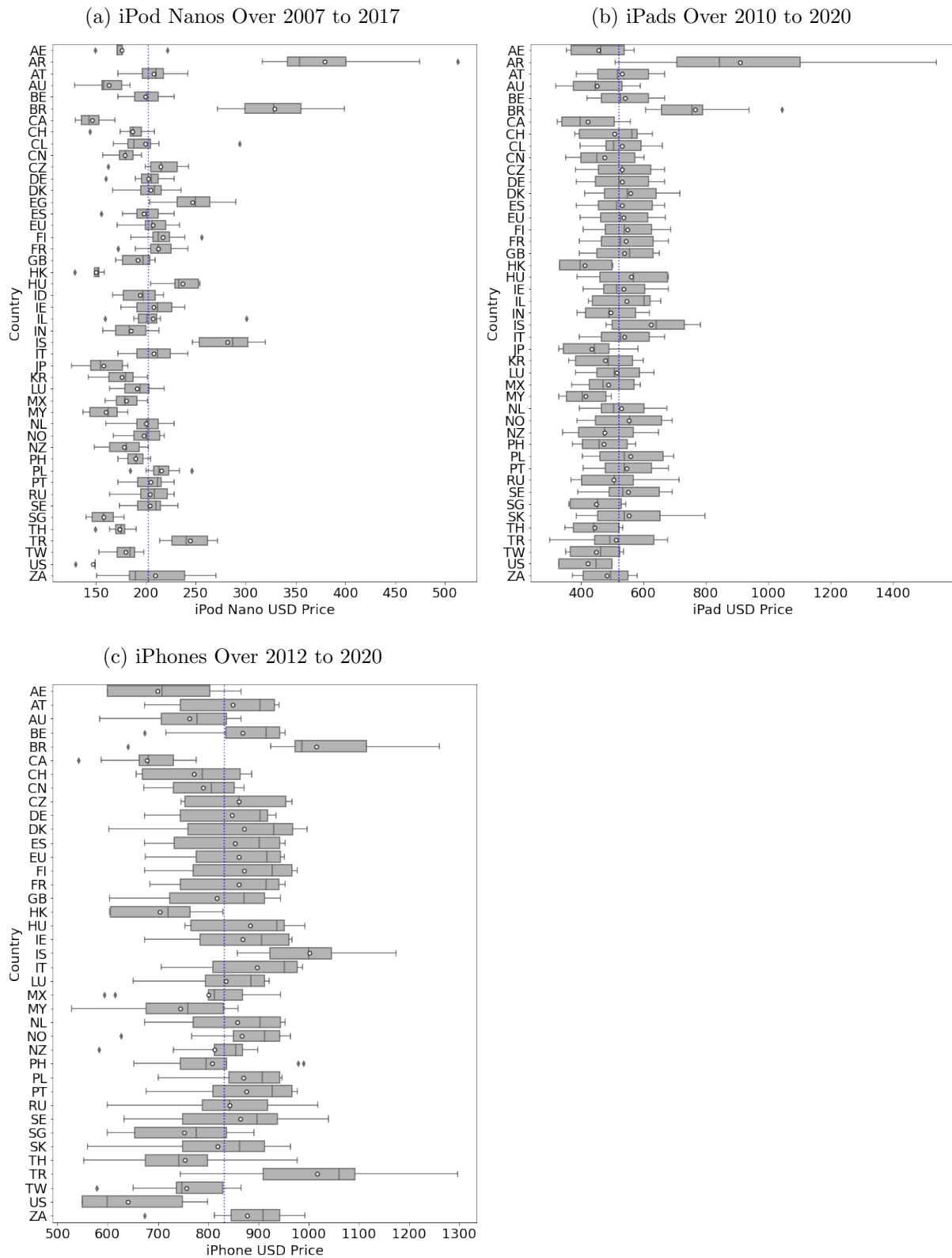
- Apple.** 2023. *Choose your Country or Region*. Copyright © 2023 Apple Inc. All rights reserved.
- Balassa, Bela.** 1964. “The purchasing-power parity doctrine: A reappraisal.” *Journal of political Economy*, 72(6): 584–596.
- Cavallo, Alberto, and Roberto Rigobon.** 2016. “The Billion Prices Project: Using Online Prices for Measurement and Research.” *Journal of Economic Perspectives*, 30: 151–178.
- Cavallo, Alberto, Brent Neiman, and Roberto Rigobon.** 2019. *Real exchange rate behavior: New evidence from matched retail goods*. Harvard Business School Working Paper, No. 20-040, January 2019.
- Chen, Chien-Fu, Chien-an Andy Wang, and Chung-Hua Shen.** 2007. “Does PPP hold for Big Mac price or consumer price index? Evidence from panel cointegration.” *Economics Bulletin*, 6(16): 1–15.
- Chortareas, Georgios, and George Kapetanios.** 2009. “Getting PPP right: identifying mean-reverting real exchange rates in panels.” *Journal of Banking & Finance*, 33(2): 390–404.
- Chortareas, Georgios, and George Kapetanios.** 2013. “How Puzzling Is The PPP Puzzle? An Alternative Half-Life Measure of Convergence to PPP.” *Journal of Applied Econometrics*, 28(3): 435–457.
- Clements, Kenneth W, Yihui Lan, and Shi Pei Seah.** 2012. “The Big Mac Index two decades on: An evaluation of burgeronomics.” *International Journal of Finance & Economics*, 17(1): 31–60.
- Click, Reid W.** 1996. “Contrarian McParity.” *Economic Letters*, 53(1996): 209–212.
- CommSec.** 2007. “CommSec iPod index: Something for nothing. Global comparisons & currency changes.” *Economic Insights, Commonwealth Securities*.
- Crucini, Mario J, and Christopher I Telmer.** 2020. “Microeconomic sources of real exchange rate variation.” *Review of Economic Dynamics*, 38: 22–40.

- Cumby, Robert E.** 1996. “Forecasting exchange rates and relative prices with the hamburger standard: Is what you want what you get with McParity?” National Bureau of Economic Research Working Paper 5675.
- Davidson-Pilon, Cameron.** 2015. *Bayesian methods for hackers: Probabilistic programming and Bayesian inference*. Addison-Wesley Professional.
- Engel, Charles.** 1999. “Accounting for US real exchange rate changes.” *Journal of Political economy*, 107(3): 507–538.
- Froot, Kenneth A, and Kenneth Rogoff.** 1996. “Perspectives on PPP and Long-Run Real Exchange Rates.” *Handbook of International Economics*, 3: 1647–1688.
- Froot, Kenneth A, Michael Kim, and Kenneth Rogoff.** 2019. “The law of one price over 700 years.” *Annals of Economics and Finance*, 20(1): 1–35.
- Fujiki, Hiroshi, and Yukinobu Kitamura.** 2004. “The Big Mac Standard: A statistical Illustration.” *Economics Bulletin*, 6(13): 1–18.
- Imbs, Jean, Haroon Mumtaz, Morten O Ravn, and Helene Rey.** 2005. “PPP strikes back: Aggregation and the real exchange rate.” *The Quarterly Journal of Economics*, 120(1): 1–43.
- International Trade Administration.** 2023. “Understanding HS Codes and the Schedule B.” Department of Commerce, United States of America.
- International Trade Centre.** 2022. “Market Access Map.” ITC Geneva.
- Jošić, Hrvoje, and Antea Barišić.** 2017. “Apple indices as a new informal measure of purchasing power parity.” *Zbornik Ekonomskog fakulteta u Zagrebu*, 15(1): 113–131.
- KPMG.** 2016-2022. “KPMG’s Corporate and Indirect Tax Rate Survey (Various Years).”
- Lutz, Matthias.** 2002. “Beyond Burgernomics and MacParity: Exchange Rate Forecasts Based on the Law of One Price.” International Conferences on Panel Data 10th International Conference on Panel Data, Berlin, July 5-6, 2002 D4-1.
- Marsh, Ian W, Evgenia Passari, and Lucio Sarno.** 2012. “Purchasing power parity in tradable goods.” 2012): *Handbook of exchange rates*, John Wiley & Sons Inc., Hoboken, New Jersey, 189–220.
- Mazumder, Sandeep.** 2016. “iPad Purchasing Parity: Farewell to the Big Mac Index.” *Economics Bulletin*, 36(4): 2128–2136.

- Obstfeld, Maurice, and Kenneth Rogoff.** 2000. “The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?” National Bureau of Economic Research Working Paper 7777.
- Officer, Lawrence H.** 2012. “Purchasing power parity in economic history.” *Handbook of exchange rates*, 159–187.
- Ong, Li Lian.** 1997. “Burgernomics: the economics of the Big Mac standard.” *Journal of International Money and Finance*, 16(6): 865–878.
- Parsley, David C, and Shang-Jin Wei.** 2007. “A prism into the PPP puzzles: The micro-foundations of Big Mac real exchange rates.” *The Economic Journal*, 117(523): 1336–1356.
- Rogoff, Kenneth.** 1996. “The purchasing power parity puzzle.” *Journal of Economic literature*, 34(2): 647–668.
- Salvatier, John, Thomas V Wieckiâ, and Christopher Fonnesbeck.** 2016. “Probabilistic programming in Python using PyMC3.” *PeerJ Computer Science* 2:e55.
- Samuelson, Paul A.** 1964. “Theoretical notes on trade problems.” *The review of economics and statistics*, 145–154.
- Seabold, S., and J. Perktold.** 2010. “Statsmodels: Econometric and Statistical Modeling with Python.” 92 – 96.
- Taylor, Alan M.** 2001. “Potential pitfalls for the purchasing-power-parity puzzle? Sampling and specification biases in mean-reversion tests of the law of one price.” *Econometrica*, 69(2): 473–498.
- Taylor, Alan M.** 2002. “A century of purchasing-power parity.” *Review of economics and statistics*, 84(1): 139–150.
- Taylor, Alan M, and Mark P Taylor.** 2004. “The purchasing power parity debate.” *Journal of economic perspectives*, 18(4): 135–158.
- Taylor, Mark P.** 2006. “Real exchange rates and purchasing power parity: Mean-reversion in economic thought.” *Applied Financial Economics*, 16(1-2): 1–17.
- UNCTAD.** 2022. “Review of Maritime Transport 2022.”
- Vo, Hai Long, and Duc Hong Vo.** 2023. “The purchasing power parity and exchange-rate economics half a century on.” *Journal of Economic Surveys*, 37(2): 446–479.

A Appendix Figures

Figure 8: Annual Dataset: Box Plots of USD Converted Prices of iPods, iPads and iPhones for Various Countries



B Exchange Rate Passthrough Analyses: PyMC Posterior Distribution Trace Plots

Figure 9: PyMC Posterior Distribution Trace Plots for CPI Base 2007

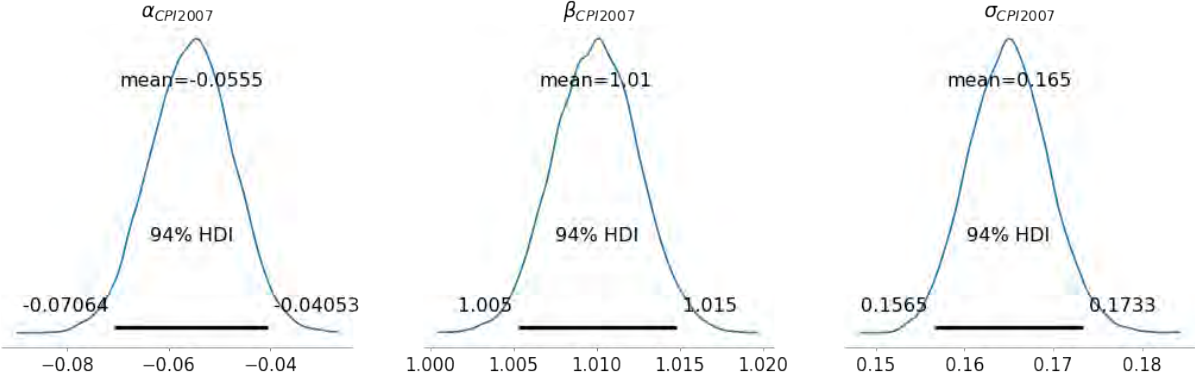


Figure 10: PyMC Posterior Distribution Trace Plots for CPI Base 2008

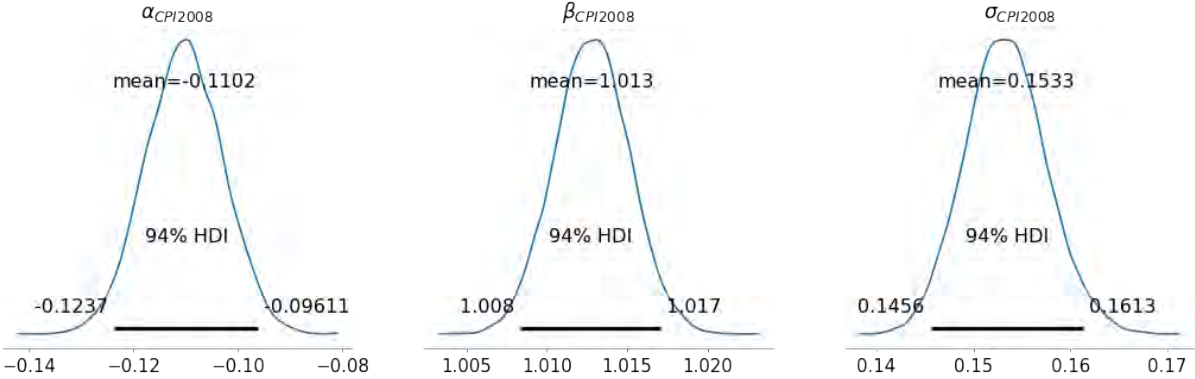


Figure 11: PyMC Posterior Distribution Trace Plots for CPI Base 2009

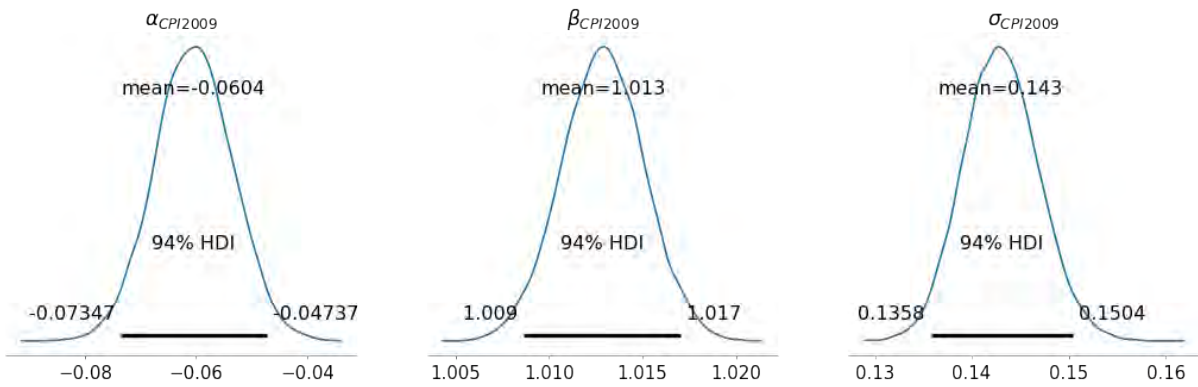


Figure 12: PyMC Posterior Distribution Trace Plots for CPI Base 2010

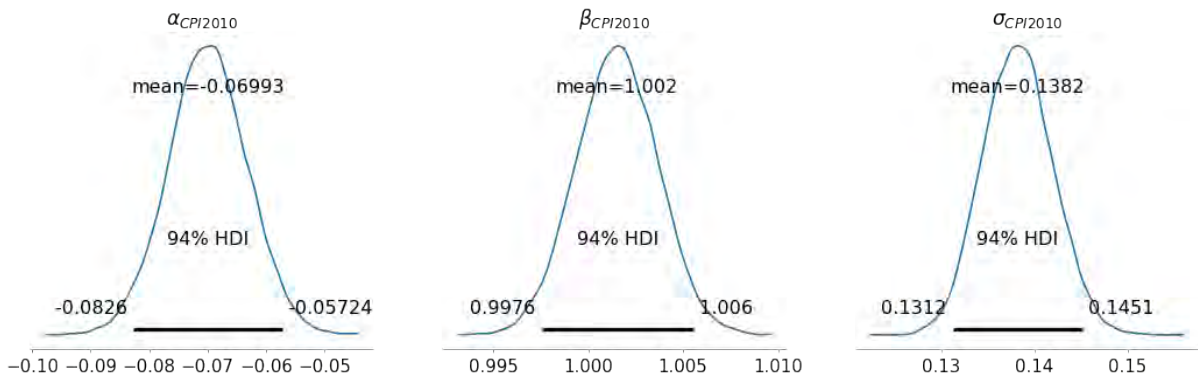


Figure 13: PyMC Posterior Distribution Trace Plots for CPI Base 2011

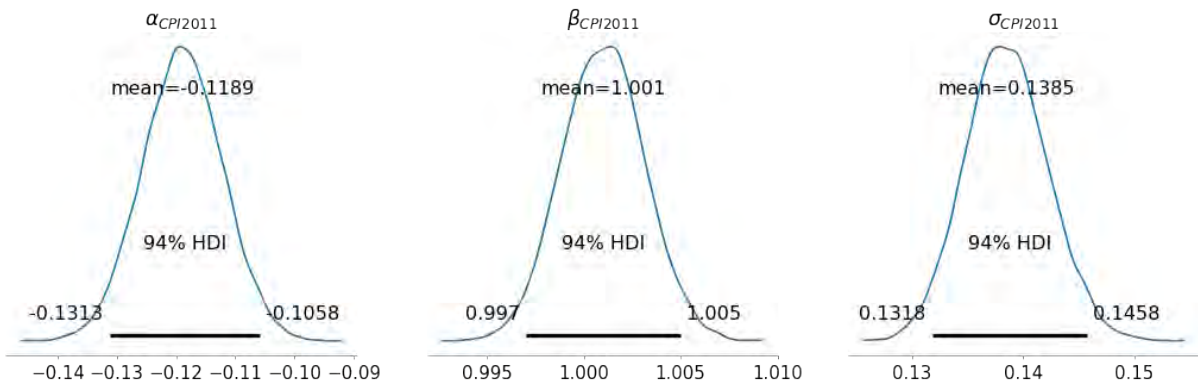


Figure 14: PyMC Posterior Distribution Trace Plots for CPI Base 2012

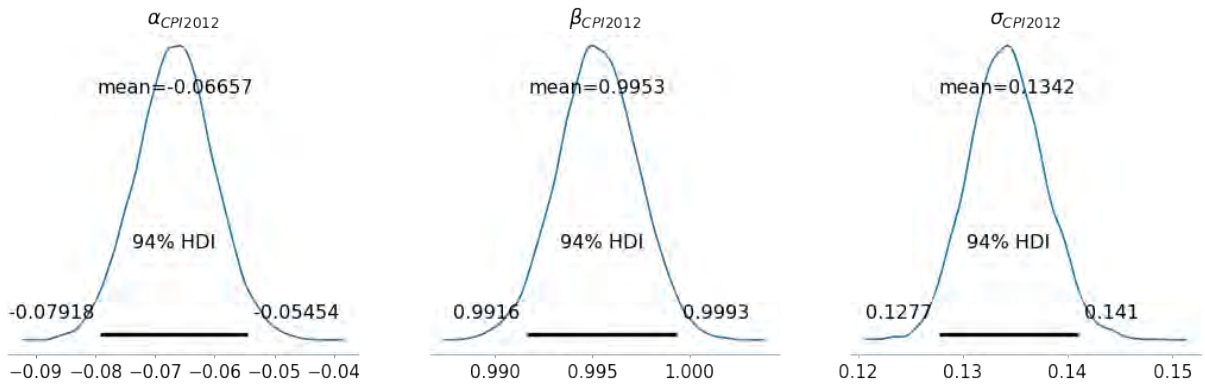


Figure 15: PyMC Posterior Distribution Trace Plots for CPI Base 2013

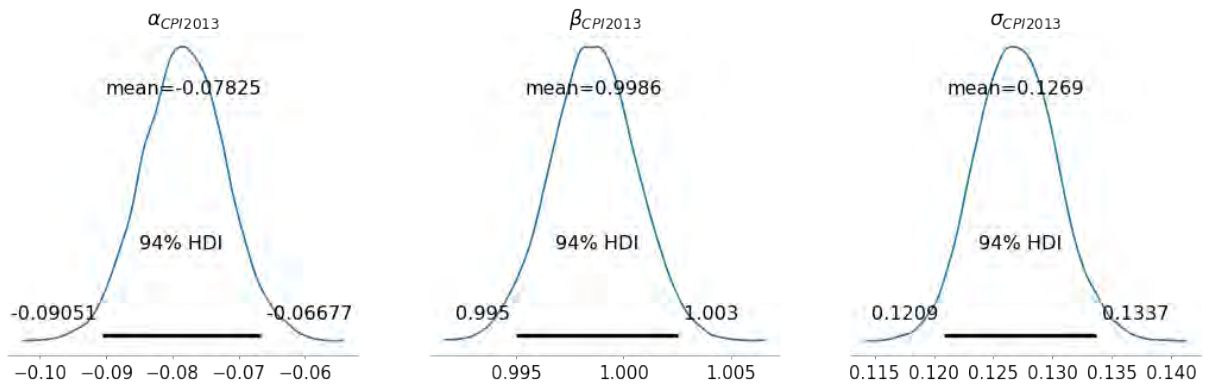


Figure 16: PyMC Posterior Distribution Trace Plots for CPI Base 2014

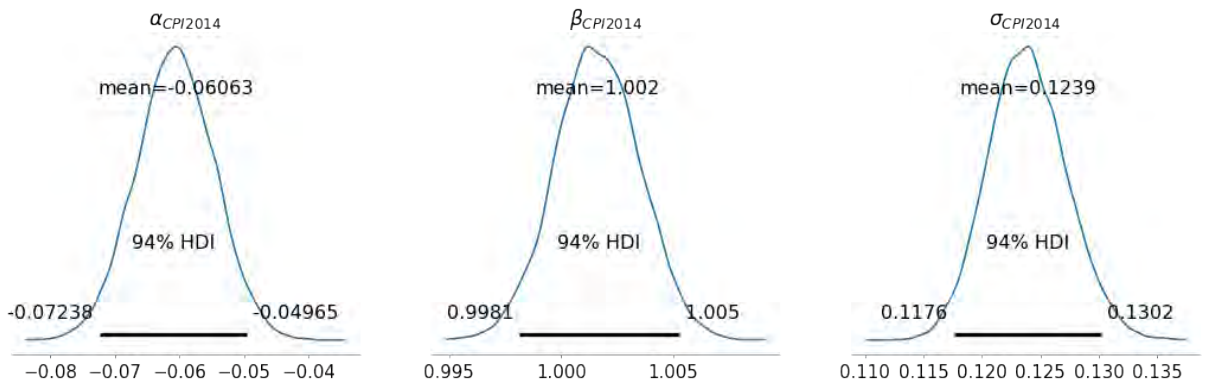


Figure 17: PyMC Posterior Distribution Trace Plots for CPI Base 2015

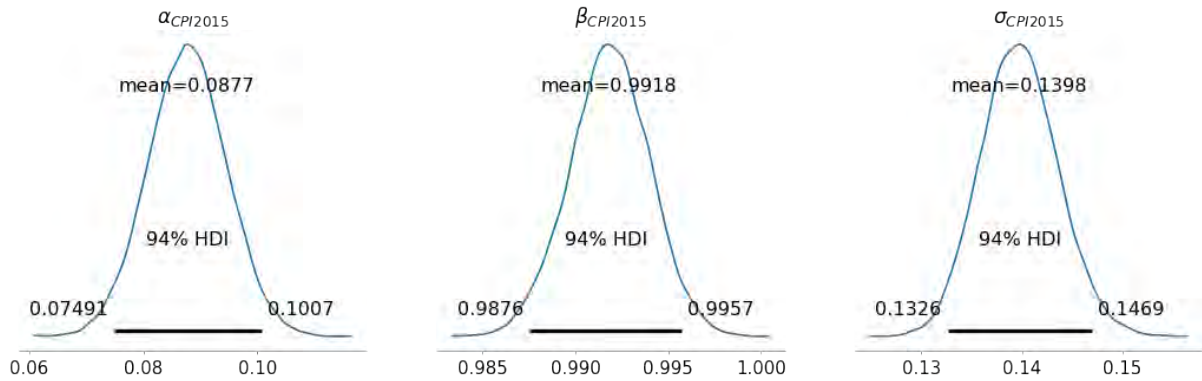


Figure 18: PyMC Posterior Distribution Trace Plots for CPI Base 2016

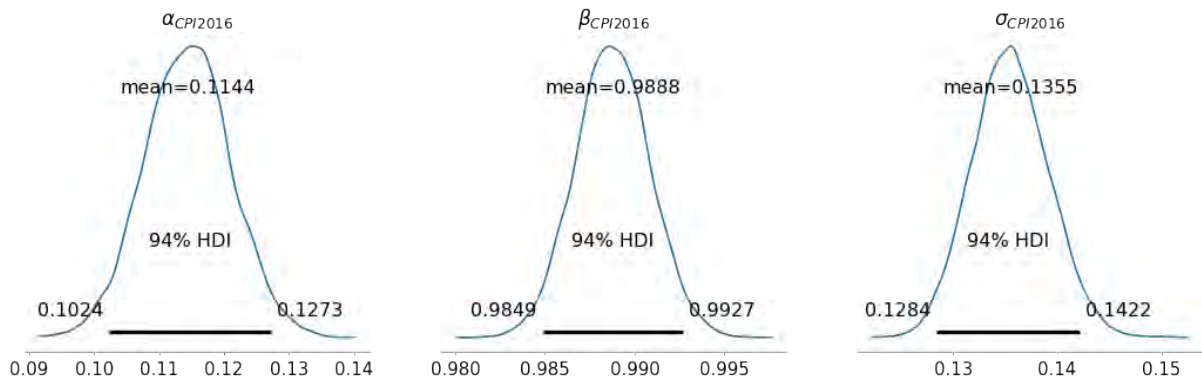


Figure 19: PyMC Posterior Distribution Trace Plots for CPI Base 2017

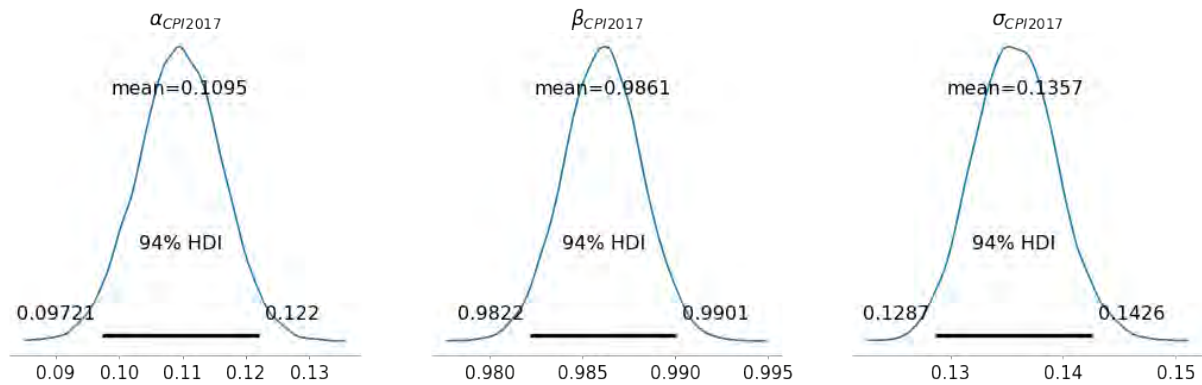


Figure 20: PyMC Posterior Distribution Trace Plots for CPI Base 2018

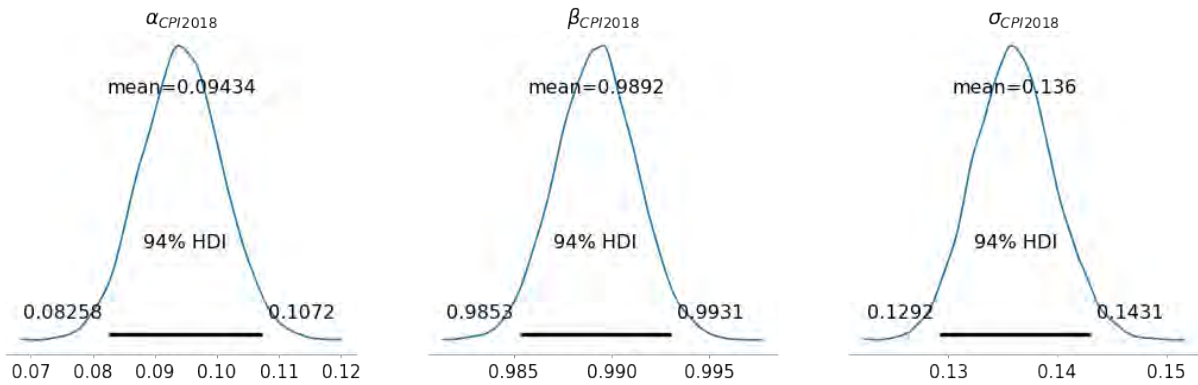


Figure 21: PyMC Posterior Distribution Trace Plots for CPI Base 2019

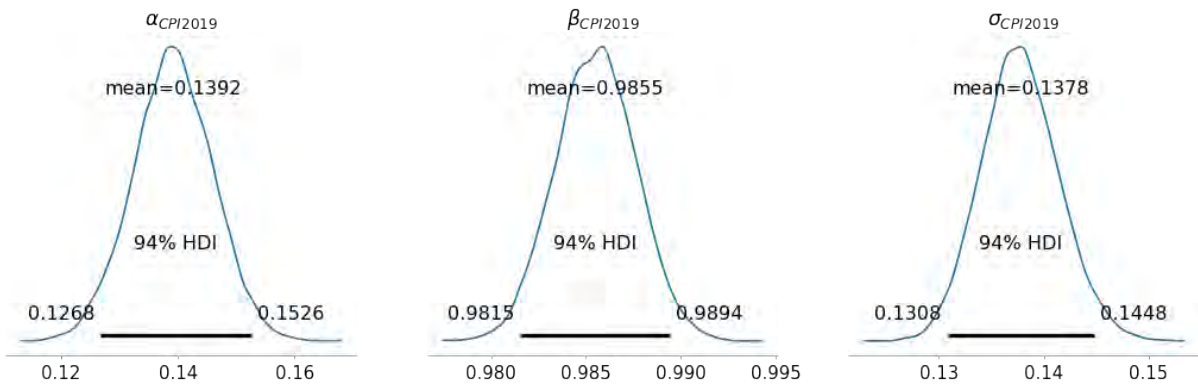


Figure 22: PyMC Posterior Distribution Trace Plots for CPI Base 2020

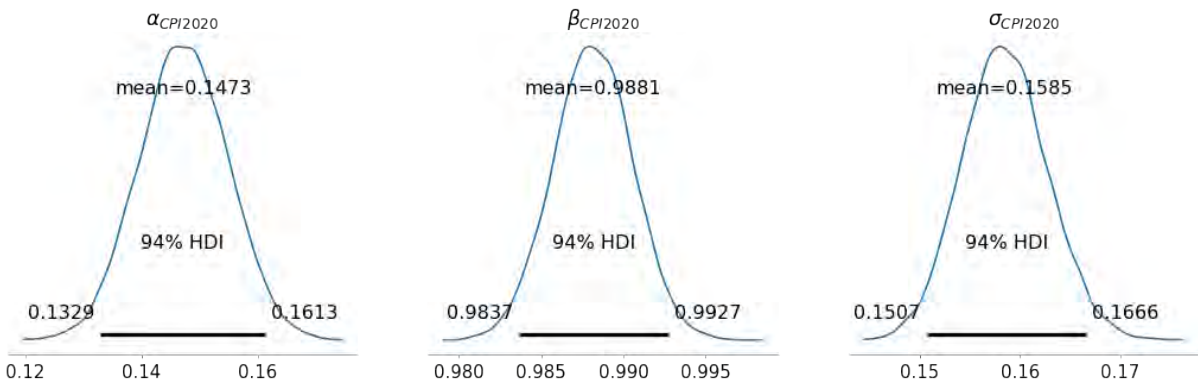


Figure 23: PyMC Posterior Distribution Trace Plots for Big Macs (excluding Transaction Costs)

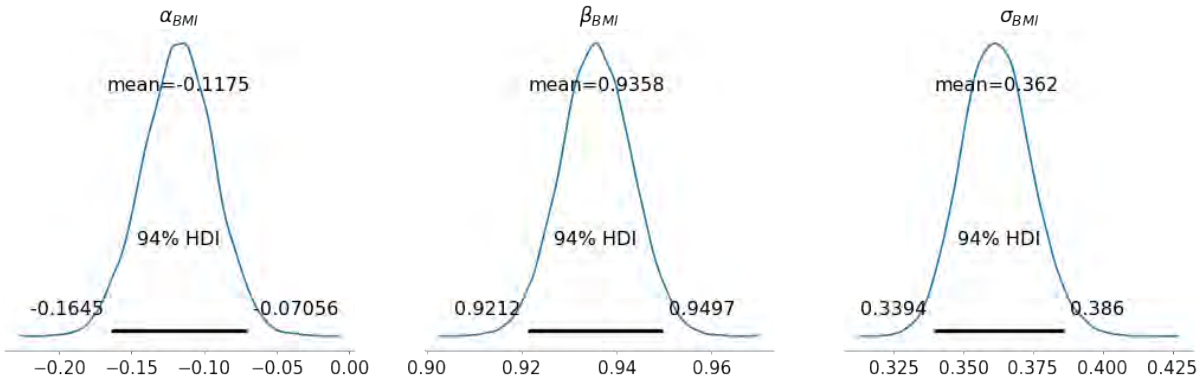


Figure 24: PyMC Posterior Distribution Trace Plots for Big Macs (including VAT or GST)

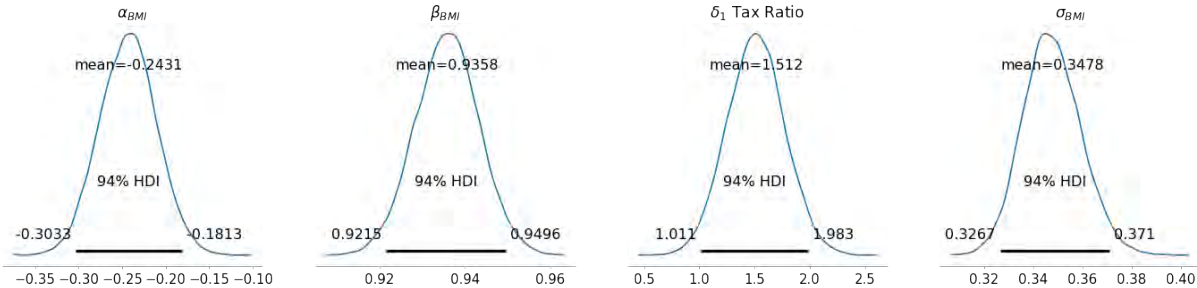


Figure 25: PyMC Posterior Distribution Trace Plots for iPods (excluding Transaction Costs)

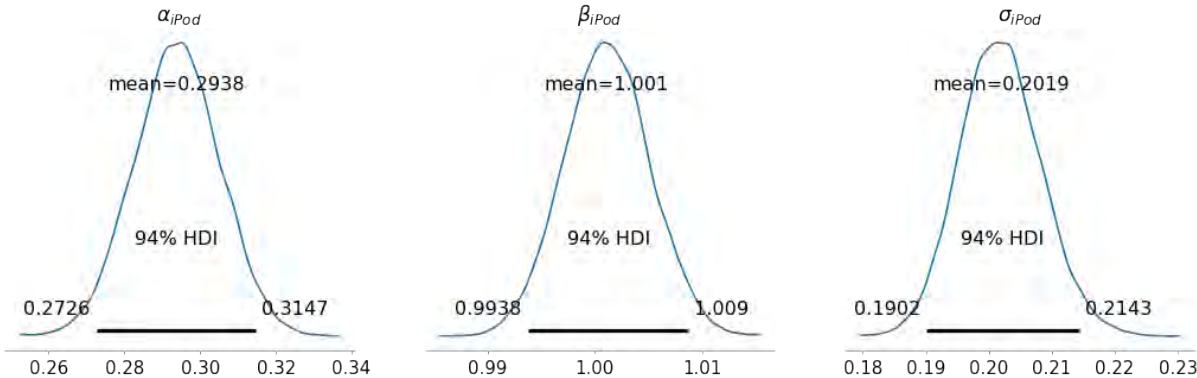


Figure 26: PyMC Posterior Distribution Trace Plots for iPods (including Transaction Costs)

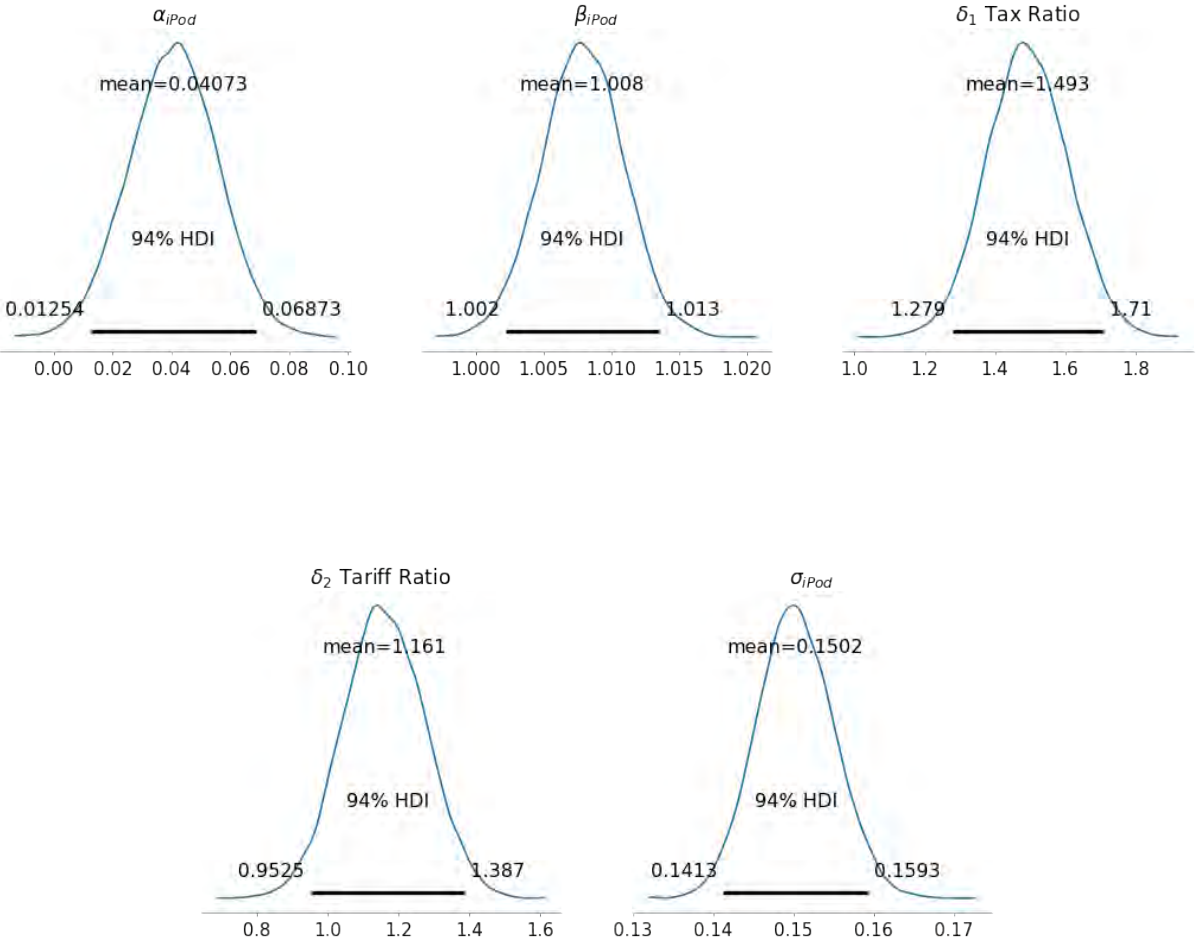


Figure 27: PyMC Posterior Distribution Trace Plots for iPads (excluding Transaction Costs)

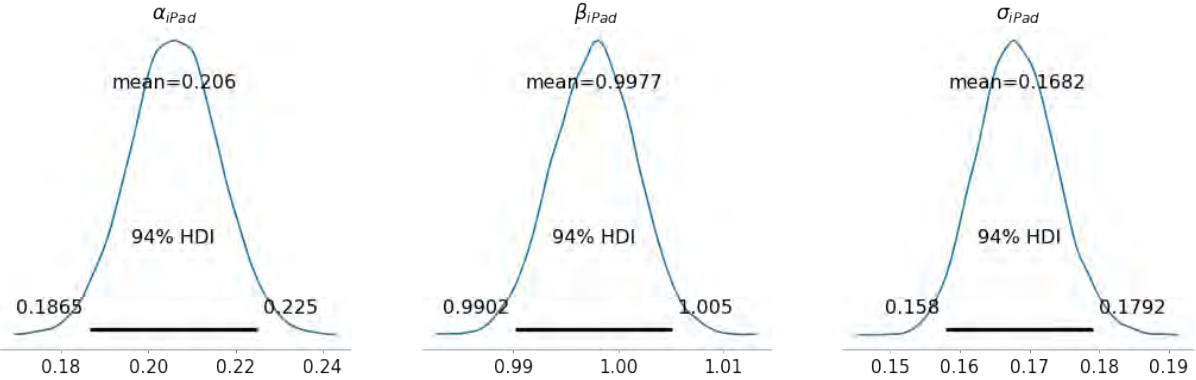


Figure 28: PyMC Posterior Distribution Trace Plots for iPads (including Transaction Costs)

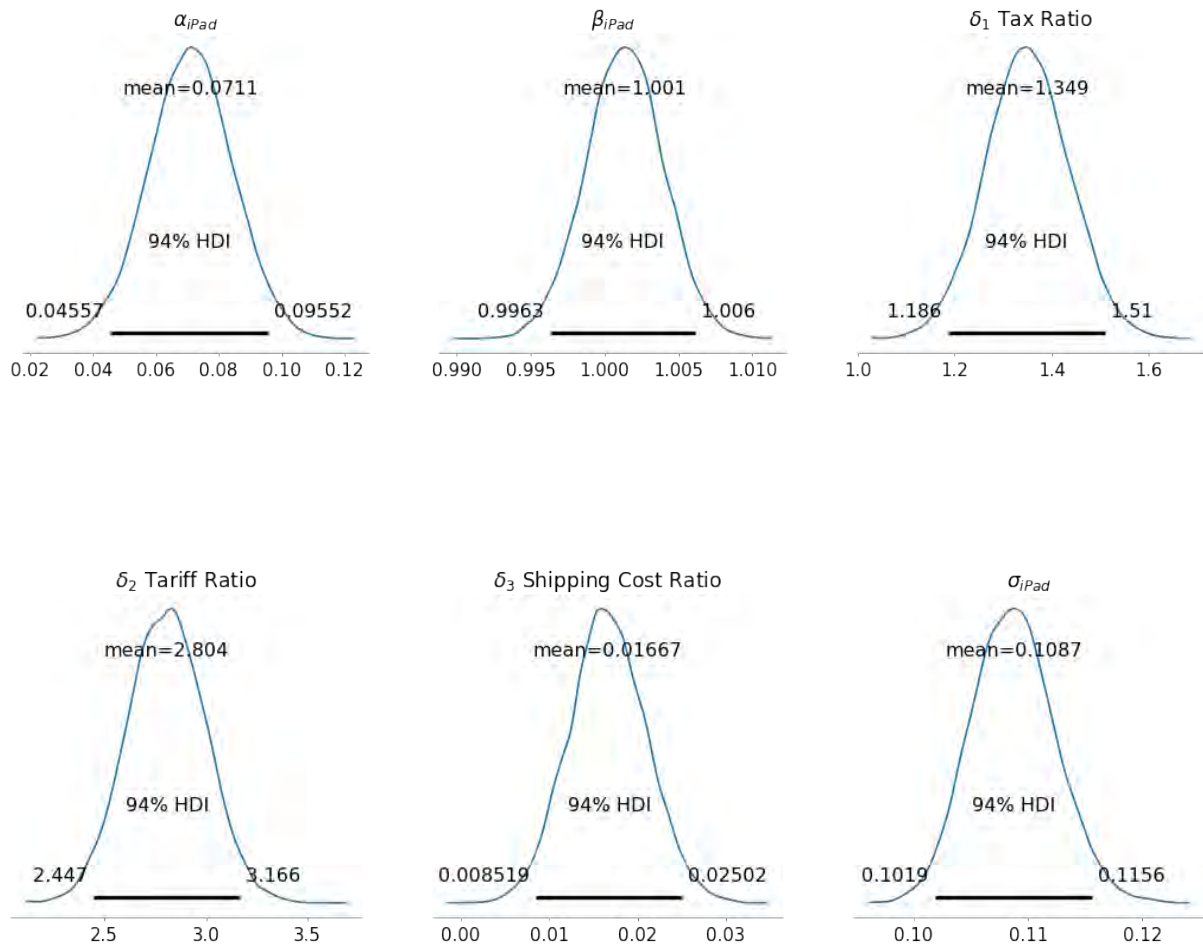


Figure 29: PyMC Posterior Distribution Trace Plots for iPhones (excluding Transaction Costs)

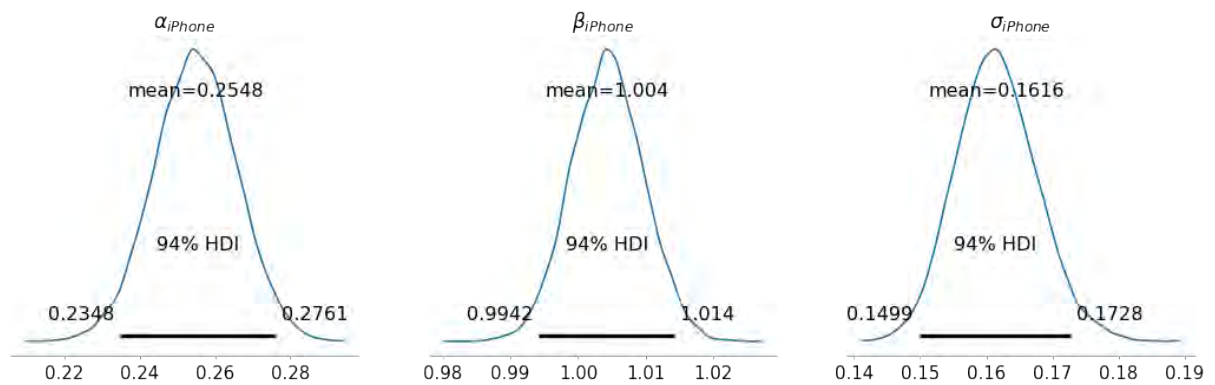
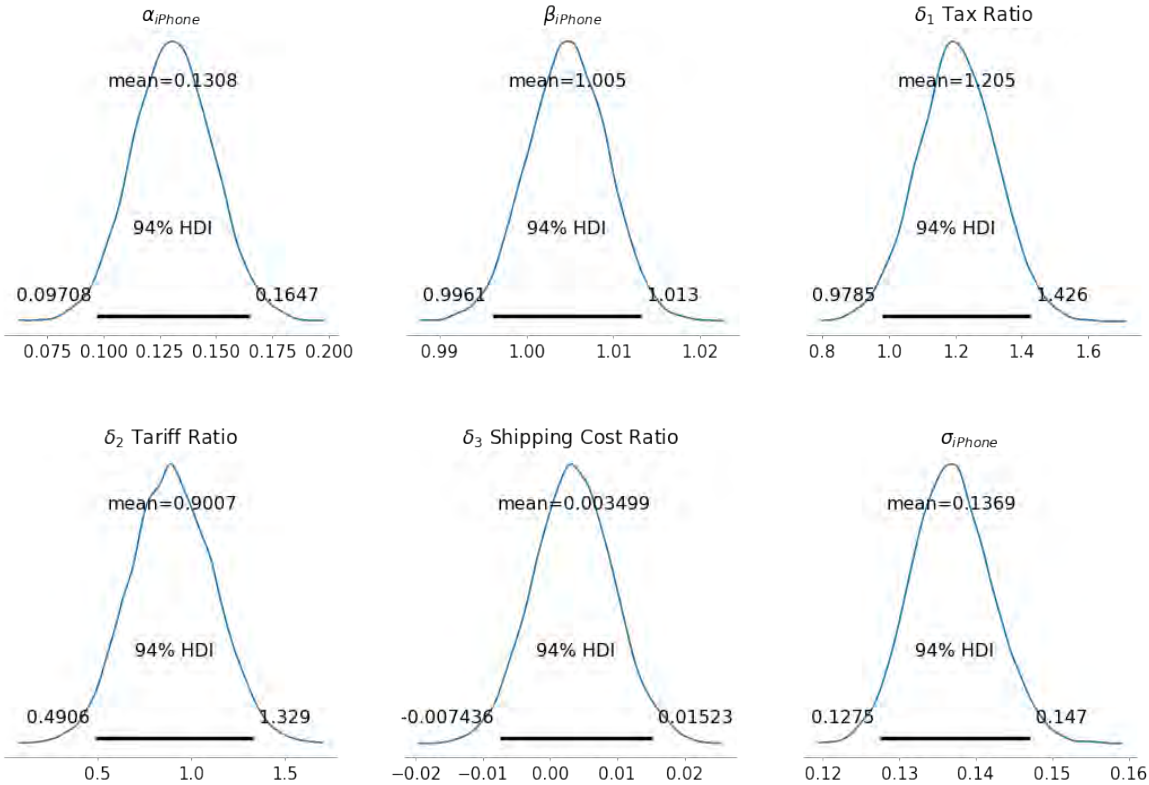


Figure 30: PyMC Posterior Distribution Trace Plots for iPhones (including Transaction Costs)



C PyMC Violin Plots of Posterior α_x and β_x Parameters

Figure 31: Violin Plots of MCMC Generated β_s

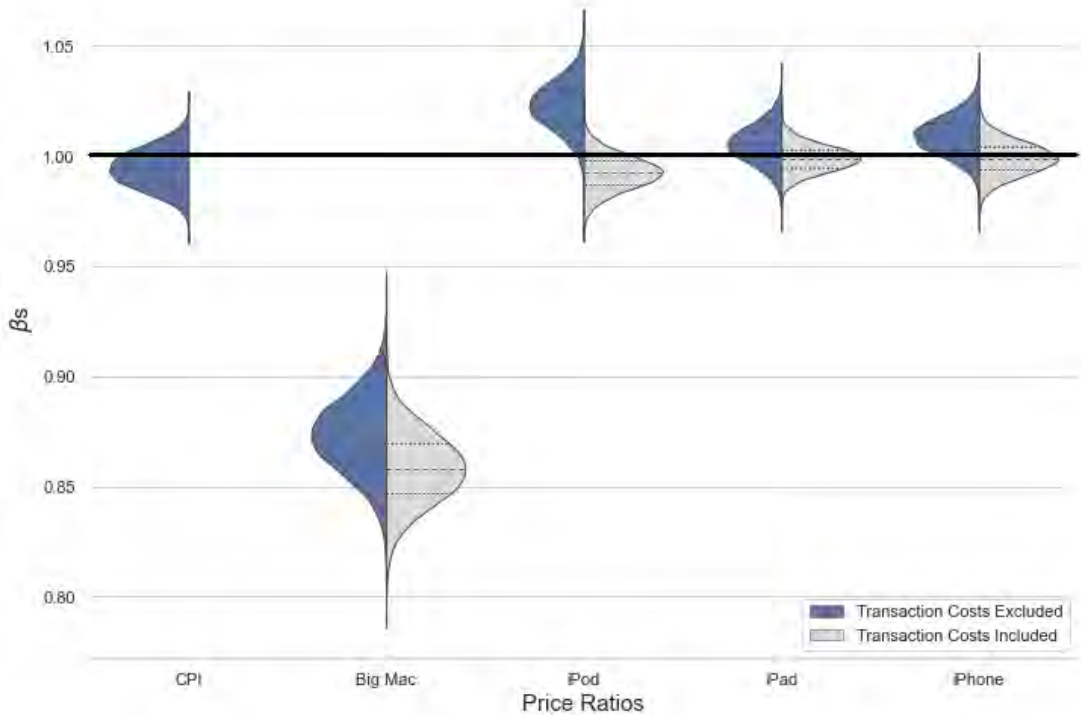
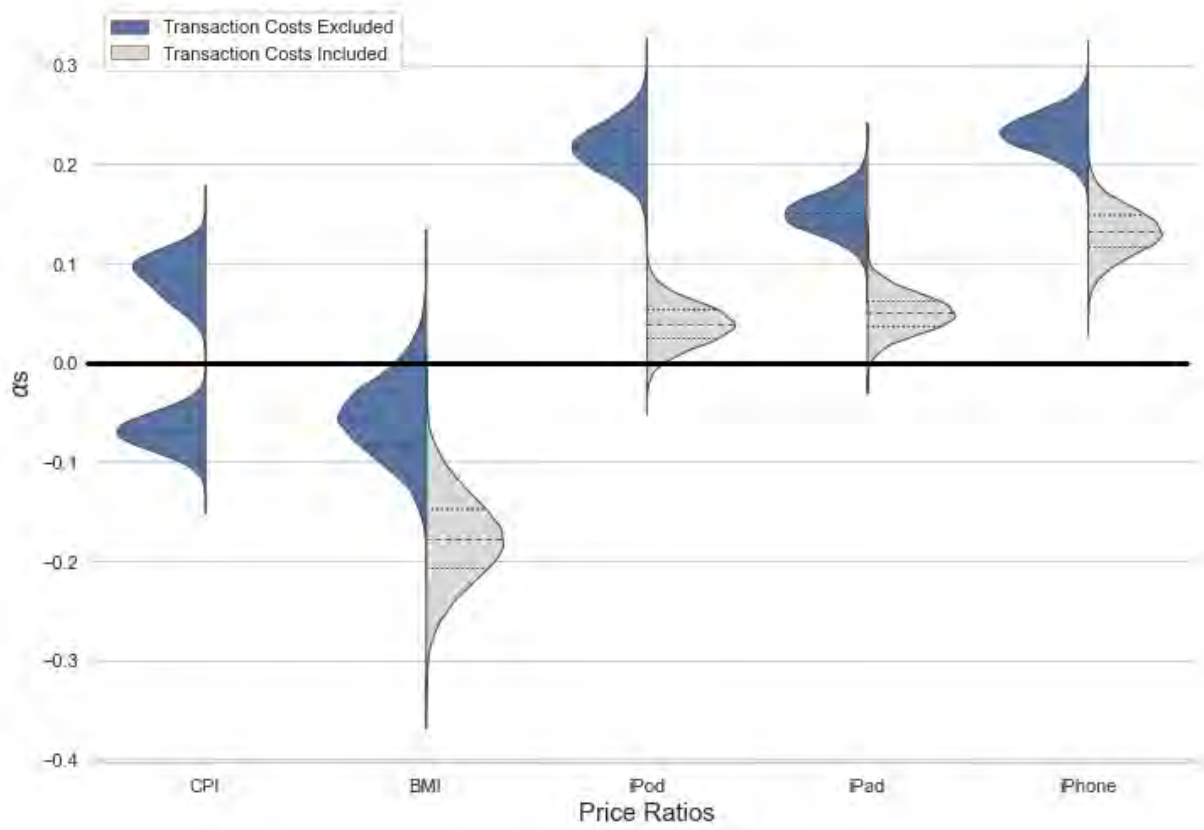


Figure 32: Violin Plots of MCMC Generated α s



D h-Period Change Analyses

Figure 33: CPI Price Data over h Period Changes

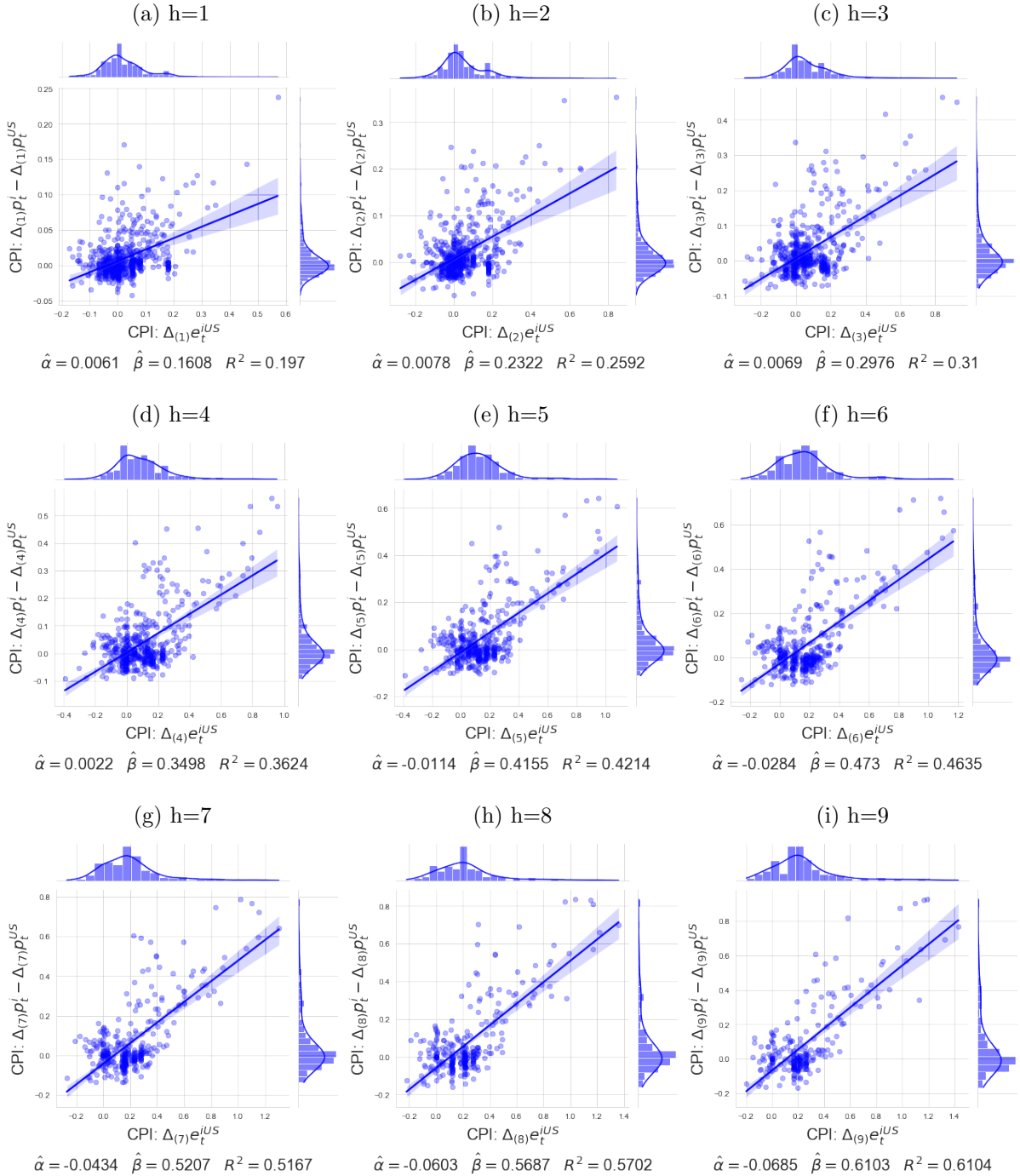


Figure 34: Big Mac Price Data over h Period Changes

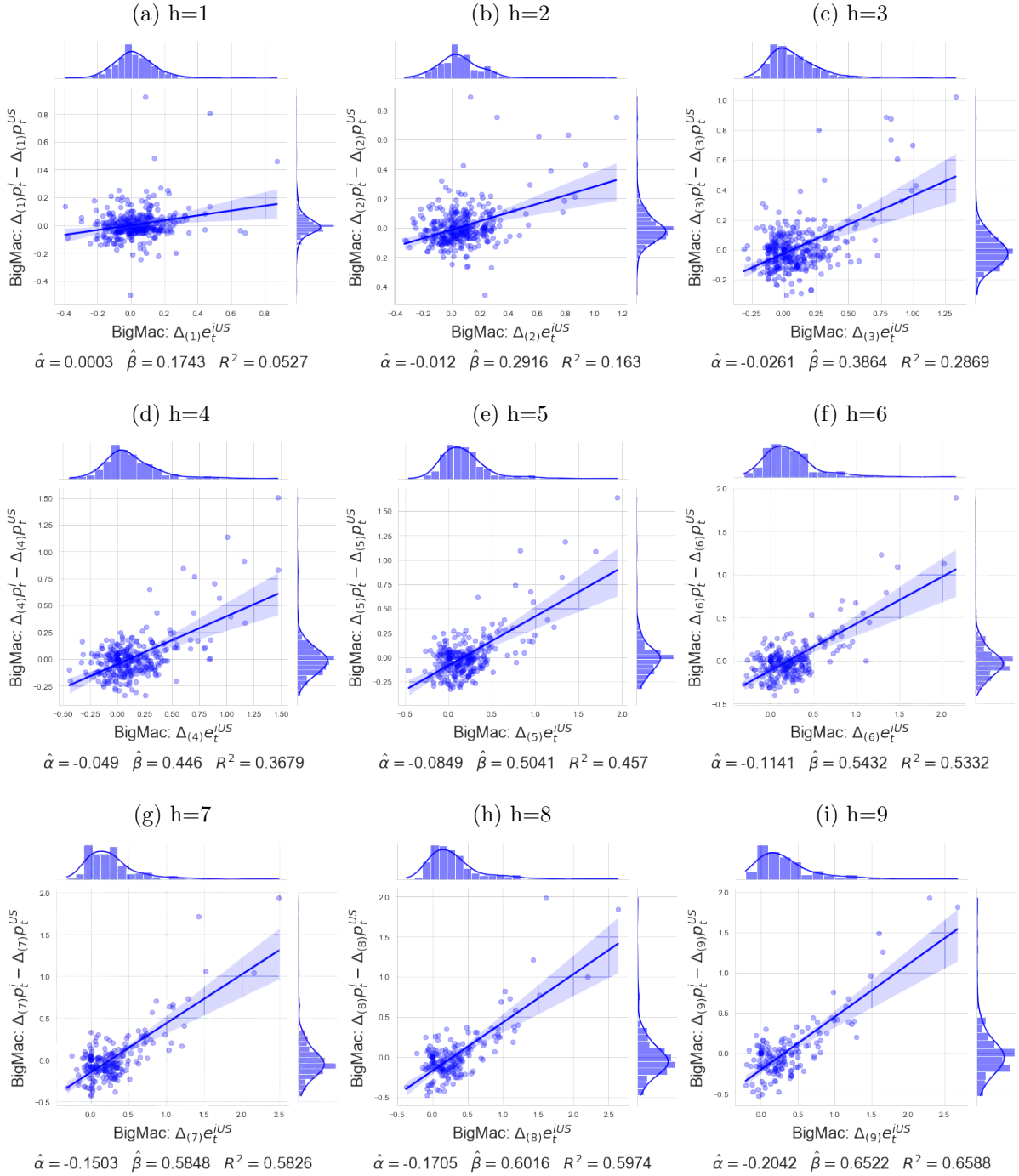


Figure 35: iPod Price Data over h Period Changes

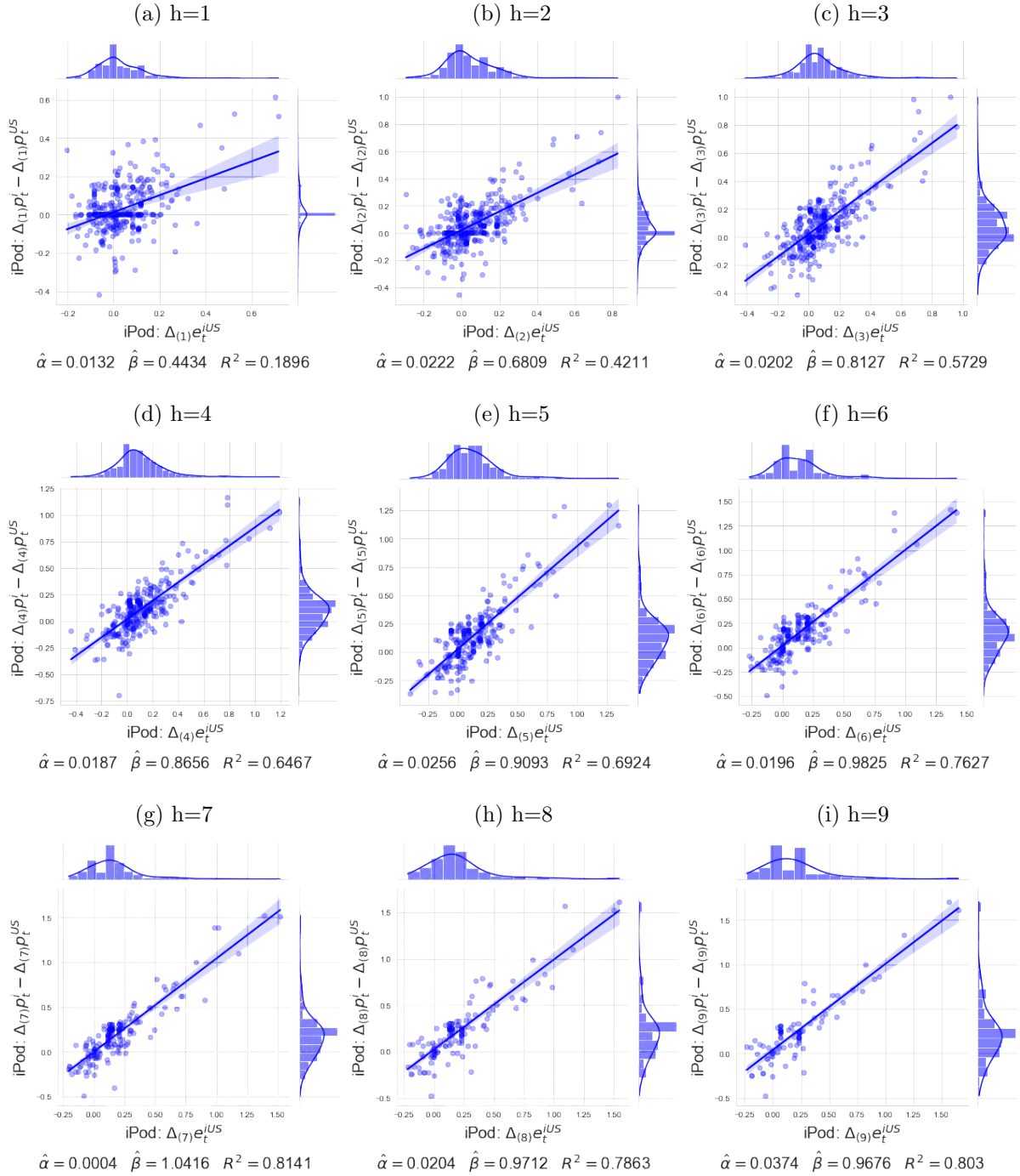


Figure 36: iPad Price Data over h Period Changes

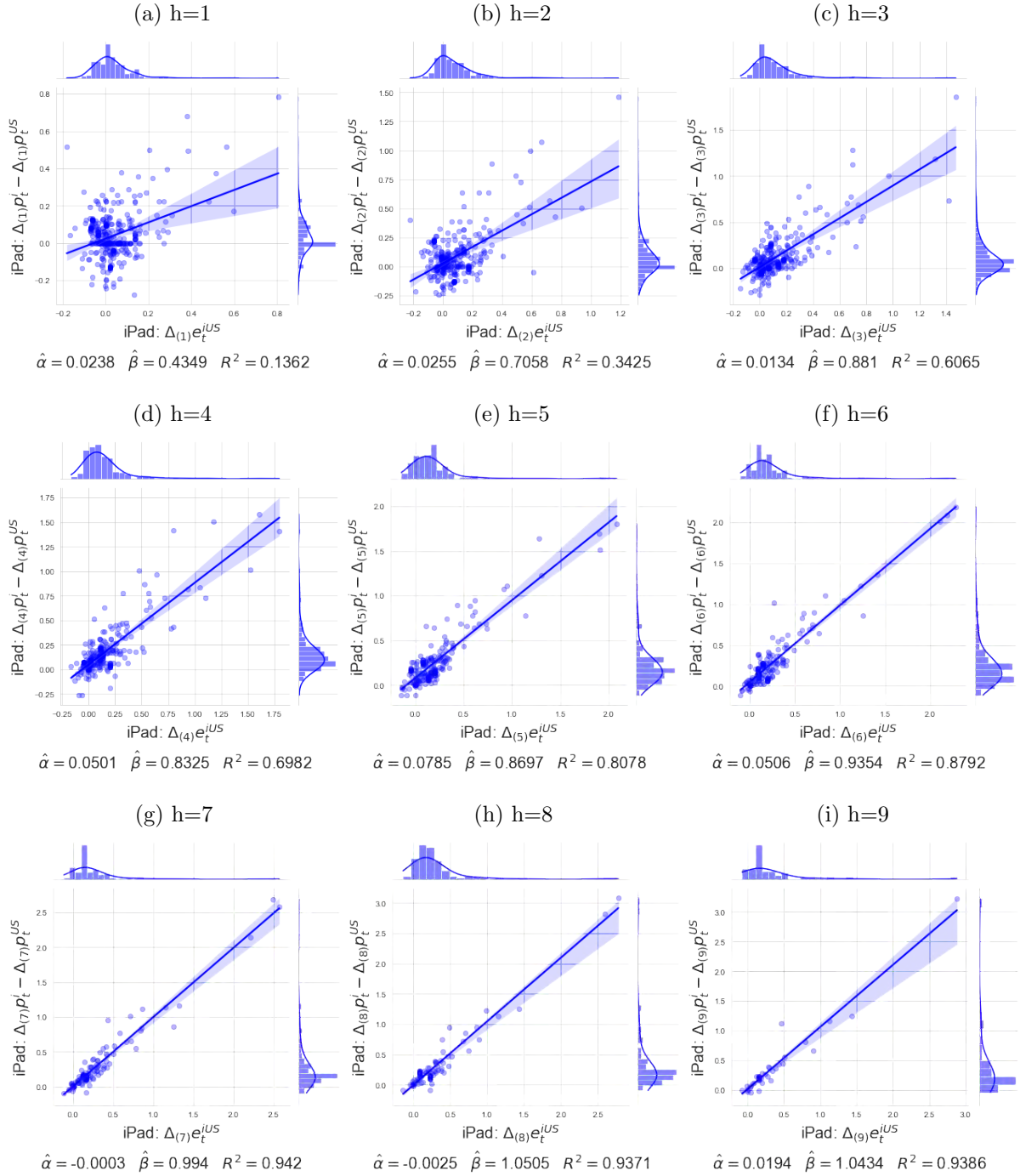
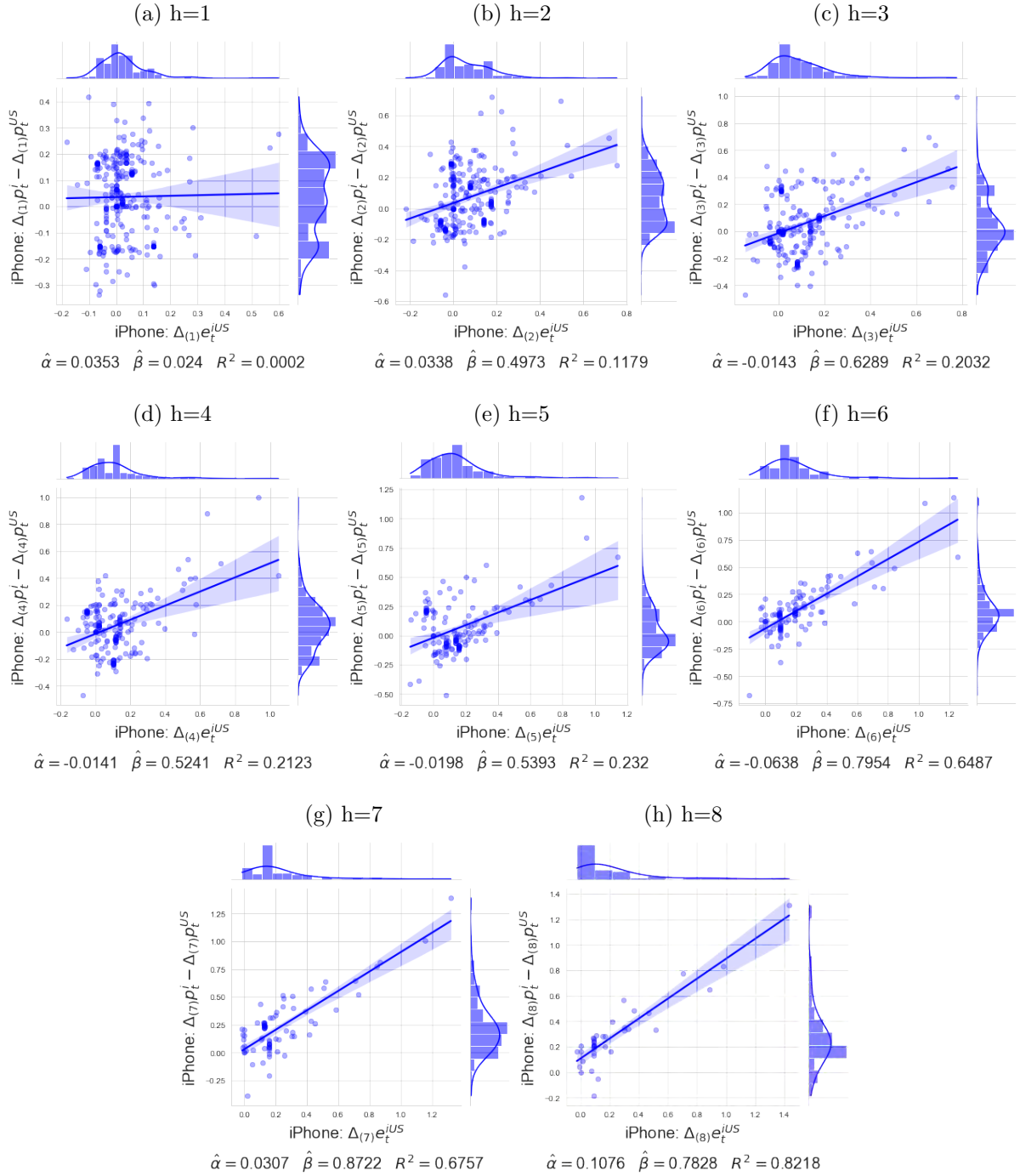


Figure 37: iPhone Price Data over h Period Changes



E Appendix Tables

F Panel Regressions Excluding Transaction Costs

Table 8: CPI Price Basket with Pooled OLS Regression Results for 49 Countries Over 2007-2020

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS CPI Base 2007	-0.0555 (0.0080)***	1.0100 (0.0025)***	686	0.9957	
Pooled OLS CPI Base 2008	-0.1103 (0.0074)***	1.0128 (0.0024)***	686	0.9963	
Pooled OLS CPI Base 2009	-0.0605 (0.0069)***	1.0129 (0.0022)***	686	0.9968	
Pooled OLS CPI Base 2010	-0.0700 (0.0067)***	1.0015 (0.0021)***	686	0.9969	
Pooled OLS CPI Base 2011	-0.1191 (0.0067)***	1.0010 (0.0021)***	686	0.9969	
Pooled OLS CPI Base 2012	-0.0665 (0.0065)***	0.9953 (0.0021)***	686	0.9971	
Pooled OLS CPI Base 2013	-0.0782 (0.0062)***	0.9986 (0.0019)***	686	0.9974	
Pooled OLS CPI Base 2014	-0.0607 (0.0060)***	1.0016 (0.0019)***	686	0.9975	
Pooled OLS CPI Base 2015	0.0877 (0.0068)***	0.9918 (0.0021)***	686	0.9968	
Pooled OLS CPI Base 2016	0.1145 (0.0066)***	0.9887 (0.0021)***	686	0.9970	
Pooled OLS CPI Base 2017	0.1096 (0.0066)***	0.9861 (0.0021)***	686	0.9970	
Pooled OLS CPI Base 2018	0.0944 (0.0066)***	0.9892 (0.0021)***	686	0.9970	
Pooled OLS CPI Base 2019	0.1392 (0.0067)***	0.9855 (0.0021)***	686	0.9969	
Pooled OLS CPI Base 2020	0.1473 (0.0077)***	0.9881 (0.0024)***	686	0.9959	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 9: CPI Price Basket with Fixed Country Effects Regression Results for 49 Countries Over 2007-2020

$$p_t^{i,\text{CPI}} - p_t^{\text{US,CPI}} = \alpha + \beta e_t^{i\text{US}} + \epsilon_t^{i\text{US,CPI}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Country Effects CPI Base 2007	1.0492 (0.0313)***	0.4469 (0.0159)***	686	0.6862	
Fixed Country Effects CPI Base 2008	1.0000 (0.0313)***	0.4469 (0.0159)***	686	0.6853	
Fixed Country Effects CPI Base 2009	1.0500 (0.0313)***	0.4469 (0.0159)***	686	0.6856	
Fixed Country Effects CPI Base 2010	1.0182 (0.0313)***	0.4469 (0.0159)***	686	0.6912	
Fixed Country Effects CPI Base 2011	0.9681 (0.0313)***	0.4469 (0.0159)***	686	0.6914	
Fixed Country Effects CPI Base 2012	1.0093 (0.0313)***	0.4469 (0.0159)***	686	0.6944	
Fixed Country Effects CPI Base 2013	1.0042 (0.0313)***	0.4469 (0.0159)***	686	0.6930	
Fixed Country Effects CPI Base 2014	1.0276 (0.0313)***	0.4469 (0.0159)***	686	0.6916	
Fixed Country Effects CPI Base 2015	1.1568 (0.0313)***	0.4469 (0.0159)***	686	0.6959	
Fixed Country Effects CPI Base 2016	1.1776 (0.0313)***	0.4469 (0.0159)***	686	0.6976	
Fixed Country Effects CPI Base 2017	1.1674 (0.0313)***	0.4469 (0.0159)***	686	0.6989	
Fixed Country Effects CPI Base 2018	1.1584 (0.0313)***	0.4469 (0.0159)***	686	0.6973	
Fixed Country Effects CPI Base 2019	1.1959 (0.0313)***	0.4469 (0.0159)***	686	0.6991	
Fixed Country Effects CPI Base 2020	1.2092 (0.0313)***	0.4469 (0.0159)***	686	0.6971	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 10: CPI Price Basket with Fixed Time Effects Regression Results for 49 Countries Over 2007-2020

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Time Effects CPI Base 2007	-0.0585 (0.0069)***	1.0115 (0.0022)***	686	0.9957	
Fixed Time Effects CPI Base 2008	-0.1133 (0.0063)***	1.0144 (0.0020)***	686	0.9963	
Fixed Time Effects CPI Base 2009	-0.0635 (0.0056)***	1.0144 (0.0018)***	686	0.9968	
Fixed Time Effects CPI Base 2010	-0.0729 (0.0054)***	1.0030 (0.0017)***	686	0.9969	
Fixed Time Effects CPI Base 2011	-0.1220 (0.0054)***	1.0025 (0.0017)***	686	0.9969	
Fixed Time Effects CPI Base 2012	-0.0695 (0.0052)***	0.9968 (0.0016)***	686	0.9971	
Fixed Time Effects CPI Base 2013	-0.0811 (0.0047)***	1.0001 (0.0015)***	686	0.9974	
Fixed Time Effects CPI Base 2014	-0.0636 (0.0045)***	1.0031 (0.0014)***	686	0.9975	
Fixed Time Effects CPI Base 2015	0.0848 (0.0055)***	0.9933 (0.0017)***	686	0.9968	
Fixed Time Effects CPI Base 2016	0.1116 (0.0053)***	0.9902 (0.0017)***	686	0.9970	
Fixed Time Effects CPI Base 2017	0.1067 (0.0053)***	0.9875 (0.0017)***	686	0.9970	
Fixed Time Effects CPI Base 2018	0.0915 (0.0053)***	0.9907 (0.0017)***	686	0.9970	
Fixed Time Effects CPI Base 2019	0.1363 (0.0054)***	0.9870 (0.0017)***	686	0.9969	
Fixed Time Effects CPI Base 2020	0.1444 (0.0066)***	0.9896 (0.0021)***	686	0.9959	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 11: CPI Price Basket with Fixed Country and Time Effects Regression Results for 49 Countries Over 2007-2020

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Country and Time Effects CPI Base 2007	0.8031 (0.0379)***	0.5724 (0.0193)***	686	0.8088	
Fixed Country and Time Effects CPI Base 2008	0.7539 (0.0379)***	0.5724 (0.0193)***	686	0.8079	
Fixed Country and Time Effects CPI Base 2009	0.8038 (0.0379)***	0.5724 (0.0193)***	686	0.8082	
Fixed Country and Time Effects CPI Base 2010	0.7720 (0.0379)***	0.5724 (0.0193)***	686	0.8139	
Fixed Country and Time Effects CPI Base 2011	0.7220 (0.0379)***	0.5724 (0.0193)***	686	0.8141	
Fixed Country and Time Effects CPI Base 2012	0.7632 (0.0379)***	0.5724 (0.0193)***	686	0.8170	
Fixed Country and Time Effects CPI Base 2013	0.7581 (0.0379)***	0.5724 (0.0193)***	686	0.8157	
Fixed Country and Time Effects CPI Base 2014	0.7815 (0.0379)***	0.5724 (0.0193)***	686	0.8143	
Fixed Country and Time Effects CPI Base 2015	0.9107 (0.0379)***	0.5724 (0.0193)***	686	0.8185	
Fixed Country and Time Effects CPI Base 2016	0.9314 (0.0379)***	0.5724 (0.0193)***	686	0.8202	
Fixed Country and Time Effects CPI Base 2017	0.9212 (0.0379)***	0.5724 (0.0193)***	686	0.8215	
Fixed Country and Time Effects CPI Base 2018	0.9122 (0.0379)***	0.5724 (0.0193)***	686	0.8199	
Fixed Country and Time Effects CPI Base 2019	0.9497 (0.0379)***	0.5724 (0.0193)***	686	0.8217	
Fixed Country and Time Effects CPI Base 2020	0.9630 (0.0379)***	0.5724 (0.0193)***	686	0.8196	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 12: CPI Price Basket with Random Effects Regression Results for 49 Countries Over 2007-2020

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Random Effects CPI Base 2007	0.1083 (0.0331)***	0.9265 (0.0099)***	686	0.9889	
Random Effects CPI Base 2008	0.0108 (0.0286)	0.9511 (0.0087)***	686	0.9926	
Random Effects CPI Base 2009	0.0226 (0.0239)	0.9706 (0.0074)***	686	0.9951	
Random Effects CPI Base 2010	-0.0012 (0.0218)	0.9665 (0.0068)***	686	0.9957	
Random Effects CPI Base 2011	-0.0492 (0.0220)**	0.9654 (0.0068)***	686	0.9957	
Random Effects CPI Base 2012	-0.0100 (0.0199)	0.9665 (0.0062)***	686	0.9962	
Random Effects CPI Base 2013	-0.0486 (0.0149)***	0.9835 (0.0047)***	686	0.9972	
Random Effects CPI Base 2014	-0.0433 (0.0121)***	0.9928 (0.0038)***	686	0.9975	
Random Effects CPI Base 2015	0.1647 (0.0229)***	0.9526 (0.0071)***	686	0.9952	
Random Effects CPI Base 2016	0.1775 (0.0209)***	0.9567 (0.0065)***	686	0.9959	
Random Effects CPI Base 2017	0.1741 (0.0211)***	0.9532 (0.0065)***	686	0.9958	
Random Effects CPI Base 2018	0.1592 (0.0212)***	0.9562 (0.0066)***	686	0.9958	
Random Effects CPI Base 2019	0.2109 (0.0222)***	0.9489 (0.0069)***	686	0.9955	
Random Effects CPI Base 2020	0.2901 (0.0308)***	0.9154 (0.0093)***	686	0.9905	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 13: Big Mac Price Basket Regression Results for 31 Countries Over 2007-2020

$$p_t^{i,BMI} - p_t^{US,BMI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,BMI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R ²	Overall
Pooled OLS	-0.1180 (0.0250)***	0.9359 (0.0076)***	434	0.9724	
Fixed Country Effects	1.1061 (0.0595)***	0.4201 (0.0249)***	434	0.6770	
Fixed Time Effects	-0.1282 (0.0234)***	0.9402 (0.0071)***	434	0.9724	
Fixed Country and Time Effects ¹⁸	0.6097 (0.0640)***	0.6293 (0.0269)***	434	0.8680	
Random Effects	0.4901 (0.0867)***	0.6797 (0.0217)***	434	0.8995	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 14: iPod Nano Price Basket Regression Results for 46 Countries Over 2007-2017

$$p_t^{i,iPod} - p_t^{US,iPod} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,iPod}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R ²	Overall
Pooled OLS	0.2939 (0.0114)***	1.0011 (0.0040)***	506	0.9920	
Fixed Country Effects	0.3984 (0.0450)***	0.9420 (0.0254)***	506	0.9885	
Fixed Time Effects	0.2936 (0.0114)***	1.0013 (0.0040)***	506	0.9920	
Fixed Country and Time Effects	0.3676 (0.0523)***	0.9594 (0.0295)***	506	0.9903	
Random Effects ¹⁹	0.3131 (0.0336)***	0.9903 (0.0110)***	506	0.9919	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 15: iPad Price Basket Regression Results for 45 Countries Over 2011-2020

$$p_t^{i,iPad} - p_t^{US,iPad} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,iPad}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	0.2061 (0.0102)***	0.9978 (0.0040)***	450	0.9930	
Fixed Country Effects	0.2572 (0.0369)***	0.9665 (0.0224)***	450	0.9920	
Fixed Time Effects	0.2061 (0.0098)***	0.9978 (0.0038)***	450	0.9930	
Fixed Country and Time Effects	0.2869 (0.0370)***	0.9483 (0.0225)***	450	0.9905	
Random Effects ²⁰	0.2152 (0.0265)***	0.9922 (0.0097)***	450	0.9929	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 16: iPhone Price Basket Regression Results for 39 Countries Over 2012-2020

$$p_t^{i,iPhone} - p_t^{US,iPhone} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,iPhone}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	0.2549 (0.0108)***	1.0043 (0.0053)***	351	0.9904	
Fixed Country Effects	0.7066 (0.0593)***	0.6374 (0.0479)***	351	0.8582	
Fixed Time Effects	0.2528 (0.0080)***	1.0060 (0.0039)***	351	0.9904	
Fixed Country and Time Effects ²¹	0.5500 (0.0411)***	0.7647 (0.0333)***	351	0.9340	
Random Effects	0.2703 (0.0216)***	0.9917 (0.0105)***	351	0.9902	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

G Panel Regressions Including Transaction Cost Estimates

Table 17: Big Mac Price Basket (Including Transaction Costs) Regression Results for 31 Countries Over 2007-2020

$$p_t^{i,\text{BMI}} - p_t^{\text{US},\text{BMI}} = \alpha + \beta e_t^{i\text{US}} + \delta_1 \ln \left(\frac{1+\tau_t^{i,\text{BMI}}}{1+\tau_t^{\text{US},\text{BMI}}} \right) + \epsilon_t^{i\text{US},\text{BMI}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	N	R^2	Overall
Pooled OLS	-0.2522 (0.0327)***	0.9357 (0.0073)***	1.6231 (0.2677)***	434	0.9746	
Fixed Country Effects	1.3121 (0.0848)***	0.4366 (0.0251)***	-2.9556 (0.8770)***	434	0.6802	
Fixed Time Effects	-0.2667 (0.0303)***	0.9401 (0.0068)***	1.6720 (0.2479)***	434	0.9746	
Fixed Country and Time Effects	0.7753 (0.0841)***	0.6388 (0.0268)***	-2.2673 (0.7572)***	434	0.8640	
Random Effects ²²	0.5868 (0.1031)***	0.6931 (0.0215)***	-1.5499 (0.7704)**	434	0.9008	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

H Balanced Panel Regressions Excluding Transaction Costs

I Balanced Panel Regressions Including Transaction Costs

Table 18: iPod Nano Price Basket (Including Transaction Costs) Regression Results for 46 Countries Over 2007-2017

$$p_t^{i,iPod} - p_t^{US,iPod} = \alpha + \beta e_t^{iUS} + \delta_1 \ln \left(\frac{1+\tau_t^{i,iPod}}{1+\tau_t^{US,iPod}} \right) + \delta_2 \ln \left(\frac{1+l_t^{i,iPod}}{1+l_t^{US,iPod}} \right) + \epsilon_t^{iUS,iPod}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	N	R^2	Overall
Pooled OLS	0.0384 (0.0152)**	1.0080 (0.0030)***	1.5089 (0.1169)***	1.1689 (0.1158)***	506	0.9956	
Fixed Country Effects	0.1892 (0.0688)***	0.9282 (0.0256)***	2.2704 (0.5860)***	0.2167 (0.2157)	506	0.9882	
Fixed Time Effects	0.0374 (0.0149)**	1.0080 (0.0030)***	1.4911 (0.1149)***	1.1983 (0.1144)***	506	0.9956	
Fixed Country and Time Effects	0.1870 (0.0743)**	0.9530 (0.0292)***	1.5962 (0.5843)***	0.4749 (0.2164)**	506	0.9923	
Random Effects ²³	0.0791 (0.0377)**	1.0017 (0.0080)***	1.7418 (0.2780)***	0.5696 (0.1827)***	506	0.9953	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 19: iPad Price Basket (Including Transaction Costs) Regression Results for 45 Countries Over 2011-2020

$$p_t^{i,iPad} - p_t^{US,iPad} = \alpha + \beta e_t^{iUS} + \delta_1 \ln \left(\frac{1+\tau_t^{i,iPad}}{1+\tau_t^{US,iPad}} \right) + \delta_2 \ln \left(\frac{1+l_t^{i,iPad}}{1+l_t^{US,iPad}} \right) + \delta_3 \ln \left(\frac{\lambda_t^{i,iPad}}{\lambda_t^{US,iPad}} \right) + \epsilon_t^{iUS,iPad}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2	Overall
Pooled OLS	0.0696 (0.0133)***	1.0013 (0.0026)***	1.3554 (0.0873)***	2.9073 (0.1916)***	0.0162 (0.0044)***	450	0.9971	
Fixed Country Effects	0.4437 (0.0790)***	0.9805 (0.0242)***	-0.1751 (0.6619)	0.4757 (0.3840)	0.1504 (0.0211)***	450	0.9887	
Fixed Time Effects	0.0620 (0.0118)***	1.0007 (0.0023)***	1.3792 (0.0769)***	2.9676 (0.1693)***	0.0118 (0.0039)**	450	0.9971	
Fixed Country and Time Effects ²⁴	0.3443 (0.0827)***	0.9506 (0.0264)***	-0.2263 (0.5929)	0.1790 (0.3467)	0.0305 (0.0237)	450	0.9907	
Random Effects	0.0830 (0.0181)***	1.0027 (0.0036)***	1.3198 (0.1192)***	2.3616 (0.2340)***	0.0233 (0.0060)***	450	0.9970	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 20: iPhone Price Basket (Including Transaction Costs) Regression Results for 39 Countries Over 2012-2020

$$p_t^{i,iP} - p_t^{US,iP} = \alpha + \beta e_t^{iUS} + \delta_1 \ln \left(\frac{1+\tau_t^{i,iP}}{1+\tau_t^{US,iP}} \right) + \delta_2 \ln \left(\frac{1+\iota_t^{i,iP}}{1+\iota_t^{US,iP}} \right) + \delta_3 \ln \left(\frac{\lambda_t^{i,iP}}{\lambda_t^{US,iP}} \right) + \epsilon_t^{iUS,iP}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R ²	Overall
Pooled OLS	0.1288 (0.0180)***	1.0047 (0.0046)***	1.2189 (0.1184)***	0.9465 (0.2313)***	0.0032 (0.0060)	351	0.9931	
Fixed Country Effects	0.6143 (0.1409)***	0.6590 (0.0499)***	2.0847 (1.1418)*	-0.1792 (0.7364)	0.1135 (0.0355)***	351	0.8549	
Fixed Time Effects	0.1227 (0.0108)***	1.0060 (0.0027)***	1.2281 (0.0710)***	0.9122 (0.1388)***	0.0003 (0.0036)	351	0.9931	
Fixed Country and Time Effects ²⁵	0.4177 (0.0859)***	0.7746 (0.0349)***	1.2189 (0.6055)**	0.2141 (0.3917)	0.0043 (0.0246)	351	0.9407	
Random Effects	0.1329 (0.0225)***	1.0032 (0.0057)***	1.2157 (0.1481)***	0.9709 (0.2822)***	0.0049 (0.0075)	351	0.9931	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 21: CPI Price Basket with Pooled OLS Regression Results

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R ²	Overall
Pooled OLS CPI Base 2012	-0.0790 (0.0150)***	0.9893 (0.0066)***	150	0.9935	
Pooled OLS CPI Base 2013	-0.0716 (0.0142)***	0.9853 (0.0062)***	150	0.9942	
Pooled OLS CPI Base 2014	-0.0572 (0.0134)***	0.9965 (0.0059)***	150	0.9949	
Pooled OLS CPI Base 2015	0.0654 (0.0148)***	1.0019 (0.0064)***	150	0.9939	
Pooled OLS CPI Base 2016	0.0986 (0.0147)***	1.0023 (0.0064)***	150	0.9940	
Pooled OLS CPI Base 2017	0.1013 (0.0140)***	0.9910 (0.0061)***	150	0.9944	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 22: CPI Price Basket with Fixed Country Effects Regression Results

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Country Effects CPI Base 2012	1.1739 (0.0353)***	0.2552 (0.0206)***	150	0.4464	
Fixed Country Effects CPI Base 2013	1.1745 (0.0353)***	0.2552 (0.0206)***	150	0.4483	
Fixed Country Effects CPI Base 2014	1.2081 (0.0353)***	0.2552 (0.0206)***	150	0.4443	
Fixed Country Effects CPI Base 2015	1.3400 (0.0353)***	0.2552 (0.0206)***	150	0.4418	
Fixed Country Effects CPI Base 2016	1.3737 (0.0353)***	0.2552 (0.0206)***	150	0.4417	
Fixed Country Effects CPI Base 2017	1.3572 (0.0353)***	0.2552 (0.0206)***	150	0.4461	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 23: CPI Price Basket with Fixed Time Effects Regression Results

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Time Effects CPI Base 2012	-0.0856 (0.0108)***	0.9931 (0.0047)***	150	0.9935	
Fixed Time Effects CPI Base 2013	-0.0782 (0.0097)***	0.9891 (0.0042)***	150	0.9941	
Fixed Time Effects CPI Base 2014	-0.0638 (0.0083)***	1.0004 (0.0036)***	150	0.9949	
Fixed Time Effects CPI Base 2015	0.0587 (0.0103)***	1.0059 (0.0045)***	150	0.9939	
Fixed Time Effects CPI Base 2016	0.0919 (0.0102)***	1.0062 (0.0044)***	150	0.9940	
Fixed Time Effects CPI Base 2017	0.0947 (0.0094)***	0.9949 (0.0041)***	150	0.9943	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 24: CPI Price Basket with Fixed Country and Time Effects Regression Results

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Fixed Country and Time Effects CPI Base 2012	0.9271 (0.0501)***	0.3998 (0.0293)***	150	0.6407	
Fixed Country and Time Effects CPI Base 2013	0.9277 (0.0501)***	0.3998 (0.0293)***	150	0.6431	
Fixed Country and Time Effects CPI Base 2014	0.9613 (0.0501)***	0.3998 (0.0293)***	150	0.6381	
Fixed Country and Time Effects CPI Base 2015	1.0932 (0.0501)***	0.3998 (0.0293)***	150	0.6349	
Fixed Country and Time Effects CPI Base 2016	1.1269 (0.0501)***	0.3998 (0.0293)***	150	0.6348	
Fixed Country and Time Effects CPI Base 2017	1.1104 (0.0501)***	0.3998 (0.0293)***	150	0.6404	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 25: CPI Price Basket with Random Effects Regression Results

$$p_t^{i,CPI} - p_t^{US,CPI} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,CPI}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Random Effects CPI Base 2012	0.1167 (0.0570)***	0.8746 (0.0239)***	150	0.9802	
Random Effects CPI Base 2013	0.0632 (0.0482)***	0.9063 (0.0205)***	150	0.9878	
Random Effects CPI Base 2014	-0.0016 (0.0331)***	0.9640 (0.0143)***	150	0.9938	
Random Effects CPI Base 2015	0.2298 (0.0532)***	0.9056 (0.0225)***	150	0.9847	
Random Effects CPI Base 2016	0.2570 (0.0523)***	0.9095 (0.0221)***	150	0.9855	
Random Effects CPI Base 2017	0.2167 (0.0452)***	0.9234 (0.0193)***	150	0.9897	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 26: Big Mac Price Basket Regression Results

$$p_t^{i,\text{BMI}} - p_t^{\text{US,BMI}} = \alpha + \beta e_t^{i\text{US}} + \epsilon_t^{i\text{US,BMI}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	-0.0553 (0.0402)	0.8734 (0.0175)***	150	0.9438	
Fixed Country Effects	1.2344 (0.0638)***	0.1181 (0.0372)***	150	0.2380	
Fixed Time Effects	-0.0641 (0.0389)	0.8785 (0.0170)***	150	0.9438	
Fixed Country and Time Effects ²⁶	0.9997 (0.0973)***	0.2555 (0.0569)***	150	0.4715	
Random Effects	0.6419 (0.1177)***	0.4651 (0.0415)***	150	0.7375	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 27: iPod Nano Price Basket Regression Results

$$p_t^{i,\text{iPod}} - p_t^{\text{US,iPod}} = \alpha + \beta e_t^{i\text{US}} + \epsilon_t^{i\text{US,iPod}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	0.2178 (0.0248)***	1.0229 (0.0108)***	150	0.9837	
Fixed Country Effects	0.5013 (0.0704)***	0.8572 (0.0410)***	150	0.9579	
Fixed Time Effects	0.2168 (0.0251)***	1.0235 (0.0109)***	150	0.9837	
Fixed Country and Time Effects ²⁷	0.5530 (0.0996)***	0.8270 (0.0581)***	150	0.9476	
Random Effects	0.2985 (0.0569)***	0.9757 (0.0229)***	150	0.9816	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 28: iPad Price Basket Regression Results

$$p_t^{i,iPad} - p_t^{US,iPad} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,iPad}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	0.1505 (0.0206)***	1.0054 (0.0090)***	150	0.9883	
Fixed Country Effects	0.2028 (0.1190)*	0.9748 (0.0695)***	150	0.9874	
Fixed Time Effects	0.1504 (0.0191)***	1.0054 (0.0083)***	150	0.9883	
Fixed Country and Time Effects	0.2320 (0.1368)*	0.9576 (0.0800)***	150	0.9860	
Random Effects ²⁸	0.1536 (0.0410)***	1.0036 (0.0176)***	150	0.9883	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 29: iPhone Price Basket Regression Results

$$p_t^{i,iPhone} - p_t^{US,iPhone} = \alpha + \beta e_t^{iUS} + \epsilon_t^{iUS,iPhone}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2	Overall
Pooled OLS	0.2331 (0.0205)***	1.0090 (0.0089)***	150	0.9885	
Fixed Country Effects	1.2264 (0.1113)***	0.4271 (0.0650)***	150	0.6597	
Fixed Time Effects	0.2276 (0.0165)***	1.0123 (0.0072)***	150	0.9885	
Fixed Country and Time Effects ²⁹	0.8254 (0.1115)***	0.6620 (0.0652)***	150	0.8716	
Random Effects	0.2801 (0.0431)***	0.9815 (0.0186)***	150	0.9878	

Note: Standard Errors in Parenthesis * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 30: Big Mac Price Basket (Including Transaction Costs) Regression Results

$$p_t^{i,\text{BMI}} - p_t^{\text{US,BMI}} = \alpha + \beta e_t^{i\text{US}} + \delta_1 \ln \left(\frac{1 + \tau_t^{i,\text{BMI}}}{1 + \tau_t^{\text{US,BMI}}} \right) + \epsilon_t^{i\text{US,BMI}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	N	R^2	Overall
Pooled OLS	-0.1953 (0.0462)***	0.8561 (0.0166)***	1.9553 (0.3827)***	150	0.9523	
Fixed Country Effects	1.0658 (0.1588)***	0.1272 (0.0380)***	1.7650 (1.5222)	150	0.2918	
Fixed Time Effects	-0.2006 (0.0445)***	0.8614 (0.0160)***	1.9116 (0.3684)***	150	0.9522	
Fixed Country and Time Effects ³⁰	0.8694 (0.1673)***	0.2590 (0.0570)***	1.4341 (1.4972)	150	0.5038	
Random Effects	0.2644 (0.1452)**	0.4844 (0.0398)***	3.9724 (1.1309)***	150	0.7884	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 31: iPod Nano Price Basket (Including Transaction Costs) Regression Results

$$p_t^{i,\text{iPod}} - p_t^{\text{US,iPod}} = \alpha + \beta e_t^{i\text{US}} + \delta_1 \ln \left(\frac{1 + \tau_t^{i,\text{iPod}}}{1 + \tau_t^{\text{US,iPod}}} \right) + \delta_2 \ln \left(\frac{1 + \lambda_t^{i,\text{iPod}}}{1 + \lambda_t^{\text{US,iPod}}} \right) + \delta_3 \ln \left(\frac{\lambda_t^{i,\text{iPod}}}{\lambda_t^{\text{US,iPod}}} \right) + \epsilon_t^{i\text{US,iPod}}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2	Overall
Pooled OLS	0.0781 (0.0231)***	0.9956 (0.0074)***	1.2834 (0.1932)***	1.6914 (0.2337)***	0.0299 (0.0073)***	150	0.9935	
Fixed Country Effects	0.2296 (0.1648)	0.9258 (0.0446)***	3.1955 (1.3211)**	0.2027 (0.4979)	0.0907 (0.0222)***	150	0.9756	
Fixed Time Effects	0.0756 (0.0230)**	0.9952 (0.0074)***	1.2838 (0.1925)***	1.7116 (0.2345)***	0.0287 (0.0073)***	150	0.9935	
Fixed Country and Time Effects	0.1908 (0.1741)	0.8689 (0.0568)***	3.7772 (1.2611)***	0.7426 (0.5059)	0.0594 (0.0259)**	150	0.9686	
Random Effects ³¹	0.1299 (0.0534)**	0.9916 (0.0164)***	1.6411 (0.4179)***	1.0640 (0.3622)**	0.0505 (0.0142)***	150	0.9923	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 32: iPad Price Basket (Including Transaction Costs) Regression Results

$$p_t^{i,iPad} - p_t^{US,iPad} = \alpha + \beta e_t^{iUS} + \delta_1 \ln \left(\frac{1+\tau_t^{i,iPad}}{1+\tau_t^{US,iPad}} \right) + \delta_2 \ln \left(\frac{1+\iota_t^{i,iPad}}{1+\iota_t^{US,iPad}} \right) + \delta_3 \ln \left(\frac{\lambda_t^{i,iPad}}{\lambda_t^{US,iPad}} \right) + \epsilon_t^{iUS,iPad}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2	Overall
Pooled OLS	0.0454 (0.0194)**	0.9993 (0.0061)***	1.4082 (0.1422)***	3.1118 (0.4069)***	0.0137 (0.0060)**	150	0.9952	
Fixed Country Effects	0.6158 (0.2189)***	1.0727 (0.0601)***	-2.1076 (1.9680)		0.2624 (0.0330)***	150	0.9287	
Fixed Time Effects	0.0386 (0.0151)**	0.9984 (0.0048)***	1.4350 (0.1107)***	3.1311 (0.3165)***	0.0098 (0.0047)**	150	0.9952	
Fixed Country and Time Effects ³²	0.5275 (0.2143)**	0.9614 (0.0762)***	-1.0465 (1.6772)		0.1394 (0.0348)***	150	0.9678	
Random Effects	0.1038 (0.0426)**	0.9998 (0.0134)***	1.3458 (0.3138)***		0.0399 (0.0128)**	150	0.9928	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 33: iPhone Price Basket (Including Transaction Costs) Regression Results

$$p_t^{i,iP} - p_t^{US,iP} = \alpha + \beta e_t^{iUS} + \delta_1 \ln \left(\frac{1+\tau_t^{i,iP}}{1+\tau_t^{US,iP}} \right) + \delta_2 \ln \left(\frac{1+\iota_t^{i,iP}}{1+\iota_t^{US,iP}} \right) + \delta_3 \ln \left(\frac{\lambda_t^{i,iP}}{\lambda_t^{US,iP}} \right) + \epsilon_t^{iUS,iP}$$

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2	Overall
Pooled OLS	0.1288 (0.0243)***	0.9986 (0.0076)***	1.2593 (0.1783)***	1.1172 (0.2825)***	-0.0015 (0.0075)	150	0.9925	
Fixed Country Effects	1.1703 (0.2617)***	0.3790 (0.0752)***	1.2340 (2.2631)	-1.1118 (0.7022)	-0.0276 (0.0378)	150	0.6223	
Fixed Time Effects	0.1256 (0.0167)***	1.0018 (0.0052)***	1.2330 (0.1222)***	1.0810 (0.1939)***	-0.0018 (0.0052)	150	0.9925	
Fixed Country and Time Effects ³³	0.7853 (0.2005)***	0.6575 (0.0743)***	0.5050 (1.4693)	-0.1034 (0.4719)	-0.0033 (0.0303)	150	0.8737	
Random Effects	0.1364 (0.0376)***	0.9913 (0.0118)***	1.3209 (0.2759)***	1.1230 (0.4008)*	-0.0012 (0.0114)	150	0.9925	

Note: Standard Errors in Parenthesis

* $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$