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Using Apple Product Prices to Evaluate the Law of One Price and Product Derived Real Exchange Rates

by
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Abstract

Empirical literature on the law of one price or purchasing power parity suggests that real exchange rate deviations are more persistent than economic theory would predict. To evaluate these deviations, I construct two novel panel datasets consisting of Apple product prices. The first dataset covers iPod, iPad, and iPhone prices across almost 50 countries spanning more than 10 years, and supports the hypothesis that the law of one price holds for some Apple products in both absolute and relative terms, particularly after controlling for transaction costs. This finding is attributable to the homogeneity of Apple products and the ease of accounting for transaction costs. The results suggest that Apple prices are better suited than often-used alternative price measures to investigate international parity conditions (e.g., the Big Mac Index and the consumer price index).

The second panel dataset consists of weekly Apple iPad prices across 35 countries from 2016 through 2021. I use this dataset to evaluate the short-term, nonlinear adjustment behavior of real exchange rates with a range of nonlinear estimation techniques, including locally-weighted scatterplot smoothing, threshold regression models, and piecewise linear approaches. I find that the stochastic law of one price hypothesis is supported. Moreover, real exchange rate half-lives derived from Apple iPads are significantly shorter (estimated to be only a few weeks) than what is typically found in the literature for similar studies on the law of one price and purchasing power parity. Overall, my findings provide new insights into the dynamics of real exchange rates, highlighting the importance of using appropriate price measures and nonlinear estimation techniques.

Key words:

Law of one price, real exchange rate, nonlinear real exchange rate adjustments, half-life, real exchange rate thresholds

Opsomming in Afrikaans

Empiriese literatuur oor die wet van een prys of koopkragpariteit dui daarop dat reële wisselkoers afwykings meer volhardend is as wat die ekonomiese teorie voorspel. Om hierdie afwykings te evalueer, bou ek twee nuwe paneel datastelle saamgestel uit Apple-produkpryse. Die eerste datastel dek iPod-, iPad- en iPhone-pryse in byna 50 lande oor meer as 10 jaar, en ondersteun die hipotese dat die wet van een prys vir sommige Apple-produkte in beide absolute en relatiewe terme geldig is, veral nadat transaksiekostes in ag geneem is. Hierdie bevinding is te wyte aan die homogeniteit van Apple-produkte en die maklikheid om transaksiekostes in te reken. Die resultate dui daarop dat Apple-pryse beter geskik is as dikwels gebruikte alternatiewe prysmetings om internasionale prys en wisselkoers gelykheidstoestande te ondersoek (bv. die Big Mac-indeks en die verbruikersprysindeks).

Ek bou ook 'n tweede paneel datastel saamgestel uit weeklikse Apple iPad-pryse in 35 lande vanaf 2016 tot 2021 om die korttermyn, nie-liniêre aanpassingsgedrag van reële wisselkoerse te evalueer. Deur gebruik te maak van 'n reeks nie-liniêre skattingstegnieke, insluitend LOWESS, drempelregressiemodelle en stuksgewyse lineêre benaderings, bevind ek dat die stochastiese wet van een prys hipotese ondersteun word. Verder is die reële wisselkoers halflewe afgelei van Apple iPad tablette aansienlik korter (geskat op net 'n paar weke) as wat tipies in die literatuur gevind word vir soortgelyke studies oor die wet van een prys en koopkragpariteit. Oor die algemeen bied my bevindinge nuwe insigte in die dinamika van reële wisselkoerse en beklemtoon die belangrikheid van die gebruik van toepaslike prysmetings en nie-liniêre skattingstegnieke.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND/OR ACRONYMS

ADF	Augmented Dickey-Fuller
APPs	Apple Product Prices
BGLM	Bayesian Generalised Linear Model
BIC	Bayesian Information Criterion
BMI	Big Mac Index
CAPTCHAs	Completely Automated Public Turing Test to Tell Computers and Humans Apart
CPI	Consumer Price Index
FEU	Foot Equivalent Units
GST	General Sales Tax
HICP	Harmonised Index of Consumer Prices
HS	Harmonised system of Tariff Codes
HTML	Hyper-Text Markup Language
ICP	International Comparisons Program
LOP	Law of One Price
LOWESS	Locally Weighted Scatterplot Smoothing
MCMC	Markov Chain Monte Carlo
OECD	Organisation for Economic Co-operation and Development
PPP	Purchasing Power Parity
RER	Real Exchange Rate
SLOP	Stochastic Law of One Price
TAR	Threshold Autoregression
UNCTAD	United Nations Conference on Trade and Development
URL	Uniform Resource Locator
VAT	Value Added Tax
WCOL	Worldwide Cost of Living (Survey)

CHAPTER 1

INTRODUCTION

The real exchange rate (RER) is a key price in any open economy and core to a number of central economic predictions such as the Law of One Price (LOP) and its extension to the Purchasing Price Parity (PPP) hypothesis. The LOP states that, absent frictions, arbitrage will ensure that the local and foreign price of a given good sold in two countries with different currencies will be equal once converted by the nominal exchange rate. If the LOP holds for all goods in a pair of countries, it implies a strict version of PPP and, equivalently, a real exchange rate of unity, which means a unit of currency in either country has equal value in real terms.

Even if PPP holds in a weaker form that allows for some frictions, RERs should be stationary. Most research finds, however, that RERs are highly persistent and deviations from PPP last so long that statistical tests of many real exchange rates would reject stationarity (Rogoff, 1996; Obstfeld and Rogoff, 2000; Vo and Vo, 2022). Rogoff (1996) and Obstfeld and Rogoff (2000) show that the half-lives of deviations last around three to five years.

These lengthy deviations from PPP have been called the *PPP puzzle* (Rogoff, 1996) and can be summarized as follows: while 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. For example, in a recent meta-analysis, Vo and Vo (2022) find that arbitrage forces and resource re-allocation are sufficient to overcome many of the measurable frictions in far less time than would be required to support the results of aggregate studies such as Rogoff (1996) and Obstfeld and Rogoff (2000).

Empirical evaluation of the PPP hypothesis is therefore constrained by the appropriateness of the data used in the empirical tests. Parsley and Wei (2007) provides strong evidence that most aggregate assessments of PPP are subject to severe data constraints that make it unlikely that their results are (or can be) conclusive. Specifically, Parsley and Wei (2007) present four data related reasons for slow real exchange rate adjustments. First, aggregate price measures consist of dissimilar price baskets (i.e. both *weights* and comparative *goods*) used across countries. Second, there is a phenomenon known as the *time aggregation bias* which occurs when nominal price or exchange rate data are averaged and collected at different points in time (Taylor, 2001). Third, the broad price measures also embed a *product aggregation bias* stemming from varying adjustment speeds for dissimilar products as well as the fact that transaction costs are likely to differ across goods (Imbs *et al.*, 2005). Fourth, a large portion of the products and services that are included in these baskets are not tradable, while PPP can only hold for tradable products (Balassa, 1964; Samuelson, 1964).[1] This dissertation contributes to this literature by constructing and analysing a unique dataset that overcomes many of these concerns.

Examining real exchange rate adjustments from a LOP perspective can potentially better reveal some of the underlying exchange rate and price dynamics compared to research on PPP (Vo and Vo, 2022). To address these issues, I have constructed two LOP datasets comprising of highly tradable homogeneous goods: Apple products. These datasets are introduced later. In addition to the aggregate dataset obstacles explored above, a fifth issue results from the fact that RERs may in fact adjust in a nonlinear fashion. By employing nonlinear econometric techniques we can also tackle the final issue that the subsequent real exchange rate adjustment speeds may vary with their initial implied valuations. With the new dataset, I show that deviations from the LOP (and larger mispricings in particular) are notably less persistent than typical measures in the literature — suggesting that 'theory' and 'reality' align more closely than what has previously been documented (albeit along a very specific dimension of electronic goods instead of general price baskets).[2]

I provide novel evidence on the strength and speed of arbitrage forces (in the face of trade frictions) that drives the law of one price in the context of Apple products, an example of a specific group of goods that is actively and physically traded globally, where the local price can differ across countries in ways that can be reliably decomposed into selling price, taxes and transport costs. Apple products are unique in this type of analysis as they are (i) uniform in attributes — the dissertation analyses the prices of unique Apple products individually, (ii) all trades imply that the item is physically exchanged, which allows me to consider the impacts of taxes and transport costs as barriers to arbitrage directly (this distinguishes it from other uniform products such as gold where the LOP holds trivially by the structure of the market for gold), and (iii) the product

[1] Aggregate price indices often devote a significant weight to non-tradable goods and services; whereas the LOP or PPP can only hold for tradables. Chapter 3 explores this in more detail.

[2] For a detailed review of the LOP and PPP literature refer to Officer (2012) and Vo and Vo (2022).

has a very wide penetration globally (which admits a broad analysis across more countries than, for example, a country pair analysis of PPP based on aggregate price indices).

The first dataset covers annual iPod, iPad, and iPhone prices across almost 50 countries spanning 14 years. Using these devices to derive RERs has several advantages compared to using other products in LOP and broad price basket measures in PPP studies. These advantages include international availability, homogeneity, and tradability. A detailed discussion on the advantages of using Apple products is discussed in Section 4.1. In addition, the Apple devices have a single point of origin which means that several transaction costs can easily be controlled for (for example tariff and shipping rates as well as local value added or sales taxes). As a result, some of the transaction costs that are bound to cause deviations from the LOP are much easier to capture and incorporate when using Apple product prices. Consequently, when controlling for these transaction costs, the evidence in favour of the LOP is far stronger than found using other price measures. Furthermore, deviations from the LOP is also notably less persistent.

The second, higher frequency, dataset consists of weekly prices of four Apple iPad devices for 35 countries spanning from the start of 2016 to end-2021. This dataset highlights some of the intricacies surrounding deviations from the LOP and (nonlinear) adjustments toward it. Using a tradable homogeneous product with a higher frequency time series, we can avoid the first four issues outlined by Parsley and Wei (2007). There are several advantages for using a shorter timeframe, higher frequency database. For example, literature that uses very long time series to generate enough statistical power are unavailable for a large number of currencies, which may generate a *survivorship bias* in tests (Froot and Rogoff, 1996).[3] Long historical periods may also include different nominal exchange rate regimes (Taylor *et al.*, 2001). Furthermore, studies using panel datasets to jointly test all of the country-specific time series raise the probability of *Type II* statistical errors.[4] This dissertation aims to circumvent these issues by utilising a higher frequency dataset of better suited

[3]According to Froot and Rogoff (1996), a *survivorship bias* could potentially overstate the validity of PPP with studies utilising long term datasets. This bias arises because the available long-run PPP data primarily pertains to countries that have consistently been among the world's wealthiest nations. On the other hand, countries that experienced rapid growth from a low economic base (for example Japan) or those that were once prosperous but no longer are (for example Argentina) have not been extensively studied. However, these particular countries might offer significant insights as the relative prices of their nontraded goods are likely to have undergone substantial changes and this is where tests of long-run PPP are most prone to failure.

[4]The use of cross-sectionally augmented Dickey–Fuller (ADF) statistics and cross-sectionally augmented versions of the t-bar test have however been proposed by Pesaran (2007) to overcome this.

products. This allows one to investigate both the panel dataset and the individual country time series to evaluate our findings. Due to data limitations, very few studies have been able to use the same dataset to focus on both the panel data aspect of the dataset as well as what the individual country time series could convey.

Some of the main findings from my analyses include the following. First, the data supports the hypothesis that the law of one price holds for some Apple products in both absolute and relative terms, as well as across a range of estimation methods. Especially after controlling for transaction costs, Apple prices adhere better to the LOP than often-used alternative price measures to investigate international parity conditions (for example the Big Mac Index and the consumer price index). Second, there is evidence of a valuation *threshold effect* for iPad derived real exchange rate deviations. Moreover, clear asymmetric effects resulting from a 'band of no arbitrage' can be discerned in that small deviations from parity are corrected comparatively slower than larger deviation. Third, the size of these valuation thresholds appears to decline as the evaluation (or time-difference period) increases. In other words, when the same initial real exchange rate deviation is evaluated over a longer timeframe, it is more likely to be eliminated. This can be explained by various information asymmetries and time lags, which appear to decrease over time, as arbitrage forces kick in. As more time passes, the more we would expect even smaller deviations to be eliminated. Accordingly, the higher frequency database actually allows us to evaluate how the valuation thresholds evolve over time. Fourth, when taking into account the nonlinearity of real exchange rate adjustments, the time it takes to correct for mispricings may be as short as a *few months*. This stands in contrast to the literature's finding that the half-lives of these adjustments generally range from three to five years (Rogoff, 1996; Vo and Vo, 2022). Fifth, there seems to be a strong association between the *estimated thresholds* from the analyses and the *actual transaction costs* particular to iPad-derived RERs. Specifically, the valuation threshold levels appear wider for countries with higher transaction costs. As such, countries with elevated transaction costs would need to see more substantial real exchange rate deviations before any actual arbitrage forces materialise. Finally, the analyses not only imply that real exchange rate adjustments are nonlinear, but that the resulting adjustments may also be *asymmetric*. That is, changes attributable to undervaluations seem to occur quicker — i.e. have larger adjustment parameters — relative to overvaluations. One explanation for this, is that local prices of Apple iPads appear notably less sticky when it comes to upward adjustments and can therefore also reinforce (or better support) nominal exchange rate depreciations during real exchange rate corrections.

The structure of the dissertation is as follows: Chapter 2 highlights some of the basic concepts and terminologies associated with the LOP and PPP. The chapter introduces the notion of stochastic LOP or PPP, which will be key in understanding why nonlinear models will be required to study dynamics pertaining to these price parity concepts. Next, the literature review contained in Chapter 3 highlights some of the most notable obstacles PPP studies typically encounter and provides a very brief summary of some of the most prominent writings on the topic. This section also justifies why Apple products are potentially better suited than various other alternative measures in conducting a study on trade or external adjustment dynamics. Chapter 4 introduces the two Apple product price datasets (annual and high frequency) I have compiled as well as some of the transaction cost measures used to control for some of the price heterogeneity, or biases, embedded within the local prices of Apple devices.

Chapter 5 describes the various estimation techniques as well as presents the derived results to evaluate the robustness of the different price measures when it comes to adherence to LOP or PPP as well as their adjustment toward it when deviations do occur. Various estimation techniques are used to evaluate exchange rate passthrough via the Apple product-derived real exchange rates and also to compare these to some of the other well-researched price ratios (for example the Big Mac Index and CPI). This is done by using *static* estimation techniques, including panel and Bayesian methods, to analyse exchange rate passthrough. In other words, whether LOP or PPP adherence occurs within the panel dataset. *Dynamic* estimation models are then considered to evaluate whether the price measures and exchange rates converge over time. The first test for convergence is done by differencing over expanding time periods and evaluating whether the changes in the prices ratios and exchange rates converge as the length of the difference period is increased. Finally, the speed of RER convergence is evaluated by estimating their respective half-lives.

Chapter 6 explores the nonlinear behaviour of iPad product derived real exchange rate adjustments. By digging deeper into the thresholds surrounding RER adjustments and consequently utilising several nonlinear estimation techniques I deal with the issue that real exchange rate adjustment speeds vary with the extent of their initial misvaluations. Specifically, even though small real exchange rate deviations can take a long time to correct, larger mispricings would likely realise much quicker adjustments. Some of the methods used to deal with these varying valuation adjustment speeds (i.e. valuation thresholds or change points) include locally-weighted scatterplot smoothing, threshold regression models, and linear piecewise regression models. These techniques are applied to both a panel dataset as well as the individual-country time series. The high frequency dataset also allows for a more-detailed investigation of real exchange rate dynamics than other studies previously done on the topic (Vo and Vo, 2022). For example, most LOP research uses annual datasets and therefore only evaluates infrequent changes in RERs. Instead, I show that there are numerous intricacies relating to the thresholds and adjustment parameters that occur over much shorter time horizons; i.e. weeks instead of years. Finally, Chapter 7 briefly summarises and concludes.

CHAPTER 2

THE LAW OF ONE PRICE AND REAL EXCHANGE RATE CONCEPTS

2.1 THE LAW OF ONE PRICE (LOP)

The law of one price states that in a competitive international market, with zero transaction costs and no barriers to trade, identical goods in different countries should trade at the same price level when expressed in the same currency. Let $P_t^{i,x}$ be the local-currency price of good x sold in country i at time t, $P_t^{j,x}$ be the local-currency price of the equivalent good sold in country j, and $\mathcal{E}_t^{ij}$ be the nominal exchange rate for country i currency units in terms of country j currency units. The relative value of good x in country j in terms of the same good in country i, i.e. the real exchange rate for good x, is then defined as:

$$Q_t^{ij,x} = \frac{\mathcal{E}_t^{ij} P_t^{j,x}}{P_t^{i,x}} \ . \tag{2.1}$$

When the real exchange rate for good x is unity ($Q_t^{ij,x} = 1$) we say that the law of one price holds in absolute terms.

2.2 PURCHASING POWER PARITY (PPP)

Purchasing Power Parity (PPP) is the generalisation of the LOP applied to a broad basket of goods representative of households' actual consumption baskets (or over a common reference basket of goods). Let $\bar{x} = [x_1, \ldots, x_n]$ be a basket of n goods, where the price of each item $P^1, \ldots, P^n$ is assigned a corresponding weight $w^1, \ldots, w^n$.[1] For country i, the general price level at time t can therefore be expressed as the weighted sum of the individual prices of each item: $P_t^i \equiv P_t^{i,\bar{x}} = \sum_{x=1}^{n} w_t^{i,x} P_t^{i,x}$. Similarly, for country j we have: $P_t^j \equiv P_t^{j,\bar{y}} = \sum_{y=1}^{m} w_t^{j,y} P_t^{j,y}$, where $\bar{y}$

[1]Under reasonable assumptions, these weights can be shown to equate with the expenditure shares of goods in a representative household's consumption basket, based on relative preferences for each type of good. These weights show how easy it is for actual aggregate price measures to differ from the theory implied by PPP. Specifically, these weights vary notably from one country to the next. What's more, a large portion of these products and services that are included in these baskets are nontradable, while PPP can only hold for tradable products. This shows why LOP is a great complimentary measure to PPP. A detailed discussion of this and other issues follows in Chapter 3.

now represents the basket of m goods. Since PPP assumes a common reference basket of identical goods, $n = m$ and $\bar{x} \equiv \bar{y}$, this implies the nominal exchange rate between country i and country j is:

$$\mathcal{E}_t^{ij} = \frac{P_t^i}{P_t^j} \ . \tag{2.2}$$

2.3 ABSOLUTE AND RELATIVE LOP OR PPP

With no time lags or any rigidities, any deviation from either equation 2.1 or 2.2 should immediately result in a potential arbitrage opportunity until the equivalent price again prevails in the two local markets. In other words, the law of one price infers the exchange rate from the price of an individual product, whereas purchasing power of parity infers the exchange rate from the general price level.

For simplicity, we take the natural logarithm of equation 2.1:

$$q_t^{ij,x} = e_t^{ij} + p_t^{j,x} - p_t^{i,x} \ , \tag{2.3}$$

where each lowercase letter represents each variable's logarithmic value (Note: for PPP the product specific x designation is dropped). Now, *absolute* LOP holds when $q_t^{ij,x} = 0$. We can reformulate equation 2.3 by adding the parameters α and β to the equation to obtain: $p_t^{i,x} - p_t^{j,x} = \alpha + \beta e_t^{ij}$. The special case of $\alpha = 0$ and $\beta = 1$ leads us to our original absolute LOP equation. Meanwhile, *relative* LOP posits that the percentage change in the exchange rate between two currencies over any one period change (i.e. where $\Delta p_t^{i,x} = p_t^{i,x} - p_{t-1}^{i,x}$ and $\Delta e_t^{ij} = e_t^{ij} - e_{t-1}^{ij}$) equals the difference between the percentage change in the good x's prices : $\Delta p_t^{i,x} - \Delta p_t^{j,x} = \beta \Delta e_t^{ij}$.

2.4 REAL EXCHANGE RATE ADJUSTMENTS

The law of one price cannot be expected to hold on a period-by-period basis. It should instead be seen as a relationship determining the long-run path of real exchange rates, notably in the absence of any time lags or trade rigidities. Equation 2.3 therefore implies that any real exchange rate deviation from zero should contemporaneously result in a potential arbitrage opportunity until equilibrating forces in the two local markets eliminate the real exchange rate misalignment. That is, should there be a temporary domestic price or exchange rate shock (for example an exogenous shock to any one of $p_t^{i,x}$, $p_t^{j,x}$ or e_t^{ij}) such that $q_t^{ij,x} = \phi_t \neq 0$ then we would expect, over some time period h, that $q_{t+h}^{ij,x} - q_t^{ij,x} = -\phi_t$. Figure 2.1, subplot (a), illustrates the expected mean-reverting adjustment for the real exchange rate, assuming that absolute LOP holds.

Empirically, we often observe a persistent bias in product-derived RERs.[2] That is, given an initial shock to the real exchange rate such that $q_t^{ij,x} = \phi_t$, we should not necessarily expect that its subsequent change will entirely offset the initial shock over some horizon h. In other words, the real exchange rate could embed a persistent bias: $q_t^{ij} = \mu^{ij} \neq 0$. It should be noted that this bias is expected to be stationary. Specifically, even though taxes, tariffs, transport costs as well as other factors captured within this bias may well evolve over time, we nevertheless expect μ^{ij} to not permanently trend away from zero. Figure 2.1, subplot (b), illustrates the evolution of an exogenous shock to the real exchange given this persistent bias. This exemplifies the notion of the relative LOP. Comprehending these basic concepts helps to introduce next notion of the stochastic law of one price.

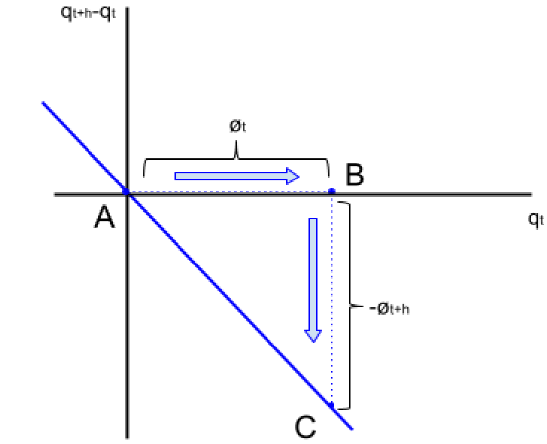
2.5 THE STOCHASTIC LAW OF ONE PRICE

The notion of the stochastic law of one price is related to the idea that real exchange rate adjustments occur in a nonlinear fashion. More specifically, real exchange rate movements may appear to be purely random, or stochastic, until a large enough deviation (or shock) occurs which pushes their valuation to a level that make it sufficiently attractive for arbitrage forces to kick in. This implies that real exchange rate movements may embed a 'band of inaction' until the gravitational pull of the arbitrage forces become more prominent alongside larger deviations (Taylor and Taylor, 2004). Nevertheless, even when these forces do take effect, it will still not be instantaneous due to various lags (for example asymmetric price information and shipping times). As stated by Obstfeld and Taylor (1997, p. 22), these valuation thresholds may therefore delineate "a region of no central tendency" among relative prices. This is most likely due to both the cost associated with arbitraging as well as uncertainties preventing trade. The concept of the stochastic law of one price thus

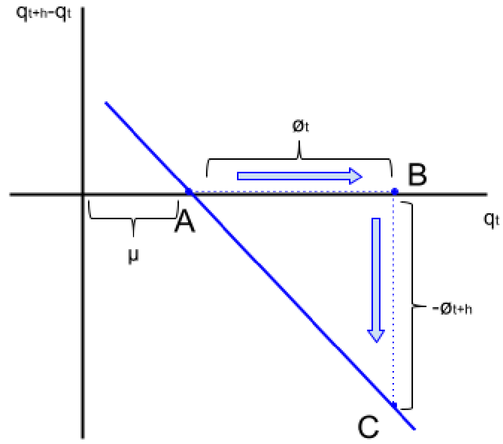
[2] Chapter 5 investigates this bias in more detail. The chapter shows that by incorporating certain transaction cost measures one is better suited to control for a notable amount of price heterogeneity in the local prices of Apple devices (in this case iPods, iPads and iPhones). In fact, the dissertation finds that after controlling for taxes, tariffs and transport costs, one gets notably closer to adhering to the absolute LOP. These transaction costs are embedded in the α parameter should Equation 2.3 be restated as the estimable equation $p_t^{i,x} - p_t^{j,x} = \alpha + \beta . e_t^{ij}$.

Figure 2.1: The Various Law of One Price Concepts Represented in terms of Real Exchange Rate adjustments
Subplot (a) depicts the expected mean-reverting adjustment for the product derived real exchange rate when absolute LOP holds. Subplot (b) shows a similar adjustment when relative LOP holds, where the real exchange rate incorporates a bias. Subplot (c) introduces a 'band of inaction' from the concept of stochastic LOP, where the real exchange rate shock must exceed the boundaries of the band for arbitrage forces to materialise. Finally, Subplot (d) is similar to (c) but with the bias removed. Note that in the case of stochastic LOP, the adjustment need not be toward the center of the band of inaction.

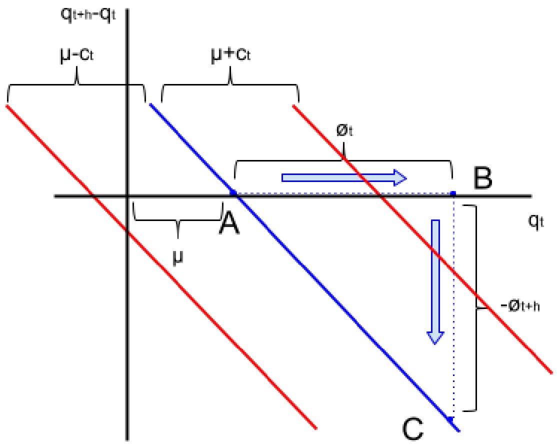
(a) Absolute LOP



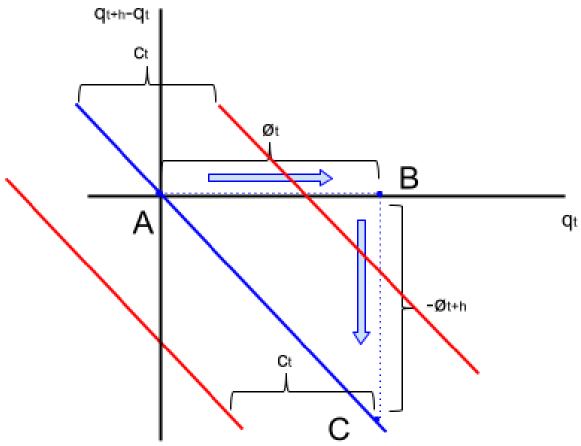
(b) Relative LOP



(c) Stochastic LOP



(d) Bias Adjusted Stochastic LOP



includes a band within which small real exchange rate deviations exhibit random walk behaviour until they push far enough (i.e. past μ^{ij} as defined earlier) for the arbitrage forces to kick in. As such, it is also clear that any analysis simply enforcing a linear relationship when evaluating the speed of adjustment toward LOP, will consequently *underestimate* the half-life of adjustments if this threshold band is not taken into account. Similarly, according to the notion of stochastic LOP, should one be able to better account for this band, the data should indicate better adherence to these parity concepts.

Expressing the notion of stochastic LOP mathematically, it simply states that the real exchange rate follows a random walk, i.e. $q_t^{ij} = \mu^{ij} + c_t^{ij}$, with $E(q_t^{ij}) = \mu^{ij}$ and $\mathrm{Var}(q_t^{ij}) = (\sigma^{c^{ij}})^2$. From this formulation, c_t^{ij} represents a threshold parameter equal to the total cost to trade which is preventing arbitrage. It is only after this threshold is breached that we expect the mean reversion properties of real exchange rates to become apparent. Thus, under this scenario, the real exchange rate fluctuates around some constant, μ^{ij}, and within a 'neutral band' where the real exchange rate is seen as being correctly priced. As explained by Taylor *et al.* (2001), within this band of inaction, when no arbitrage trade takes place, the adjustment process can even be divergent so that the real exchange rate spends most of the time *away* from parity. We use Figure 2.1 subplot (c) to illustrate the evolution of a shock to the real exchange rate which embeds a bias μ^{ij} as well as including this previously described band of inaction (i.e. $\mu^{ij} \pm c_t^{ij}$). In this case the external shock to the real exchange rate needs to be large enough to push the valuation outside of this band of inaction before arbitraging becomes profitable. Also note that the stochastic law of one price does not require that the real exchange rate adjusts toward the centre of the band of inaction following a shock. Arbitrage forces will only pull toward the edge of the thresholds (i.e. $\mu^{ij} \pm c_t^{ij}$). The width of the band is critical in these analyses. If too wide, all permutations of theories will be contained within this band and one would not be able to infer anything, while if it's too narrow all of the data points would lie outside of it and the hypothesis of the stochastic LOP will consequently be rejected (Clements *et al.*, 2012).

The next section will introduce the dataset I have compiled to explore whether the LOP holds for Apple products. In addition, the dissertation also investigates whether Apple product derived-RERs appear to adhere to the notion of stochastic law of one price which also imply their adjustments should occur in a nonlinear fashion.

CHAPTER 3

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). While 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.[1] This Rogoff (1996, p. 647) defined as "the PPP puzzle". 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 (i.e. whether parity held as well as the speed of adjustment toward it when deviations occurred). Consequently, most of what we know surrounding RERs originates from studies that use some variant of aggregate price indices. That is, mostly due to their availability, the vast majority of research has been dedicated on studying these parity concepts on broad baskets of prices, and most commonly, on the consumer price index (CPI).

Most of the remaining literature utilised other broad price measures, such as producer-, retail-, wholesale-, export- or terms of trade price indices, wage rate indicators and even components or

[1] The 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.

subcomponents of the mentioned price indices (see, for example, Taylor (2002), Taylor (2006), Officer (2012) and Vo and Vo (2022)). Despite the considerable attention general price indices have received in PPP studies, their use entails several obstacles and biases researchers then need to attempt to overcome.

The first obstacle studies using 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 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 'nontradables' — 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 over 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 using composite indices in analyses. Regarding the first, Taylor (2001) has shown 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.

Imbs *et al.* (2005, p. 4) have also investigated an *aggregation bias* causing positive persistence in RERs due to the underlying components having "heterogeneous dynamics" that vary with the characteristics of goods. 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 RERs from indices are further magnified with the choice of a specific base period where PPP is assumed hold (Marsh *et al.*, 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 nontradable component — that 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 conduct their analyses.[2]

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 the LOP is notably less voluminous than that of PPP. There are several helpful LOP databases, which are assessed in Section 3.1.1 to 3.1.4, though each of these also have several drawbacks.

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. Research on the topic also generally suffer from low statistical power. Studies have tried to overcome this by either using longer timespans (for example Froot *et al.* (2019)) or by utilising multiple country panel datasets (for example Chortareas and Kapetanios (2009)). Both of these options however 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 are high (Taylor and Taylor, 2004).

[2]See, for example, Cavallo and Rigobon (2016), Cavallo *et al.* (2019), Crucini and Telmer (2020) and Vo and Vo (2022)

3.1 POTENTIAL SOLUTIONS TO THE PPP PROBLEM

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 nontradable component (Engel, 1999).

A few of the most prominent databases featured in some of the LOP research are briefly explored below. Additionally, each subsection from 3.1.1 to 3.1.4 also expands on some of the potential issues surrounding each of the more readily available datasets for use in LOP analyses.

3.1.1 The World Bank's International Comparisons Program (ICP)

The World Bank's International Comparison Program (ICP) is not only the largest international statistical program in the world, but also one of the most complex, as described in World Bank (2013) and World Bank (2020). The ICP collects and aggregates matched product prices for over a thousand products, as listed in their detailed survey product list, covering a broad range of goods and services from over 170 participating countries. The primary objective of this dataset is to calculate PPP indices, which allows for the calculation of comparable price and volume measures of GDP and its expenditure components for country-to-country comparisons.

One of the main drawbacks of this dataset is its low frequency of publication, which takes over five years to complete due to its complexity. This makes the dataset outdated even at the time of its publication. For example, as of 2023, the most recent ICP covered the period from 2011 to 2017, while the next comparison will only be conducted for the reference year 2021. Additionally, each dataset round also uses updated product lists and methodologies, which further complicates the interpretation of time dimension for any panel data analysis based on the ICP.

For research purposes, the ICP dataset has been utilised to study the long-run validity of PPP for the Organization for Economic Cooperation and Development (OECD) and G6 countries under flexible exchange rates, as seen in Oh (1996).[3] The ICP data and results can be accessed through the ICP website (`icp.worldbank.org`) and the World Bank's Databank (`databank.worldbank.org`),

[3] The Group of Six (G6) includes the following advanced industrialised economies: the United States, France, the United Kingdom, Germany, Japan, and Italy.

where users can apply for access to more granular unpublished results and underlying data, as outlined in the ICP Data Access and Archive Policy.

3.1.2 The Economist Intelligence Unit's Worldwide Cost of Living (WCOL) Survey

The Worldwide Cost of Living (WCOL) is a twice-yearly survey conducted by the *Economist Intelligence Unit* (EIU) in order to provide comparisons on the cost of living in over 170 cities around the world. This comparison is based on the prices of over 200 goods and services.[4] The survey spans over 30 years which consists of goods and services including: food, drink, clothing, household supplies and personal care items, home rents, transport, utility bills, private schools, domestic help and recreational costs.

The aim of the survey is to compile a ranking system on the cost of living in various cities around the world. One of the reports' primary applications is for global corporations' human resources divisions and finance managers to estimate fair compensation policies and/or cost-of-living allowances for relocating employees, expatriates as well as business travelers. It is also used by companies to map price trends and to determine optimum pricing for their products across different international locations. Governments, investment agencies and city representatives also use the report to understand the relative expensiveness of cities.

Though more updated and higher in frequency than the World Bank's ICP survey (the WCOL is published annually), similar dataset methodological issues also arise for the WCOL. That is, various products as well as their volumes are not directly comparable and evolve over time. As such, both the ICP and EIU datasets are tailored more toward cross-sectional comparisons than for time series analyses. Studies that have used this dataset in a LOP analyses include Crucini and Shintani (2008) and Crucini and Telmer (2020).[5]

3.1.3 The Economist Magazine's Big Mac Index (BMI)

The Economist magazine's 'Big Mac Index' compares international prices of a single iconic product that is available in comparable form throughout most of the world. More specifically, The McDon-

[4] Refer to the website `store.eiu.com/product/worldwide-cost-of-living-2022` for more information.

[5] Though smaller in scale, Mercer has also developed a similar cost of living city ranking. Refer to `www.mercer.com/our-thinking/career/cost-of-living.htm`. The Union Bank of Switzerland (UBS) also has a less detailed version of the EIU's WCOL.

ald's Big Mac hamburger is an *equally weighted* amalgam of some non-tradables, including rent, electricity and labour; as well as a few tradables: beef, bread, lettuce and cheese. Even though this index started off as a lighthearted indicator of currency valuations in order to make purchasing power parity more digestible to non-economists, over time the BMI has managed to attract a notable amount of research interest. Articles that have delved into the BMI as a measure of LOP include Cumby (1996), Click (1996), Pakko and Pollard (1996), Ong (1997), Lutz *et al.* (2001), Parsley and Wei (2007), Chen *et al.* (2007), Cox (2008) and Clements *et al.* (2012).

Although the BMI solves the problem of equalising component weights across countries, there are still several other issues embedded within the hamburgers' prices when used in global comparisons. First, estimations on the non-tradable component of the Big Mac varies from over 55% according to cost function estimations by Parsley and Wei (2007) to as much as 94% according to Lutz *et al.* (2001).[6] This implies that Big Macs predominantly reflect the cost of non-traded goods whereas LOP/PPP only holds for tradable products. As such, Big Mac derived real exchange rate deviations may simply resonate input-cost differences across countries instead of actual currency valuations Pakko and Pollard (2003).

Second, even the most prominent tradable items constituting the Big Mac are not perfectly homogeneous. For example, as highlighted by Pakko and Pollard (2003) beef prices in Indian Big Macs are made with chicken patties (i.e. the "Maharaja Mac"), in Islamic countries it is made with halal beef, while Israel uses kosher beef. Finally, the BMI is only compiled annually (and more recently bi-annually) which again limits time dimension for time-series or panel investigations.

3.1.4 Eurostat's Harmonised Index of Consumer Prices (HICP)

The HICP dataset includes prices of various consumer goods and services acquired by households (Eurostat, 2018). The main purpose of the dataset is to provide a consistent or harmonised measure of CPI inflation in European Union member states as well as some additional European countries. More specifically, the HICP data is mainly used by the European Central Bank to evaluate price stability for setting monetary policy as well as to assess price convergence criteria for a country in

[6] Parsley and Wei (2007) found that the non-tradable inputs, particularly labour, accounts for most of the price tag of Big Macs. More specifically, according to their estimations, the price of labour alone amounted to approximately 45.6% of the burger's cost. Meanwhile rent (4.6% of the Big Mac's sticker price) and electricity (5.1%) were found to be some of the other prominent non-tradable inputs.

the process of joining the European monetary union. The primary requirement for the HICP is that price variations between countries should only reflect differences in price changes or expenditure patterns, and should not be the result of differences in methodologies (for example basket weightings). As such, the HICP aims for product price comparability. The HICP includes data on prices grouped in up to 295 product categories. Though the monthly data frequency is somewhat higher than the others listed above, the dataset is limited in scope since it only covers certain European nations.

Table 3.1: LOP Dataset Summary

	Most Recent Dataset Attribute			
Dataset	No. Countries	No. Products	Timespan	Frequency
ICP	176 Countries	155 Basic Survey Headings	2011 - 2017	Annual
WCOL	172 Cities	Over 200 Products	1990 - Current	Annual
BMI	72 Countries	1 Hamburger	1986 - Current	Bi-Annual
HICP	39 Countries	295 Products	1996 - Current	Monthly

Note: Earlier Dataset Versions Generally Contain Fewer Countries, Products and Frequencies

3.1.5 Web Scraping Price Datasets

As exemplified by some of the prominent datasets outlined above, it is difficult to find a *current*, *large* (i.e. both in time and cross-sectional dimension), *high frequency* dataset that also contains comparable and highly tradable products that are simultaneously available in a large number of countries. Not surprisingly, most of the literature on both LOP therefore generally suffers from either a relatively small number of comparable observations and/or inconsistencies in comparing products (Vo and Vo, 2022). Studies have tried to overcome this by either using longer timespans, analysing only a few specific countries, or by utilising multiple country panel datasets over shorter periods.[7] Both of these options however 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

[7]Examples of long timespan studies on LOP and/or PPP include Glen (1992), Lothian and Taylor (1996), Hegwood and Papell (1998) and Froot *et al.* (2019). A few of the panel data studies on the topic include Oh (1996), Chen *et al.* (2007), Chortareas and Kapetanios (2009) and Chen *et al.* (2019).

probability of *Type II* statistical inferencing errors are high. Taylor (2001, p. 490) captures the main data challenges researchers studying the LOP or PPP face:

> To meet the desired [data] standard we would be hoping that hundreds of price inspectors would leave a hundred or more capital cities on the final day of each month, scour every market in all representative locations, for all products, and come back at the end of a very long day, with a synchronized set of observations from Seoul to Santiago, from Vancouver to Vanuatu. We cannot pretend that this happens.

With the use of the internet age, combined with the increasing availability of online price data, the collecting of daily prices (as outlined by Taylor above) via web scraping has actually become more feasible.[8] *The Economist* magazine has dubbed the movement toward troves of timely, granular, high-frequency data as the "third wave" in economics (The Economist, 2021).[9] Web scraping allows researchers to compile customised, high-frequency, real-time data that will allow numerous investigations that were previously limited to mostly official statistical agencies. Accordingly, some of the most recent research on LOP has been conducted with authors compiling their own web scraped datasets. In most cases, these studies were conducted on matched retail products.

Though the web scraping process is simple in theory, it presents challenges, especially when attempting to scrape data from numerous different websites (i.e. price sources). For each of these websites one is required to navigate the HyperText Markup Language (HTML) layout as well as write custom scripts to extract the elements, which can be time-consuming. This becomes more difficult when each of the various websites' HTML layout changes via web updates, forcing the scraper to re-navigate the new website format and potentially modify the scraping code to account for these changes. Finally, matching the various products that then were extracted further complicates the process, especially should products differ slightly between various retailers (for example ketchup in the United States may be different brands and involve different volumes than tomato sauce in the United Kingdom). As a result, creating a continuous time series from the data obtained from web scraping can be problematic.

A few prominent papers employing web scraping in their data collection methods include Cav-

[8]Web scraping is the process of writing customised software to collect large amounts of data from the internet.

[9]According to the magazine this follows the first wave that emerged with Adam Smith and the 'Wealth of Nations' in 1776. This was followed by the second wave in the 20$^{\text{th}}$ century with John Maynard Keynes and his ideas on the role of the government in managing the economic cycle as well as with Milton Friedman shaping monetary policy.

allo and Rigobon (2016), Cavallo *et al.* (2019), Crucini and Telmer (2020) and Benedetti *et al.* (2022). Chapters 5 and 6 also utilise web scraping to collect prices on Apple electronics in order to respectively evaluate exchange rate passthrough as well as the nonlinearity of real exchange rate adjustments. The motivation for scraping and compiling the Apple product prices dataset for use in a study on the LOP are explored in Chapter 4.

CHAPTER 4

DATASET COMPILATION AND MOTIVATION FOR USING APPLE PRODUCTS IN LOP RESEARCH

4.1 ADVANTAGES OF USING APPLE PRODUCTS IN A STUDY ON LOP

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 (as outlined in Chapter 3). In particular: the first reason why using APPs are such a good tool for an in-depth LOP analyses is that these products are widely available internationally. According to Apple's website, it currently has online iStores in over 100 countries.[1] 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 are 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.*

4.2 ISSUES SURROUNDING APPLE PRODUCTS IN A STUDY ON LOP

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

[1] Refer to `apple.com/choose-country-region/`

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 influence the price of iPhones in the various domestic markets significantly. Thus, the annual dataset will instead focus on other Apple products such as iPods in the earlier years (in Chapter 5) and subsequently on iPads in Chapter 6. The high frequency database meanwhile will focus on different iPad varieties. 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.

4.3 METHODOLOGY: APPLE PRODUCT PRICE DATASET COMPILATION

For the analyses conducted in Chapters 5 and 6, I have compiled and utilised two different panel datasets. Chapter 5 employs a database that consists of the domestic prices of three entry-level Apple devices. More specifically, it is an annual dataset including the APPs prices of almost 50 countries spanning 14 years from 2007 to 2020 which consists of: iPod Nanos on 48 countries from 2007 to 2017, iPads on 45 countries from 2011 to 2020 and iPhones on 39 countries from 2012 to 2020. The dissertation will refer to this dataset as the *annual dataset*. For Chapter 6, I scraped and compiled a weekly panel dataset that extracted the domestic prices of four iPad devices on 35 countries over a six-year period (i.e. from the beginning of 2016 to end-2021). The four Apple iPad devices used are: iPad Pros (Large Screen), iPad Pros (Small Screen), iPad Airs and iPad minis. The dissertation will refer to the latter panel as the *high frequency dataset*. The following subsections explore in more detail the step-by-step processes that were followed in compiling the two panel datasets. Since these panels basically employed the same scraping techniques (the main difference being the Python script's looping sequences to extract the data) and utilised the same primary data source (the Internet Archive Wayback Machine), I shall first explore these two aspects of the data collection process.

4.3.1 Data Sources and Data Collection Process

Regarding the web scraping process, the BeautifulSoup library package in Python was used for parsing the HyperText Markup Language (HTML) documents and extracting the price data from Apple's various global online retail stores to compile both datasets.[2] Python, combined with the BeautifulSoup package, allows the writing of scripts that query web servers, submission of requests as well as the retrieval of the applicable data elements. This can then be parsed to extract the various devices' characteristics (for example product description and prices) which are then stored in a database. In Section 3.1.5 the dissertation addresses some of the key issues surrounding web scraping when it comes to constructing a retail price dataset. This includes: the complexity of compiling various scripts when extracting data from a large array of different data company sources, and of dealing with websites that are continuously updated (i.e. HTML layouts that evolve). The latter problem is further amplified when combined with the first problem of various price providers. Finally, it can also be painstaking to subsequently match all the different elements (i.e. various sources' products which may embed dissimilar characteristic and/or volumetric discrepancies).

Fortunately, with the dataset compilation process I was only faced with the second issue of HTML scripts evolving along with Apple's website changes and/or updates. What's more, since I scraped the official retail website of Apple for the various countries — which are all sub-directories of the main Apple site — each country's website HTML layout was nearly identical, and the various products are accordingly easily matched. Finally, the HTML changes that do take place, seem to occur almost instantly across all the various country sites. This implies that one is essentially only required to write a *single* script navigating the HTML code, which can then be applied across *all* the countries in order to extract their product and price data. Given this, I was able to program a dictionary of the various countries and then use the same scraper script to 'loop' through them at each point in time (i.e. download a cross section of data for each date) in order to retrieve the price data.[3] The same country website layout simplified the data collection process tremendously, since normally one would be required to write various scripts to navigate each country's site or data source individually.

[2]Refer to Richardson (2022) for more information on the BeautifulSoup library package in Python.

[3]This technique was applied to the annual database. For the high frequency database I first chose a specific country, and then iterated through the dates. More detail of the scraping process is described in Sections 4.3.2 and 4.3.3.

The Internet Archive's *The Wayback Machine*, was the primary price source used in order to compile a database on the historical prices from Apple's online retail shops. *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. The *Wayback Machine* works by periodically crawling the web and capturing websites and these snapshots are then stored and archived. When a user requests a web page that is in the archive, they are then directed to a snapshot that was taken closest to the date they are requesting. However, in more recent years of the Internet Archive's existence, these websites are catalogued almost daily (at least for the most popular websites).

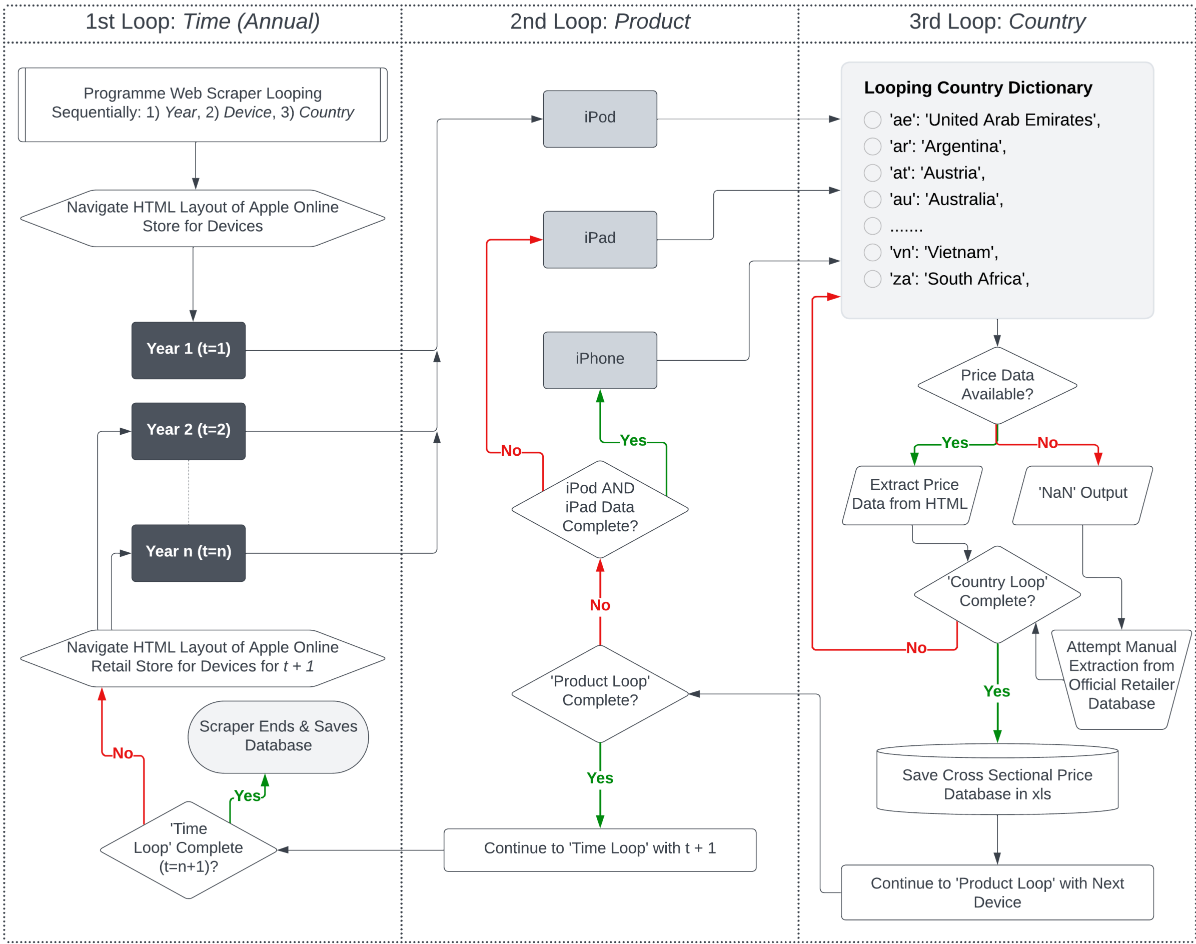
One of the main benefits of using *The Wayback Machine* as the data source on APPs, is that it is a fairly simple process of programming a scraper to navigate the historical archives. This compares well to the alternative of having to run a scraping algorithm consistently for every day, week, etc. and to then instantly reconfigure the code if it was discovered that the website's HTML layout has changed (and the required data could not be retrieved). However, by using the Internet Archive, it is easy to pinpoint *beforehand* the exact dates where a website's layout changed and to then program the scraper's script accordingly to correctly reroute and retrieve the required HTML elements for each stretch of time. In other words, one can catalogue, in advance, all the HTML navigation and script changes required. Then one can scrape and retrieve an entire price panel for all the various countries in a single run. The following two subsections provide more detail on each of the two dataset collection processes. The main difference between the *annual* and *high frequency* datasets is the sequence of loops that was programmed.

4.3.2 *Annual Frequency* Panel Dataset: Step-by-Step Description of Scraping Process

In the earlier years of the Internet Archive (for example early 2000s), website captures occurred notably less often than more recently (for example later 2010s). Furthermore, less web-page detail was also generally captured. This, combined with the fact that Apple's online store was initially only available in a small number of countries, means that a retrospective extraction of a high frequency dataset over a longer timeframe on APPs is currently unfeasible. As such, in order to extend the APPs dataset over as long period as possible, I opted to compile an annual dataset.

This dataset included a relatively long timespan of 14 years. However, during that time Apple's website layout was updated at least every year. As such, it was easier compiling different scripts that extracted, or cycled, one year at a time through the data cross-sections (comprising prices on all the products for the different countries). For each calendar year, the price data was retrieved as close to the year-midpoint as possible, i.e. around June/July. The primary price source was Apple's online store, while the secondary sources were 'Apple Premium Resellers' as directed from the official Apple country site at that time. Since Apple's online store expanded over time to include more countries, the price data from the resellers were used more extensively in the earlier periods of the dataset.

Figure 4.1: Flowchart of Web Scraping Process for Annual Dataset
The compiled script sequentially loops through 1) time, 2) products and 3) countries to extract data. The primary price source used was Apple's online store for each country and if unavailable a redirected link to a 'Apple Premium Reseller' was used.



A basic flowchart of the scraping process is illustrated in Figure 4.1.[4] Specifically, the scraper was programmed to sequentially loop through 1) time, 2) products and 3) countries. At each point in time (i.e. every year) I was first required to navigate the HTML layout of the Apple store's website for that specific year and accordingly retrieve the HTML sections in order to extract the correct device information and price elements. For every price datapoint, the entry level device and most basic specifications were used (i.e. the 'from' price and associated device accompanying that price). Following this, the web scraper was then used to extract a cross sectional database for that specific year on all the devices' prices that were available across all the various countries included in Apple's online store.

If the country's store was not yet active at the time and/or the price or device information could not be retrieved, a 'not available' (i.e. NaN) value was assigned to that entry in the dataset. Following the scraping process, I then attempted to manually navigate the Internet Archives by following redirection links to the official Apple resellers from the original online store in order to extract the price and device information to populate the missing values. Constructing as complete database as possible by only navigating historical archives was a time consuming process.

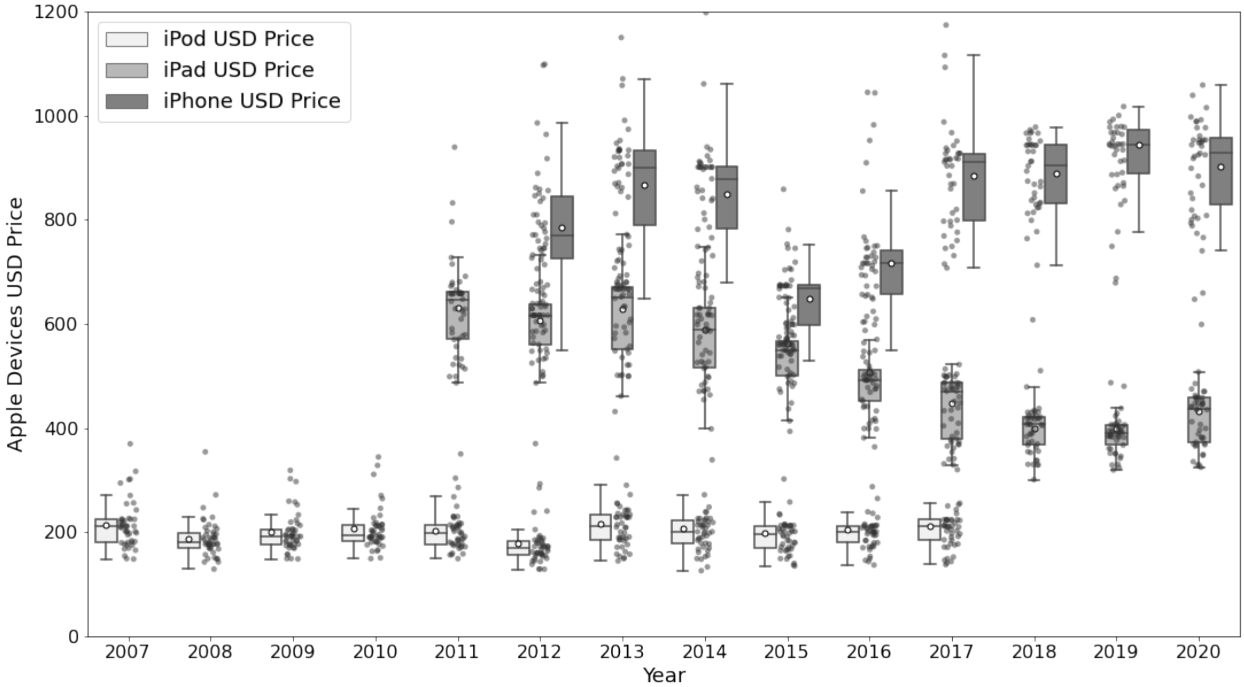
Figure 4.2 uses box plots to summarise the distributions of the scraped annual price data.[5] The average exchange rate value for the month the data was retrieved (extracted and calculated from Bloomberg) in order to convert the domestic prices to USD. From these box plots, one can visualise some of 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 more costly 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

[4]The script used to scrape the *Wayback Machine* Internet Archive is available on Github at: `https://github.com/wal0007/APPS/`.

[5]The 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.

2016 appearing to be exceptions).

Figure 4.2: Box Plots Showing the USD Price of the Three Apple Products on the *Annual Dataset* from 2007 to 2020



Figures B.30 (a) to (c) in Appendix B utilises box plots to show the distributions of 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 greenback 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 also appears wider than for the other devices. This could be because of the various deals existing with different telecommunications operators.

4.3.3 *High Frequency* Panel Dataset: Step-by-Step Description of Scraping Process

It was possible to also construct a higher frequency dataset from end-2015 when the Internet Archive captured (popular) websites more frequently and Apple's online store had by then expanded to include a fairly large cross section of countries. One of the main benefits of using the Internet Archive and Apple Store combo as price sources to scrape data is that the website Uniform Resource Locator (URL) address used to retrieve the information has a consistent format. Thus, it is easy to iterate through the URL sequence. More specifically, the general website address for scraping information on iPad models, as done in the high frequency database, is:

`https://web.archive.org/web/YYYYMMDD/https://www.apple.com/XX/shop/buy-ipad/ipad-pro`

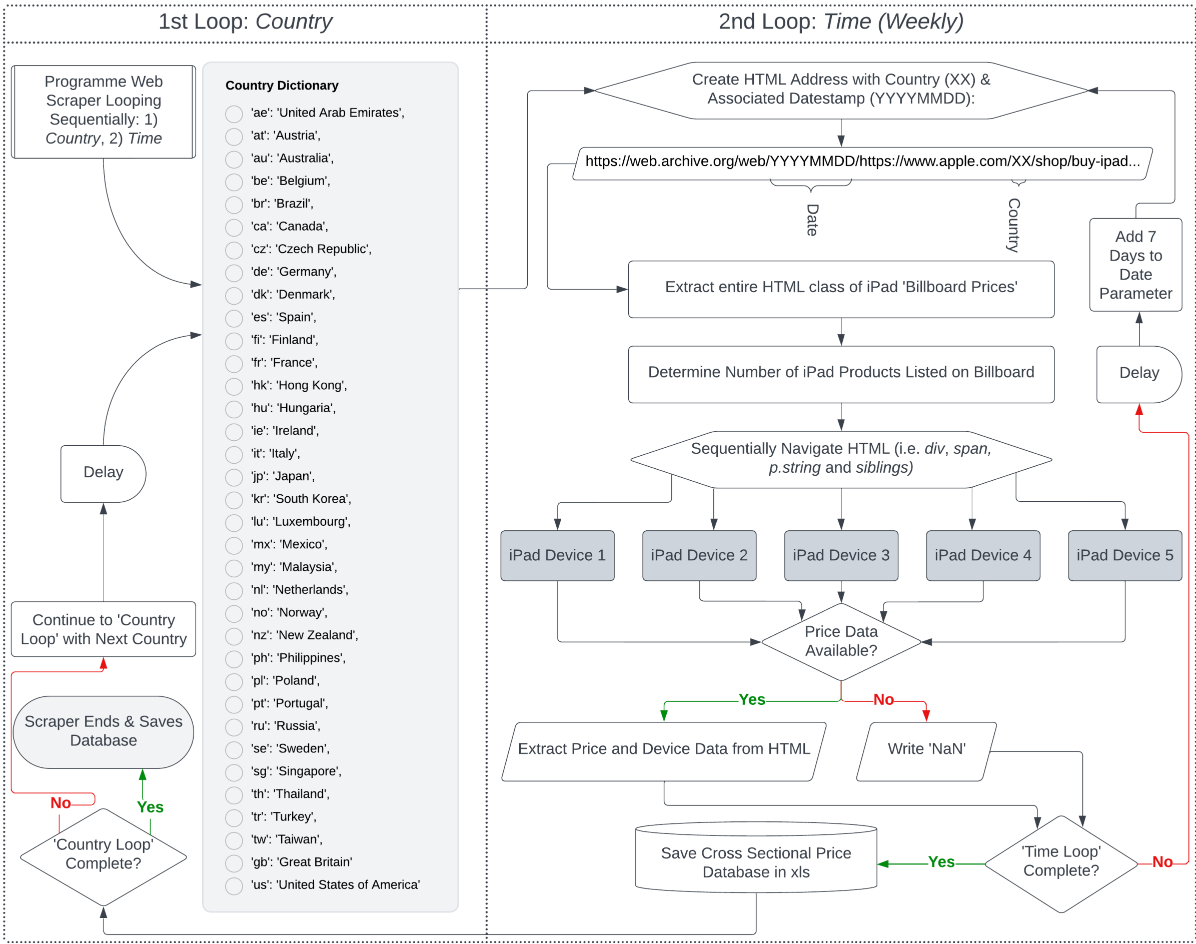
Where 'YYYYMMDD' is a variable placeholder for the date in a Year, Month, Day format (i.e. YYYYMMDD) and the 'XX's in the address above represents the appropriate country store code (for example taking the value 'AE' for United Arab Emirates, 'AT' for Austria, etc.). As such, having configured and written the appropriate scripts to navigate Apple's HTML layout changes, one can then cycle through all the dates and countries to combine these into a single panel database. A basic flowchart of this exact scraping process for the high frequency dataset is illustrated in Figure 4.3.[6]

By sequentially looping first through each country and by then cycling through all the dates to retrieve the price and device information, one is able to create price time series for each country that can then be combined into a larger panel database. Again, box plots of the converted USD prices for the four iPad versions across 2016 to 2021 is shown in Figure 4.4. For the different iPad varieties, the entry-level iPad Air and iPad Mini varieties have seen their average USD prices for each year across all countries (represented by the dots) remain mostly stable over the evaluation period. Meanwhile, the mean prices of the higher-end iPad Pro models have gradually increased over the six-year observation period. Overall, the price distributions (size of the boxes and whiskers) for the different devices do not appear to have changed significantly over 2016 to 2021.

Figures B.31 (a) to (d) in Appendix B illustrate the distributions of the converted USD prices

[6] The 'delay' sequences in the script is discussed in Section 4.3.6 which explores in more detail some of the obstacles I encountered during the construction processes of the datasets.

Figure 4.3: Flowchart of Web Scraping Process for High Frequency Dataset
The compiled script sequentially loops through 1) country and 2) time and simultaneously extract all the different iPad varieties' data.

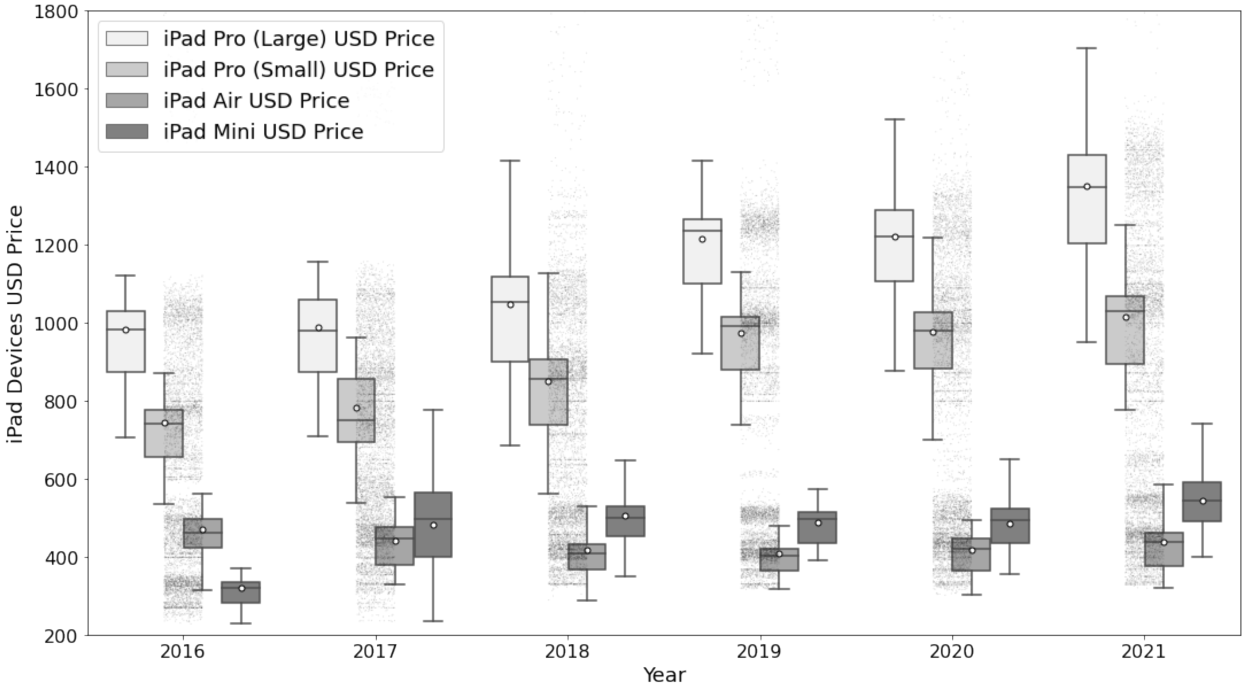


for each country for the different tablets. For all four devices, Brazil appears to be an expensive outlier compared to the other countries. Another interesting observation is that the USD prices of the relatively cheaper iPads and particularly the iPad Minis appear to have more variation in cost between the different countries in the sample than the two premium iPad Pro devices.

4.3.4 Transaction Costs on Apple Products

As mentioned, one of the main benefits of using Apple devices in a 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' I control for is the local taxes

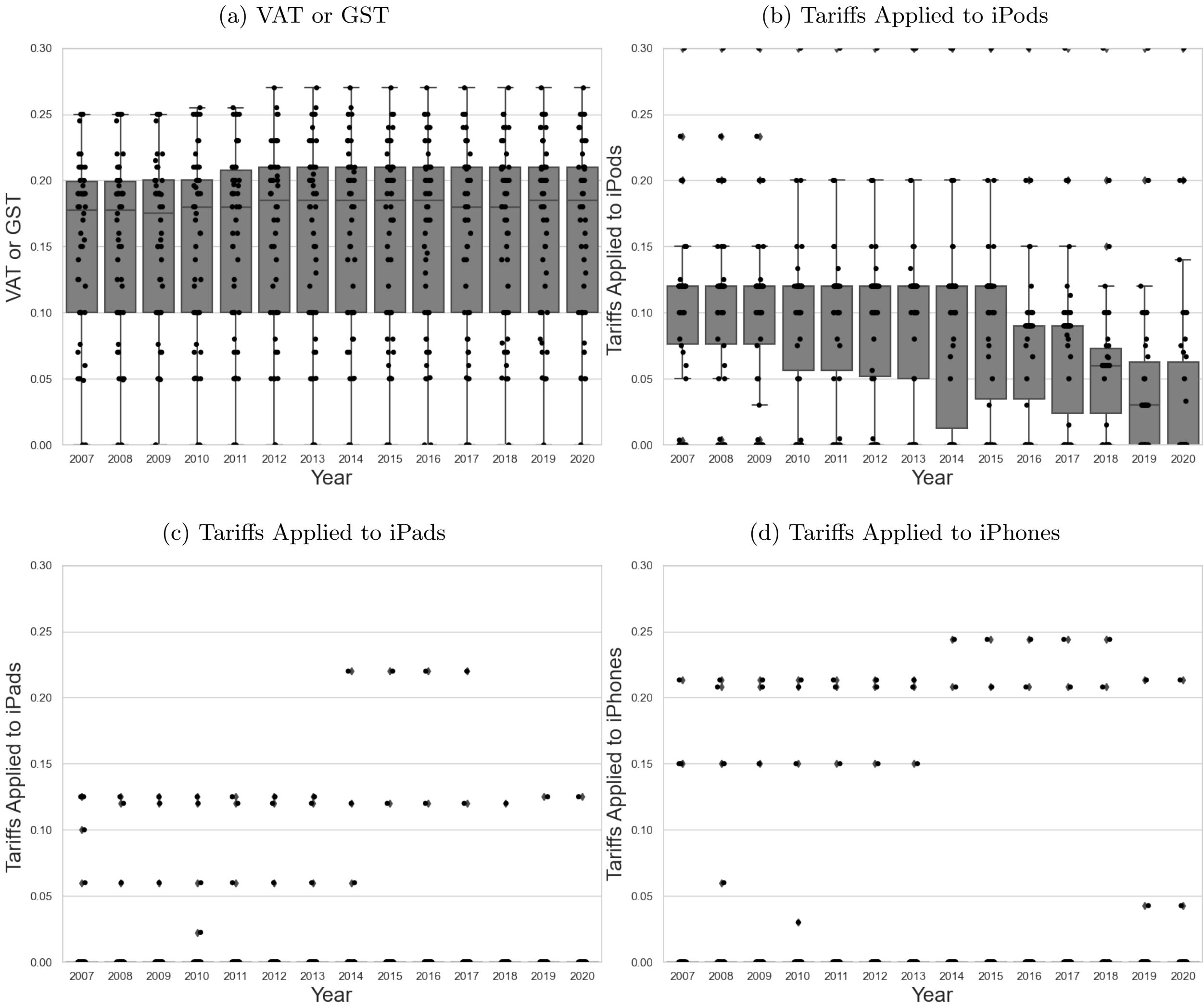
Figure 4.4: Box Plots Showing the USD Price of the Four Apple iPad Devices for the *High Frequency Dataset* from 2016 to 2021



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, i.e. from 2007 to 2020 (refer to KPMG (2016-2022)). For the United States, the average tax rate on of all the states were used (excluding Puerto Rico). A box plot of the VAT or GST tax rates is shown in Figure 4.3.4 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 between countries ranging from 0% (for Hong Kong) up to over 27% in Hungary.

Second, since all of the 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, I can also control for any import duties embedded in these products' prices. All of the applied tariff rates were sourced from the International Trace Centre's

Figure 4.5: Various Transaction Costs Embedded in Apple Devices (y-axis limited to 30%)



Market Access Map (InternationalTradeCentre, 2022).[7] Figure 4.3.4, subplots (b) to (d), illustrate with box plots the tariff rates that 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

[7]For 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 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` for more information on the HS codes.

impose (fairly high) import levies on these devices for the sample of 51 countries evaluated. As such, those that do impose import tariffs on these two products show up as outliers in the box plots.

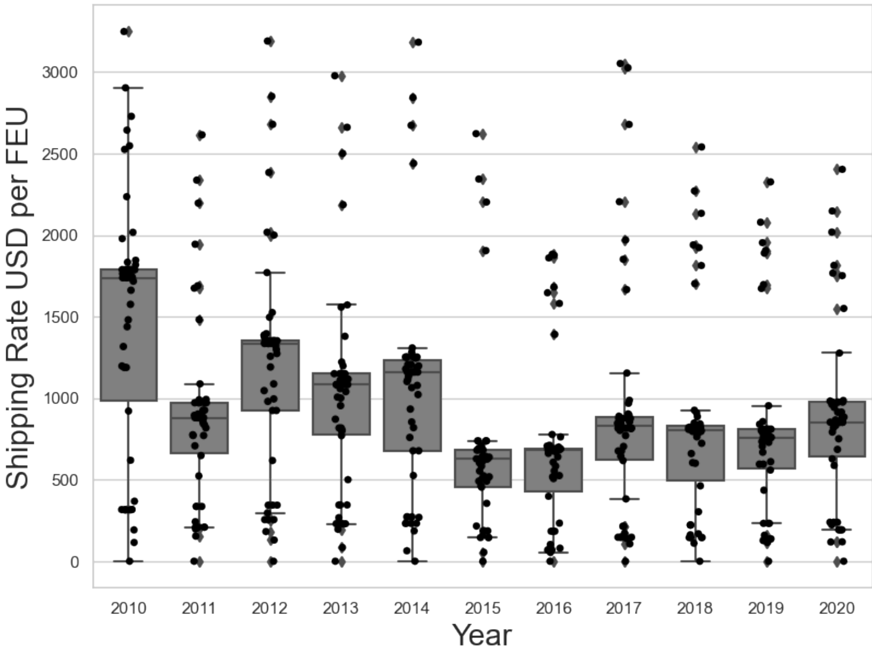
For shipping costs, container freight market rates were used from the United Nations Conference on Trade and Development (UNCTAD) Review of Marine Transport (UNCTAD, 2022). Currently the only freight rates that are tracked are on some of the main global shipping routes.[8] All of these shipping rates 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 that is also a main shipping route to Shanghai. This distance is multiplied with the UNCTAD's standard shipping rate on that main route. For example, for Argentina this calculation entailed taking the distance of Buenos Aires to Shanghai as a ratio of the distance of Santos (Brazil) to Shanghai (i.e. the main shipping route) times the standardised shipping rate from Santos to Shanghai. This calculation methodology was followed for all of the 51 countries in the sample. Figure 4.6 illustrates the evolution of shipping rates for the countries included in the analyses. Finally, the exchange rate data on the Apple device dataset were sourced directly from Bloomberg. The average exchange rate price for the month that the device's sticker price was scraped was used in this analysis.

4.3.5 Obstacles Encountered in the Data Collection Process and How These Were Overcome

As mentioned previously, one of the main challenges in compiling the two (price scraped) datasets was the changes in the HTML layout that occurred with website updates. It took considerable time to pinpoint all the exact dates regarding the updates in scraping the high frequency database. For the annual database, it was necessary to write different scripts for each year to navigate the varying HTML layout and extract the necessary product and price information. In contrast, the

[8] These 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 4.6: Shipping Rate, USD per 20 or 40 Foot Equivalent Units (FEU) from 2010 to 2020



task of collecting data for the APPs was made easier because the websites of the various country stores had the same basic layout. This required updating the script *once* for each HTML change, rather than for every country every time there was a change in a specific country's website. In other words, I was only required to change the script as often as the main Apple store directory's layout changed. This compares to a 'worst case scenario' of the number of countries being scraped times the frequency of script changes for each country's retail website.

Another obstacle, encountered both during the scraping process as well as later in the analyses, concerned product comparisons and evolutions. Apple consumer products like the iPod (since discontinued), iPhone and iPad have different specifications. This includes different versions, storage capacity, colours etc. In addition, products with similar specifications are regularly replaced with updates over time. For the database I attempted to create a *continuous* time series out of products that were frequently upgraded as technology improved. The discontinuity of the devices was therefore a key challenge in the analysis. This is partially addressed using statistical techniques. During data collection, product continuity was attempted by consistently using the entry-level product for each device category (i.e. the 'from' price and associated good in Apple's product billboard).

The primary datasource, *The Wayback Machine*, is not a perfect historical archive of websites and there are several limitations regarding the site's capability. More specifically, the snapshots of websites are often incomplete, and the Internet Archive may not be able to capture all the elements of a webpage (for example interactive elements or forms). Furhtermore, some websites, including some premium Apple resellers, were not found in the archive. Data scrubbing was also necessary to address inconsistencies in elements such as currency symbols, thousands separators, and hidden HTML elements that made the prices difficult to decipher as numbers. This meant that the price formats were often inconsistent or unreadable on some of the datasheets. Accordingly, time was spent cleaning the price data for several countries.

As noted in Figure 4.3, 'delays' at different points in the scraping script had to be incorporated. This is because most websites, like the Internet Archive, have limits on the number of requests that can be submitted from a single internet service provider (ISP) address over a certain timeframe. As the intensity of requests can overload the domain's servers, several domains block these perceived risks or attacks. As such, it was necessary to construct the high frequency script to periodically pause while browsing and extracting data as well as incorporating a 'user agent' in the web scraper.[9] In addition, instead of running the entire country dictionary in one instance, it was necessary to break up the scraping over several days.

4.3.6 Other Potential Obstacles Encountered with Scraping and Data Mining

There are several challenges faced by data mining and web scraping, aside from the ones encountered by this particular study. These include geo-blocking, Completely Automated Public Turing Test to tell Computers and Humans Apart (CAPTCHAs), and legal restrictions. The first challenge, geo-blocking, occurs when websites restrict access to certain users based solely on their geographic location, making it difficult to scrape prices from certain regions. One potential solution to this challenge is using virtual private networks (VPNs) that can change a user's ISP location. Websites also often use CAPTCHAs to prevent automated scraping of their site, particularly if they detect scraper or bot activity. This can make it difficult, or even impossible, to scrape prices without

[9]A user agent is a piece of text that tells a website who is accessing it. It is typically used to identify the user's browser and operating system. In scraping scripts, the user agent is used to make the script appear as if it is being run by a human user, rather than a bot. This is important because many websites will block bots from accessing their content.

bypassing the CAPTCHAs. Finally, legal restrictions on web scraping have become increasingly complex and varied by country.

One major legal restriction on web scraping is copyright infringement. Websites often contain copyrighted material, such as images and text, which cannot be copied or used without the owner's express permission. Scraping such material can be considered copyright infringement and result in legal action against the scraper (data collector).

Privacy is another legal restriction, as some websites collect personal information from their users, such as names, addresses, and financial information, which can then be used for unauthorised purposes. This is problematic if the data collected includes sensitive information, like medical or financial records. In addition to these specific restrictions, there are broader laws related to web scraping and data usage. For example, the Computer Fraud and Abuse Act (CFAA) and the Electronic Communications Privacy Act (ECPA) in the United States prohibit unauthorised access to computers and networks, including web scraping. In Europe, the General Data Protection Regulation (GDPR) provides specific protections for personal data, requiring organisations to obtain explicit consent from individuals before collecting and using their personal data and giving individuals the right to request their data be deleted.

In South Africa, the Electronic Communications and Transactions Act (ECTA) of 2002 governs the collection, processing, and use of personal information, while the Protection of Personal Information Act (POPI) addresses some aspects of web scraping, regulating the collection, storage, and use of personal information with the goal of protecting privacy. As far as I am aware, I haven't contravened any of the laws in the different jurisdictions with the compiling and scraping of the datasets.

CHAPTER 5

STATIC AND DYNAMIC EVALUATION OF EXCHANGE RATE PASSTHROUGH WITH THE APPLE PRODUCTS DATASET

In this chapter various estimation techniques are employed to evaluate the robustness of different price measures, including the APPs, Big Macs, and CPIs when adhering to LOP or PPP as well as their subsequent adjustments when deviations occur. First, *static* estimation techniques including panel and Bayesian methods are used to evaluate whether LOP or PPP adherence occurs 'in aggregate' for the entire panel dataset. Next, *dynamic* models are employed to evaluate whether price measures and exchange rates converge over time. Furthermore, analyses are done on half-lives to evaluate the speed at which price ratio and exchange rate convergence occurs.

5.1 STATIC EXCHANGE RATE PASSTHROUGH

5.1.1 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 equation specified in Section 2.3:[1]

$$p_t^{i,x} - p_t^{\mathrm{US},x} = \alpha_x + \beta_x e_t^{i\mathrm{US}} + \epsilon_t^{i\mathrm{US},x} \tag{5.1}$$

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 $\epsilon_t^{i\mathrm{US},x}$ parameters in Equation 5.1 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 4.3.4 to restate Equation 5.1 as:

[1] Where product x = [CPI, Big Macs, iPods, iPads, iPhones].

$$p_t^{i,x} - p_t^{\mathrm{US},x} = \alpha_x + \beta_x e_t^{i\mathrm{US}} + \delta_{x1} \ln\left(\frac{1+\tau_t^{i,x}}{1+\tau_t^{\mathrm{US},x}}\right) + \delta_{x2} \ln\left(\frac{1+\iota_t^{i,x}}{1+\iota_t^{\mathrm{US},x}}\right) + \delta_{x3} \ln\left(\frac{\lambda_t^{i,x}}{\lambda_t^{\mathrm{US},x}}\right) + \epsilon_t^{i\mathrm{US},x} \quad (5.2)$$

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.

5.1.2 Results: Panel Regressions

Panel unit root and cointegration tests are first performed on the various 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. $p_t^{i,x} - p_t^{\mathrm{US},x}$) or associated logarithmic exchange rate variables (i.e. $e_t^{i\mathrm{US}}$) each contained a unit root. Subsequently, both the Kao as well as Westerlund panel cointegration tests were performed, and the null hypothesis of 'no cointegration' was strongly rejected for the various price measures and exchange rates.

Tables A.1 to A.9 in Appendix A.1 reports some of the various panel regression specifications for Equation 5.1, on the relative price ratios: CPI, Big Macs and APPs.[2] 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_xs (though statistically significant) are generally small, while the β_xs 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

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

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 5.1:

Table 5.1: Panel Regressions Summary

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

	Price Ratio (x)				
Coefficient	CPI	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.7220 to 0.9630	0.6097	0.3131	0.2152	0.5500
	(0.0379)***	(0.0640)***	(0.0336)***	(0.0265)***	(0.0411)***
$\hat{\beta}_x$	0.5724	0.6293	0.9903	0.9922	0.7647
	(0.0193)***	(0.0269)***	(0.0110)***	(0.0097)***	(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 $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$

As pointed out by 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 either 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. Even though the iPhone price ratios perform well in the pooled and random effects model in Table A.9 (indicating LOP potentially holds), this price ratio fairs notably worse once country fixed effects are included. The regressions in Tables A.1 to A.5 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 except in the basic pooled panel regressions.

Table 5.2: Panel Regressions Summary on Balanced Panel Dataset: Same 25 Countries Over 2012 to 2017

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

	Price Ratio (x)				
Coefficient	CPI	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.9271 to 1.1269	0.9997	0.5530	0.1536	0.8254
	(0.0501)***	(0.0973)***	(0.0996)***	(0.0410)***	(0.1115)***
$\hat{\beta}_x$	0.3998	0.2555	0.8270	1.0036	0.6620
	(0.0293)***	(0.0581)***	(0.0581)***	(0.0176)***	(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 *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*

Table 5.2 summarises the most relevant balanced regression results from tables A.14 to A.22 in Appendix A.3 which utilises 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.[3] 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 5.1. 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 5.1 change once transaction costs are introduced. Table 5.3 summarises the most appropriate regression specifications from Appendix A.2 (i.e. Tables A.10 to A.13) when also including the various transaction

[3]When 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.

cost measures (as specified in Equation 5.2). Table 5.4 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 A.12), 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.[4] In addition, the estimation method in Table 5.3 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 the specifications appear to be quite sensitive regarding the effects (for example fixed or random) used.

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

[4]What's more, in the balanced panel iPad regression in Table 5.4, though the $\hat{\alpha}_{\text{iPad}}$ still appears fairly large, it has become statistically less significant.

Table 5.3: Panel Regressions Summary Including Transaction Costs

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

	Price Ratio (x)			
Coefficient(x)	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.5868	0.0791	0.3443	0.4177
	(0.1031)***	(0.0377)**	(0.0827)***	(0.0859)***
$\hat{\beta}_x$	0.6931	1.0017	0.9506	0.7746
	(0.0215)***	(0.0080)***	(0.0264)***	(0.0349)***
$\hat{\delta}_{x1}$	-1.5499	1.7418	-0.2263	0.12189
	(0.7704)**	(0.2780)***	(0.5929)	(0.6055)**
$\hat{\delta}_{x2}$		0.5696	0.1790	0.2141
		(0.1827)***	(0.3467)	(0.3917)
$\hat{\delta}_{x3}$			0.0305	0.0043
			(0.0237)	(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 $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$

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.[5] Similar to the technique employed by Fujiki and Kitamura (2004), I have evaluated *various* panel models before including the most appropriate one (shown in the summaries: Table 5.1 to Table 5.4). Also, none of the 'outlier' countries are included that experienced either hyperinflation or currency

[5]Our 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 5.4: Panel Regressions Summary Including Transaction Costs on Balanced Panel Dataset: Same 25 Countries Over 2012 to 2017

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

	Price Ratio (x)			
Coefficient(x)	Big Mac	iPods	iPads	iPhones
$\hat{\alpha}_x$	0.8694	0.1299	0.5275	0.7853
	(0.1673)***	(0.0534)**	(0.2143)**	(0.2005)***
$\hat{\beta}_x$	0.2590	0.9916	0.9614	0.6575
	(0.0570)***	(0.0164)***	(0.0762)***	(0.0743)***
$\hat{\delta}_{x1}$	1.4341	1.6411	-1.0465	0.5050
	(1.4972)	(0.4179)***	(1.6772)	(1.4693)
$\hat{\delta}_{x2}$		1.0640		-0.1034
		(0.3622)**		(0.4719)
$\hat{\delta}_{x3}$		0.0505	0.1394	-0.0033
		(0.0142)***	(0.0348)***	(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 $\quad$ *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*

rebasing.[6] 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 extend iPads, adhere fairly well to the LOP.

5.1.3 Bayesian Generalised Linear Model Estimations

PyMC is a powerful library package that's available in the Python programming language (Salvatier *et al.*, 2016). By utilising this package, it's possible to run Markov chain Monte Carlo (MCMC)

[6] This 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 $\hat{\beta}_{\mathrm{iPod}}$ with fixed country and time effects in Table A.7 from 0.9594 to 1.0063.

algorithms to construct a Bayesian Generalised Linear Model (BGLM) to evaluate some of the relationships specified in Equations 5.1 and 5.2. 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 5.1 to evaluate exchange rate passthrough in terms of a probability distribution function to yield:

$$p_t^{i,x} - p_t^{\mathrm{US},x} \sim \mathcal{N}\left(\alpha_x + \beta_x e_t^{i\mathrm{US}}, \sigma_t^{i\mathrm{US},x^2}\right) \tag{5.3}$$

According to this specification, $p_t^{i,x} - p_t^{\mathrm{US},x}$ 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. $\alpha_x + \beta_x e_t^{i\mathrm{US}}$) with a variance of $\sigma_t^{i\mathrm{US},x^2}$. According to Davidson-Pilon (2015), there are numerous advantages to the Bayesian approach outlined in Equation 5.3. 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 5.1 and 5.2, 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 $\sigma_t^{i\mathrm{US},x^2}$).

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 4.3.4). 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.

5.1.4 Results: Bayesian Generalised Linear Model Estimations

By employing a BGLM model with the linear specification defined in Equation 5.3 and by having specified the priors as follow:[7]

$$\sigma_t^{i\text{US},x} \sim HN\left(\sigma_{\sigma_t^{\text{US}i,x}} = 10\right) \tag{5.4}$$

$$\alpha_x \sim \mathcal{N}\left(\mu_{\alpha_x} = 0, \sigma_{\alpha_x} = 1\right) \tag{5.5}$$

$$\beta_x \sim \mathcal{N}\left(\mu_{\beta_x} = 1, \sigma_{\beta_x} = 1\right) \tag{5.6}$$

and employing the BGLM specification:

$$p_t^{i,x} - p_t^{\text{US},x} = \alpha_x + \beta_x e_t^{i\text{US}} + \sigma_t^{i\text{US},x} \tag{5.7}$$

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 B Figures B.1 to B.14 for the various CPI bases and B.15, B.17, B.19 and B.21 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 $\sigma_t^{i\text{US,Big Macs}}$ 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

[7]The 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.

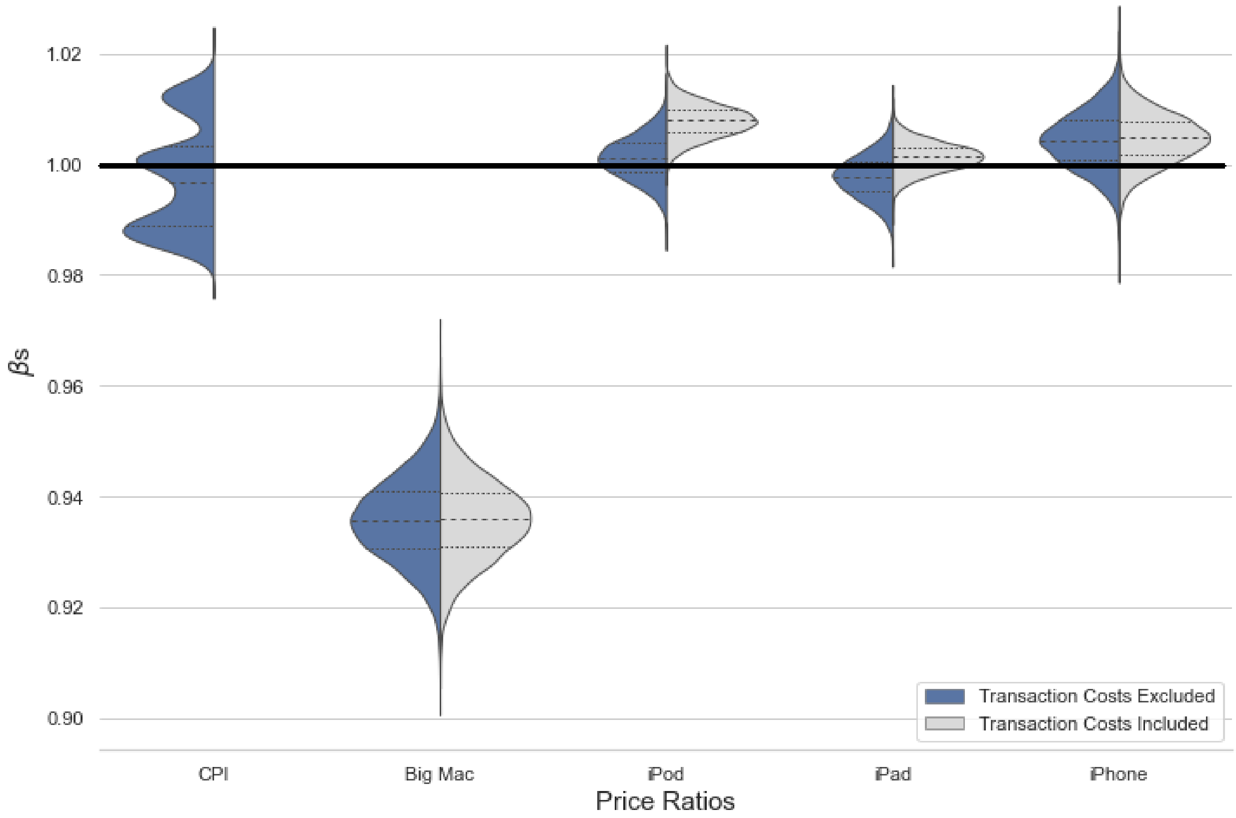
are notable. Meanwhile for iPods, iPads and iPhones these values are: 0.2019, 0.1682 and 0.1616 respectively, which is roughly *half* of the deviation from the BGLM compared to these derived from the BMI price measures. Third, in general, the coefficients for the maximum posterior estimates generally correspond with the coefficients from the regressions in Appendix A Tables A.1 and A.2. Finally, it again seems as though, the APPs adhere better to the notion of relative LOP; with their respective β_xs, 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 5.7 to account for these input costs by re-specifying the BGLM as:

$$p_t^{i,x} - p_t^{\mathrm{US},x} = \alpha_x + \beta_x e_t^{i\mathrm{US}} + \delta_{x1} \ln\left(\frac{1+\tau_t^{i,x}}{1+\tau_t^{\mathrm{US},x}}\right) + \delta_{x2} \ln\left(\frac{1+\iota_t^{i,x}}{1+\iota_t^{\mathrm{US},x}}\right) + \delta_{x3} \ln\left(\frac{\lambda_t^{i,x}}{\lambda_t^{\mathrm{US},x}}\right) + \sigma_t^{i\mathrm{US},x} \quad (5.8)$$

Once including for the effect of transaction costs in the various BGLM models (refer to Figures B.16, B.18, B.20, B.22), the posterior deviation for Big Macs (i.e. $\sigma_t^{i\mathrm{US,Big\ Mac}}$) declines only slightly to 0.35, while the comparable values for $\sigma_t^{i\mathrm{US,iPod}}$, $\sigma_t^{i\mathrm{US,iPad}}$ and $\sigma_t^{i\mathrm{US,iPhone}}$ 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 5.1 which illustrates — via the use of violin plots — the distributions of the MCMC generated β_xs for each of the price ratios). Overall, the β_xs 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 $\beta_{\mathrm{Big\ Mac}}$s does not include 'unity' in their distributions. Again, for the β_{CPI}s, 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.

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

Figure 5.1: Violin Plots of MCMC Generated βs



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 naught 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 B.23 and B.24 in Appendix B 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 βs still include 'one'.

Figure 5.2: Violin Plots of MCMC Generated αs

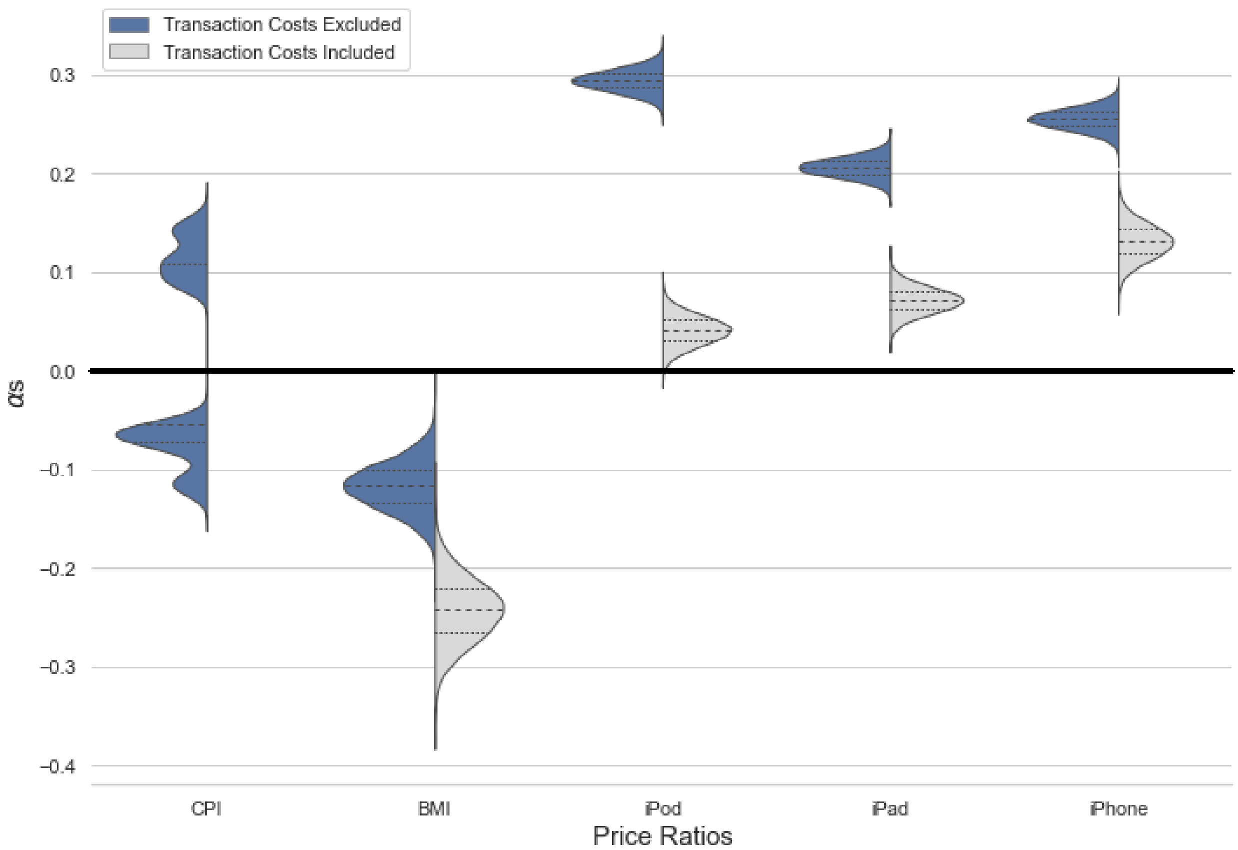
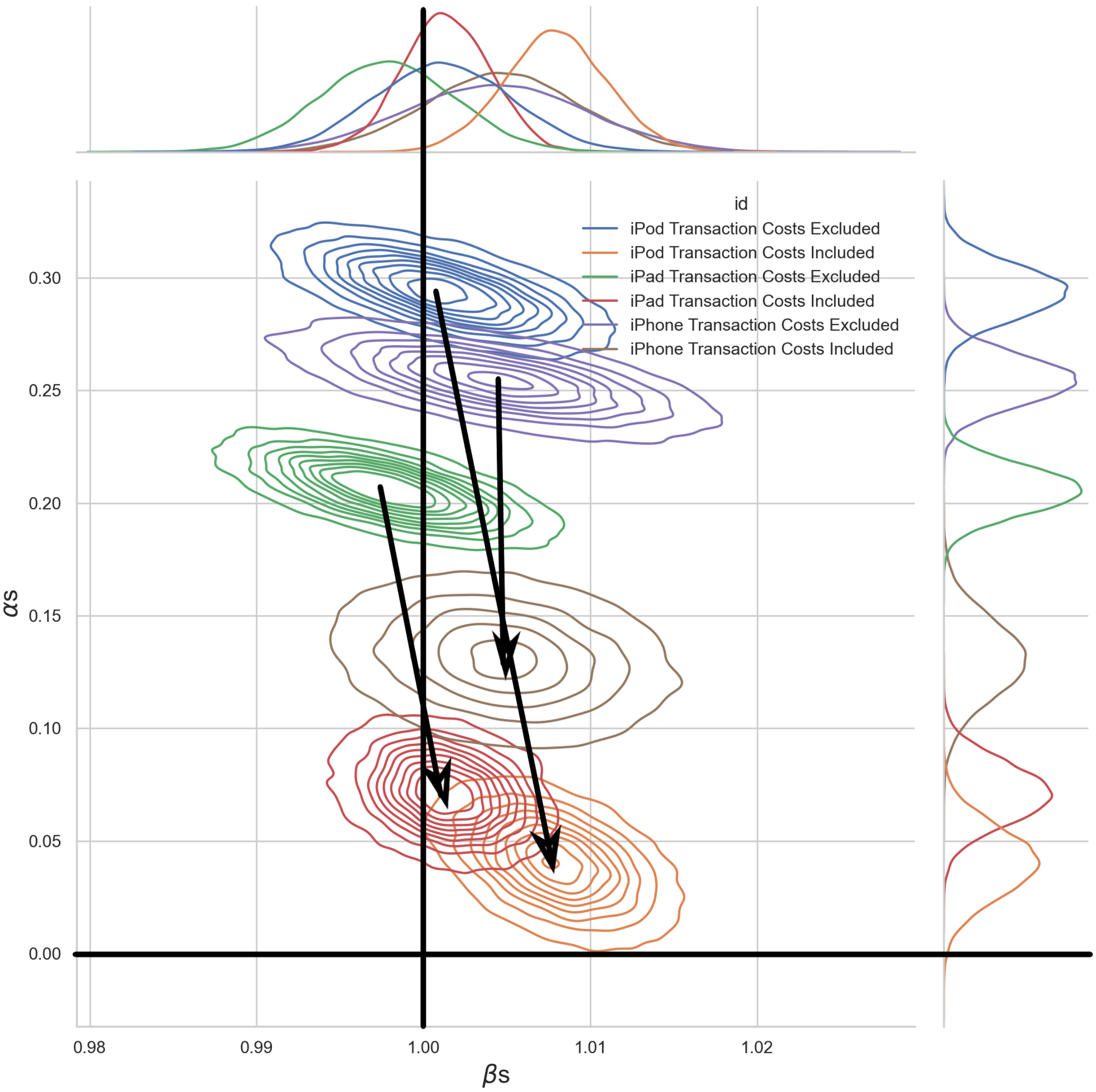


Figure 5.3 illustrates a joint kernel density plot of the MCMC generated α_xs and β_xs for the APPs. Again, this chart clearly illustrates how the β_xs are distributed around '1' both before and after including transaction costs, though the α_xs have shifted noticeably lower after transaction costs were accounted for.

Figure 5.3: Kernel Density Joint Plots of MCMC Generated αs and βs Prior- and Post-Transaction Costs



5.2 DYNAMIC ESTIMATIONS AND THE SPEED OF ADJUSTMENT

5.2.1 *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:

$$\Delta p_t^{i,x} - \Delta p_t^{\mathrm{US},x} = \beta_x \Delta e_t^{i\mathrm{US}} + \epsilon_t^{i\mathrm{US},x} \tag{5.9}$$

Equation 5.9 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 *et al.* (2012) on Big Macs). More specifically, we can formulate:

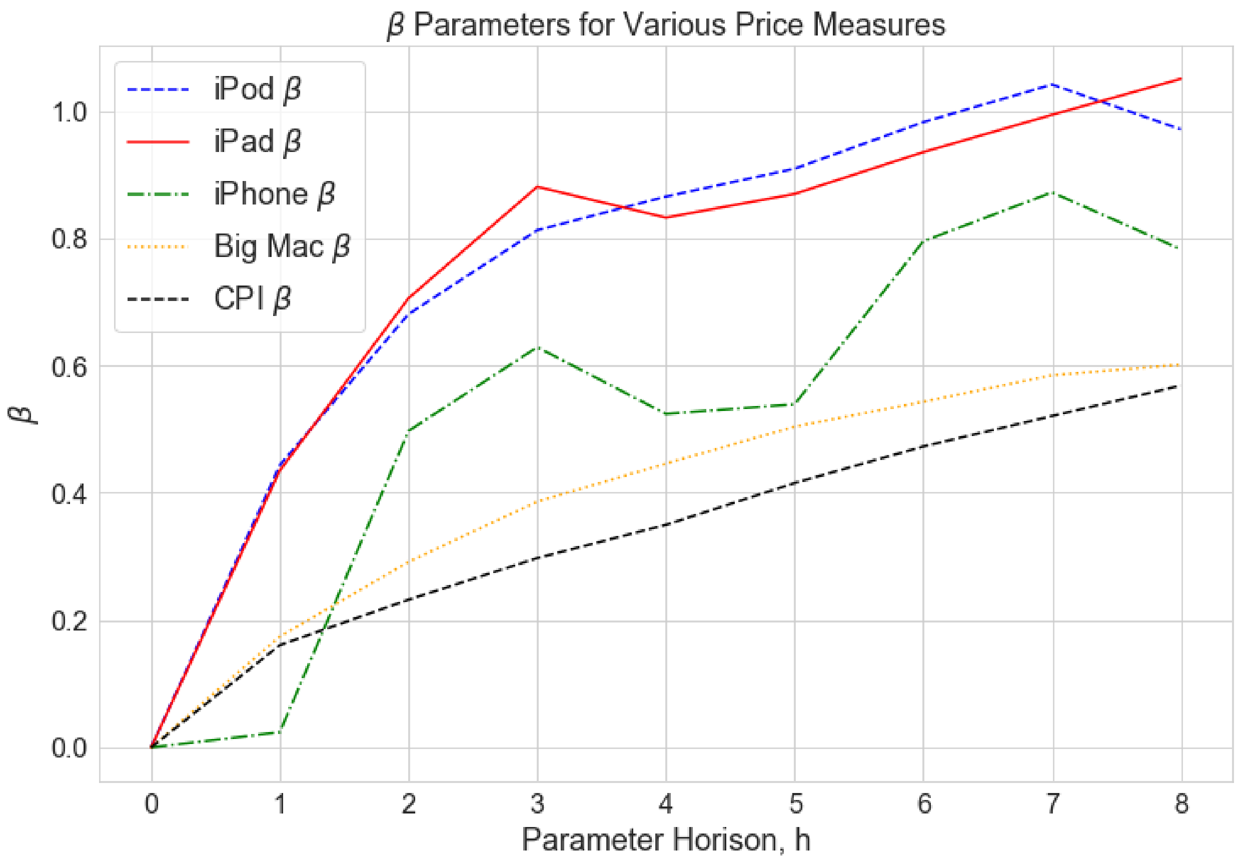
$$\Delta^{(h)} p_t^{i,x} - \Delta^{(h)} p_t^{\mathrm{US},x} = \beta_{h,x} \Delta^{(h)} e_t^{i\mathrm{US}} + \epsilon_t^{i\mathrm{US},x} \tag{5.10}$$

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 $\Delta^{(h)} e_t^{i\mathrm{US}} = e_t^{i\mathrm{US}} - e_{t-h}^{i\mathrm{US}}$. Equation 5.9 is thus simply Equation 5.10 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.

5.2.2 Results: *h* Period Analyses

Figures B.25 through B.29 in Appendix B 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 5.4 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.

Figure 5.4: APPs, Big Mac and CPI βs over h Period Changes



5.2.3 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:

$$q_t^{i\text{US},x} \equiv p_t^{i,x} - p_t^{\text{US},x} - e_t^{i\text{US}} = \epsilon_t^{i\text{US},x} \tag{5.11}$$

By calculating $q_t^{i\mathrm{US},x}$ 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.

5.2.4 Results: Real Exchange Rate Stationarity Panel Tests

Table 5.5 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 5.5 indicate that the RER deviations calculated from the APPs 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 *et al.* (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.

5.2.5 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

Table 5.5: Real Exchange Rate Unit Root Tests

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

Note: p-values in Parenthesis $\quad$ *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*

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 5.12 in the following AR(1) process:

$$\Delta q_t^{i\mathrm{US},x} = \rho_x q_{t-1}^{i\mathrm{US},x} + \epsilon_t^{i\mathrm{US},x} \tag{5.12}$$

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 $\hat{\rho}_x$ found to be closer to 0, the RER will appear to follow a random walk since the equation above will approximate $\Delta q_t^{i\mathrm{US},x} = \epsilon_t^{i\mathrm{US},x}$.

5.2.6 Half-life Analyses Results:

Table 5.6 shows the $\hat{\rho}_x$ estimates (as formulated in Equation 5.12) 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 $\hat{\rho}_{\text{CPI}}$s 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.

Table 5.6: Panel Half-Life Estimates

	$\Delta q_t^{i\text{US},x} = \rho_x q_{t-1}^{i\text{US},x} + \epsilon_t^{i\text{US},x}$				
$\hat{\rho}_x$:	CPI	Big Mac	iPods	iPads	iPhones
Pooled OLS	-0.0635 to -0.2117	-0.0771	-0.1649	-0.2984	-0.6040
Standard Error	(0.0181)*** to (0.0211)***	(0.0192)***	(0.0253)***	(0.0334)***	(0.0513)***
Half-life (Years)	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
Standard Error	(0.0270)***	(0.0447)***	(0.0505)***	(0.0528)***	(0.0649)***
Half-life (Years)	2.76	1.14	0.48	0.34	0.00

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

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. $P_t^{i,x_{\text{net}}}$) 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:

$$P_t^{i,x_{\text{net}}} = \frac{P_t^{i,x}}{(1+\tau_t^{i,x})(1+\iota_t^{i,x})} \tag{5.13}$$

From these *net* domestic prices, we can subsequently derive their associated *net* RERs, i.e. $\Delta q_t^{i\mathrm{US},x_{\mathrm{net}}}$. The half-lives estimated from these *net* relative price ratios are shown in Table 5.7. Interestingly, I 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 5.6. 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 5.7: Panel Half-Life Estimates on *Net* Price Ratios

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

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

CHAPTER 6

EXPLORING THE NONLINEARITY OF IPAD DERIVED REAL EXCHANGE RATE ADJUSTMENTS

This Chapter of the dissertation aims to discover whether real exchange rate adjustments exhibit nonlinear behaviour using the *high frequency* panel dataset. In other words, even though small real exchange rate deviations ($q_t^{ij,x} < |c_t^{ij}|$, i.e. deviations that are less than a certain 'band of no arbitrage') can take a long time to correct; it may well be that larger mispricings subsequently realise notably quicker adjustments. This is the basic premise of the stochastic LOP concept defined in Section 2.5.

In order to investigate this phenomenon logarithmic real exchange rates were compiled between 34 countries (i) and the United States (US) as the base country. That is $q_t^{i\mathrm{US},x}$ values are derived from the four different Apple iPad devices (x) on a weekly basis since the start of 2016 to end-2021 (i.e. using the *high frequency* dataset outlined in Section 4.3.3). On average, across all 35 countries and all four iPad varieties, the domestic prices of the devices changed fairly infrequently. More specifically, price changes were observed only about five times, on average, over the six-year period (i.e. price changes occurred slightly less than once per year). These averages however do not reflect the large dispersion between countries. For example, higher CPI inflation countries (e.g. Brazil, Mexico, Russia and Turkey) witnessed about twice the number of price changes compared to the other, lower inflation countries included in the dataset. In fact, the former four countries recorded almost eight price changes on average over the six-year period, compared to only about four price changes for the rest. Finally, price increases were observed more than twice as often as price decreases.

Figures 6.1 (a) to (d) utilises box plots to show the distributions of these real exchange rates for each country as compiled from the four different products. The average real exchange rate for each device over all the different countries and time periods t are illustrated as dotted vertical blue lines. Interestingly, all these mean product real exchange rates (i.e. average over country and time or $\bar{q}^x$s) for the different iPads are approximately 0.2. This signifies that the different devices cost, on average, 20% more in non-US countries. Meanwhile, the averages for the individual countries (i.e. $\bar{q}^{i\mathrm{US},x}$) are shown as white dots which are located inside each of the grey boxes in the different subplots. The boxes represent the inter-quartile range of real exchange rates observed for each country, while the vertical lines located inside each box represents the country median for each iPad.

6.1 BIAS ADJUSTED REAL EXCHANGE RATES

From the box plots in Figure 6.1, it becomes clear that there are frequent departures from the absolute LOP. What's more, the majority of $q_t^{i\mathrm{US},x}$s fluctuate substantially around their respective means. The vast majority of these country means are also notably larger than zero. The exceptions appear to be Canada, Hong Kong, Japan and to some extent, Malaysia. Meanwhile, the Brazilian real exchange rate is the most overvalued versus the greenback over the sample period. Also noteworthy is the persistence and consistency of these biases across the different devices.

t-value tests were conducted to investigate whether the means of the real exchange rates calculated for different countries for the four products are equal to zero at a 95% confidence level. It was found that for both iPad Pro Large and Small screen devices 30 out of the 34 countries had significant t-values for the country means, while for iPad Air and iPad Minis these averages were significant in 27 and 28 cases respectively out of 34 countries. Similar to the finding of Clements *et al.* (2012), when evaluating the real exchange rates derived from Big Macs, the real exchange rates obtained from iPad devices appear to be biased indicators of absolute currency values. As with the analyses performed in the literature, we can control for this bias by subtracting the sample means for each country. That is, the bias-adjusted real exchange rate can be calculated by obtaining:

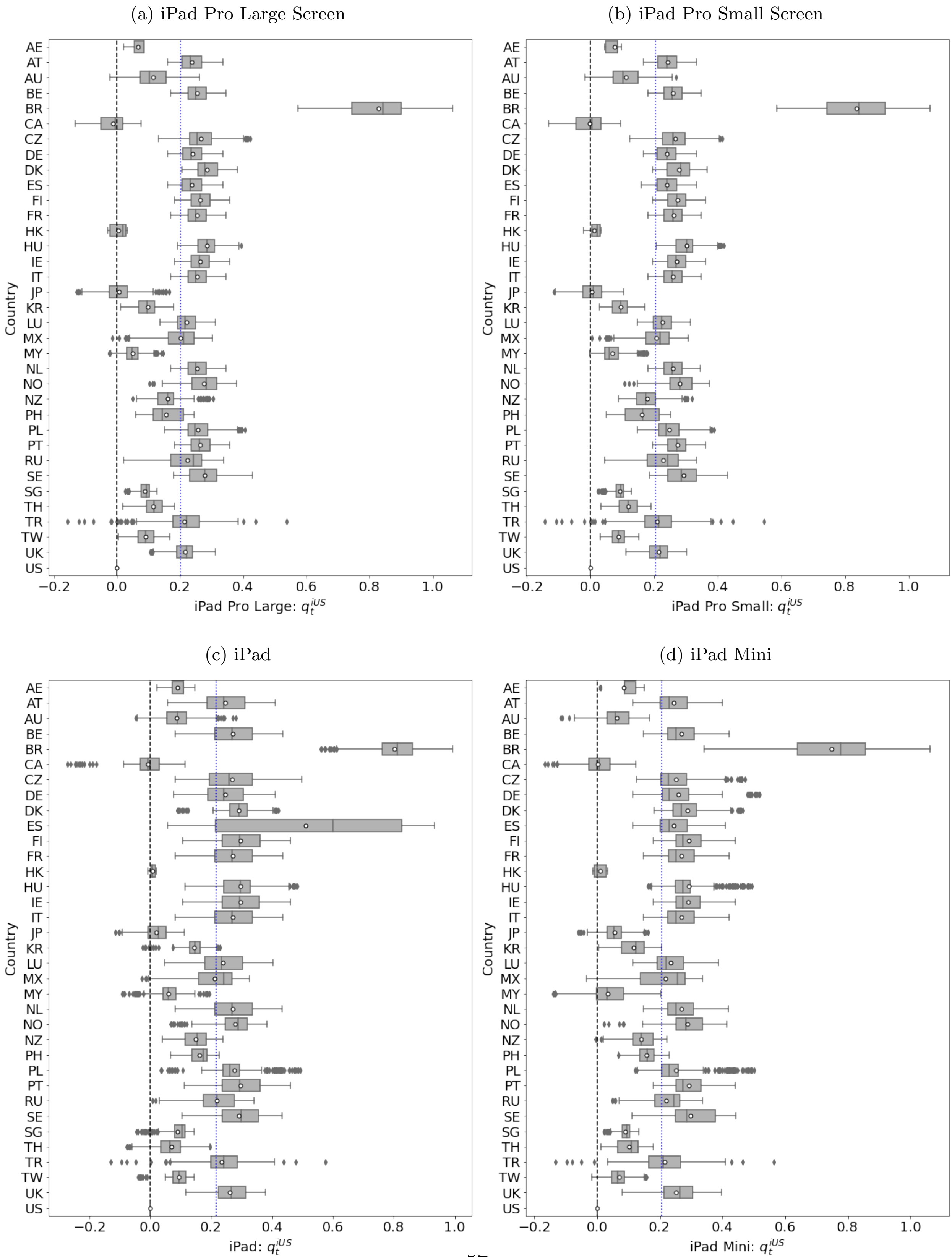
$$\tilde{q}_t^{i\mathrm{US},x} = q_t^{i\mathrm{US},x} - \bar{q}^{i\mathrm{US},x} \ , \tag{6.1}$$

where $\bar{q}^{i\mathrm{US},x} = 1/t \sum_t q_t^{i\mathrm{US},x}$ is the sample (country) mean. From this, the currency is over- (or undervalued) if $\tilde{q}_t^{i\mathrm{US},x} > 0$ ($\tilde{q}_t^{i\mathrm{US},x} < 0$).

6.2 REAL EXCHANGE RATE CONVERGENCE AND HALF-LIVES

In this section we'll evaluate both the persistence and nonlinearity of real exchange rate deviations as derived from the four iPad products. This is similar to the analyses conducted by Parsley and

Figure 6.1: Box Plots of Real Exchange Rates Derived From iPad Devices in 35 Countries from 2016 to 2021



Wei (2007) on Big Mac hamburgers. We'll first introduce the linear model to evaluate convergence and then expand this to nonlinear techniques. According to Rogoff (1996) and Obstfeld and Rogoff (2000), the PPP literature generally indicates a half-life speed of around three- to five years. To calculate the speed of convergence, one estimates $\hat{\rho}_d^{i\mathrm{US},x}$ in Equation 6.2 in the following AR(1) process:

$$\Delta^{(d)}\tilde{q}_t^{i\mathrm{US},x} = \rho_d^{i\mathrm{US},x}\tilde{q}_{t-d}^{i\mathrm{US},x} + \epsilon_t^{i\mathrm{US},x} \ , \tag{6.2}$$

Where $\Delta^{(d)}\tilde{q}_t^{i\mathrm{US},x} = \tilde{q}_t^{i\mathrm{US},x} - \tilde{q}_{t-d}^{i\mathrm{US},x}$ and $\tilde{q}_t^{i\mathrm{US},x}$ is the bias-adjusted real exchange rate. As discussed in Section 2.5, one can evaluate the persistence of real exchange rate deviations by analysing how any *initial* real exchange rate deviation (for example at time $t-d$) *subsequently* adjusts over period d. The respective price ratios' half-lives (in years) can then be derived by calculating: $(d/52)\log(0.5)/\log(1+\hat{\rho}_d^{i\mathrm{US},x})$. Since the difference periods are in weeks, the half-lives need to be adjusted by a factor of $d/52$ in order to convert to years. As is evident from this formula, the closer $\hat{\rho}_d^{i\mathrm{US},x}$ gets to -1, the shorter the estimated period half-life will be. Meanwhile, should $\hat{\rho}_d^{i\mathrm{US},x}$ found to be closer to zero, the real exchange rate will appear to follow a random walk since the equation above will approximate $\Delta^{(d)}\tilde{q}_t^{i\mathrm{US},x} = \epsilon_t^{i\mathrm{US},x}$. This model however enforces a hypothesis that real exchange rate adjustments are both continuous and of constant speed, irrespective of the size of the deviation from the LOP (Taylor *et al.*, 2001).

6.3 THE NONLINEARITY OF REAL EXCHANGE RATE ADJUSTMENTS

According to Taylor *et al.* (2001), the notion that real exchange rate adjustments may occur in a nonlinear fashion dates back at least to Heckscher (1916) and Cassel (1918).[1] A few publications since that have investigated the nonlinearity of real exchange rates include: Obstfeld and Taylor (1997), Taylor *et al.* (2001), Chortareas *et al.* (2002), O'Connell and Wei (2002), Sarno *et al.* (2004), Cushman and Michael (2011), Chen *et al.* (2019) and Drissi and Boukhatem (2020). The literature expanded to focus on the nonlinearity of real exchange rate adjustments because only using single parameter estimates incorrectly combines different regimes. For example, a single

[1]Heckscher (1916) argued that transport costs may see price discrepancies arising without precipitating goods arbitrage.

adjustment coefficient does not distinguish between the low speed of convergence for deviations smaller than the arbitrage costs as well as faster convergence for larger deviations (Parsley and Wei, 2007, p. 1346). In other words, simply using linear estimates result in upwardly biased half-lives.

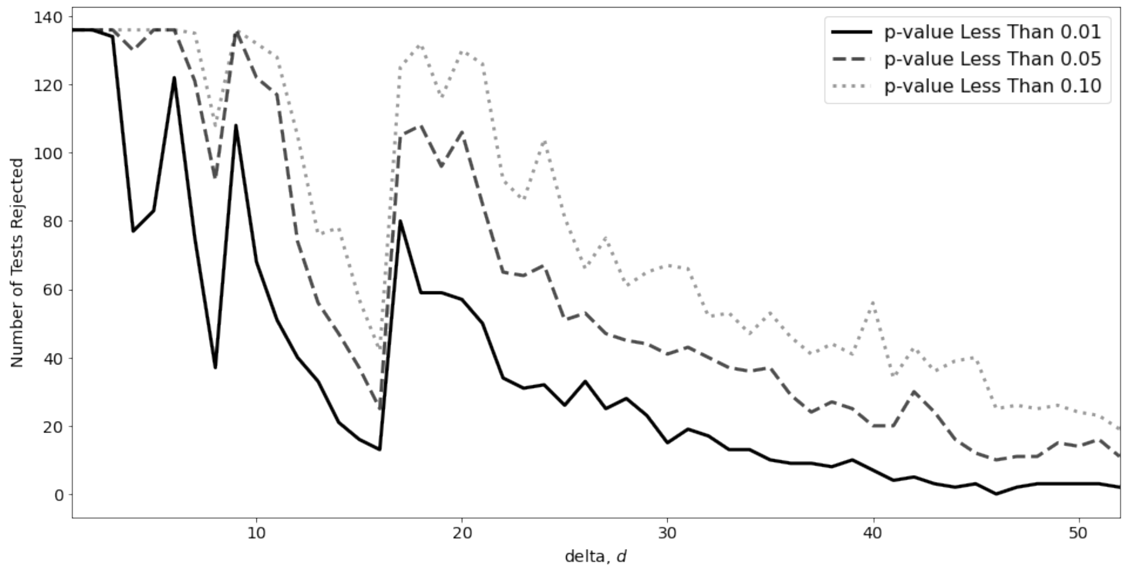
As a result and as outlined by the stochastic LOP or PPP model in Section 2.5, the real exchange rate, when within a certain (limited) distance from parity, may appear to follow a random walk. In other words, the real exchange rate may not display any convergence tendencies and only becomes mean-reverting once a specific 'threshold' is breached that gives rise to the marginal benefit of arbitrage exceeding the marginal cost thereof. Once this threshold level is crossed, the real exchange rate's gravitational pull toward parity may become increasingly strong as the distance from parity increase. This dissertation employs a variety of techniques to investigate the possibility that real exchange rate adjustments behave in a nonlinear fashion. These includes: 1) locally-weighted scatterplot smoothing (LOWESS), 2) threshold regressions (TARs) and 3) piecewise regression models.

6.3.1 Panel and Country Unit Root and Co-integration Tests

Numerous panel statistic as well as individual country time series unit root tests were performed to test the iPad-derived real exchange rates (i.e. $q_t^{i\mathrm{US},x}$s). Contrary to the large number of studies investigating real exchange rate unit root behaviour, we were in most cases able to reject the unit root null hypothesis at conventional significance levels. In fact, the null hypothesis that each of the four iPad-derived real exchange rate panels contained a unit root were rejected at a 90% confidence level when utilising various panel unit root tests. These included the Levin-Lin-Chu, Harris-Tzavalis, Breitung, Im-Pesaran-Shin and Fischer-type (which includes the Augmented Dickey-Fuller and Phillips-Peron) tests. At a 95% confidence level we could reject 23 out of the 24 null hypotheses (i.e. six statistical tests across four product panels) that the data contains a unit root. We could not however reject the Hadri LM stationarity tests that *all* panels are stationary for the individual country $q_t^{i\mathrm{US},x}$s. The same panel autocorrelation tests were also performed on the real exchange rate *changes* for a subset of deltas (i.e $\Delta^{(d)}q_t^{i\mathrm{US},x}$ for $d = 12, 24, 36, 48$). However, as the time difference d increased, fewer null hypotheses of 'no panel unit root' could be rejected. Specifically for $d = 12$, we were able to reject all 24 hypotheses tests of no unit root at a 90%

confidence level. Meanwhile, when d increased to 24, only 21 out of 24 hypotheses were rejected, with $d = 36$ this figure declined to 20 rejections. For $d = 48$ only about half of the panels were found not to contain a unit root.

Figure 6.2: Number of Augmented Dickey Fuller Unit Root Tests Rejected (out of 136 Country Time Series) over Various Significance Levels Calculated on $\Delta^{(d)}q_t^{i\mathrm{US},x}$s Over Deltas ($d$)



We also performed ADF unit root tests on all the individual country real exchange rate time series.[2] At a 10% significance level, we could only reject 51 out of the 136 hypotheses tests (we tested a number of time series based on four devices across 34 countries) that these individual time series *did not* contain unit roots. My analyses however primarily involved investigating the *change* in real exchange rates. Consequently, we also performed the ADF tests on the $\Delta^{(d)}q_t^{i\mathrm{US},x}$s for each country over $d = 1, 2, ..., 52$. The finding was similar to that of Taylor *et al.* (2001), the use of differences on the real exchange rate time series appear to induce stationarity. The results of these hypotheses tests are plotted in Figure 6.2. Each line plot represents the number of null hypotheses that were rejected (out of a total number of 136) that each country real exchange rate change, at a specific d (i.e. $\Delta^{(d)}q_t^{i\mathrm{US},x}$), contained a unit root. For small period changes, for example $d < 30$), most of the hypotheses were generally rejected at a 90% confidence level that the individual country real exchange rate changes contained unit roots. Most time series however contained unit roots at

[2]These tests were performed in Python using Seabold and Perktold (2010). The p-values were obtained through regression surface approximation from MacKinnon (1994), but using the updated 2010 tables.

larger deltas. One should therefore keep in mind that the estimates in my analyses at larger ds may be less efficient. That said, Taylor *et al.* (2001) demonstrated via Monte Carlo simulations that standard univariate unit root tests have very low power to reject a false null hypothesis of unit root behaviour when the true model is nonlinearly mean reverting.

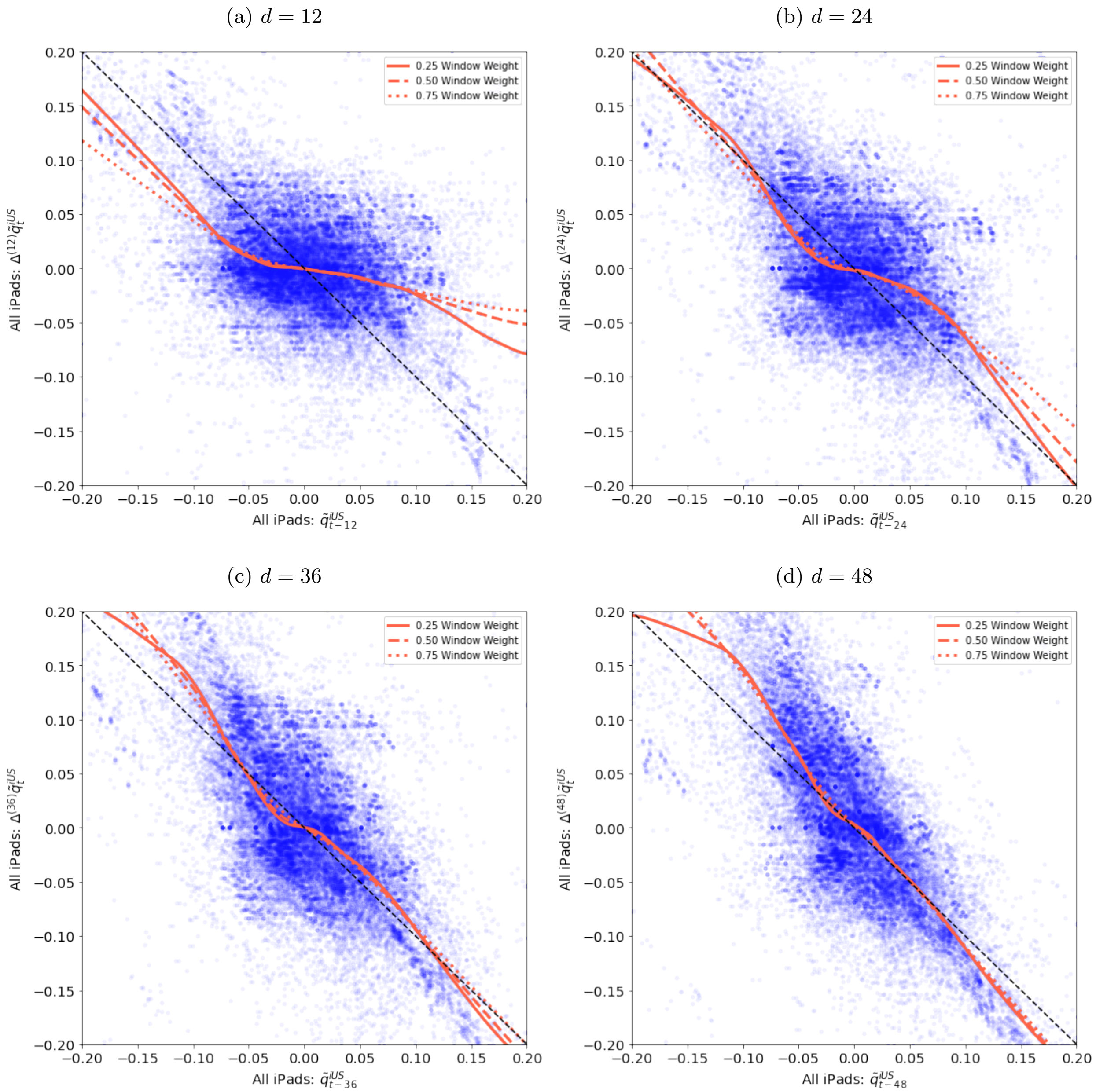
6.3.2 Locally-Weighted Scatterplot Smoothing

The first method used to investigate the nonlinearity of real exchange rate adjustments is locally-weighted scatter-plot smoothing (LOWESS or LOESS). This is a non parametric regression method that smooths data by slicing it into smaller sections. More specifically, the technique attempts to fit linear models for datapoints based on local, or nearby, linear fits.[3] The Figures in 6.3 (a) to (d) illustrates the LOWESS scatter-plot fit for the sample mean adjusted lagged real exchange rates derived from all the iPad devices (i.e. $\tilde{q}_{t-d}^{i\text{US},x}\ \forall\ x$) on the x-axis versus the subsequent d period change in the real exchange rates (i.e. $\Delta^{(d)}\tilde{q}_{t}^{i\text{US},x}$ for $d = 12, 24, 36, 48$) on the y-axis. Figures B.33 to B.36 shows the LOWESS plots for the four individual iPad models. The various datapoints are semi-transparent in order to avoid excessive overlapping of observations. This also helps distinguish the distribution of the data. The analyses incorporated different proportional window weights for each estimation, including 0.25, 0.5 and 0.75 which are represented by the solid, dashed and dotted lines respectively. A 45°-line is also included in each scatter-plot as a reference if the subsequent real exchange rate adjustments occur proportionally to each initial real exchange rate deviations. To make the charts more directly comparable, both the x- and y-axes are cut off at -0.2 and 0.2 respectively.

Several interesting patterns emerge from LOWESS analyses. First, as the delta, d, increases, the datapoints appear to converge to the 45°-line. This means that as the window length is increased, the initial deviations are a better indicator of the subsequent real exchange rate adjustment we can expect. Second, there appears to be a valuation 'threshold effect' for real exchange rate deviations. That is, when the valuation deviations are small (i.e. 'close' to zero on the x axis), the subsequent adjustment to eliminate these deviations are basically insignificant. This effect is more prominent over smaller difference periods d. This is evident by the flatter 'inner' slope of the LOWESS

[3]The LOWESS estimations were performed using Python with the statsmodels package by Seabold and Perktold (2010) and the Figures are rendered using Matplotlib by Hunter (2007).

Figure 6.3: LOWESS Scatterplots on All iPad Derived Lagged Real Exchange Rates vs Subsequent Change in Real Exchange Rates Over Different Horizons (d)



estimates around zero. In other words, the mean reverting nature of real exchange rates are noticeably *less* when the associated valuation discrepancy is also *small*. This again supports the notion of stochastic law of one price. Third, after about 12- to 24-weeks, it appears as though the outer deviations (or 'valuation wings') have converged to the 45°-line (i.e. the deviations and subsequent corrections are equivalent).

Meanwhile, inside the 'thresholds', the regression slope has now become slightly negative. This again supports the finding that real exchange rate half-lives are significantly shorter than the literature's three- to five-years; at least when valuation discrepancies are large enough. Meanwhile, when the valuation discrepancies are small, real exchange rate adjustments can take a longer and may even appear to follow a random walk. Fourth, the valuation thresholds or 'area of no arbitrage' appears to decrease as the delta increases. Finally, it also appears as though negative real exchange rate deviations are more inclined to subsequently 'overshoot' than do positive real exchange rate deviations (the LOWESS regressions line for $d > 30$ is parallel to, but *above* the 45°-line).

In summary, it appears that smaller real exchange rate deviations over shorter time differences d can take notably longer to dissipate, while large deviations tend to disappear even over short periods, but even more so as these differences increase. Even though the LOWESS analyses is visually and intuitively appealing, they are not directly interpretable. In other words, one still can't exactly pinpoint the exact values of these potential valuation thresholds nor the slope of the inner or outer adjustment parameter estimates. In the remaining sections other statistical techniques are employed to derive estimations for these.

6.3.3 Threshold Regression Models

A threshold regression is an extension of the linear model by allowing estimates to vary across regions. These 'regions' are identified by threshold variable(s) separating the areas.[4] These models are superior at potentially capturing breaks, asymmetries or change points observed in many macroeconomic time series. What's more, one can either specify a known number of thresholds or allow a measure like the Bayesian information criterion (BIC) being minimised to specify the

[4] The Threshold Autoregression (TAR) was initially proposed by Tong (1980). Also refer to Tong (2012). For a survey of threshold regression models in economics, refer to Hansen (1997).

quantity of these breaks. These methods have more recently become popular in order to model the potential nonlinear behaviour of real exchange rates (Obstfeld and Taylor, 1997; O'Connell, 1998; Baum *et al.*, 2001; Taylor, 2001; O'Connell and Wei, 2002; Sarno *et al.*, 2004; Smallwood, 2008; Chen *et al.*, 2019; Vo and Vo, 2022).[5] Formally, we can consider a threshold regression in a similar fashion to the way we evaluated the nonlinearity of real exchange rates via the LOWESS method in Section 6.3.2. Specifically, the subsequent d-period change in the real exchange rate derived from product x between countries i and j can be formulated by equations in two regions split by the threshold parameter $c_d^{ij,x}$. Mathematically this can be represented as:

$$\Delta^{(d)}\tilde{q}_t^{ij,x} = \begin{cases} \rho_{1,d}^{ij,x}(|\tilde{q}_{t-d}^{ij,x}| - c_d^{ij,x}) + \epsilon_t^{ij,x}\Phi[|\tilde{q}_{t-d}^{ij,x}| > c_d^{ij,x}] \\ \rho_{0,d}^{ij,x}|\tilde{q}_{t-d}^{ij,x}| + \epsilon_t^{ij,x}\Phi[|\tilde{q}_{t-d}^{ij,x}| \leq c_d^{ij,x}] \end{cases} \tag{6.3}$$

The lagged explanatory variables (in this case lagged real exchange rate) have different parameters depending on the region applicable to the equation. The $\Phi[.]$ represents an indicator function whether or not the equation applicable is within the threshold (i.e. $\leq c_d^{ij,x}$) or outside of it (i.e. $> c_d^{ij,x}$). After specifying the equation, a grid search was performed to find both the potential thresholds as well as the applicable parameter estimates.

6.3.3.1 Panel Threshold Regressions

The output of the fixed effect panel threshold regressions are shown in Table 6.1.[6] Again, the United States (US) was used as the base country j = US. From this analysis, several points of interest emerge. First, a 'threshold effect' again appears to emerge for the real exchange rate adjustments. The thresholds also tend to vary by device and difference period (or delta, d). For example, the average threshold across the four devices when $d = 12$ is 11.5%, while only 6% when $d = 24$. Overall, for three of the devices it appears as though the thresholds $c_d^{i\text{US},x}$ tend to decline (at least initially) as d increase. This makes sense since there most likely exist various lags and information

[5]Other nonlinear techniques to evaluate RER adjustments that are also explored by some of these papers include Smooth Transition Autoregressive (STAR), Exponential STAR (ESTAR) and logistic STAR (LSTAR) models. These allow for smooth transitions between regimes. An alternative suggestion to these approaches has been to use nonlinear Vector Error Correcting (VEC) models and threshold co-integration analyses. Overall, the literature mentioned generally appears to be in agreement that RERs adjust in a nonlinear fashion. I have not discovered any papers evaluating the nonlinearity of product-derived RERs.

[6]The panel Threshold regressions were performed by using Stata's fixed effect panel model 'xthreg' and are based on the method proposed by Hansen (1999).

asymmetries before arbitrage forces can kick in, which implies as more time passes, the likelier even smaller deviations will be eliminated.

Second, especially over smaller difference periods (ds), the inner adjustment estimates (i.e. $\hat{\rho}_0$) are only about one third of the outer regressive parameters (i.e. $\hat{\rho}_1$). Accordingly, the derived half-lives of the inner estimates also tend to be notably longer than in the outer regimes. Again, faster adjustments for larger deviations are supportive of the stochastic LOP theory. Third, as the time difference (d) increase, *both* the inner and outer adjustment parameters tend to decline, or equivalently, the half-lives tend to decrease. When the difference window reaches 36 weeks, the half-lives of the outer parameters for three of the four Apple devices are approximately zero. This implies that larger deviations are eliminated within 36 weeks. At the same delta, the half-lives inside the thresholds (deviations that are on average less than 9.6% across all the devices) still record half-lives close to six months on average. Fourth, the panel TAR models' fit appear to improve as the time difference increase. These findings also support the observations from the LOWESS analyses.

Finally, the half-lives in both the inner and outer thresholds are significantly shorter than the literature's finding of 'three to five years'.[7] In fact, even over shorter deltas (or time differences), the half-lives derived for the outer thresholds are merely between 0.16 to 0.26 years. Also, by using a higher frequency database one can delve into notably more detail regarding real exchange rate adjustments and perform more analyses without losing too much degrees of freedom on the dataset. More detail is provided by also evaluating some of the findings emerging from the evaluation of individual countries.

6.3.3.2 Individual Country Threshold Regressions

Threshold regressions were performed on all the *individual* countries over different deltas. The output from these regressions are summarised (i.e. the various countries' parameter means and medians) in Table 6.2. All of the individual country and product regressions are recorded in Appendix A Tables B.1 to B.16. For these regressions the Bayesian Information Criterion (BIC) was used to determine both whether a threshold exists, and if that optimal threshold was found,

[7]Refer to Rogoff (1996) for a meta study on adjustment speeds and half-lives captured by the literature. One of the findings was that the speed of convergence to PPP is extremely slow, with deviations appearing to damp out at a rate of only 15% per year, consistent with half-lives of three to five years.

Table 6.1: Panel Threshold Regression Persistence Estimates

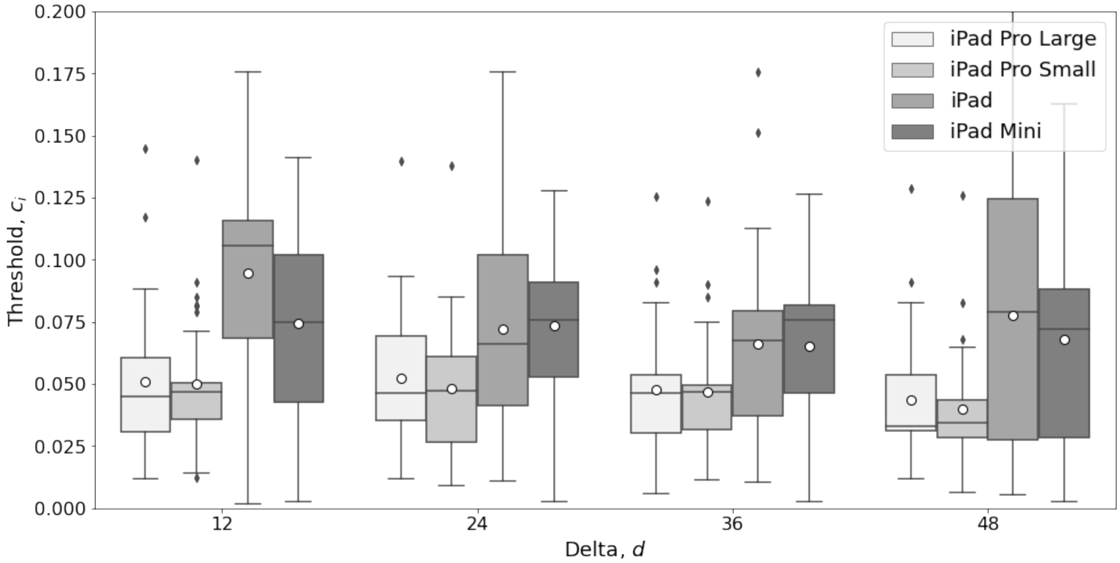
	Panel Threshold Regressions Over Different Devices and Deltas								
Product	Delta d	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$	Overall R^2
iPad Pro L	12	-0.332	(0.009)***	-0.643	(0.017)***	0.124	0.40	0.16	0.22
iPad Pro S	12	-0.321	(0.009)***	-0.582	(0.017)***	0.124	0.41	0.18	0.20
iPad	12	-0.174	(0.013)***	-0.460	(0.008)***	0.098	0.84	0.26	0.26
iPad Mini	12	-0.186	(0.010)***	-0.481	(0.010)***	0.113	0.78	0.24	0.20
Average	12	-0.253	(0.010)	-0.541	(0.013)	0.115	0.61	0.21	0.22
iPad Pro L	24	-0.401	(0.023)***	-0.770	(0.011)***	0.045	0.63	0.22	0.37
iPad Pro S	24	-0.433	(0.022)***	-0.738	(0.011)***	0.048	0.56	0.24	0.35
iPad	24	-0.168	(0.024)***	-0.658	(0.009)***	0.067	1.74	0.30	0.37
iPad Mini	24	-0.287	(0.018)***	-0.749	(0.011)***	0.080	0.94	0.23	0.34
Average	24	-0.322	(0.022)	-0.729	(0.010)	0.060	0.97	0.25	0.36
iPad Pro L	36	-0.733	(0.024)***	-1.055	(0.011)***	0.046	0.36	0	0.51
iPad Pro S	36	-0.685	(0.027)***	-1.023	(0.011)***	0.043	0.42	0	0.49
iPad	36	-0.839	(0.011)***	-0.556	(0.016)***	0.215	0.26	0.59	0.43
iPad Mini	36	-0.485	(0.020)***	-1.000	(0.012)***	0.077	0.72	0.06	0.46
Average	36	-0.685	(0.021)	-0.908	(0.013)	0.095	0.44	0.16	0.47
iPad Pro L	48	-0.764	(0.040)***	-1.184	(0.011)***	0.031	0.44	0	0.58
iPad Pro S	48	-1.233	(0.013)***	-1.041	(0.017)***	0.087	0	0	0.59
iPad	48	-1.100	(0.012)***	-0.539	(0.014)***	0.168	0	0.83	0.52
iPad Mini	48	-1.158	(0.012)***	-0.781	(0.022)***	0.172	0	0.42	0.56
Average	48	-1.064	(0.019)	-0.886	(0.016)	0.114	0.11	0.31	0.56

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

it is reported in the table under the c_i parameter. For the vast majority of countries and deltas, thresholds seem to exist for real exchange rate adjustments.

Figure 6.4 illustrates, via the use of box plots, the ranges of the derived thresholds for the various devices over different deltas. It appears that the thresholds can actually vary notably for the different countries and devices. For example, for both iPod Pro Large Screen and Small screen devices the thresholds average around 5% when $d = 12$ and declines to around 4% when d reaches 48. For these devices, the inter-quartile ranges of these $\hat{c}_d^{iUS,x}$s over the different countries are fairly small; i.e. approximately two to three percentage points. Meanwhile, the average threshold levels for the two cheaper variants, the iPads and iPad minis, are found to be notably larger and more

Figure 6.4: Box Plots of Country Thresholds $c_d^{i\text{US}}$ from TAR Estimates for the Different Devices over Various Deltas (d)

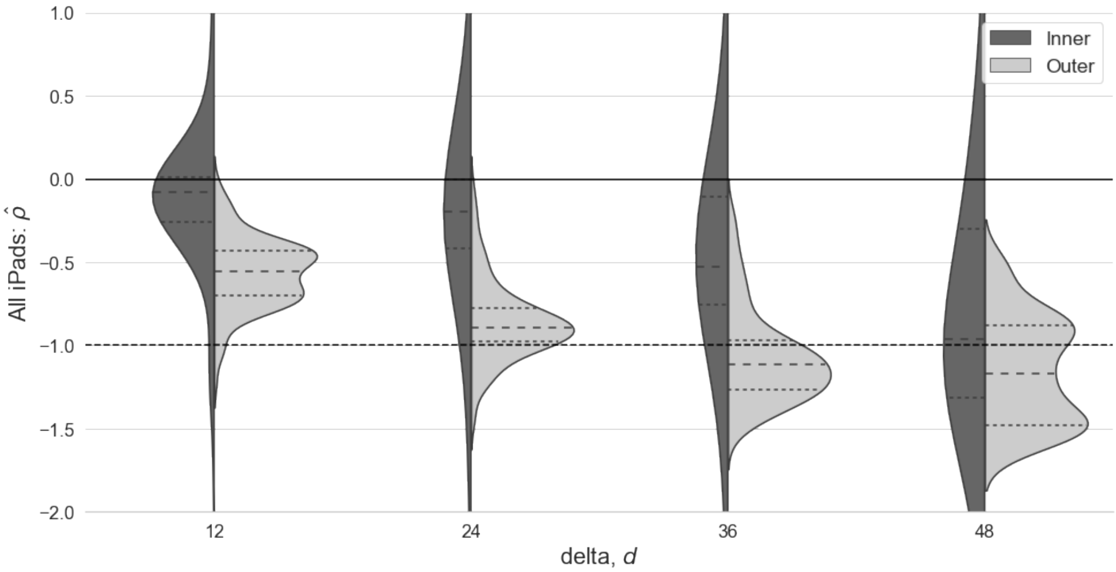


varied. For example, for these two devices the estimated thresholds are 9.5% and 7.4% respectively when $d = 12$ while only declining to 7.8% and 6.8% each when the time difference reaches almost one year (or more precisely 48 weeks). It does however make sense that the thresholds for the cheaper devices should be larger.[8] If several of the transaction costs (for example transportation, etc) are fixed — and assuming they don't vary notably between these different variants — then larger real exchange rate deviations are consequently required on lower priced goods before these fixed costs are offset enough for the arbitraging forces to kick in. Also, since there are various lags and rigidities inhibiting arbitrage, it also seems appropriate that the thresholds tend to decline as d increase. In other words, given the same initial deviation, when evaluated over a longer timeframe d, is more likely to be eliminated.

Next, Figure 6.5 employs violin plots to show the distributions for the 'inner' $\hat{\rho}_0$ and 'outer' $\hat{\rho}_1$ estimates. Again, as was found with the panel threshold regressions, the $\hat{\rho}_1$s are notably *smaller* than the $\hat{\rho}_0$s. This again implies *shorter* half-lives when the initial deviations exceed the various thresholds $c_d^{i\text{US}}$. The threshold effect also again tends to decrease as d increases (i.e. both the inner and outer parameter estimates converge, at least to some extent, as the time difference lengthens).

[8]From Figure 4.4 which plots the converted USD price of the various devices over time, it is clear that the iPads and iPad Minis tend to cost less than half of the iPad Pro devices.

Figure 6.5: Violin Plots of Inner $\hat{\rho}_0$ and Outer $\hat{\rho}_1$ TAR Estimates for all Devices over Various Deltas (d)



What's more, the outer coefficients are fairly stable (i.e. narrowly distributed) across the different countries and time differences, especially compared to the $\hat{\rho}_0$s which appear notably more volatile and have a wider distribution across the different deltas. Also noteworthy is that one observes non-mean reverting real exchange rates (i.e. $\hat{\rho}_0$s that are larger or equal to zero) only for the inner parameter estimates. In other words, in several cases when the real exchange rate deviations are small, they do not mean revert but sometimes appear to follow a random walk. In these cases, the half-lives are infinite. In the other cases, pertaining to the inner threshold, they do mean revert, but at noticeably slower speeds than in the outer threshold regions. Meanwhile, in the outer thresholds, the real exchange rates are almost always mean reverting. Also, real exchange rate adjustment speeds in the outer thresholds are generally significantly quicker and the half-lives are shorter.

For example, taking the 99% confidence bands for each country's inner and outer adjustment estimates over the various devices and deltas, it was found that for 242 out of the 565 (or 42%) threshold regressions, the $\hat{\rho}_0$s included zero. Meanwhile, only four out of the 510 regressions confidence bands for $\hat{\rho}_1$s, or less than 1% of the number of regressions, included zero.[9] This again

[9]There are 565 threshold regressions in total, but the Bayesian Information Criterion found that only 510 of these contained thresholds.

validates the stochastic LOP that for several countries small real exchange rate deviations either do not correct (i.e. follow a random walk), or they take notably longer to adjust. Large deviations however tend to quickly mean revert.

Next, both the $\hat{\rho}_0$s and $\hat{\rho}_1$s decline (or equivalently, the half-lives decrease) as the delta increases. In fact, when d reaches 36, almost three quarters of the outer adjustment coefficients tend to be smaller than -1. This either implies negligible half-lives, or that *complete convergence* for the vast majority of countries occurs within 36 weeks. Again, real exchange rate convergence (at least for ones derived from iPads) appears to be notably quicker than the literature's finding that half-lives are around three- to five years. Finally, after around $d = 36$, it appears as though the $\hat{\rho}_1$s reached their optimum adjustment, and the subsequent coefficients estimated at $d = 48$ become somewhat more varied or less concentrated around the median. Overall, from the regression estimates, there again appears to be strong support that the 'stochastic LOP' holds.

6.3.3.3 Threshold Levels and Transaction Costs

According to several authors, frictions due to transaction costs and uncertainties are responsible for the resulting thresholds that inhibits real exchange rate adjustment (Obstfeld and Taylor, 1997; Baum *et al.*, 2001; Taylor *et al.*, 2001; O'Connell and Wei, 2002; Chari *et al.*, 2002; Sarno *et al.*, 2004; Chen *et al.*, 2019; Drissi and Boukhatem, 2020). These transaction costs include ones that can be measured, for example tariffs or non-tariff barriers and different local tax rates on products; as well as frictions that are more difficult to quantify: for example information costs or lack of labour mobility (Rogoff, 1996). As explored in Section 4.3.4, one of the main benefits of using Apple devices in a LOP analyses is that one is able to control for a notable amount price heterogeneity, specifically regarding the transaction costs embedded in these devices' prices. One of these 'input costs' controlled for, is that of 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 in this dissertation. The exact week any VAT or GST rate was changed from 2016 to 2021 was recorded in the dataset (KPMG, 2016-2022). For the United States, the average tax rate on of all the states were used, excluding Puerto Rico.[10]

[10]Also refer to Section 4.3.4 for more details on the transaction costs database that was compiled.

Figure 6.6: Violin Plots of Inner $\hat{\rho}_0$ and Outer $\hat{\rho}_1$ TAR Estimates for Individual Devices over Various Deltas (d)

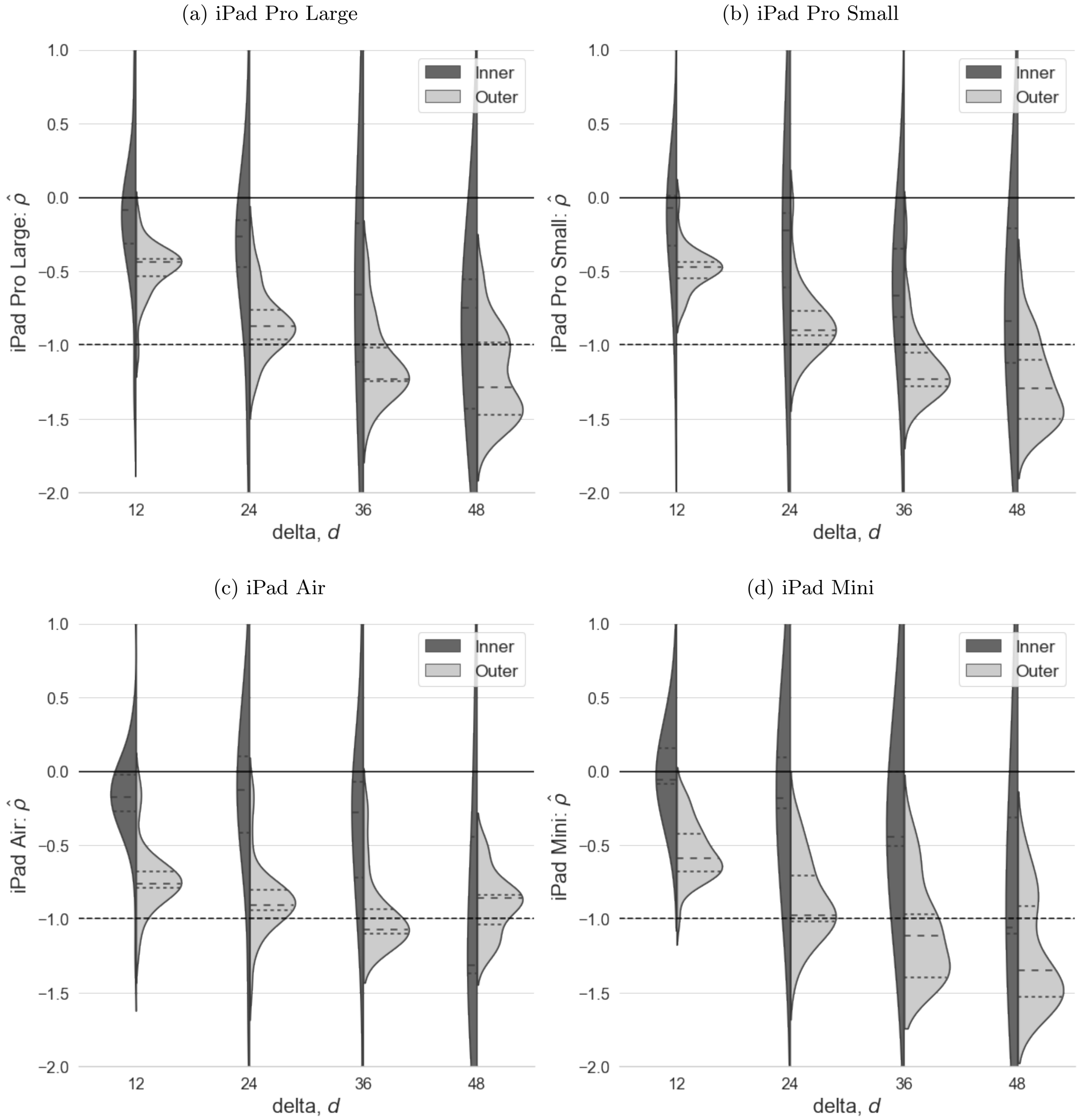


Table 6.2: Summary Statistics of Country Threshold Regression Persistence Estimates

	Averages of Country Estimates, Tables B.3 to B.16							
Product	Delta d	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
iPad Pro Large	12	-0.104	(0.113)	-0.483	(0.051)***	0.051	1.454	0.243
iPad Pro Small	12	-0.108	(0.138)	-0.481	(0.054)***	0.050	1.396	0.244
iPad	12	-0.154	(0.076)**	-0.723	(0.048)***	0.095	0.957	0.124
iPad Mini	12	0.152	(0.115)	-0.543	(0.050)***	0.074	∞	0.204
iPad Pro Large	24	-0.250	(0.139)*	-0.852	(0.063)***	0.053	1.112	0.168
iPad Pro Small	24	-0.609	(0.233)***	-0.842	(0.064)***	0.048	0.340	0.173
iPad	24	-0.302	(0.124)**	-0.869	(0.052)***	0.072	0.888	0.158
iPad Mini	24	0.214	(0.196)	-0.876	(0.059)***	0.073	∞	0.153
iPad Pro Large	36	-0.827	(0.198)***	-1.113	(0.064)***	0.048	0.273	0
iPad Pro Small	36	-0.758	(0.184)***	-1.130	(0.068)***	0.047	0.338	0
iPad	36	-0.408	(0.124)***	-0.970	(0.054)***	0.066	0.916	0.137
iPad Mini	36	-0.012	(0.180)	-1.084	(0.063)***	0.065	39.946	0
iPad Pro Large	48	-0.853	(0.169)***	-1.208	(0.063)***	0.043	0.334	0
iPad Pro Small	48	-0.738	(0.236)***	-1.262	(0.064)***	0.040	0.477	0
iPad	48	-0.780	(0.221)***	-0.897	(0.063)***	0.078	0.423	0.281
iPad Mini	48	-0.395	(0.199)**	-1.238	(0.067)***	0.068	1.274	0
	Medians Country of Estimates, Tables B.3 to B.16							
Product	Delta d	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
iPad Pro Large	12	-0.088	(0.073)	-0.435	(0.050)***	0.045	1.726	0.280
iPad Pro Small	12	-0.075	(0.066)	-0.472	(0.052)***	0.047	2.052	0.250
iPad	12	-0.173	(0.058)***	-0.759	(0.046)***	0.106	0.842	0.112
iPad Mini	12	-0.056	(0.066)	-0.587	(0.052)***	0.075	2.750	0.181
iPad Pro Large	24	-0.264	(0.094)***	-0.870	(0.064)***	0.046	1.046	0.157
iPad Pro Small	24	-0.224	(0.083)***	-0.898	(0.063)***	0.048	1.261	0.140
iPad	24	-0.129	(0.088)	-0.905	(0.053)***	0.066	2.316	0.136
iPad Mini	24	-0.185	(0.083)**	-0.974	(0.062)***	0.076	1.564	0.088
iPad Pro Large	36	-0.659	(0.110)***	-1.232	(0.068)***	0.046	0.447	0
iPad Pro Small	36	-0.664	(0.102)***	-1.232	(0.070)***	0.047	0.440	0
iPad	36	-0.281	(0.106)***	-1.071	(0.054)***	0.068	1.455	0
iPad Mini	36	-0.446	(0.102)	-1.116	(0.064)***	0.076	0.813	0
iPad Pro Large	48	-0.749	(0.153)***	-1.284	(0.060)***	0.033	0.463	0
iPad Pro Small	48	-0.840	(0.136)***	-1.296	(0.063)***	0.034	0.349	0
iPad	48	-1.314	(0.104)***	-0.862	(0.056)***	0.079	0	0.323
iPad Mini	48	-1.056	(0.090)**	-1.352	(0.066)***	0.072	0	0

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*

Second, since all of the Apple devices are shipped from a single origin China to the various importing countries, it's also important to account for the different import tariffs that each country levies on these products. Specifically, using the applicable harmonised system (HS) of tariff codes 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 of the applied tariff rates were sourced from the International Trace Centre's Market Access Map (InternationalTradeCentre, 2022). iPads were associated with the HS code 847130 which applies to all "data-processing machines, automatic, portable, weighing less than 10kg, consisting of a central processing unit, a keyboard and a display."[11] The total transaction cost used in this analyses was simply the average VAT or GST rate plus the average import tariff on iPads over the dataset period.

Figure 6.7 uses scatterplots with robust regressions to plot transaction costs versus the estimated threshold levels from Section 6.3.3.2 over various deltas (d). Overall, it appears as though the thresholds levels increase (are larger) for countries with higher average transaction costs. Again, this makes sense, since countries with higher transaction costs would need to see more substantial real exchange rate deviations before any actual arbitrage forces can kick in. Even though a large section of the real exchange rate literature has attributed the resulting thresholds to transaction costs, none could be found that have directly compared the estimated thresholds with transaction costs.[12]

The threshold regressions in this section have enriched our understanding regarding the nonlinear adjustment of iPad derived real exchange rates. However, from the specification above *symmetrical* thresholds were assumed as well as the same adjustment parameters for both over and undervaluations. What's more, one also can't derive confidence bands for the threshold estimates. The dissertation therefore also employed piecewise-linear estimation techniques in order to evaluate real exchange rate nonlinearity. This method imposes the least number of restrictions on the models being estimated. In fact, the only hyper-parameter used is to define the number of break points.

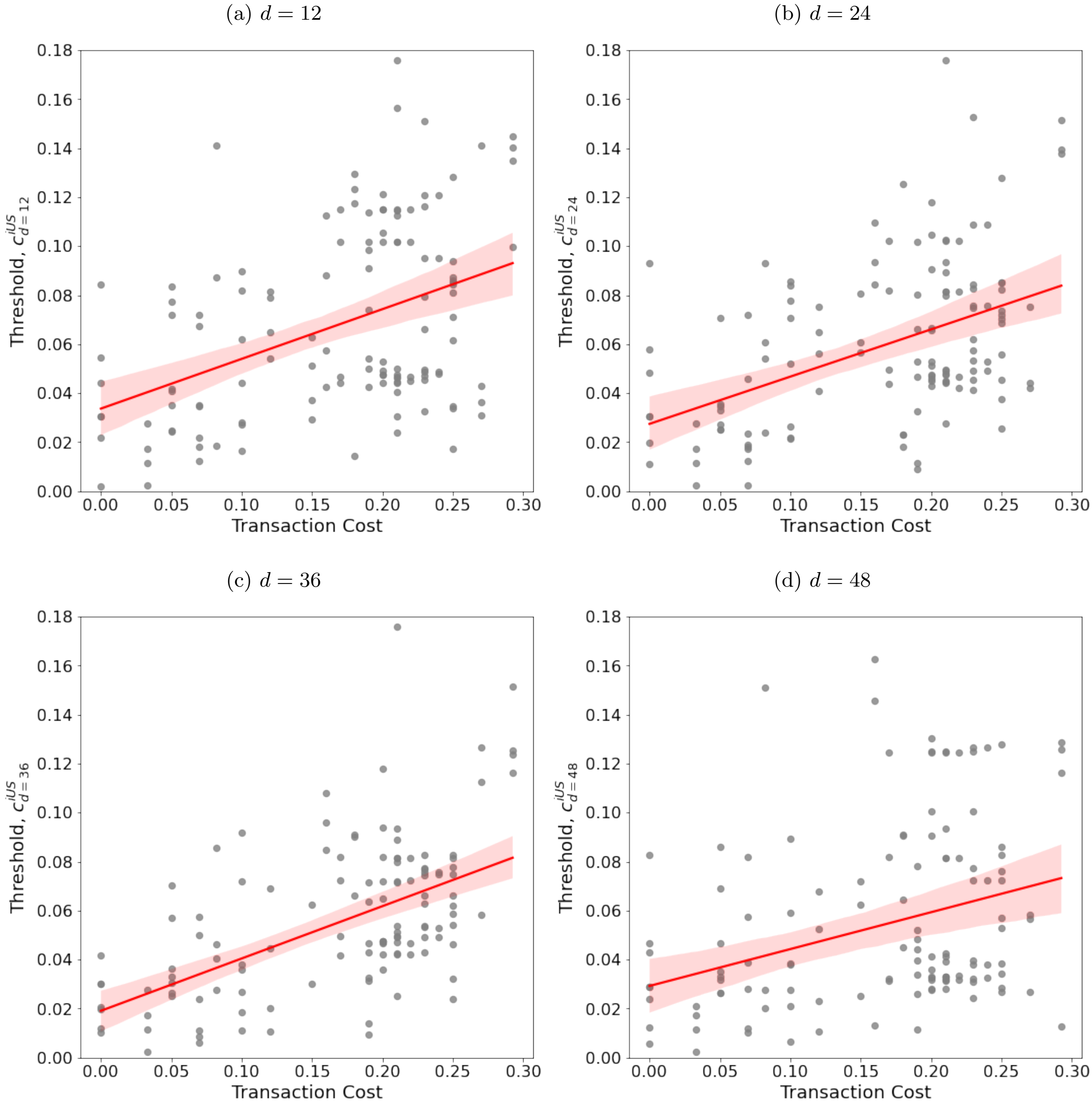
6.3.4 Piecewise Regressions Model with Unknown Break Points

Muggeo (2003) has developed a nonlinear regression technique whereby piecewise terms in the

[11]Refer to `trade.gov/harmonized-system-hs-codes` for more information on the HS codes.

[12]Refer to Obstfeld and Taylor (1997); Michael *et al.* (1997); Baum *et al.* (2001); Taylor *et al.* (2001); O'Connell and Wei (2002); Chari *et al.* (2002); Sarno *et al.* (2004); Chen *et al.* (2019); Drissi and Boukhatem (2020).

Figure 6.7: Robust Regression Scatterplots of Transaction Costs vs Estimated Threshold Levels over Various Deltas, (d)



regression models are fit *simultaneously* along with the break- or change-point(s). This method therefore incorporates the change-points parameters as part of the estimation model itself.[13] More specifically, the technique reduces the investigation to a linear framework, where the regression function is continuous, but the first derivatives of the function are not. The two, or more, line segments along with the switch-points are estimated at the same time via iterative fitting of linear models. From this multi-phase model, Pilgrim (2021) compiled a Python package utilising Muggeo's algorithms. Within this package, confidence bands for all the model estimates are derived.

The general form of the model for two change points (or three segmented areas, i.e. 'left', 'middle' and 'right') using the real exchange rate specification from Equation 6.4. In order to simplify the expression, the iUS-country and x-product superscripts for all the different real exchange rate variables are omitted.

$$\Delta^{(d)}\tilde{q}_t = \delta_d + \rho_{l,d}\tilde{q}_{t-d} + \rho_{m,d}(\tilde{q}_{t-d} - \psi_0)H(\tilde{q}_{t-d} - \psi_0) + \rho_{r,d}(\tilde{q}_{t-d} - \psi_1)H(\tilde{q}_{t-d} - \psi_1) + \epsilon_t \ , \quad (6.4)$$

From this equation, δ_d represents the intercept and $\rho_{l,d}$, $\rho_{m,d}$ and $\rho_{r,d}$ are the estimated slope coefficients for the left, middle and right areas of the two change-point model. The ψ_0 and ψ_1 parameters indicate the break-point positions while the $H(.)$ function is the Heaviside step function (similar to the indicator function $\Phi[.]$ in the threshold regressions).[14] Finally, ϵ_t is the error term. Since this equation cannot be solved directly via linear estimation techniques, a linear approximation via a multivariate Taylor expansion which is derived around initial guesses for the breakpoints ψ_0 and ψ_1 is used:

$$\begin{aligned}\Delta^{(d)}\tilde{q}_t \approx \delta_d + \rho_{l,d}\tilde{q}_{t-d} + \rho_{m,d}(\tilde{q}_{t-d} - \psi_0^{(0)})H(\tilde{q}_{t-d} - \psi_0^{(0)}) - \rho_{m,d}(\psi_0 - \psi_0^{(0)})H(\tilde{q}_{t-d} - \psi_0^{(0)}) + \\ \rho_{r,d}(\tilde{q}_{t-d} - \psi_1^{(0)})H(\tilde{q}_{t-d} - \psi_1^{(0)}) - \rho_{r,d}(\psi_1 - \psi_1^{(0)})H(\tilde{q}_{t-d} - \psi_1^{(0)}) + ... + \epsilon_t \ , \quad (6.5)\end{aligned}$$

[13]Note, the terms thresholds, change-points, break-points, switch-points and transition-points are often interchangeably used to indicate the area where an 'abrupt' change occurs between the dependent and explanatory variables. Similarly, the piecewise regression model is also frequently referred to as a broken-line, multi-phase or segmented regression model.

[14]The Heaviside function assigns a value of zero for negative arguments and one for positive arguments.

This Taylor expansion then becomes a linear expression that can be estimated and an iterative process can then be used until the breakpoint estimates converge. As Pilgrim (2021) however explains, the "Muggeo method" is not guaranteed to converge to a global optimum (i.e. the technique can also produce a local optimum, or might not converge at all). To address this problem, a bootstrap restarting method is used that generates a non-parametric bootstrap of the data via resampling to discover new changepoint values that may represent a better global solution. By repeating this process several times, the algorithm attempts to converge as well as escape local optima. The number of times this process runs can be controlled in Python with the *nboot* parameter. Though this raises the likelihood of convergence, it comes at the cost of computation time.

6.3.4.1 Panel Piecewise Regressions: All Countries including all iPad devices

Figure 6.8 illustrates the piecewise regression output derived from the nonlinear real exchange rate analyses. The four scatterplots show the sample mean adjusted lagged real exchange rates derived from all the iPad devices (i.e. $\tilde{q}_{t-d}^{i\mathrm{US},x}\ \forall\ x$) on the x-axis versus the subsequent d-period change in the real exchange rates (i.e. $\Delta^{(d)}\tilde{q}_t^{i\mathrm{US},x}$ for four samples of $d = 1, 12, 24, 30$) on the y-axis. (Note, though a sample of only four deltas are shown, the piecewise regression analyses was performed for every $d = 1, 2, ..., 30$). This is similar to the LOWESS analyses conducted in Section 6.3.2 on a smaller sample of deltas. The segmented regression fit is represented by the 'kinked' solid red lines in each scatterplot. Additionally, the various change points are included as vertical blue lines while their respective confidence intervals are illustrated as translucent blue bands. Similar to the LOWESS analyses, it again appears as though there exists valuation thresholds for real exchange rate adjustments. These become more evident (i.e. 'flatter' inner slope vs 'steeper' outer slopes) as well as increasingly certain (i.e. narrower confidence bands) as the evaluation period d increases. Contrary to the LOWESS analyses, it is possible to derive parameter estimates with confidence bands for each coefficient of the various regressions.

The left, middle and right area adjustment parameter estimates (i.e. $\hat{\rho}_{l,d}$, $\hat{\rho}_{m,d}$ and $\hat{\rho}_{r,d}$) as well as their respective 95% confidence bands over various deltas from $d = 1, 2, ...30$ are plotted in Figure 6.9 (a).[15] Again, it is clear that the middle adjustment coefficients (or $\hat{\rho}_{m,d}$s) are basically zero for

[15] The change-points surrounding the inner threshold became more unstable to estimate as the delta increased. For large deltas, the piecewise regression model discovered nonsensical "kinks" at significant undervaluations (i.e. far to the left of zero). As a result, the deltas for 26, 27 and 29 were omitted and the regressions for $d > 30$ excluded.

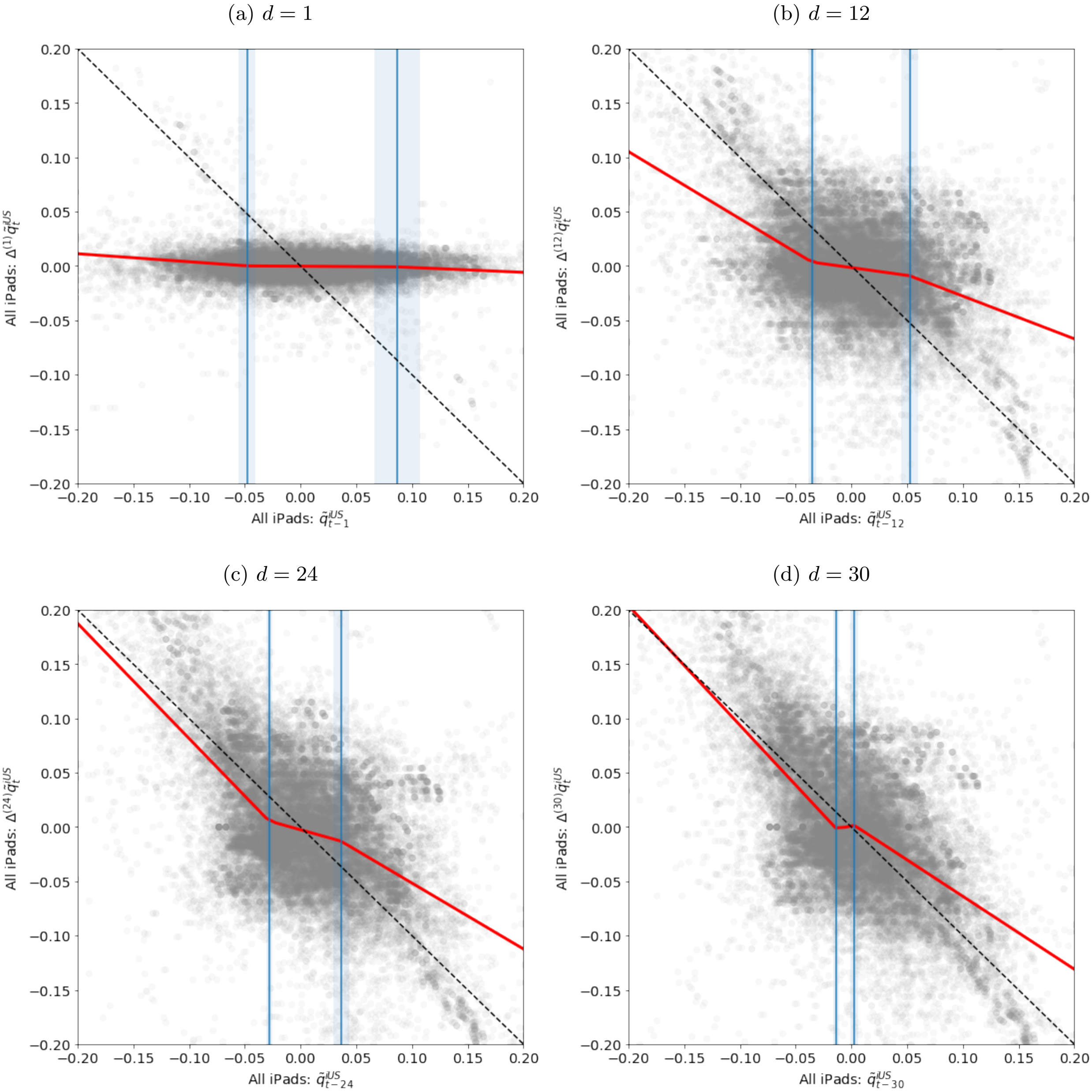
$d < 5$ while only declining slightly over larger deltas. That said, the uncertainty of this parameter again increases to around naught over $d > 25$. This once more supports the notion of the stochastic LOP; that is that small real exchange rate deviations may follow a random walk, or at least, take notably longer to correct. Meanwhile, both the outer parameter estimates (i.e. $\hat{\rho}_{l,d}$ and $\hat{\rho}_{r,d}$) imply significantly quicker adjustments; or equivalently, shorter half-lives. After around $d = 20$, the 95% confidence interval for $\hat{\rho}_{l,d}$ includes -1. Meanwhile for $\hat{\rho}_{r,d}$ at $d = 30$, the 95% confidence band, at -0.65 to -0.69, is somewhat larger than $\hat{\rho}_{l,d}$. Nonetheless, this larger estimate still implies a very short half-life of only 0.36 years when the difference period is 30 weeks.

In addition to the finding that real exchange rate adjustments exhibit nonlinear behaviour, the analyses also imply that the subsequent adjustments are *asymmetric*. That is, changes attributable to undervaluations (i.e. $\tilde{q}_t < 0$) seem to occur notably quicker relative to overvaluations. Upon closer investigation, this finding is perhaps not all that surprising. For example, given a notably large real exchange rate undervaluation shock it implies that either the nominal exchange rate needs to appreciate (i.e. $e_t^{ij,x}$ decrease), and/or the local price relative to the US price is required to increase (i.e. $p_t^{i,x} - p^{US,x}$ rises). From economic theory we'd expect that price adjustments can more easily occur upward rather than downward.[16] Thus, the local prices of iPads may be more fluid when it comes to price increases and more sticky to downward pressure. This phenomenon also seems to be supported by my Apple product price dataset. For example, for the different devices over the 35 countries we've recorded, 470 domestic price increases (i.e. $\Delta p_t^{i,x} > 0$) were recorded over the various devices; more than double the number of decreases (i.e. $\Delta p_t^{i,x} < 0$) which came in at 198. What's more, the average price increase over all the devices came in at 15% versus only -7% for the downward price adjustments. In other words, in the database the frequency of recorded price increases was more than twice that of declines and the average absolute size of such price hikes were more than double the size of price decreases.

Subplot (b) in Figure 6.9 shows the estimated change-point parameters along with their associated confidence bands derived from the piecewise regressions. Theses change-points get closer to zero as the difference period d increases. Also, the confidence bands around these estimates also appear to narrow over d. Finally, even though the threshold estimates for overvaluations (i.e. $\hat{\psi}_1$) appear

[16] This is also observed empirically. For example, Cavallo (2018) presents several findings on 'price stickiness' using scraped data from online retailers.

Figure 6.8: Panel Piecewise Regressions Over Different Horizons (d)

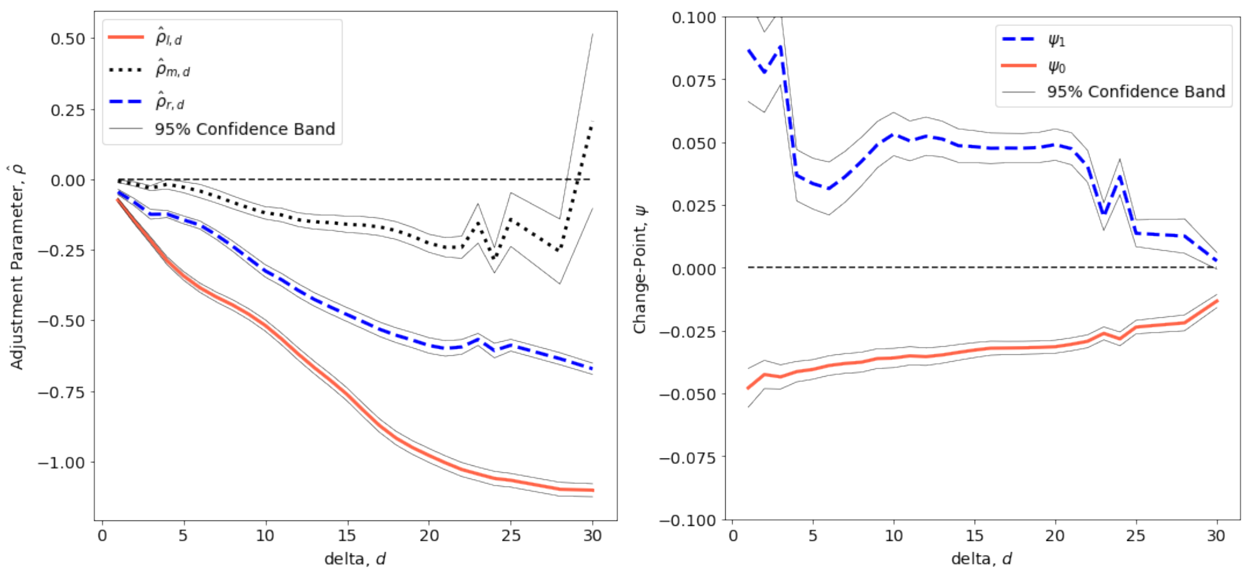


(a) $d = 1$ (b) $d = 12$ (c) $d = 24$ (d) $d = 30$

slightly more volatile than the threshold coefficients for undervaluations, $\hat{\psi}_0$, the change-points are still fairly symmetrical around naught. Thus larger deviations for both under- and overvaluations have to be of approximately of similar absolute size before the more significant adjustment parameters kick in. Finally, the change-points derived from the piece-wise model mostly concurs with those derived from the threshold regression (TAR) analyses in Section 6.3.3.1 where the thresholds are around 5% at lower deltas. The convergence of the change point estimates, $\hat{\psi}_0$ and $\hat{\psi}_1$, to zero as d increases is however significantly more noticeable in the piecewise regressions. Or, similarly, the absolute decline in thresholds over d are more apparent in the segmented regressions.

Figure 6.9: Panel Piecewise Regression Parameters With 95% Confidence Bands Over Different Horizons (d)

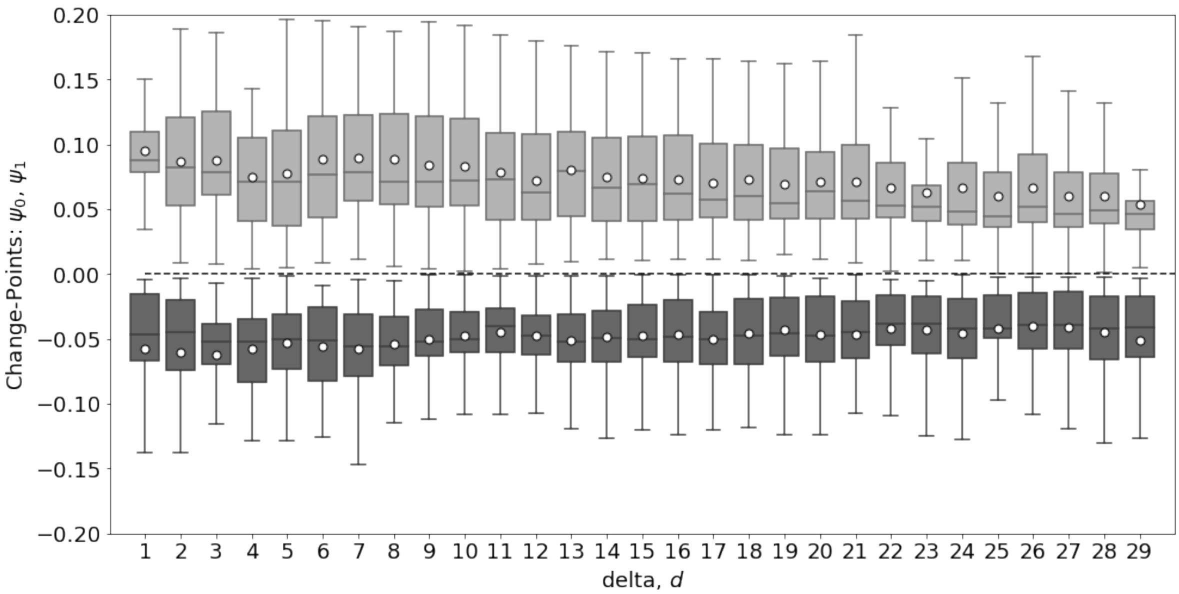
(a) Adjustment Parameters (b) Change-point Parameters



6.3.4.2 Piecewise Regressions: Individual Countries and Devices

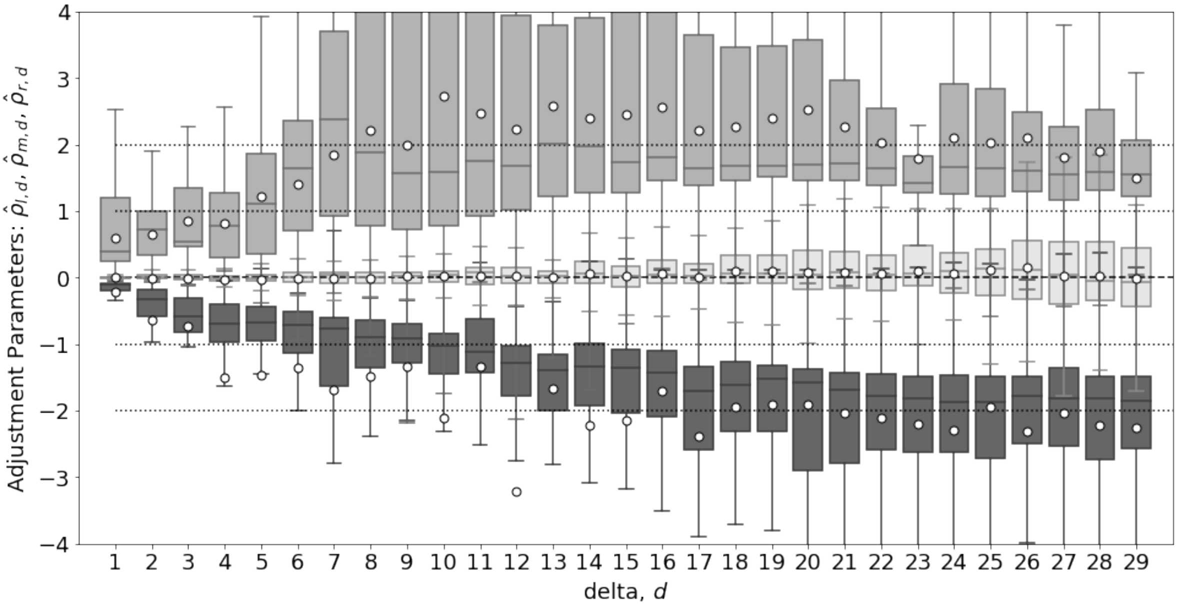
The piecewise regression analysis was also performed over the various deltas for all of the individual countries included. Figure 6.10 utilises box plots to show the distributions of the $\hat{\psi}_0$s and $\hat{\psi}_1$s break-point parameters for all the individual countries over all of the iPad devices. The averages are again included as white dots and the medians via the horizontal lines inside the grey inter-quartile boxes. Similar to the aggregate panel, it appears as though both thresholds for the individual countries converge to naught over d (i.e. the average, median and range of change-points decline over the size of the difference period). One interesting finding that became more apparent in the individual country analyses is that the real exchange rate overvalaution thresholds (i.e. $\hat{\psi}_1$s) appears to be larger in absolute size than the $\hat{\psi}_0$s, especially over shorter deltas. The distributions of $\hat{\psi}_0$s and $\hat{\psi}_1$s however do appear to become more symmetrical over larger ds. The reason for this could be similar to my argument regarding the asymmetry observed between the 'left' and 'right' adjustment parameters (i.e. $\hat{\rho}_{l,d}$ vs $\hat{\rho}_{r,d}$) outlined in Section 6.3.4.1 above. That is, due to sticky domestic prices and fluid nominal exchange rates, one could be witnessing more upward domestic price adjustments during real exchange rate undervaluations than price decreases during overvaluations. As a result, we could therefore also witness a potentially larger threshold for overvaluations before real exchange rate adjustments can rapidly occur.

Figure 6.10: Box Plots of Country Change-Points derived from Piecewise Linear Regressions over Various Deltas (d)



Finally, Figure 6.10 plots the individual adjustment parameters for the three regions over d. The darkest shaded box-plots represent the leftmost region adjustment parameter, $\hat{\rho}_{l,d}$, while the lightest shade denotes the distributions of the countries' middle adjustment coefficients $\hat{\rho}_{m,d}$. In order to plot all the box-plots onto one chart, the absolute value of the right region's adjustment parameters (i.e. $|\hat{\rho}_{r,d}|$) are included as the uppermost boxes. First to note is that the average and median of the inner parameters, $\hat{\rho}_{m,d}$s, are close to zero. The inter-quartile range of these parameters are

Figure 6.11: Box Plots of Country Adjustment Parameter Estimates from Piecewise Linear Regressions over Various Deltas (d)



also significantly closer to zero than the 'outer' adjustment parameters. This is again supportive of stochastic LOP. Meanwhile, though the $\hat{\rho}_{l,d}$s appear to be smaller than the $\hat{\rho}_{r,d}$s at lower deltas, the potential asymmetry between the two parameters is less noticeable than in the panel dataset. The distribution of $\hat{\rho}_{r,d}$s are however notably wider than the $\hat{\rho}_{l,d}$s. The same box plot analyses for the individual countries over the individual iPad devices are also given in Figures B.37 to B.40 in Appendix B.

CHAPTER 7

CONCLUSION

The central topic explored in this dissertation 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 primarily due to limited datasets on which to explore the topic. As such, I have constructed two new datasets, consisting of APPs, as well as their associated transaction or input costs, in order to evaluate what relationships and dynamics (that have not been explored in existing publications) can be revealed. Specifically, by using a more suitable product from a global conglomerate, like Apple, on which to conduct these LOP investigations, compared to the existing literature, I have found both better overall adherence to the LOP as well as notably less sticky RERs.

In addition, I was 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 — I have been able to eliminate a notable amount of price heterogeneity across the respective markets. This has helped 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.

Next, I investigated whether the APPs derived real exchange rates better adhere to the notion of the stochastic law of one price. Similar to real exchange rates derived from other products, I discovered that the real exchange rates implied by Apple iPads exhibit a persistent bias. I therefore used mean-adjusted real exchange rates to account for these biases. The various estimation techniques support the following main findings: First, real exchange rate adjustments derived from iPad products appear to embed a 'threshold effect'. Specifically, the real exchange rate adjustments appear to behave more like unit root processes when they don't deviate too far from fair value. Meanwhile, more prominent valuation discrepancies become significantly more mean reverting. Second, the size of these thresholds appears to decline as our evaluation window or difference period increases. Third, given the non-linearity of RER adjustments, the correction of mispricings may only take a few months compared to the literature's finding that RER half-lives last around three- to five years. Fourth, there seems to be a strong association between the estimated thresholds from the analyses and the actual transaction costs particular to iPads. Finally, the analyses imply that real exchange rate adjustments may be *asymmetric*. That is, changes attributed to undervaluations seem to occur quicker — i.e. have larger adjustment parameters — relative to overvaluations.

That said, 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.

There are several contributions that are unique in this dissertation. This includes the new datasets and their associated transaction costs used in the analysis. In addition, since the frequency of the second dataset is notably higher than most of the studies, I was also able to investigate noticeably smaller adjustment slices. Several of the dissertation's interesting findings (for example the declining threshold levels over extending difference periods) would not have been possible over longer (for example annual) timeframes. This finding supports the notion that asymmetric price information, lags and uncertainties (or equivalently, the 'band of no arbitrage') decrease over time as valuation discrepancies are arbitraged.

Finally, some of the new estimation techniques, including Bayesian formulations as well as 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 real exchange rates mean-revert in a nonlinear fashion and that the persistence of RER deviations from the LOP last only a few months. Some of the dissertation'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.

Recommended areas for future research include using the new APPs datasets to evaluate how suited these relative product price ratios are at forecasting future exchange rate movements (or at least how they compare to the benchmark random walk process). This dissertation has primarily focused on the aggregate (panel) aspects of RER adjustments. Consideration should be given to exploring in more depth the individual country adjustment parameters and thresholds dynamics using the high frequency Apple iPad dataset. Finally, scraping new price (and other microeconomics) datasets may reveal new and interesting dynamics that could further enhance our grasp of some of the existing macroeconomic literature.

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APPENDIX A

ADDITIONAL TABLES

A.1 PANEL REGRESSIONS EXCLUDING TRANSACTION COSTS

Table A.1: CPI Price Basket with Pooled OLS Regression Results for 49 Countries Over 2007-2020

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

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

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

Table A.2: 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	0.4469	686	0.6862
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2008	1.0000	0.4469	686	0.6853
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2009	1.0500	0.4469	686	0.6856
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2010	1.0182	0.4469	686	0.6912
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2011	0.9681	0.4469	686	0.6914
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2012	1.0093	0.4469	686	0.6944
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2013	1.0042	0.4469	686	0.6930
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2014	1.0276	0.4469	686	0.6916
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2015	1.1568	0.4469	686	0.6959
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2016	1.1776	0.4469	686	0.6976
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2017	1.1674	0.4469	686	0.6989
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2018	1.1584	0.4469	686	0.6973
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2019	1.1959	0.4469	686	0.6991
	(0.0313)***	(0.0159)***		
Fixed Country Effects CPI Base 2020	1.2092	0.4469	686	0.6971
	(0.0313)***	(0.0159)***		

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

Table A.3: CPI Price Basket with Fixed Time 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 Time Effects CPI Base 2007	-0.0585	1.0115	686	0.9957
	(0.0069)***	(0.0022)***		
Fixed Time Effects CPI Base 2008	-0.1133	1.0144	686	0.9963
	(0.0063)***	(0.0020)***		
Fixed Time Effects CPI Base 2009	-0.0635	1.0144	686	0.9968
	(0.0056)***	(0.0018)***		
Fixed Time Effects CPI Base 2010	-0.0729	1.0030	686	0.9969
	(0.0054)***	(0.0017)***		
Fixed Time Effects CPI Base 2011	-0.1220	1.0025	686	0.9969
	(0.0054)***	(0.0017)***		
Fixed Time Effects CPI Base 2012	-0.0695	0.9968	686	0.9971
	(0.0052)***	(0.0016)***		
Fixed Time Effects CPI Base 2013	-0.0811	1.0001	686	0.9974
	(0.0047)***	(0.0015)***		
Fixed Time Effects CPI Base 2014	-0.0636	1.0031	686	0.9975
	(0.0045)***	(0.0014)***		
Fixed Time Effects CPI Base 2015	0.0848	0.9933	686	0.9968
	(0.0055)***	(0.0017)***		
Fixed Time Effects CPI Base 2016	0.1116	0.9902	686	0.9970
	(0.0053)***	(0.0017)***		
Fixed Time Effects CPI Base 2017	0.1067	0.9875	686	0.9970
	(0.0053)***	(0.0017)***		
Fixed Time Effects CPI Base 2018	0.0915	0.9907	686	0.9970
	(0.0053)***	(0.0017)***		
Fixed Time Effects CPI Base 2019	0.1363	0.9870	686	0.9969
	(0.0054)***	(0.0017)***		
Fixed Time Effects CPI Base 2020	0.1444	0.9896	686	0.9959
	(0.0066)***	(0.0021)***		

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

Table A.4: CPI Price Basket with Fixed Country and Time 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 and Time Effects CPI Base 2007	0.8031	0.5724	686	0.8088
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2008	0.7539	0.5724	686	0.8079
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2009	0.8038	0.5724	686	0.8082
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2010	0.7720	0.5724	686	0.8139
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2011	0.7220	0.5724	686	0.8141
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2012	0.7632	0.5724	686	0.8170
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2013	0.7581	0.5724	686	0.8157
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2014	0.7815	0.5724	686	0.8143
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2015	0.9107	0.5724	686	0.8185
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2016	0.9314	0.5724	686	0.8202
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2017	0.9212	0.5724	686	0.8215
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2018	0.9122	0.5724	686	0.8199
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2019	0.9497	0.5724	686	0.8217
	(0.0379)***	(0.0193)***		
Fixed Country and Time Effects CPI Base 2020	0.9630	0.5724	686	0.8196
	(0.0379)***	(0.0193)***		

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

Table A.5: CPI Price Basket with Random 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
Random Effects CPI Base 2007	0.1083	0.9265	686	0.9889
	(0.0331)***	(0.0099)***		
Random Effects CPI Base 2008	0.0108	0.9511	686	0.9926
	(0.0286)	(0.0087)***		
Random Effects CPI Base 2009	0.0226	0.9706	686	0.9951
	(0.0239)	(0.0074)***		
Random Effects CPI Base 2010	-0.0012	0.9665	686	0.9957
	(0.0218)	(0.0068)***		
Random Effects CPI Base 2011	-0.0492	0.9654	686	0.9957
	(0.0220)**	(0.0068)***		
Random Effects CPI Base 2012	-0.0100	0.9665	686	0.9962
	(0.0199)	(0.0062)***		
Random Effects CPI Base 2013	-0.0486	0.9835	686	0.9972
	(0.0149)***	(0.0047)***		
Random Effects CPI Base 2014	-0.0433	0.9928	686	0.9975
	(0.0121)***	(0.0038)***		
Random Effects CPI Base 2015	0.1647	0.9526	686	0.9952
	(0.0229)***	(0.0071)***		
Random Effects CPI Base 2016	0.1775	0.9567	686	0.9959
	(0.0209)***	(0.0065)***		
Random Effects CPI Base 2017	0.1741	0.9532	686	0.9958
	(0.0211)***	(0.0065)***		
Random Effects CPI Base 2018	0.1592	0.9562	686	0.9958
	(0.0212)***	(0.0066)***		
Random Effects CPI Base 2019	0.2109	0.9489	686	0.9955
	(0.0222)***	(0.0069)***		
Random Effects CPI Base 2020	0.2901	0.9154	686	0.9905
	(0.0308)***	(0.0093)***		

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

Table A.6: Big Mac Price Basket Regression Results for 31 Countries Over 2007-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2 Overall
Pooled OLS	-0.1180	0.9359	434	0.9724
	(0.0250)***	(0.0076)***		
Fixed Country Effects	1.1061	0.4201	434	0.6770
	(0.0595)***	(0.0249)***		
Fixed Time Effects	-0.1282	0.9402	434	0.9724
	(0.0234)***	(0.0071)***		
Fixed Country and Time Effects[1]	0.6097	0.6293	434	0.8680
	(0.0640)***	(0.0269)***		
Random Effects	0.4901	0.6797	434	0.8995
	(0.0867)***	(0.0217)***		

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

Table A.7: iPod Nano Price Basket Regression Results for 46 Countries Over 2007-2017

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

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

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

Table A.8: iPad Price Basket Regression Results for 45 Countries Over 2011-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2 Overall
Pooled OLS	0.2061	0.9978	450	0.9930
	(0.0102)***	(0.0040)***		
Fixed Country Effects	0.2572	0.9665	450	0.9920
	(0.0369)***	(0.0224)***		
Fixed Time Effects	0.2061	0.9978	450	0.9930
	(0.0098)***	(0.0038)***		
Fixed Country and Time Effects	0.2869	0.9483	450	0.9905
	(0.0370)***	(0.0225)***		
Random Effects[3]	0.2152	0.9922	450	0.9929
	(0.0265)***	(0.0097)***		

Note: Standard Errors in Parenthesis $\quad$ $^{*}p<0.10$ $^{**}p<0.05$ $^{***}p<0.01$

Table A.9: iPhone Price Basket Regression Results for 39 Countries Over 2012-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2 Overall
Pooled OLS	0.2549	1.0043	351	0.9904
	(0.0108)***	(0.0053)***		
Fixed Country Effects	0.7066	0.6374	351	0.8582
	(0.0593)***	(0.0479)***		
Fixed Time Effects	0.2528	1.0060	351	0.9904
	(0.0080)***	(0.0039)***		
Fixed Country and Time Effects[4]	0.5500	0.7647	351	0.9340
	(0.0411)***	(0.0333)***		
Random Effects	0.2703	0.9917	351	0.9902
	(0.0216)***	(0.0105)***		

Note: Standard Errors in Parenthesis $\quad$ $^{*}p<0.10$ $^{**}p<0.05$ $^{***}p<0.01$

A.2 PANEL REGRESSIONS INCLUDING TRANSACTION COST ESTIMATES

Table A.10: Big Mac Price Basket (Including Transaction Costs) Regression Results for 31 Countries Over 2007-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	N	R^2 Overall
Pooled OLS	-0.2522	0.9357	1.6231	434	0.9746
	(0.0327)***	(0.0073)***	(0.2677)***		
Fixed Country Effects	1.3121	0.4366	-2.9556	434	0.6802
	(0.0848)***	(0.0251)***	(0.8770)***		
Fixed Time Effects	-0.2667	0.9401	1.6720	434	0.9746
	(0.0303)***	(0.0068)***	(0.2479)***		
Fixed Country and Time Effects	0.7753	0.6388	-2.2673	434	0.8640
	(0.0841)***	(0.0268)***	(0.7572)***		
Random Effects[5]	0.5868	0.6931	-1.5499	434	0.9008
	(0.1031)***	(0.0215)***	(0.7704)**		

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

Table A.11: iPod Nano Price Basket (Including Transaction Costs) Regression Results for 46 Countries Over 2007-2017

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	N	R^2 Overall
Pooled OLS	0.0384	1.0080	1.5089	1.1689	506	0.9956
	(0.0152)**	(0.0030)***	(0.1169)***	(0.1158)***		
Fixed Country Effects	0.1892	0.9282	2.2704	0.2167	506	0.9882
	(0.0688)***	(0.0256)***	(0.5860)***	(0.2157)		
Fixed Time Effects	0.0374	1.0080	1.4911	1.1983	506	0.9956
	(0.0149)**	(0.0030)***	(0.1149)***	(0.1144)***		
Fixed Country and Time Effects	0.1870	0.9530	1.5962	0.4749	506	0.9923
	(0.0743)**	(0.0292)***	(0.5843)***	(0.2164)**		
Random Effects[6]	0.0791	1.0017	1.7418	0.5696	506	0.9953
	(0.0377)**	(0.0080)***	(0.2780)***	(0.1827)***		

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

Table A.12: iPad Price Basket (Including Transaction Costs) Regression Results for 45 Countries Over 2011-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2 Overall
Pooled OLS	0.0696	1.0013	1.3554	2.9073	0.0162	450	0.9971
	(0.0133)***	(0.0026)***	(0.0873)***	(0.1916)***	(0.0044)***		
Fixed Country Effects	0.4437	0.9805	-0.1751	0.4757	0.1504	450	0.9887
	(0.0790)***	(0.0242)***	(0.6619)	(0.3840)	(0.0211)***		
Fixed Time Effects	0.0620	1.0007	1.3792	2.9676	0.0118	450	0.9971
	(0.0118)***	(0.0023)***	(0.0769)***	(0.1693)***	(0.0039)**		
Fixed Country and Time Effects[7]	0.3443	0.9506	-0.2263	0.1790	0.0305	450	0.9907
	(0.0827)***	(0.0264)***	(0.5929)	(0.3467)	(0.0237)		
Random Effects	0.0830	1.0027	1.3198	2.3616	0.0233	450	0.9970
	(0.0181)***	(0.0036)***	(0.1192)***	(0.2340)***	(0.0060)***		

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

Table A.13: iPhone Price Basket (Including Transaction Costs) Regression Results for 39 Countries Over 2012-2020

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2 Overall
Pooled OLS	0.1288	1.0047	1.2189	0.9465	0.0032	351	0.9931
	(0.0180)***	(0.0046)***	(0.1184)***	(0.2313)***	(0.0060)		
Fixed Country Effects	0.6143	0.6590	2.0847	-0.1792	0.1135	351	0.8549
	(0.1409)***	(0.0499)***	(1.1418)*	(0.7364)	(0.0355)***		
Fixed Time Effects	0.1227	1.0060	1.2281	0.9122	0.0003	351	0.9931
	(0.0108)***	(0.0027)***	(0.0710)***	(0.1388)***	(0.0036)		
Fixed Country and Time Effects[8]	0.4177	0.7746	1.2189	0.2141	0.0043	351	0.9407
	(0.0859)***	(0.0349)***	(0.6055)**	(0.3917)	(0.0246)		
Random Effects	0.1329	1.0032	1.2157	0.9709	0.0049	351	0.9931
	(0.0225)***	(0.0057)***	(0.1481)***	(0.2822)***	(0.0075)		

Note: Standard Errors in Parenthesis — *$^{*}p<0.10$ $^{**}p<0.05$ $^{***}p<0.01$*

A.3 BALANCED PANEL REGRESSIONS EXCLUDING TRANSACTION COSTS

Table A.14: CPI Price Basket with Pooled OLS Regression Results

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

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

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

Table A.15: CPI Price Basket with Fixed Country Effects Regression Results

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

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

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

Table A.16: CPI Price Basket with Fixed Time Effects Regression Results

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

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

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

Table A.17: CPI Price Basket with Fixed Country and Time Effects Regression Results

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

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

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

Table A.18: CPI Price Basket with Random Effects Regression Results

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

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

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

Table A.19: 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	0.8734	150	0.9438
	(0.0402)	(0.0175)***		
Fixed Country Effects	1.2344	0.1181	150	0.2380
	(0.0638)***	(0.0372)***		
Fixed Time Effects	-0.0641	0.8785	150	0.9438
	(0.0389)	(0.0170)***		
Fixed Country and Time Effects[9]	0.9997	0.2555	150	0.4715
	(0.0973)***	(0.0569)***		
Random Effects	0.6419	0.4651	150	0.7375
	(0.1177)***	(0.0415)***		

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

Table A.20: 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	1.0229	150	0.9837
	(0.0248)***	(0.0108)***		
Fixed Country Effects	0.5013	0.8572	150	0.9579
	(0.0704)***	(0.0410)***		
Fixed Time Effects	0.2168	1.0235	150	0.9837
	(0.0251)***	(0.0109)***		
Fixed Country and Time Effects[10]	0.5530	0.8270	150	0.9476
	(0.0996)***	(0.0581)***		
Random Effects	0.2985	0.9757	150	0.9816
	(0.0569)***	(0.0229)***		

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

Table A.21: iPad Price Basket Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2 Overall
Pooled OLS	0.1505	1.0054	150	0.9883
	(0.0206)***	(0.0090)***		
Fixed Country Effects	0.2028	0.9748	150	0.9874
	(0.1190)*	(0.0695)***		
Fixed Time Effects	0.1504	1.0054	150	0.9883
	(0.0191)***	(0.0083)***		
Fixed Country and Time Effects	0.2320	0.9576	150	0.9860
	(0.1368)*	(0.0800)***		
Random Effects[11]	0.1536	1.0036	150	0.9883
	(0.0410)***	(0.0176)***		

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

Table A.22: iPhone Price Basket Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	N	R^2 Overall
Pooled OLS	0.2331	1.0090	150	0.9885
	(0.0205)***	(0.0089)***		
Fixed Country Effects	1.2264	0.4271	150	0.6597
	(0.1113)***	(0.0650)***		
Fixed Time Effects	0.2276	1.0123	150	0.9885
	(0.0165)***	(0.0072)***		
Fixed Country and Time Effects[12]	0.8254	0.6620	150	0.8716
	(0.1115)***	(0.0652)***		
Random Effects	0.2801	0.9815	150	0.9878
	(0.0431)***	(0.0186)***		

Note: Standard Errors in Parenthesis $\quad {}^{*}p<0.10$ ${}^{**}p<0.05$ ${}^{***}p<0.01$

A.4 BALANCED PANEL REGRESSIONS INCLUDING TRANSACTION COSTS

Table A.23: Big Mac Price Basket (Including Transaction Costs) Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta_1}$	N	R^2 Overall
Pooled OLS	-0.1953	0.8561	1.9553	150	0.9523
	(0.0462)***	(0.0166)***	(0.3827)***		
Fixed Country Effects	1.0658	0.1272	1.7650	150	0.2918
	(0.1588)***	(0.0380)***	(1.5222)		
Fixed Time Effects	-0.2006	0.8614	1.9116	150	0.9522
	(0.0445)***	(0.0160)***	(0.3684)***		
Fixed Country and Time Effects[13]	0.8694	0.2590	1.4341	150	0.5038
	(0.1673)***	(0.0570)***	(1.4972)		
Random Effects	0.2644	0.4844	3.9724	150	0.7884
	(0.1452)**	(0.0398)***	(1.1309)***		

Note: Standard Errors in Parenthesis $\quad ^{*}p<0.10 \; ^{**}p<0.05 \; ^{***}p<0.01$

Table A.24: iPod Nano Price Basket (Including Transaction Costs) Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta_1}$	$\hat{\delta_2}$	$\hat{\delta_3}$	N	R^2 Overall
Pooled OLS	0.0781	0.9956	1.2834	1.6914	0.0299	150	0.9935
	(0.0231)***	(0.0074)***	(0.1932)***	(0.2337)***	(0.0073)***		
Fixed Country Effects	0.2296	0.9258	3.1955	0.2027	0.0907	150	0.9756
	(0.1648)	(0.0446)***	(1.3211)**	(0.4979)	(0.0222)***		
Fixed Time Effects	0.0756	0.9952	1.2838	1.7116	0.0287	150	0.9935
	(0.0230)**	(0.0074)***	(0.1925)***	(0.2345)***	(0.0073)***		
Fixed Country and Time Effects	0.1908	0.8689	3.7772	0.7426	0.0594	150	0.9686
	(0.1741)	(0.0568)***	(1.2611)***	(0.5059)	(0.0259)**		
Random Effects[14]	0.1299	0.9916	1.6411	1.0640	0.0505	150	0.9923
	(0.0534)**	(0.0164)***	(0.4179)***	(0.3622)**	(0.0142)***		

Note: Standard Errors in Parenthesis $\quad ^{*}p<0.10 \; ^{**}p<0.05 \; ^{***}p<0.01$

Table A.25: iPad Price Basket (Including Transaction Costs) Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2 Overall
Pooled OLS	0.0454	0.9993	1.4082	3.1118	0.0137	150	0.9952
	(0.0194)**	(0.0061)***	(0.1422)***	(0.4069)***	(0.0060)**		
Fixed Country Effects	0.6158	1.0727	-2.1076		0.2624	150	0.9287
	(0.2189)***	(0.0601)***	(1.9680)		(0.0330)***		
Fixed Time Effects	0.0386	0.9984	1.4350	3.1311	0.0098	150	0.9952
	(0.0151)**	(0.0048)***	(0.1107)***	(0.3165)***	(0.0047)**		
Fixed Country and Time Effects[15]	0.5275	0.9614	-1.0465		0.1394	150	0.9678
	(0.2143)**	(0.0762)***	(1.6772)		(0.0348)***		
Random Effects	0.1038	0.9998	1.3458		0.0399	150	0.9928
	(0.0426)**	(0.0134)***	(0.3138)***		(0.0128)**		

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

Table A.26: iPhone Price Basket (Including Transaction Costs) Regression Results

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

Estimation:	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta}_1$	$\hat{\delta}_2$	$\hat{\delta}_3$	N	R^2 Overall
Pooled OLS	0.1288	0.9986	1.2593	1.1172	-0.0015	150	0.9925
	(0.0243)***	(0.0076)***	(0.1783)***	(0.2825)***	(0.0075)		
Fixed Country Effects	1.1703	0.3790	1.2340	-1.1118	-0.0276	150	0.6223
	(0.2617)***	(0.0752)***	(2.2631)	(0.7022)	(0.0378)		
Fixed Time Effects	0.1256	1.0018	1.2330	1.0810	-0.0018	150	0.9925
	(0.0167)***	(0.0052)***	(0.1222)***	(0.1939)***	(0.0052)		
Fixed Country and Time Effects[16]	0.7853	0.6575	0.5050	-0.1034	-0.0033	150	0.8737
	(0.2005)***	(0.0743)***	(1.4693)	(0.4719)	(0.0303)		
Random Effects	0.1364	0.9913	1.3209	1.1230	-0.0012	150	0.9925
	(0.0376)***	(0.0118)***	(0.2759)***	(0.4008)*	(0.0114)		

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

B.1 THRESHOLD AUTOREGRESSIONS FOR VARIOUS DEVICES OVER VARIOUS DELTAS

Table B.1: Threshold Autoregression Persistence Estimates for iPad Pro Large Devices, $d = 12$

	i =iPad Pro Large, $d = 12$, No. Observations: 302						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	0.947	(0.145)***	-0.132	(0.025)***	0.012	∞	1.13
AT	-0.097	(0.066)	-0.423	(0.050)***	0.048	1.568	0.291
AU	0.694	(0.254)***	-0.437	(0.046)***	0.028	∞	0.278
BE	-0.047	(0.074)	-0.429	(0.049)***	0.044	3.323	0.285
BR	-0.042	(0.055)	-0.572	(0.055)***	0.145	3.728	0.188
CA	-1.324	(0.207)***	-0.341	(0.043)***	0.025	0	0.384
CZ	0.821	(0.217)***	-0.348	(0.041)***	0.030	∞	0.374
DE	-0.134	(0.059)**	-0.458	(0.056)***	0.054	1.112	0.261
DK	0.174	(0.112)	-0.399	(0.046)***	0.035	∞	0.314
ES	-0.099	(0.067)	-0.420	(0.050)***	0.048	1.534	0.294
FI	-0.088	(0.069)	-0.441	(0.051)***	0.048	1.736	0.275
FR	-0.047	(0.074)	-0.429	(0.049)***	0.044	3.323	0.285
HK	0.012	(0.022)	-0.522	(0.047)***	0.031	∞	0.217
HU	-1.264	(0.167)***	-0.411	(0.051)***	0.031	0	0.302
IE	-0.089	(0.070)	-0.443	(0.051)***	0.046	1.716	0.273
IT	-0.052	(0.073)	-0.430	(0.049)***	0.045	2.995	0.285
JP	-0.317	(0.073)***	-0.679	(0.067)***	0.084	0.42	0.141
KR	-0.491	(0.047)***				0.237	
LU	-0.044	(0.073)	-0.429	(0.049)***	0.044	3.555	0.285
MX	-0.270	(0.066)***	-0.669	(0.065)***	0.088	0.508	0.145
MY	-1.228	(0.247)***	-0.540	(0.052)***	0.018	0	0.206
NL	-0.042	(0.073)	-0.433	(0.049)***	0.045	3.728	0.282
NO	-0.169	(0.066)**	-0.481	(0.058)***	0.084	0.864	0.244
NZ	-0.316	(0.087)***	-0.622	(0.061)***	0.063	0.421	0.164
PH	0.022	(0.041)	-0.668	(0.052)***	0.079	∞	0.145
PL	-0.357	(0.045)***				0.362	
PT	-0.086	(0.067)	-0.444	(0.052)***	0.049	1.779	0.273
RU	-0.225	(0.082)***	-1.044	(0.056)***	0.074	0.628	0
SE	1.664	(0.614)***	-0.350	(0.043)***	0.017	∞	0.371
SG	-0.541	(0.047)***				0.205	
TH	0.253	(0.200)	-0.433	(0.053)***	0.022	∞	0.282
TR	-0.483	(0.096)***	-0.796	(0.073)***	0.117	0.242	0.101
TW	0.091	(0.129)	-0.255	(0.038)***	0.024	∞	0.543
UK	-0.368	(0.045)***				0.349	
Average	-0.104	0.113	-0.483	0.051	0.051	1.454	0.243
Median	-0.088	0.073	-0.435	0.050	0.045	1.726	0.280
Std Dev	0.565	0.106	0.166	0.009	0.030		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.2: Threshold Autoregression Persistence Estimates for iPad Pro Small Devices, $d = 12$

	i =iPad Pro Small, $d = 12$, No. Observations: 290						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-0.303	(0.037)***	-0.020	(0.037)	0.028	0.443	7.918
AT	-0.029	(0.064)	-0.470	(0.052)***	0.049	5.435	0.252
AU	-0.183	(0.064)***	-0.636	(0.065)***	0.082	0.791	0.158
BE	0.013	(0.069)	-0.463	(0.050)***	0.046	∞	0.257
BR	-0.016	(0.055)	-0.497	(0.049)***	0.140	9.917	0.233
CA	-1.036	(0.134)***	-0.239	(0.041)***	0.035	0	0.586
CZ	0.368	(0.150)**	-0.359	(0.043)***	0.041	∞	0.36
DE	-0.113	(0.062)*	-0.435	(0.054)***	0.050	1.334	0.28
DK	-0.110	(0.048)**	-0.558	(0.065)***	0.071	1.373	0.196
ES	-0.024	(0.063)	-0.537	(0.054)***	0.050	6.585	0.208
FI	-0.012	(0.065)	-0.483	(0.051)***	0.049	13.25	0.242
FR	-0.019	(0.068)	-0.472	(0.051)***	0.048	8.339	0.25
HK	0.032	(0.033)	-0.436	(0.046)***	0.031	∞	0.279
HU	-0.977	(0.156)***	-0.356	(0.052)***	0.036	0.042	0.363
IE	-0.040	(0.066)	-0.485	(0.052)***	0.047	3.918	0.241
IT	0.013	(0.068)	-0.465	(0.050)***	0.047	∞	0.256
JP	-0.445	(0.050)***				0.272	
KR	-1.742	(0.267)***	-0.455	(0.052)***	0.017	0	0.264
LU	0.013	(0.069)	-0.463	(0.050)***	0.046	∞	0.257
MX	-1.145	(0.191)***	-0.490	(0.053)***	0.042	0	0.238
MY	-0.436	(0.046)***				0.279	
NL	0.015	(0.069)	-0.467	(0.050)***	0.046	∞	0.254
NO	-0.254	(0.059)***	-0.650	(0.070)***	0.085	0.546	0.152
NZ	-0.258	(0.108)**	-0.561	(0.057)***	0.051	0.536	0.194
PH	0.034	(0.041)	-0.745	(0.054)***	0.082	∞	0.117
PL	-0.192	(0.065)***	-0.492	(0.065)***	0.079	0.75	0.236
PT	-0.012	(0.065)	-0.483	(0.051)***	0.049	13.25	0.242
RU	-0.385	(0.068)***	-0.770	(0.080)***	0.091	0.329	0.109
SE	0.290	(0.190)	-0.383	(0.045)***	0.034	∞	0.331
SG	-0.796	(0.144)***	-0.406	(0.052)***	0.018	0.101	0.307
TH	1.471	(0.438)***	-0.389	(0.049)***	0.012	∞	0.325
TR	3.175	(1.518)**	-0.694	(0.060)***	0.014	∞	0.135
TW	-0.243	(0.063)***	-0.567	(0.070)***	0.042	0.575	0.191
UK	-0.334	(0.043)***				0.394	
Average	-0.108	0.138	-0.481	0.054	0.050	1.396	0.244
Median	-0.075	0.066	-0.472	0.052	0.047	2.052	0.250
Std Dev	0.769	0.253	0.140	0.009	0.026		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.3: Threshold Autoregression Persistence Estimates for iPad Devices, $d = 12$

	i =iPad, $d = 12$, No. Observations: 302						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-0.826	(0.132)***	-0.091	(0.023)***	0.017	0.091	1.677
AT	-0.041	(0.042)	-0.762	(0.046)***	0.115	3.821	0.111
AU	-0.352	(0.058)***	-0.809	(0.060)***	0.090	0.369	0.097
BE	-0.025	(0.041)	-0.759	(0.045)***	0.115	6.318	0.112
BR	-0.225	(0.063)***	-0.900	(0.055)***	0.135	0.628	0.069
CA	-0.218	(0.054)***	-0.764	(0.037)***	0.084	0.65	0.111
CZ	-0.177	(0.050)***	-0.705	(0.059)***	0.156	0.821	0.131
DE	-0.022	(0.045)	-0.789	(0.047)***	0.114	7.19	0.103
DK	-0.237	(0.060)***	-0.848	(0.044)***	0.081	0.591	0.085
ES	0.295	(0.120)**	-0.247	(0.033)***	0.176	∞	0.564
FI	-0.033	(0.039)	-0.785	(0.045)***	0.121	4.767	0.104
FR	-0.025	(0.041)	-0.759	(0.045)***	0.115	6.318	0.112
HK	1.159	(0.458)**	-0.154	(0.026)***	0.002	∞	0.956
HU	-0.250	(0.059)***	-0.759	(0.060)***	0.141	0.556	0.112
IE	-0.020	(0.042)	-0.748	(0.044)***	0.116	7.918	0.116
IT	-0.024	(0.041)	-0.759	(0.044)***	0.115	6.585	0.112
JP	-0.493	(0.083)***	-0.906	(0.061)***	0.054	0.235	0.068
KR	-0.463	(0.058)***	-0.747	(0.048)***	0.062	0.257	0.116
LU	-0.024	(0.041)	-0.759	(0.044)***	0.115	6.585	0.112
MX	-0.277	(0.066)***	-0.695	(0.057)***	0.113	0.493	0.135
MY	-0.169	(0.077)**	-0.857	(0.053)***	0.087	0.864	0.082
NL	-0.027	(0.041)	-0.757	(0.045)***	0.115	5.844	0.113
NO	-0.241	(0.063)***	-1.011	(0.052)***	0.086	0.58	0
NZ	-1.252	(0.203)***	-0.566	(0.052)***	0.030	0	0.192
PH	-0.090	(0.060)	-0.743	(0.052)***	0.054	1.696	0.118
PL	-0.241	(0.062)***	-0.720	(0.051)***	0.151	0.58	0.126
PT	-0.033	(0.039)	-0.784	(0.046)***	0.121	4.767	0.104
RU	-0.417	(0.058)***	-1.217	(0.068)***	0.098	0.296	0
SE	0.209	(0.071)***	-0.639	(0.040)***	0.087	∞	0.157
SG	-0.076	(0.046)*	-0.614	(0.039)***	0.067	2.024	0.168
TH	-0.303	(0.056)***	-0.585	(0.052)***	0.072	0.443	0.182
TR	-0.412	(0.081)***	-1.044	(0.075)***	0.123	0.301	0
TW	-0.269	(0.052)***	-0.675	(0.039)***	0.041	0.51	0.142
UK	0.366	(0.096)***	-0.638	(0.041)***	0.053	∞	0.157
Average	-0.154	0.076	-0.723	0.048	0.095	0.957	0.124
Median	-0.173	0.058	-0.759	0.046	0.106	0.842	0.112
Std Dev	0.369	0.074	0.216	0.011	0.039		

Note: Standard Errors in Parenthesis *p<0.10; **p<0.05; ***p<0.01
Average and Median Half-Life calculated from Average and Median Estimates

Table B.4: Threshold Autoregression Persistence Estimates for iPad Mini Devices, $d = 12$

	i =iPad Mini, $d = 12$, No. Observations: 302						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	3.095	(0.665)***	-0.184	(0.030)***	0.003	∞	0.787
AT	-0.043	(0.048)	-0.712	(0.055)***	0.106	3.639	0.129
AU	0.249	(0.102)**	-0.516	(0.043)***	0.044	∞	0.22
BE	-0.085	(0.049)*	-0.681	(0.058)***	0.102	1.801	0.14
BR	0.495	(0.132)***	-0.159	(0.039)***	0.100	∞	0.924
CA	-0.112	(0.053)**	-0.486	(0.043)***	0.078	1.347	0.24
CZ	1.921	(0.474)***	-0.381	(0.042)***	0.024	∞	0.333
DE	0.249	(0.078)***	-0.684	(0.047)***	0.102	∞	0.139
DK	0.042	(0.081)	-0.385	(0.043)***	0.062	∞	0.329
ES	-0.067	(0.048)	-0.679	(0.056)***	0.112	2.307	0.141
FI	-0.132	(0.055)**	-0.584	(0.059)***	0.095	1.13	0.182
FR	-0.078	(0.049)	-0.690	(0.058)***	0.102	1.97	0.137
HK	0.084	(0.032)***	-0.193	(0.029)***	0.022	∞	0.746
HU	0.136	(0.182)	-0.317	(0.043)***	0.043	∞	0.42
IE	-0.060	(0.073)	-0.486	(0.050)***	0.066	2.585	0.24
IT	-0.085	(0.049)*	-0.681	(0.058)***	0.102	1.801	0.14
JP	-0.293	(0.107)***	-0.638	(0.056)***	0.044	0.461	0.157
KR	0.346	(0.177)*	-0.263	(0.038)***	0.027	∞	0.524
LU	-0.085	(0.049)*	-0.681	(0.058)***	0.102	1.801	0.14
MX	-0.064	(0.160)	-0.473	(0.042)***	0.057	2.418	0.25
MY	-0.020	(0.052)	-0.751	(0.053)***	0.141	7.918	0.115
NL	-0.087	(0.049)*	-0.678	(0.058)***	0.102	1.757	0.141
NO	-0.171	(0.059)***	-0.639	(0.061)***	0.094	0.853	0.157
NZ	-0.053	(0.129)	-0.517	(0.051)***	0.037	2.937	0.22
PH	-0.036	(0.048)	-0.732	(0.057)***	0.065	4.363	0.121
PL	0.701	(0.296)**	-0.336	(0.041)***	0.032	∞	0.391
PT	-0.132	(0.055)**	-0.584	(0.059)***	0.095	1.13	0.182
RU	0.293	(0.144)**	-0.702	(0.048)***	0.043	∞	0.132
SE	-0.096	(0.045)**	-0.591	(0.058)***	0.128	1.585	0.179
SG	-0.339	(0.075)***	-0.600	(0.057)***	0.035	0.386	0.175
TH	0.163	(0.119)	-0.427	(0.041)***	0.035	∞	0.287
TR	-0.435	(0.077)***	-0.989	(0.079)***	0.129	0.28	0.035
TW	-0.089	(0.042)**	-0.425	(0.043)***	0.072	1.716	0.289
UK	-0.049	(0.047)	-0.622	(0.053)***	0.121	3.184	0.164
Average	0.152	0.115	-0.543	0.050	0.074	∞	0.204
Median	-0.056	0.066	-0.587	0.052	0.075	2.750	0.181
Std Dev	0.645	0.128	0.185	0.010	0.036		

Note: Standard Errors in Parenthesis *$^*p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.5: Threshold Autoregression Persistence Estimates for iPad Pro Large Devices, $d = 24$

	i =iPad Pro Large, $d = 24$, No. Observations: 290						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	1.893	(0.182)***	-0.271	(0.031)***	0.012	∞	1.012
AT	-0.262	(0.090)***	-0.826	(0.064)***	0.047	1.053	0.183
AU	-0.439	(0.070)***	-1.189	(0.079)***	0.086	0.553	0
BE	-0.196	(0.094)**	-0.874	(0.063)***	0.045	1.466	0.154
BR	-0.236	(0.072)***	-0.751	(0.067)***	0.140	1.188	0.23
CA	-1.925	(0.245)***	-0.495	(0.049)***	0.025	0	0.468
CZ	0.867	(0.326)***	-0.580	(0.051)***	0.028	∞	0.369
DE	-0.265	(0.092)***	-0.839	(0.065)***	0.047	1.039	0.175
DK	-0.193	(0.099)*	-0.963	(0.066)***	0.046	1.492	0.097
ES	-0.290	(0.089)***	-0.809	(0.065)***	0.048	0.934	0.193
FI	-0.393	(0.080)***	-0.944	(0.073)***	0.053	0.641	0.111
FR	-0.196	(0.094)**	-0.874	(0.063)***	0.045	1.466	0.154
HK	0.044	(0.023)*	-1.076	(0.047)***	0.031	∞	0
HU	-0.635	(0.078)***	-0.965	(0.087)***	0.075	0.317	0.095
IE	-0.304	(0.090)***	-0.877	(0.066)***	0.046	0.883	0.153
IT	-0.152	(0.100)	-0.859	(0.061)***	0.042	1.94	0.163
JP	-0.729	(0.082)***	-1.285	(0.076)***	0.093	0.245	0
KR	-1.479	(0.179)***	-0.858	(0.058)***	0.027	0	0.164
LU	-0.147	(0.095)	-0.866	(0.062)***	0.044	2.012	0.159
MX	-0.374	(0.073)***	-1.018	(0.074)***	0.093	0.683	0
MY	-1.454	(0.083)***	-0.963	(0.064)***	0.054	0	0.097
NL	-0.172	(0.094)*	-0.879	(0.063)***	0.045	1.695	0.151
NO	-0.245	(0.100)**	-0.680	(0.062)***	0.074	1.138	0.281
NZ	-0.481	(0.100)***	-1.005	(0.068)***	0.061	0.488	0
PH	0.517	(0.094)***	-0.711	(0.046)***	0.056	∞	0.258
PL	-0.392	(0.076)***	-0.726	(0.073)***	0.084	0.643	0.247
PT	-0.366	(0.079)***	-0.943	(0.072)***	0.053	0.702	0.112
RU	-0.741	(0.090)***	-1.029	(0.063)***	0.080	0.237	0
SE	-0.869	(0.083)***	-0.484	(0.071)***	0.072	0.157	0.484
SG	-1.493	(0.171)***	-0.857	(0.058)***	0.017	0	0.164
TH	0.236	(0.212)	-0.919	(0.071)***	0.024	∞	0.127
TR	2.681	(1.031)***	-1.205	(0.060)***	0.018	∞	0
TW	-0.117	(0.126)	-0.486	(0.054)***	0.033	2.571	0.481
UK	-0.191	(0.126)	-0.856	(0.060)***	0.046	1.509	0.165
Average	-0.250	0.139	-0.852	0.063	0.053	1.112	0.168
Median	-0.264	0.094	-0.870	0.064	0.046	1.046	0.157
Std Dev	0.838	0.166	0.210	0.010	0.026		

Note: Standard Errors in Parenthesis **p<0.10; **p<0.05; ***p<0.01*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.6: Threshold Autoregression Persistence Estimates for iPad Pro Small Devices, $d = 24$

	i =iPad Pro Small, $d = 24$, No. Observations: 278						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-0.621	(0.047)***	-0.040	(0.047)	0.028	0.33	7.837
AT	-0.342	(0.075)***	-0.914	(0.076)***	0.053	0.764	0.13
AU	-0.373	(0.079)***	-1.061	(0.075)***	0.078	0.685	0
BE	-0.159	(0.082)*	-0.934	(0.066)***	0.050	1.847	0.118
BR	-0.206	(0.069)***	-0.658	(0.057)***	0.138	1.387	0.298
CA	-1.480	(0.158)***	-0.409	(0.050)***	0.036	0	0.608
CZ	0.134	(0.166)	-0.586	(0.054)***	0.044	∞	0.363
DE	-3.876	(0.915)***	-0.623	(0.055)***	0.011	0	0.328
DK	-0.415	(0.070)***	-0.938	(0.085)***	0.069	0.597	0.115
ES	-0.242	(0.091)***	-0.820	(0.066)***	0.048	1.155	0.187
FI	-0.190	(0.081)**	-0.932	(0.067)***	0.049	1.518	0.119
FR	-0.147	(0.087)*	-0.926	(0.065)***	0.048	2.012	0.123
HK	0.083	(0.039)**	-0.895	(0.054)***	0.031	∞	0.142
HU	-0.696	(0.060)***				0.269	
IE	-0.052	(0.097)	-0.842	(0.061)***	0.042	5.991	0.173
IT	-0.101	(0.089)	-0.898	(0.063)***	0.047	3.005	0.14
JP	-0.803	(0.059)***				0.197	
KR	-2.445	(0.230)***	-0.820	(0.059)***	0.021	0	0.187
LU	-0.159	(0.082)*	-0.934	(0.066)***	0.050	1.847	0.118
MX	-0.465	(0.084)***	-1.074	(0.074)***	0.084	0.511	0
MY	0.220	(0.200)	-0.945	(0.056)***	0.024	∞	0.11
NL	-0.161	(0.083)*	-0.932	(0.066)***	0.049	1.822	0.119
NO	-0.273	(0.062)***	-1.047	(0.073)***	0.085	1.003	0
NZ	-0.585	(0.082)***	-1.038	(0.080)***	0.081	0.364	0
PH	-0.028	(0.055)	-1.106	(0.063)***	0.075	11.265	0
PL	-0.350	(0.083)***	-0.738	(0.074)***	0.075	0.743	0.239
PT	-0.190	(0.081)**	-0.932	(0.067)***	0.049	1.518	0.119
RU	-8.639	(2.600)***	-0.794	(0.059)***	0.009	0	0.202
SE	0.313	(0.397)	-0.700	(0.057)***	0.025	∞	0.266
SG	-1.473	(0.177)***	-0.815	(0.062)***	0.018	0	0.19
TH	2.653	(0.512)***	-0.783	(0.062)***	0.012	∞	0.209
TR	1.147	(0.723)	-1.220	(0.062)***	0.023	∞	0
TW	-0.668	(0.058)***				0.29	
UK	-0.128	(0.141)	-0.750	(0.060)***	0.043	2.336	0.231
Average	-0.609	0.233	-0.842	0.064	0.048	0.340	0.173
Median	-0.224	0.083	-0.898	0.063	0.048	1.261	0.140
Std Dev	1.709	0.455	0.220	0.009	0.027		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.7: Threshold Autoregression Persistence Estimates for iPad Devices, $d = 24$

	i =iPad, $d = 24$, No. Observations: 290						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-1.467	(0.157)***	-0.194	(0.029)***	0.017	0	1.483
AT	0.385	(0.100)***	-0.831	(0.044)***	0.066	∞	0.18
AU	-0.358	(0.063)***	-0.933	(0.060)***	0.084	0.722	0.118
BE	-0.128	(0.067)*	-0.923	(0.054)***	0.102	2.336	0.125
BR	-0.698	(0.066)***	-1.135	(0.074)***	0.151	0.267	0
CA	0.398	(0.179)**	-0.785	(0.038)***	0.035	∞	0.208
CZ	0.009	(0.096)	-0.899	(0.054)***	0.090	∞	0.14
DE	0.562	(0.112)***	-0.865	(0.045)***	0.066	∞	0.16
DK	0.083	(0.164)	-0.856	(0.043)***	0.037	∞	0.165
ES	0.630	(0.150)***	-0.457	(0.043)***	0.176	∞	0.524
FI	-0.159	(0.064)**	-0.948	(0.055)***	0.109	1.847	0.108
FR	0.302	(0.105)***	-0.784	(0.046)***	0.067	∞	0.209
HK	-0.384	(0.047)***	-0.144	(0.052)***	0.011	0.66	2.058
HU	-1.510	(0.252)***	-0.720	(0.052)***	0.042	0	0.251
IE	0.019	(0.077)	-0.876	(0.049)***	0.083	∞	0.153
IT	-0.129	(0.067)*	-0.923	(0.054)***	0.102	2.316	0.125
JP	-0.828	(0.082)***	-1.447	(0.063)***	0.058	0.182	0
KR	-1.821	(0.252)***	-0.864	(0.043)***	0.022	0	0.16
LU	-0.129	(0.067)*	-0.923	(0.054)***	0.102	2.316	0.125
MX	-0.422	(0.081)***	-1.043	(0.064)***	0.109	0.584	0
MY	-0.237	(0.106)**	-1.179	(0.054)***	0.061	1.183	0
NL	-0.128	(0.067)*	-0.924	(0.054)***	0.102	2.336	0.124
NO	-0.436	(0.079)***	-0.968	(0.057)***	0.082	0.559	0.093
NZ	-0.403	(0.093)***	-0.935	(0.065)***	0.057	0.62	0.117
PH	0.148	(0.084)*	-0.769	(0.048)***	0.041	∞	0.218
PL	-0.404	(0.070)***	-0.911	(0.060)***	0.152	0.618	0.132
PT	-0.159	(0.064)**	-0.951	(0.056)***	0.109	1.847	0.106
RU	0.106	(0.295)	-0.929	(0.049)***	0.033	∞	0.121
SE	0.612	(0.122)***	-0.810	(0.044)***	0.070	∞	0.193
SG	-0.038	(0.072)	-0.806	(0.044)***	0.046	8.258	0.195
TH	-0.516	(0.070)***	-0.880	(0.064)***	0.072	0.441	0.151
TR	-3.547	(0.636)***	-1.160	(0.059)***	0.023	0	0
TW	-0.088	(0.096)	-0.805	(0.041)***	0.027	3.473	0.196
UK	0.451	(0.114)***	-0.959	(0.047)***	0.051	∞	0.1
Average	-0.302	0.124	-0.869	0.052	0.072	0.888	0.158
Median	-0.129	0.088	-0.905	0.053	0.066	2.316	0.136
Std Dev	0.796	0.107	0.235	0.009	0.040		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.8: Threshold Autoregression Persistence Estimates for iPad Mini Devices, $d = 24$

	i =iPad Mini, $d = 24$, No. Observations: 290						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	5.269	(0.842)***	-0.380	(0.038)***	0.003	∞	0.669
AT	-0.285	(0.065)***	-1.150	(0.069)***	0.105	0.954	0
AU	-0.059	(0.104)	-0.744	(0.054)***	0.052	5.261	0.235
BE	-0.240	(0.080)***	-0.985	(0.064)***	0.082	1.166	0.076
BR	-0.005	(0.085)	-0.408	(0.062)***	0.204	63.823	0.61
CA	-0.194	(0.088)**	-0.730	(0.051)***	0.070	1.483	0.244
CZ	-0.048	(0.110)	-0.870	(0.058)***	0.080	6.504	0.157
DE	0.084	(0.091)	-1.217	(0.063)***	0.102	∞	0
DK	0.096	(0.118)	-0.760	(0.055)***	0.056	∞	0.224
ES	-0.176	(0.077)**	-0.996	(0.062)***	0.094	1.653	0.058
FI	-0.290	(0.083)***	-0.974	(0.066)***	0.076	0.934	0.088
FR	-0.236	(0.077)***	-1.011	(0.065)***	0.090	1.188	0
HK	0.263	(0.061)***	-0.276	(0.035)***	0.020	∞	0.991
HU	0.115	(0.225)	-0.595	(0.054)***	0.044	∞	0.354
IE	-0.144	(0.100)	-0.922	(0.060)***	0.057	2.058	0.125
IT	-0.240	(0.080)***	-0.985	(0.064)***	0.082	1.166	0.076
JP	-0.394	(0.106)***	-1.203	(0.066)***	0.048	0.639	0
KR	-0.200	(0.070)***	-0.613	(0.064)***	0.071	1.434	0.337
LU	-0.240	(0.080)***	-0.985	(0.064)***	0.082	1.166	0.076
MX	-0.718	(0.048)***				0.253	
MY	0.328	(0.074)***	-1.035	(0.045)***	0.093	∞	0
NL	-0.239	(0.080)***	-0.986	(0.064)***	0.081	1.171	0.075
NO	-0.103	(0.074)	-0.863	(0.062)***	0.085	2.943	0.161
NZ	-0.619	(0.055)***				0.332	
PH	-0.254	(0.061)***	-1.033	(0.075)***	0.065	1.092	0
PL	0.136	(0.171)	-0.640	(0.054)***	0.062	∞	0.313
PT	-0.290	(0.083)***	-0.974	(0.066)***	0.076	0.934	0.088
RU	-0.431	(0.133)***	-1.006	(0.059)***	0.053	0.567	0
SE	-0.235	(0.060)***	-1.111	(0.072)***	0.128	1.194	0
SG	6.698	(2.708)**	-0.866	(0.054)***	0.002	∞	0.159
TH	0.646	(0.296)**	-0.599	(0.047)***	0.019	∞	0.35
TR	-0.934	(0.087)***	-1.412	(0.078)***	0.125	0.118	0
TW	0.270	(0.139)*	-0.489	(0.044)***	0.025	∞	0.476
UK	-0.069	(0.051)	-1.212	(0.055)***	0.118	4.475	0
Average	0.214	0.196	-0.876	0.059	0.073	∞	0.153
Median	-0.185	0.083	-0.974	0.062	0.076	1.564	0.088
Std Dev	1.482	0.458	0.264	0.010	0.039		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.9: Threshold Autoregression Persistence Estimates for iPad Pro Large Devices, $d = 36$

	i =iPad Pro Large, $d = 36$, No. Observations: 278						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	2.840	(0.186)***	-0.416	(0.032)***	0.012	∞	0.892
AT	-0.663	(0.100)***	-1.233	(0.072)***	0.047	0.441	0
AU	0.525	(0.361)	-1.194	(0.057)***	0.027	∞	0
BE	-0.659	(0.116)***	-1.235	(0.069)***	0.042	0.446	0
BR	-0.395	(0.086)***	-0.785	(0.065)***	0.126	0.955	0.312
CA	-2.149	(0.202)***	-0.712	(0.057)***	0.031	0	0.386
CZ	-0.155	(0.166)	-1.010	(0.062)***	0.054	2.849	0
DE	-0.677	(0.106)***	-1.239	(0.071)***	0.046	0.425	0
DK	-0.113	(0.317)	-1.242	(0.061)***	0.024	4.002	0
ES	0.131	(0.249)	-1.100	(0.060)***	0.025	∞	0
FI	-0.875	(0.089)***	-1.320	(0.079)***	0.053	0.231	0
FR	-0.658	(0.116)***	-1.236	(0.069)***	0.042	0.447	0
HK	0.069	(0.016)***	-1.534	(0.032)***	0.030	∞	0
HU	-1.251	(0.107)***	-0.929	(0.077)***	0.058	0	0.181
IE	-0.865	(0.091)***	-1.279	(0.079)***	0.054	0.24	0
IT	-0.654	(0.114)***	-1.243	(0.069)***	0.042	0.452	0
JP	-1.271	(0.048)***				0	
KR	-1.136	(0.056)***				0	
LU	-0.628	(0.115)***	-1.232	(0.068)***	0.042	0.485	0
MX	-0.656	(0.074)***	-1.464	(0.080)***	0.096	0.45	0
MY	-1.796	(0.077)***	-1.245	(0.051)***	0.046	0	0
NL	-0.752	(0.096)***	-1.285	(0.075)***	0.051	0.344	0
NO	-0.532	(0.092)***	-1.136	(0.075)***	0.083	0.632	0
NZ	-1.041	(0.059)***				0	
PH	1.234	(0.168)***	-0.802	(0.048)***	0.045	∞	0.296
PL	-0.586	(0.097)***	-1.019	(0.075)***	0.074	0.544	0
PT	-0.852	(0.089)***	-1.319	(0.079)***	0.053	0.251	0
RU	-8.189	(1.966)***	-1.241	(0.050)***	0.009	0	0
SE	-1.384	(0.100)***	-0.836	(0.074)***	0.066	0	0.265
SG	-2.991	(0.694)***	-1.088	(0.058)***	0.006	0	0
TH	0.026	(0.217)	-1.324	(0.073)***	0.024	∞	0
TR	-1.867	(0.119)***	-1.141	(0.067)***	0.091	0	0
TW	0.078	(0.119)	-0.498	(0.053)***	0.033	∞	0.696
UK	-0.237	(0.129)*	-1.163	(0.062)***	0.048	1.774	0
Average	-0.827	0.198	-1.113	0.064	0.048	0.273	0
Median	-0.659	0.110	-1.232	0.068	0.046	0.447	0
Std Dev	1.610	0.330	0.254	0.012	0.026		

Note: Standard Errors in Parenthesis $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$
Average and Median Half-Life calculated from Average and Median Estimates

Table B.10: Threshold Autoregression Persistence Estimates for iPad Pro Small Devices, $d = 36$

	i =iPad Pro Small, $d = 36$, No. Observations: 266						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-0.817	(0.057)***	-0.210	(0.056)***	0.028	0.283	2.036
AT	-0.669	(0.103)***	-1.226	(0.075)***	0.047	0.434	0
AU	-0.285	(0.214)	-1.237	(0.061)***	0.038	1.43	0
BE	-0.665	(0.096)***	-1.290	(0.077)***	0.050	0.439	0
BR	-0.334	(0.094)***	-0.710	(0.060)***	0.124	1.181	0.388
CA	-1.869	(0.183)***	-0.666	(0.058)***	0.036	0	0.438
CZ	0.077	(0.213)	-0.952	(0.062)***	0.043	∞	0.158
DE	-3.436	(0.735)***	-1.031	(0.061)***	0.014	0	0
DK	-0.686	(0.097)***	-1.302	(0.075)***	0.054	0.414	0
ES	-0.638	(0.104)***	-1.259	(0.073)***	0.047	0.472	0
FI	-0.684	(0.094)***	-1.286	(0.078)***	0.049	0.417	0
FR	-0.690	(0.101)***	-1.282	(0.075)***	0.048	0.41	0
HK	0.115	(0.040)***	-1.274	(0.053)***	0.030	∞	0
HU	-0.948	(0.064)***				0.162	
IE	-0.604	(0.107)***	-1.220	(0.074)***	0.043	0.518	0
IT	-0.621	(0.103)***	-1.263	(0.074)***	0.047	0.495	0
JP	-3.121	(0.920)***	-0.895	(0.064)***	0.012	0	0.213
KR	-3.159	(0.549)***	-1.113	(0.061)***	0.011	0	0
LU	-0.665	(0.096)***	-1.290	(0.077)***	0.050	0.439	0
MX	-0.785	(0.085)***	-1.447	(0.071)***	0.085	0.312	0
MY	0.115	(0.189)	-1.279	(0.054)***	0.028	∞	0
NL	-0.663	(0.096)***	-1.290	(0.077)***	0.049	0.441	0
NO	-0.523	(0.082)***	-1.244	(0.069)***	0.075	0.648	0
NZ	-0.398	(0.244)	-1.138	(0.062)***	0.030	0.946	0
PH	-0.210	(0.074)***	-1.118	(0.071)***	0.069	2.036	0
PL	-0.549	(0.104)***	-1.029	(0.076)***	0.066	0.603	0
PT	-0.684	(0.094)***	-1.286	(0.078)***	0.049	0.417	0
RU	-0.168	(0.213)	-1.283	(0.061)***	0.043	2.609	0
SE	-1.110	(0.061)***				0	
SG	-1.197	(0.061)***				0	
TH	2.504	(0.636)***	-1.157	(0.065)***	0.011	∞	0
TR	-1.786	(0.120)***	-1.130	(0.070)***	0.090	0	0
TW	-0.548	(0.055)***				0.604	
UK	-0.077	(0.179)	-0.998	(0.060)***	0.036	5.989	0.077
Average	-0.758	0.184	-1.130	0.068	0.047	0.338	0
Median	-0.664	0.102	-1.232	0.070	0.047	0.440	0
Std Dev	1.028	0.204	0.244	0.008	0.024		

Note: Standard Errors in Parenthesis *p<0.10; **p<0.05; ***p<0.01
Average and Median Half-Life calculated from Average and Median Estimates

Table B.11: Threshold Autoregression Persistence Estimates for iPad Devices, $d = 36$

	i =iPad, $d = 36$, No. Observations: 278						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-2.106	(0.159)***	-0.306	(0.029)***	0.017	0	1.314
AT	0.098	(0.124)	-1.068	(0.052)***	0.065	∞	0
AU	-0.686	(0.072)***	-0.927	(0.071)***	0.092	0.414	0.183
BE	-0.087	(0.107)	-1.089	(0.054)***	0.072	5.272	0
BR	-0.776	(0.064)***	-1.097	(0.071)***	0.151	0.321	0
CA	-1.278	(0.093)***	-0.814	(0.047)***	0.070	0	0.285
CZ	-0.304	(0.109)***	-1.186	(0.060)***	0.089	1.324	0
DE	0.162	(0.139)	-1.106	(0.054)***	0.064	∞	0
DK	-0.116	(0.221)	-1.021	(0.046)***	0.032	3.892	0
ES	0.799	(0.153)***	-0.552	(0.045)***	0.176	∞	0.598
FI	-0.152	(0.101)	-1.098	(0.055)***	0.075	2.911	0
FR	-0.066	(0.108)	-1.091	(0.054)***	0.072	7.028	0
HK	-0.656	(0.063)***	-0.226	(0.056)***	0.010	0.45	1.873
HU	-0.574	(0.094)***	-1.163	(0.064)***	0.112	0.562	0
IE	-0.234	(0.088)***	-1.161	(0.057)***	0.083	1.8	0
IT	-0.109	(0.106)	-1.092	(0.054)***	0.072	4.158	0
JP	-2.429	(0.331)***	-1.074	(0.052)***	0.020	0	0
KR	-1.482	(0.161)***	-0.927	(0.046)***	0.036	0	0.183
LU	-0.109	(0.106)	-1.092	(0.054)***	0.072	4.158	0
MX	-0.713	(0.093)***	-1.171	(0.067)***	0.108	0.384	0
MY	-0.258	(0.166)	-1.130	(0.054)***	0.041	1.608	0
NL	-0.099	(0.106)	-1.091	(0.054)***	0.072	4.603	0
NO	-0.658	(0.087)***	-1.100	(0.064)***	0.081	0.447	0
NZ	-0.725	(0.057)***				0.372	
PH	1.206	(0.201)***	-0.607	(0.043)***	0.020	∞	0.514
PL	-0.905	(0.051)***				0.204	
PT	0.204	(0.139)	-1.034	(0.052)***	0.063	∞	0
RU	0.394	(0.295)	-1.059	(0.048)***	0.033	∞	0
SE	0.648	(0.167)***	-1.025	(0.050)***	0.059	∞	0
SG	-0.375	(0.072)***	-0.856	(0.054)***	0.058	1.021	0.248
TH	-0.991	(0.051)***				0.102	
TR	-1.165	(0.061)***				0	
TW	-0.306	(0.110)***	-0.974	(0.048)***	0.026	1.314	0.131
UK	-0.014	(0.159)	-0.955	(0.056)***	0.046	34.036	0.155
Average	-0.408	0.124	-0.970	0.054	0.066	0.916	0.137
Median	-0.281	0.106	-1.071	0.054	0.068	1.455	0
Std Dev	0.733	0.063	0.239	0.008	0.037		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.12: Threshold Autoregression Persistence Estimates for iPad Mini Devices, $d = 36$

	i =iPad Mini, $d = 36$, No. Observations: 278						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	7.221	(0.921)***	-0.569	(0.040)***	0.003	∞	0.57
AT	-0.482	(0.082)***	-1.410	(0.066)***	0.094	0.73	0
AU	1.194	(0.523)**	-0.967	(0.058)***	0.018	∞	0.141
BE	-0.508	(0.086)***	-1.399	(0.066)***	0.082	0.677	0
BR	-1.015	(0.173)***	-0.346	(0.057)***	0.116	0	1.13
CA	-0.427	(0.149)***	-0.966	(0.055)***	0.057	0.862	0.142
CZ	-0.203	(0.118)*	-1.292	(0.060)***	0.080	2.115	0
DE	-0.167	(0.140)	-1.421	(0.089)***	0.072	2.626	0
DK	0.043	(0.170)	-1.074	(0.058)***	0.046	∞	0
ES	-0.465	(0.084)***	-1.400	(0.064)***	0.094	0.767	0
FI	-0.553	(0.090)***	-1.405	(0.068)***	0.076	0.596	0
FR	-0.504	(0.087)***	-1.394	(0.066)***	0.082	0.684	0
HK	0.399	(0.072)***	-0.445	(0.043)***	0.020	∞	0.815
HU	-0.574	(0.102)***	-0.975	(0.073)***	0.126	0.562	0.13
IE	-0.490	(0.094)***	-1.393	(0.066)***	0.077	0.713	0
IT	-0.508	(0.086)***	-1.399	(0.066)***	0.082	0.677	0
JP	-0.469	(0.122)***	-1.006	(0.069)***	0.042	0.758	0
KR	-0.420	(0.076)***	-0.730	(0.073)***	0.072	0.881	0.367
LU	-0.508	(0.086)***	-1.399	(0.066)***	0.082	0.677	0
MX	-0.918	(0.050)***				0.192	
MY	0.001	(0.102)	-1.040	(0.055)***	0.086	∞	0
NL	-0.510	(0.086)***	-1.400	(0.066)***	0.081	0.673	0
NO	-0.271	(0.137)**	-1.046	(0.067)***	0.062	1.518	0
NZ	-0.697	(0.080)***	-1.116	(0.090)***	0.062	0.402	0
PH	3.274	(0.715)***	-0.684	(0.057)***	0.011	∞	0.417
PL	-0.382	(0.157)**	-0.915	(0.062)***	0.077	0.997	0.195
PT	-0.553	(0.090)***	-1.405	(0.068)***	0.076	0.596	0
RU	0.013	(0.303)	-1.263	(0.055)***	0.032	∞	0
SE	0.042	(0.140)	-1.144	(0.058)***	0.078	∞	0
SG	0.167	(0.467)	-1.051	(0.058)***	0.009	∞	0
TH	-1.157	(0.087)***	-0.530	(0.057)***	0.050	0	0.636
TR	-0.640	(0.200)***	-1.206	(0.064)***	0.066	0.47	0
TW	-0.005	(0.164)	-0.662	(0.058)***	0.025	95.734	0.442
UK	-0.334	(0.065)***	-1.315	(0.067)***	0.118	1.181	0
Average	-0.012	0.180	-1.084	0.063	0.065	39.946	0
Median	-0.446	0.102	-1.116	0.064	0.076	0.813	0
Std Dev	1.460	0.191	0.318	0.010	0.031		

Note: Standard Errors in Parenthesis $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$
Average and Median Half-Life calculated from Average and Median Estimates

Table B.13: Threshold Autoregression Persistence Estimates for iPad Pro Large Devices, $d = 48$

	i =iPad Pro Large, $d = 48$, No. Observations: 266						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	2.923	(0.200)***	-0.588	(0.035)***	0.012	∞	0.722
AT	-0.663	(0.166)***	-1.435	(0.061)***	0.033	0.588	0
AU	-1.000	(0.102)***	-1.627	(0.072)***	0.059	0.0	0
BE	-0.726	(0.157)***	-1.488	(0.060)***	0.032	0.494	0
BR	-0.538	(0.087)***	-0.993	(0.070)***	0.128	0.829	0.129
CA	-1.711	(0.168)***	-0.916	(0.065)***	0.035	0	0.258
CZ	-0.248	(0.206)	-1.242	(0.061)***	0.041	2.245	0
DE	-0.743	(0.155)***	-1.468	(0.061)***	0.034	0.471	0
DK	-1.460	(0.059)***				0	
ES	-0.684	(0.165)***	-1.429	(0.061)***	0.033	0.555	0
FI	-0.935	(0.152)***	-1.497	(0.060)***	0.033	0.234	0
FR	-0.725	(0.157)***	-1.489	(0.060)***	0.032	0.496	0
HK	0.095	(0.030)***	-1.380	(0.045)***	0.029	∞	0
HU	-1.633	(0.104)***	-0.953	(0.074)***	0.058	0	0.209
IE	-0.944	(0.170)***	-1.455	(0.060)***	0.031	0.222	0
IT	-0.729	(0.158)***	-1.489	(0.060)***	0.032	0.49	0
JP	-1.431	(0.086)***	-1.057	(0.063)***	0.083	0	0
KR	-1.630	(0.117)***	-1.020	(0.066)***	0.038	0	0
LU	-0.743	(0.158)***	-1.486	(0.060)***	0.031	0.471	0
MX	-4.013	(1.032)***	-1.092	(0.056)***	0.013	0	0
MY	-0.613	(0.221)***	-1.417	(0.047)***	0.020	0.674	0
NL	-0.755	(0.159)***	-1.486	(0.060)***	0.031	0.455	0
NO	-0.306	(0.128)**	-1.346	(0.066)***	0.057	1.752	0
NZ	-1.427	(0.096)***	-0.968	(0.093)***	0.072	0	0.186
PH	0.393	(0.145)***	-0.851	(0.057)***	0.052	∞	0.336
PL	-0.060	(0.367)	-1.149	(0.062)***	0.024	10.341	0
PT	-0.946	(0.154)***	-1.499	(0.060)***	0.032	0.219	0
RU	-1.947	(0.140)***	-1.210	(0.053)***	0.052	0	0
SE	-1.568	(0.087)***	-0.899	(0.091)***	0.072	0	0.279
SG	-1.037	(0.061)***				0	
TH	-1.320	(0.126)***	-0.888	(0.093)***	0.039	0	0.292
TR	-1.976	(0.125)***	-0.990	(0.067)***	0.091	0	0.139
TW	0.287	(0.106)***	-0.539	(0.052)***	0.033	∞	0.826
UK	-0.188	(0.211)	-1.325	(0.058)***	0.028	3.072	0
Average	-0.853	0.169	-1.208	0.063	0.043	0.334	0
Median	-0.749	0.153	-1.284	0.060	0.033	0.463	0
Std Dev	1.033	0.161	0.285	0.012	0.024		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.14: Threshold Autoregression Persistence Estimates for iPad Pro Small Devices, $d = 48$

	i =iPad Pro Small, $d = 48$, No. Observations: 254						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-0.260	(0.081)***	-0.854	(0.052)***	0.021	2.125	0.333
AT	-0.924	(0.118)***	-1.503	(0.063)***	0.041	0.248	0
AU	0.329	(0.319)	-1.543	(0.058)***	0.028	∞	0
BE	-0.826	(0.144)***	-1.500	(0.059)***	0.032	0.366	0
BR	-0.481	(0.097)***	-0.930	(0.065)***	0.126	0.976	0.241
CA	-1.392	(0.140)***	-0.861	(0.069)***	0.047	0	0.324
CZ	-0.193	(0.219)	-1.228	(0.061)***	0.043	2.984	0
DE	-1.076	(0.106)***	-1.466	(0.068)***	0.044	0	0
DK	-1.067	(0.092)***	-1.630	(0.072)***	0.053	0	0
ES	-0.674	(0.202)***	-1.430	(0.059)***	0.028	0.571	0
FI	-0.962	(0.120)***	-1.513	(0.063)***	0.038	0.196	0
FR	-0.901	(0.141)***	-1.505	(0.059)***	0.033	0.277	0
HK	0.176	(0.067)***	-1.124	(0.060)***	0.029	∞	0
HU	-1.756	(0.112)***	-0.909	(0.069)***	0.057	0	0.267
IE	-1.010	(0.114)***	-1.485	(0.065)***	0.040	0	0
IT	-0.845	(0.138)***	-1.510	(0.060)***	0.033	0.343	0
JP	-1.301	(0.133)***	-0.866	(0.066)***	0.043	0	0.318
KR	-5.847	(1.405)***	-1.250	(0.062)***	0.006	0	0
LU	-0.826	(0.144)***	-1.500	(0.059)***	0.032	0.366	0
MX	-1.205	(0.048)***				0	
MY	-0.076	(0.184)	-1.340	(0.052)***	0.028	8.095	0
NL	-0.835	(0.142)***	-1.502	(0.060)***	0.033	0.355	0
NO	0.262	(0.207)	-1.228	(0.057)***	0.034	∞	0
NZ	-0.143	(0.333)	-1.374	(0.069)***	0.025	4.146	0
PH	-0.314	(0.084)***	-1.115	(0.075)***	0.068	1.698	0
PL	-1.138	(0.063)***				0	
PT	-0.962	(0.120)***	-1.513	(0.063)***	0.038	0.196	0
RU	2.683	(1.575)*	-1.280	(0.062)***	0.012	∞	0
SE	-1.490	(0.075)***	-1.178	(0.099)***	0.083	0	0
SG	-1.296	(0.052)***				0	
TH	2.059	(0.825)**	-1.092	(0.067)***	0.010	∞	0
TR	-2.101	(0.172)***	-1.050	(0.064)***	0.065	0	0
TW	-0.088	(0.091)	-0.553	(0.063)***	0.032	6.946	0.795
UK	-0.617	(0.166)***	-1.296	(0.060)***	0.036	0.667	0
Average	-0.738	0.236	-1.262	0.064	0.040	0.477	0
Median	-0.840	0.136	-1.296	0.063	0.034	0.349	0
Std Dev	1.283	0.341	0.265	0.008	0.022		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.15: Threshold Autoregression Persistence Estimates for iPad Devices, $d = 48$

	i =iPad, $d = 48$, No. Observations: 266						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	-2.263	(0.183)***	-0.484	(0.034)***	0.017	0	0.967
AT	-1.316	(0.069)***	-0.857	(0.084)***	0.125	0	0.329
AU	-0.813	(0.081)***	-1.152	(0.073)***	0.090	0.382	0
BE	-1.315	(0.068)***	-0.853	(0.084)***	0.125	0	0.334
BR	4.292	(2.015)**	-0.988	(0.047)***	0.013	∞	0.145
CA	-1.782	(0.093)***	-0.877	(0.043)***	0.069	0	0.305
CZ	0.800	(0.564)	-1.242	(0.056)***	0.039	∞	0
DE	-0.002	(0.273)	-1.225	(0.056)***	0.040	319.594	0
DK	-1.646	(0.085)***	-0.893	(0.049)***	0.076	0	0.286
ES	0.380	(0.142)***	-0.590	(0.051)***	0.233	∞	0.718
FI	-1.319	(0.068)***	-0.837	(0.083)***	0.126	0	0.353
FR	-1.313	(0.068)***	-0.857	(0.084)***	0.125	0	0.329
HK	-1.392	(0.144)***	-0.492	(0.051)***	0.006	0	0.945
HU	0.335	(0.511)	-1.138	(0.056)***	0.027	∞	0
IE	-1.345	(0.068)***	-0.842	(0.081)***	0.125	0	0.347
IT	-1.316	(0.068)***	-0.852	(0.084)***	0.124	0	0.335
JP	-1.195	(0.115)***	-0.715	(0.058)***	0.047	0	0.51
KR	-1.503	(0.145)***	-0.867	(0.048)***	0.038	0	0.317
LU	-1.316	(0.068)***	-0.852	(0.084)***	0.124	0	0.335
MX	-1.235	(0.080)***	-0.895	(0.075)***	0.146	0	0.284
MY	-1.044	(0.053)***				0	
NL	-1.314	(0.068)***	-0.849	(0.084)***	0.125	0	0.338
NO	-0.776	(0.088)***	-1.197	(0.068)***	0.086	0.428	0
NZ	-0.840	(0.063)***				0.349	
PH	0.017	(0.174)	-0.565	(0.047)***	0.023	∞	0.769
PL	-1.645	(0.119)***	-0.922	(0.055)***	0.101	0	0.251
PT	-1.320	(0.068)***	-0.843	(0.084)***	0.127	0	0.346
RU	-0.545	(0.177)***	-1.170	(0.051)***	0.048	0.813	0
SE	2.087	(0.574)***	-1.112	(0.053)***	0.027	∞	0
SG	-2.277	(0.583)***	-0.752	(0.045)***	0.012	0	0.459
TH	-1.378	(0.070)***	-0.718	(0.066)***	0.082	0	0.505
TR	-1.508	(0.135)***	-0.968	(0.070)***	0.091	0	0.186
TW	-0.411	(0.117)***	-1.019	(0.051)***	0.026	1.209	0
UK	-0.293	(0.308)	-1.092	(0.056)***	0.028	1.845	0
Average	-0.780	0.221	-0.897	0.063	0.078	0.423	0.281
Median	-1.314	0.104	-0.862	0.056	0.079	0	0.323
Std Dev	1.243	0.348	0.200	0.015	0.052		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

Table B.16: Threshold Autoregression Persistence Estimates for iPad Mini Devices, $d = 48$

	i =iPad Mini, $d = 48$, No. Observations: 266						
Country	Inner $\hat{\rho}_0$	Inner SE	Outer $\hat{\rho}_1$	Outer SE	Threshold c_i	Half-life $\hat{\rho}_0$	Half-life $\hat{\rho}_1$
AE	8.546	(0.971)***	-0.808	(0.040)***	0.003	∞	0.388
AT	-1.061	(0.082)***	-1.546	(0.068)***	0.100	0	0
AU	-1.204	(0.063)***				0	
BE	-1.095	(0.090)***	-1.528	(0.066)***	0.082	0	0
BR	-1.098	(0.181)***	-0.489	(0.061)***	0.116	0	0.953
CA	-1.387	(0.073)***	-0.923	(0.067)***	0.086	0	0.25
CZ	0.374	(0.363)	-1.392	(0.055)***	0.033	∞	0
DE	-1.035	(0.135)***	-1.624	(0.098)***	0.078	0	0
DK	0.809	(0.424)*	-1.273	(0.056)***	0.028	∞	0
ES	-1.071	(0.088)***	-1.515	(0.065)***	0.094	0	0
FI	-1.119	(0.094)***	-1.538	(0.066)***	0.072	0	0
FR	-1.113	(0.088)***	-1.524	(0.067)***	0.090	0	0
HK	-0.074	(0.045)	-1.461	(0.091)***	0.024	8.322	0
HU	-1.052	(0.063)***				0	
IE	-1.101	(0.097)***	-1.527	(0.065)***	0.077	0	0
IT	-1.095	(0.090)***	-1.528	(0.066)***	0.082	0	0
JP	1.340	(0.600)**	-0.735	(0.062)***	0.012	∞	0.482
KR	0.757	(0.450)*	-0.689	(0.055)***	0.021	∞	0.548
LU	-1.095	(0.090)***	-1.528	(0.066)***	0.082	0	0
MX	-1.244	(0.069)***	-0.839	(0.070)***	0.163	0	0.35
MY	-0.711	(0.069)***	-1.350	(0.077)***	0.151	0.515	0
NL	-1.095	(0.090)***	-1.529	(0.066)***	0.081	0	0
NO	-0.457	(0.239)*	-1.277	(0.068)***	0.038	1.048	0
NZ	-0.759	(0.082)***	-1.352	(0.093)***	0.062	0.45	0
PH	2.836	(0.736)***	-0.846	(0.061)***	0.011	∞	0.342
PL	-1.099	(0.060)***				0	
PT	-1.119	(0.094)***	-1.538	(0.066)***	0.072	0	0
RU	-2.779	(0.400)***	-1.326	(0.053)***	0.026	0	0
SE	-1.052	(0.073)***	-1.548	(0.084)***	0.128	0	0
SG	-1.361	(0.137)***	-0.969	(0.064)***	0.028	0	0.184
TH	-1.038	(0.074)***	-0.555	(0.066)***	0.057	0	0.79
TR	0.281	(0.320)	-1.173	(0.062)***	0.045	∞	0
TW	-0.262	(0.167)	-0.907	(0.071)***	0.026	2.106	0.269
UK	-0.793	(0.064)***	-1.542	(0.073)***	0.130	0.406	0
Average	-0.395	0.199	-1.238	0.067	0.068	1.274	0
Median	-1.056	0.090	-1.352	0.066	0.072	0	0
Std Dev	1.834	0.214	0.344	0.012	0.041		

Note: Standard Errors in Parenthesis *$^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$*
Average and Median Half-Life calculated from Average and Median Estimates

APPENDIX B

ADDITIONAL FIGURES

B.1 EXCHANGE RATE PASSTHROUGH ANALYSES: PYMC POSTERIOR DISTRIBUTION TRACE PLOTS

Figure B.1: PyMC Posterior Distribution Trace Plots for CPI Base 2007

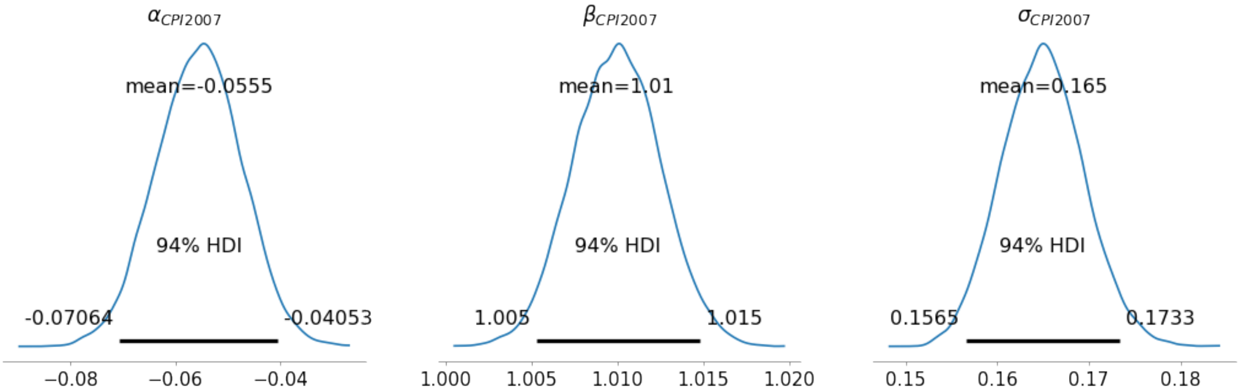


Figure B.2: PyMC Posterior Distribution Trace Plots for CPI Base 2008

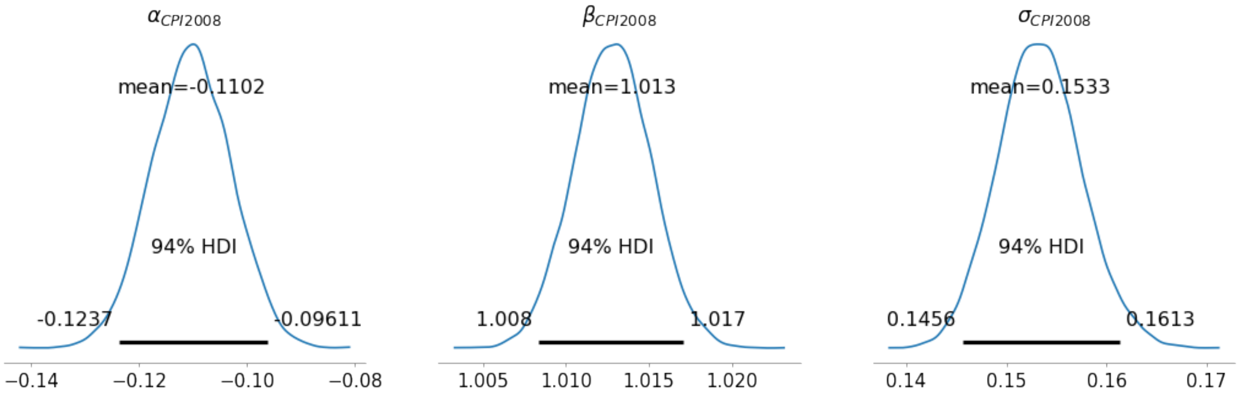


Figure B.3: PyMC Posterior Distribution Trace Plots for CPI Base 2009

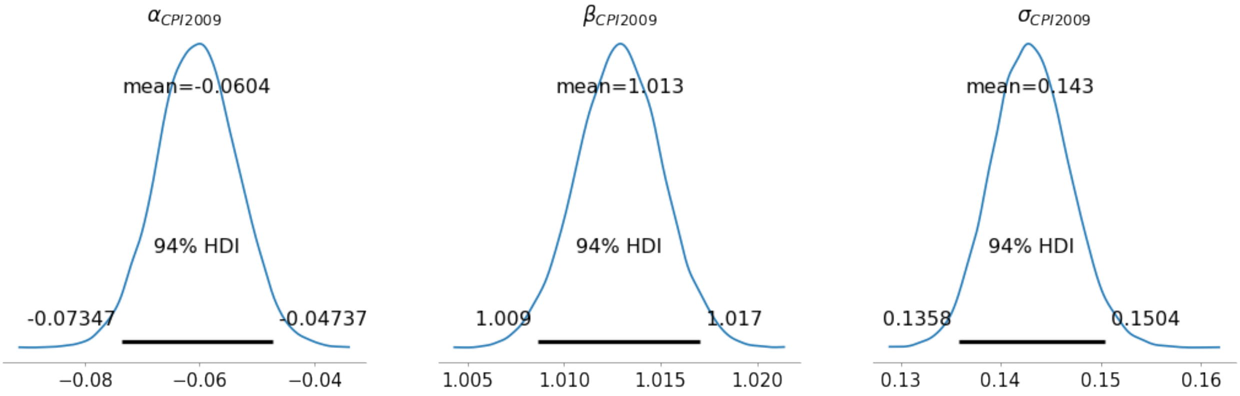


Figure B.4: PyMC Posterior Distribution Trace Plots for CPI Base 2010

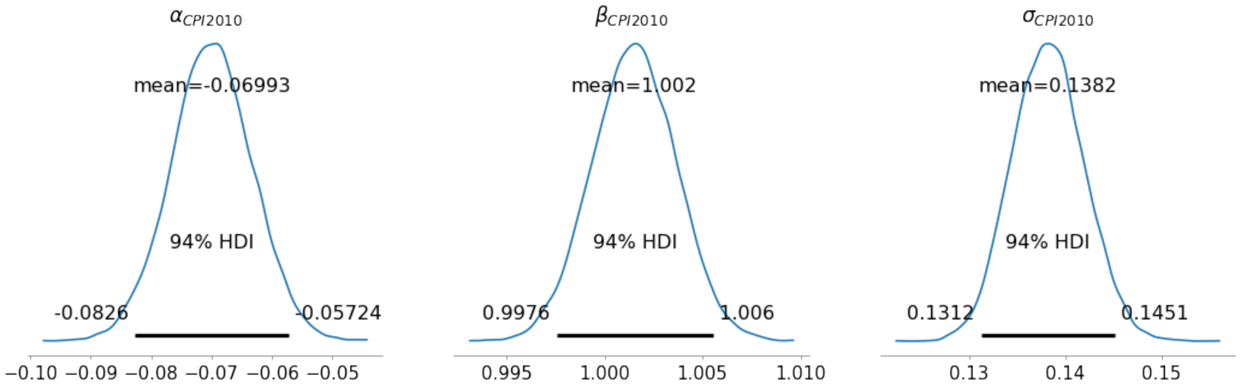


Figure B.5: PyMC Posterior Distribution Trace Plots for CPI Base 2011

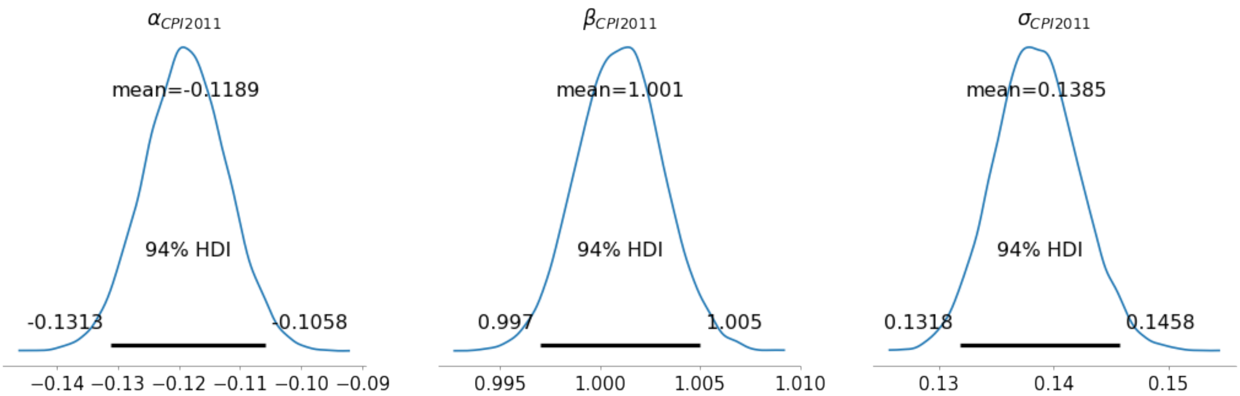


Figure B.6: PyMC Posterior Distribution Trace Plots for CPI Base 2012

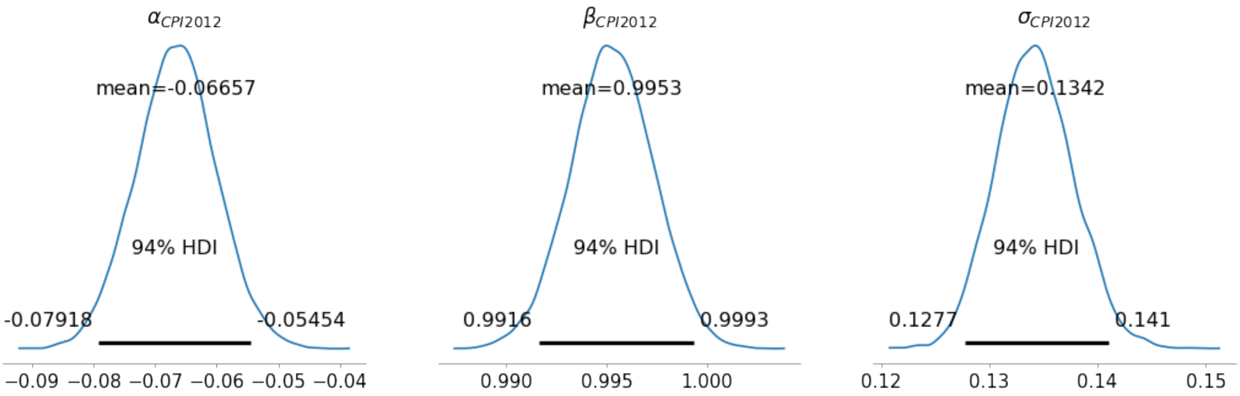


Figure B.7: PyMC Posterior Distribution Trace Plots for CPI Base 2013

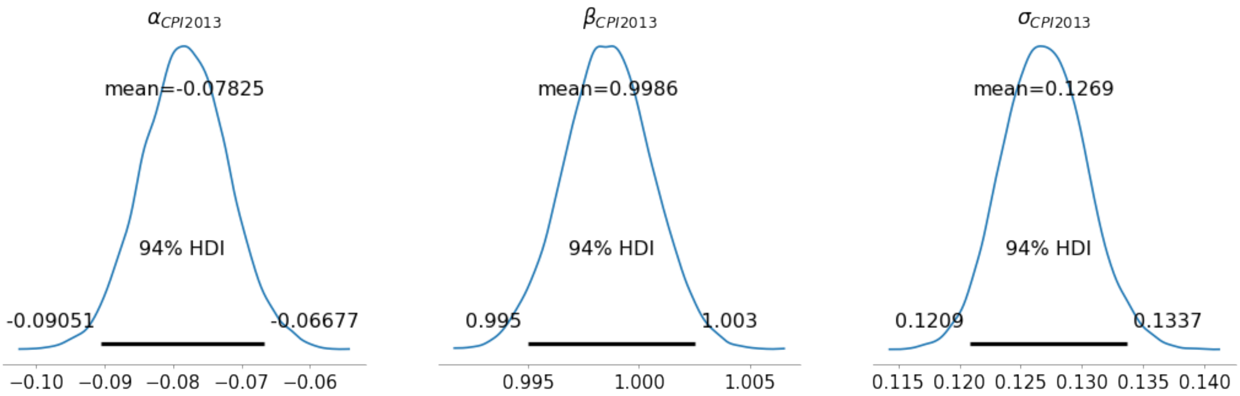


Figure B.8: PyMC Posterior Distribution Trace Plots for CPI Base 2014

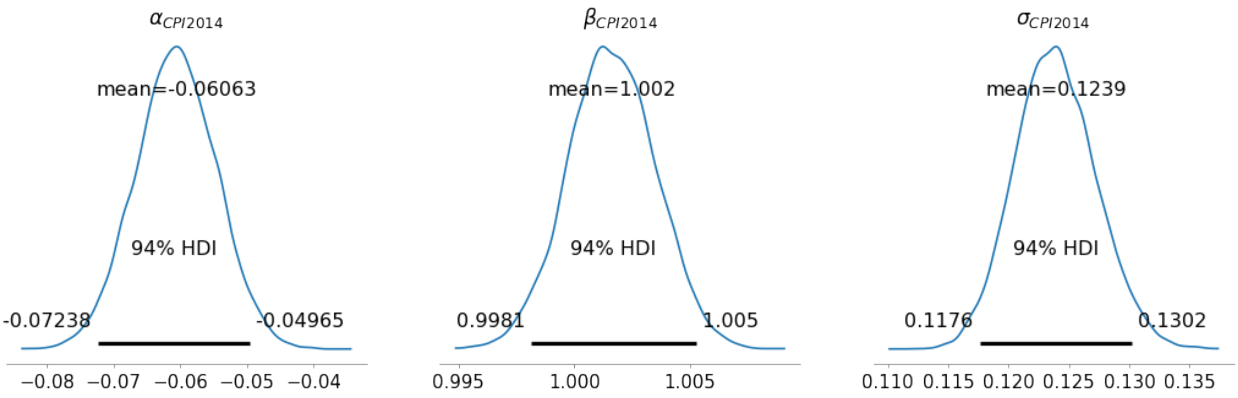


Figure B.9: PyMC Posterior Distribution Trace Plots for CPI Base 2015

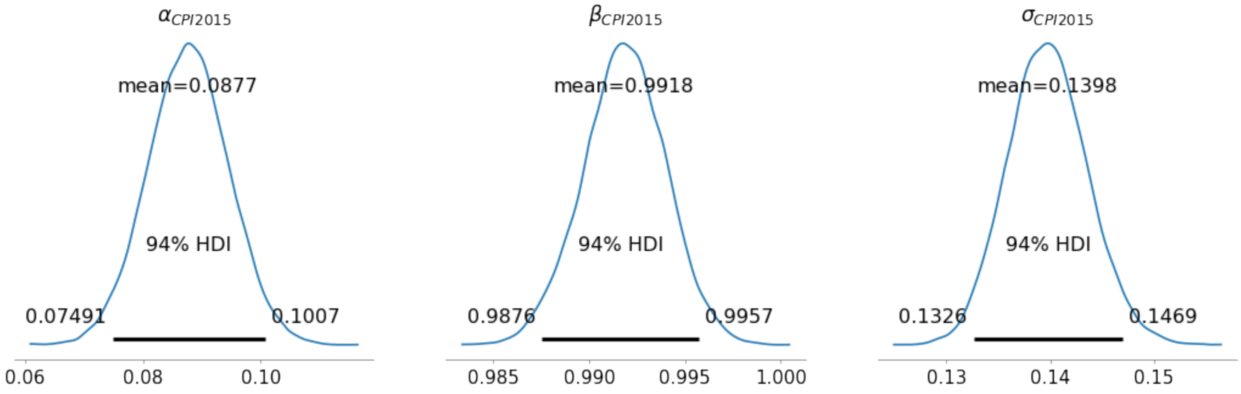


Figure B.10: PyMC Posterior Distribution Trace Plots for CPI Base 2016

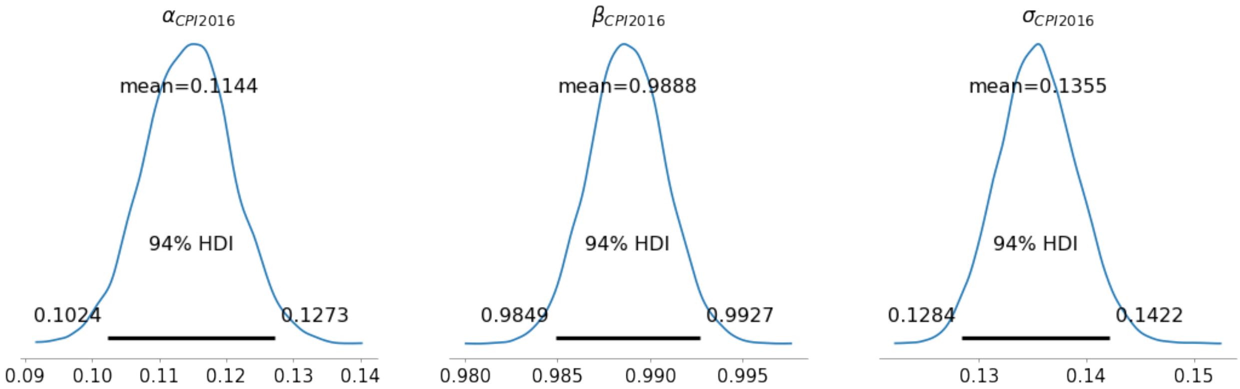


Figure B.11: PyMC Posterior Distribution Trace Plots for CPI Base 2017

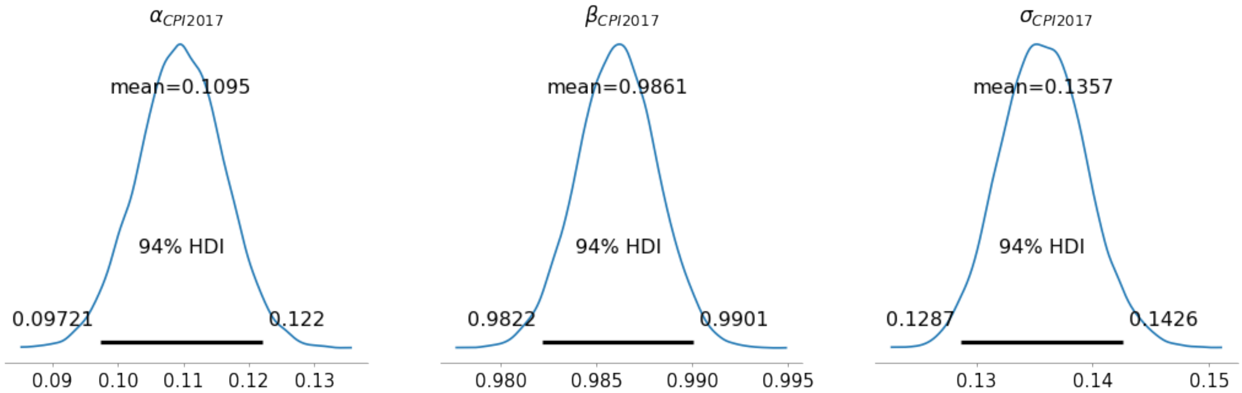


Figure B.12: PyMC Posterior Distribution Trace Plots for CPI Base 2018

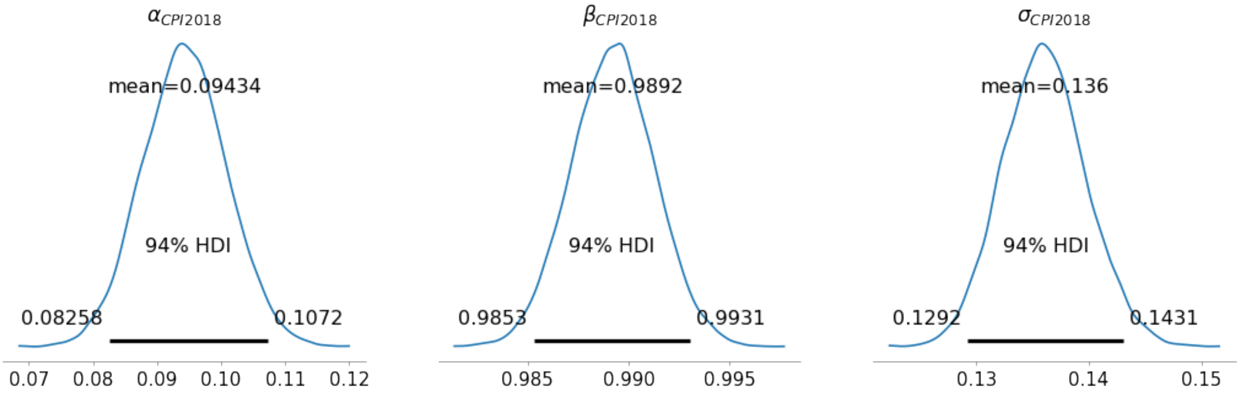


Figure B.13: PyMC Posterior Distribution Trace Plots for CPI Base 2019

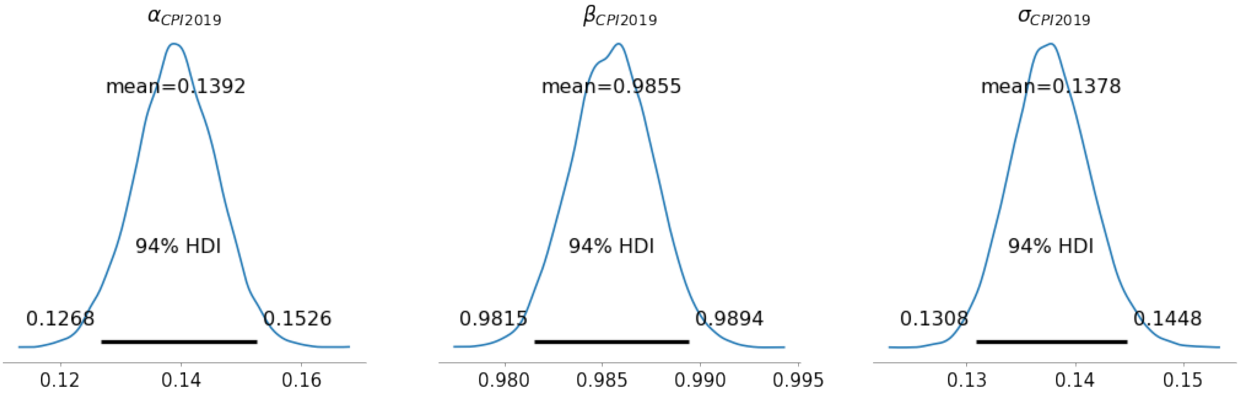


Figure B.14: PyMC Posterior Distribution Trace Plots for CPI Base 2020

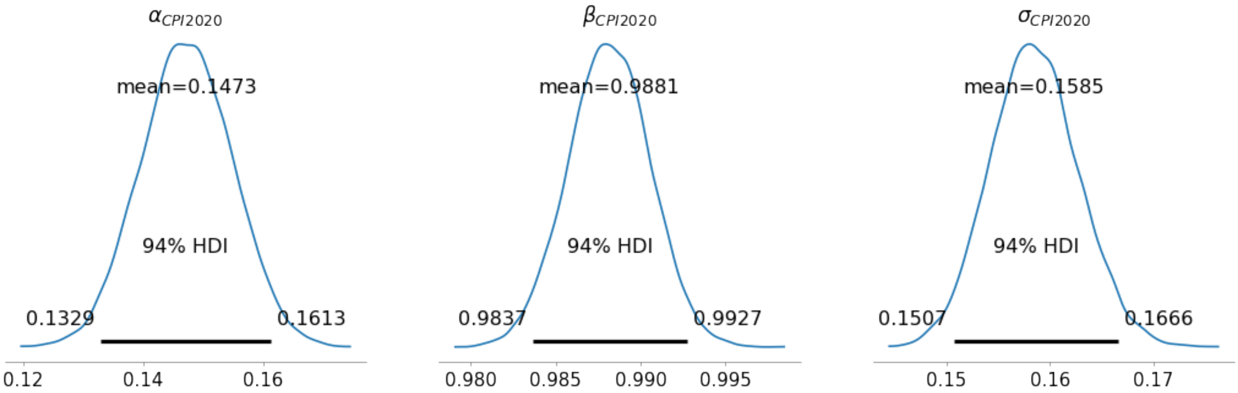


Figure B.15: PyMC Posterior Distribution Trace Plots for Big Macs (excluding Transaction Costs)

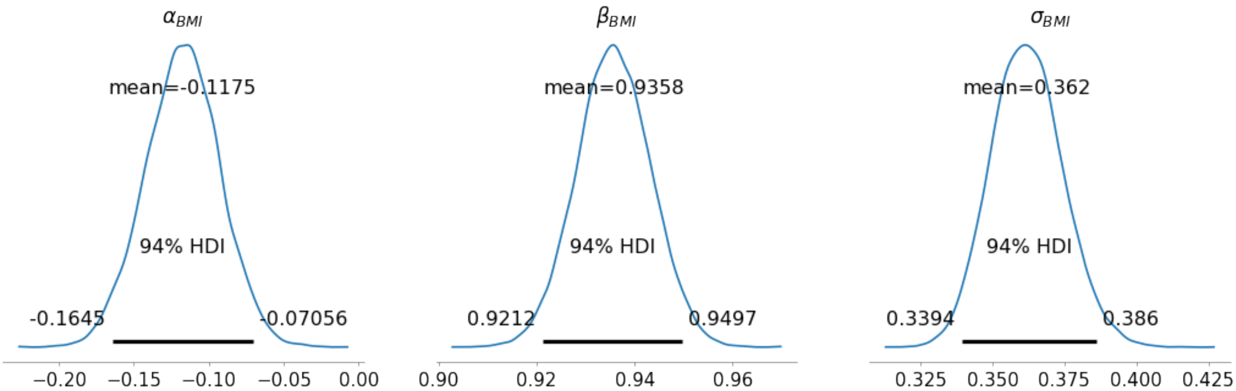


Figure B.16: PyMC Posterior Distribution Trace Plots for Big Macs (including VAT or GST)

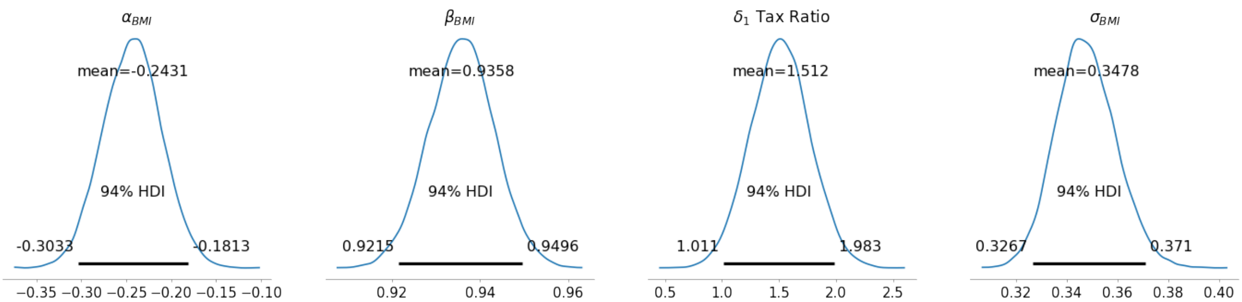


Figure B.17: PyMC Posterior Distribution Trace Plots for iPods (excluding Transaction Costs)

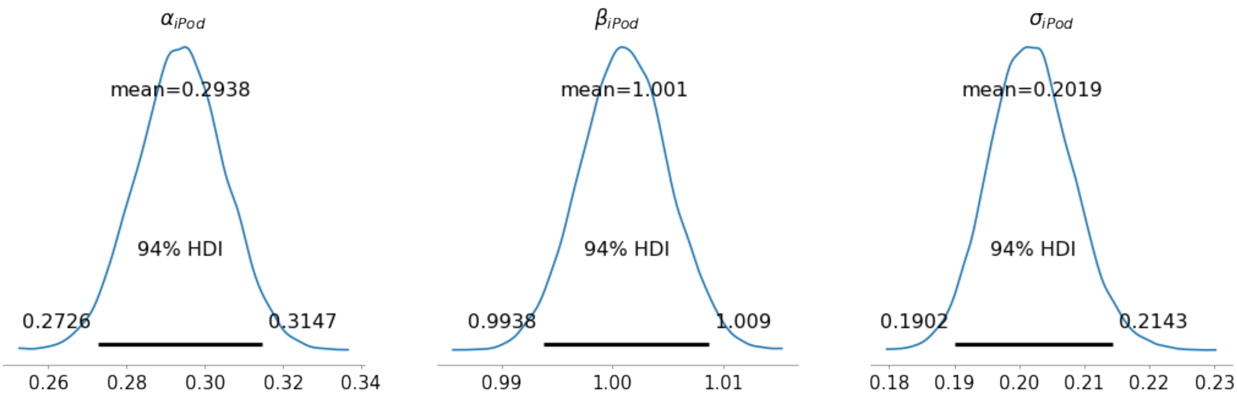


Figure B.18: PyMC Posterior Distribution Trace Plots for iPods (including Transaction Costs)

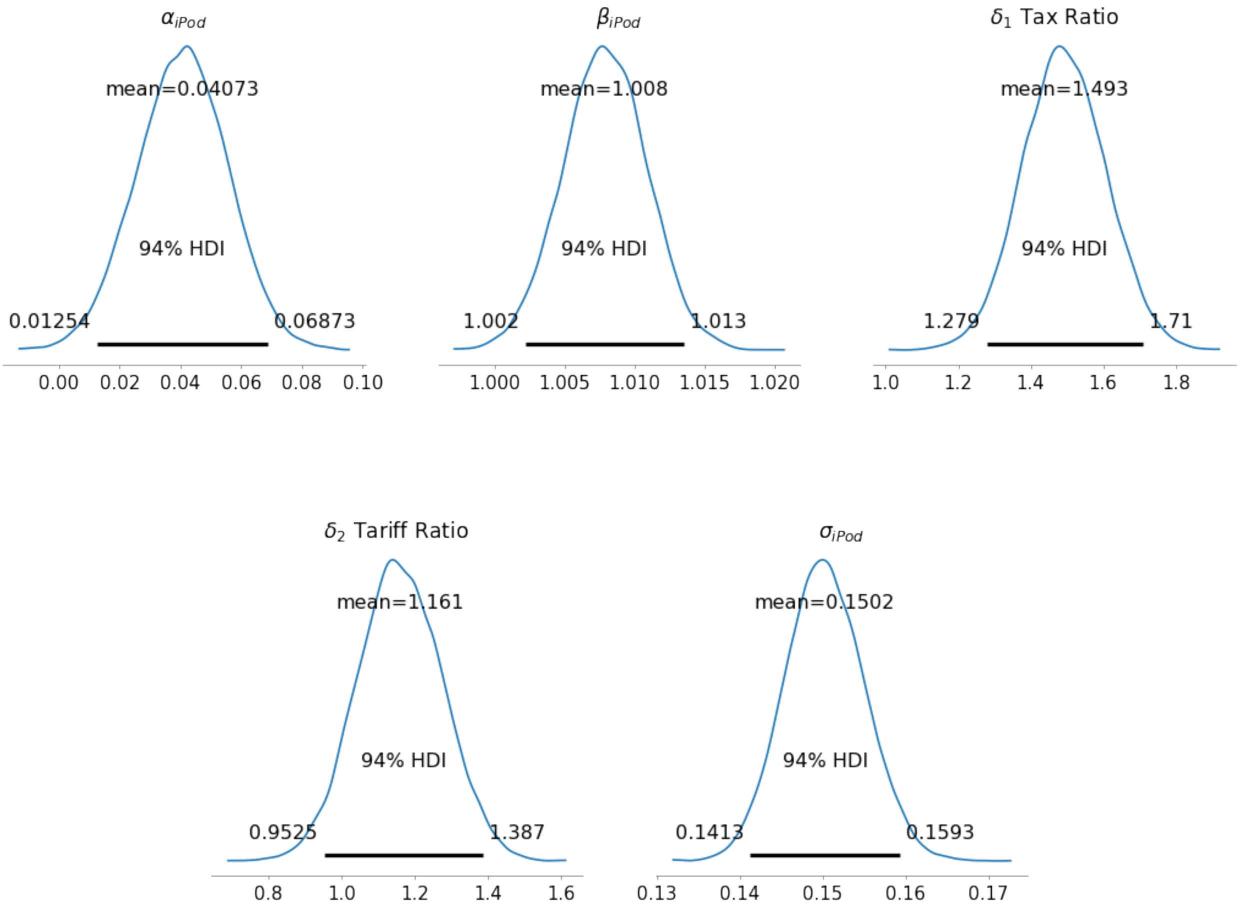


Figure B.19: PyMC Posterior Distribution Trace Plots for iPads (excluding Transaction Costs)

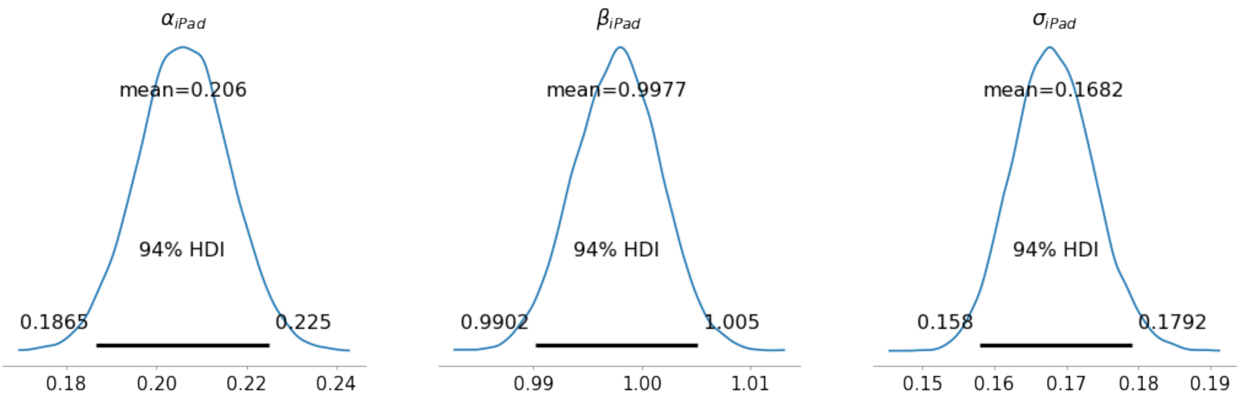


Figure B.20: PyMC Posterior Distribution Trace Plots for iPads (including Transaction Costs)

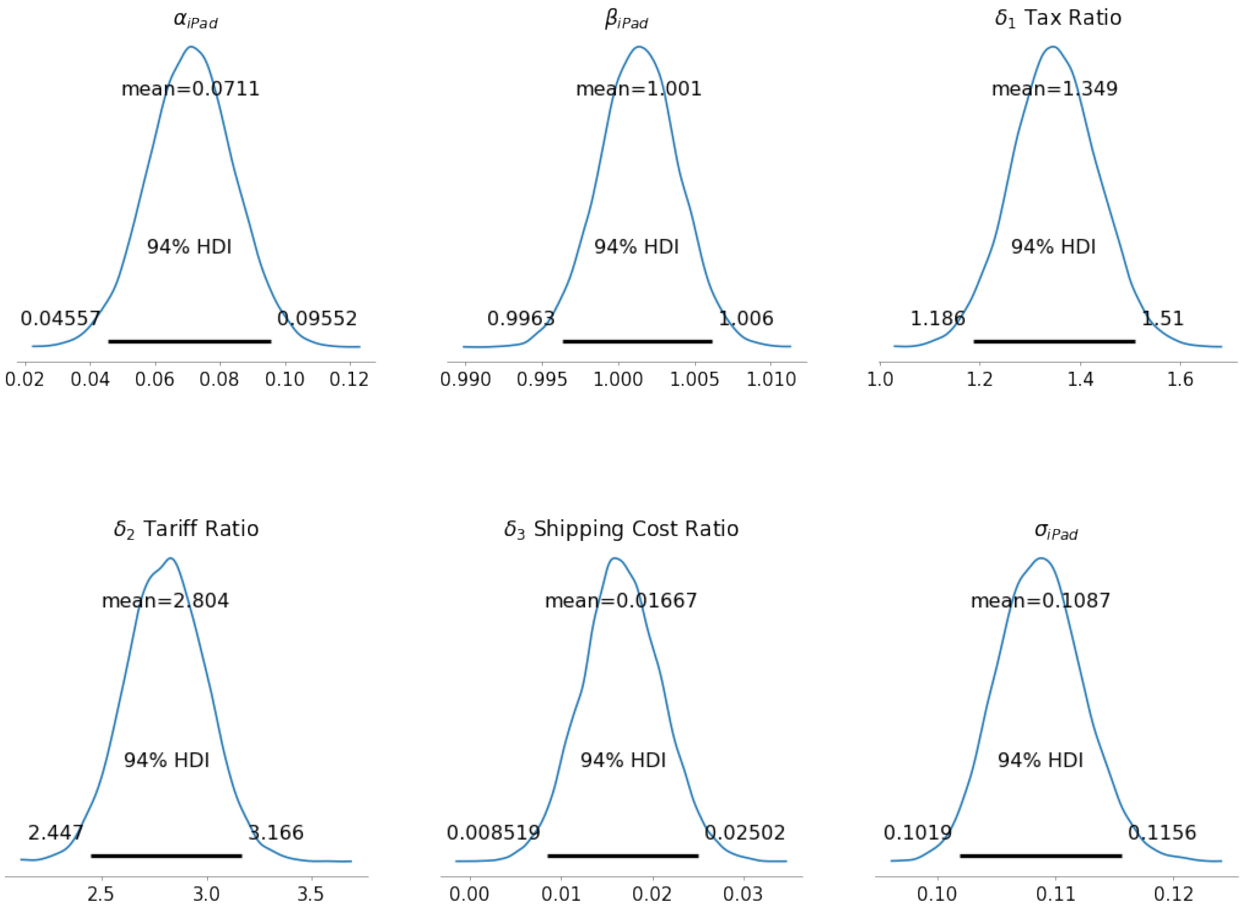


Figure B.21: PyMC Posterior Distribution Trace Plots for iPhones (excluding Transaction Costs)

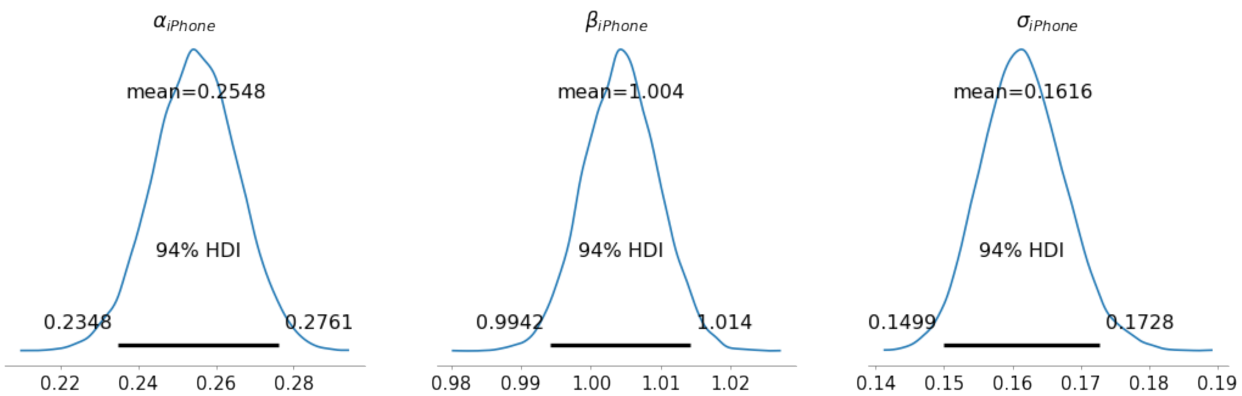
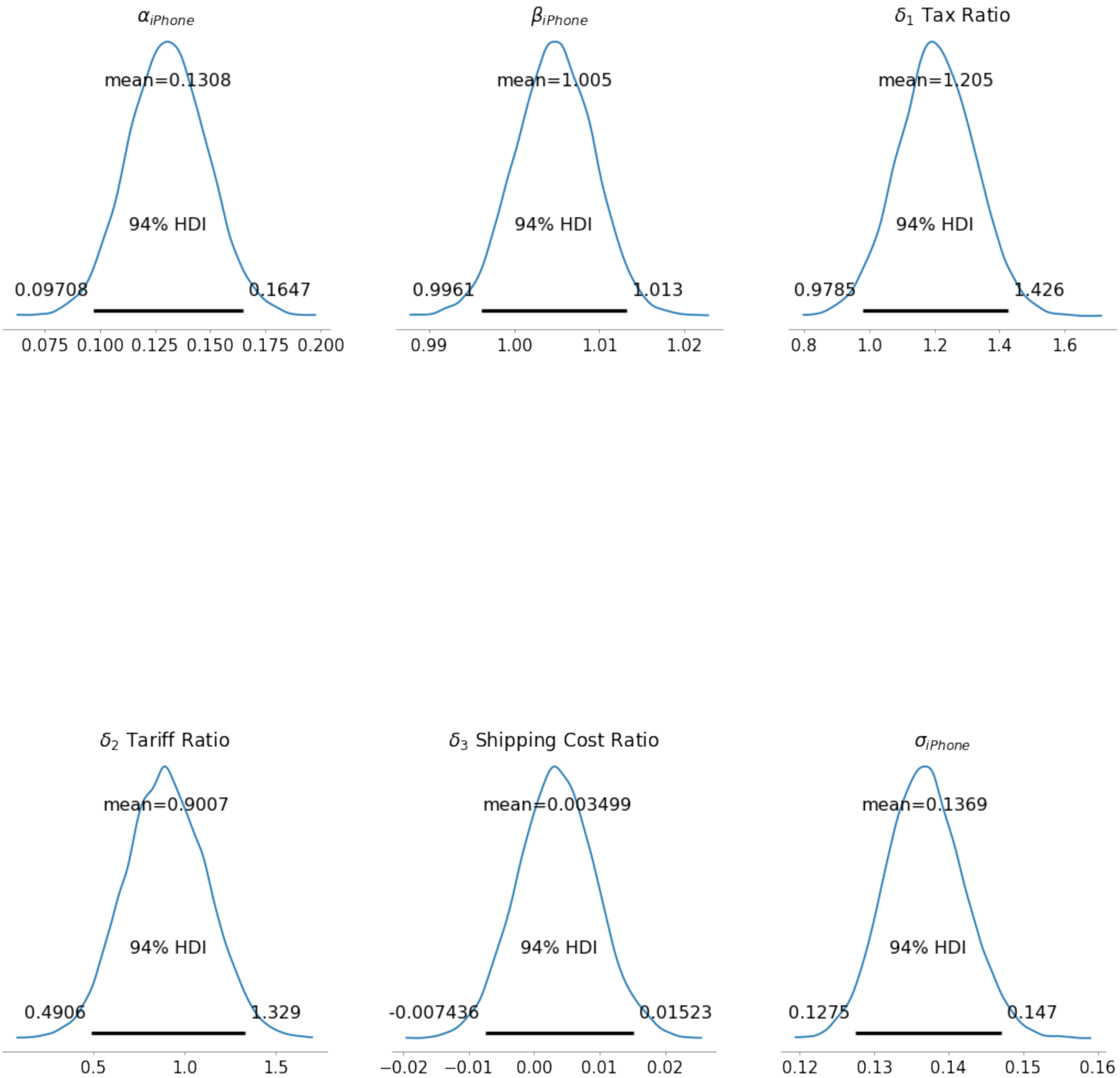


Figure B.22: PyMC Posterior Distribution Trace Plots for iPhones (including Transaction Costs)



B.2 PYMC VIOLIN PLOTS OF POSTERIOR α_X AND β_X PARAMETERS

Figure B.23: Violin Plots of MCMC Generated βs

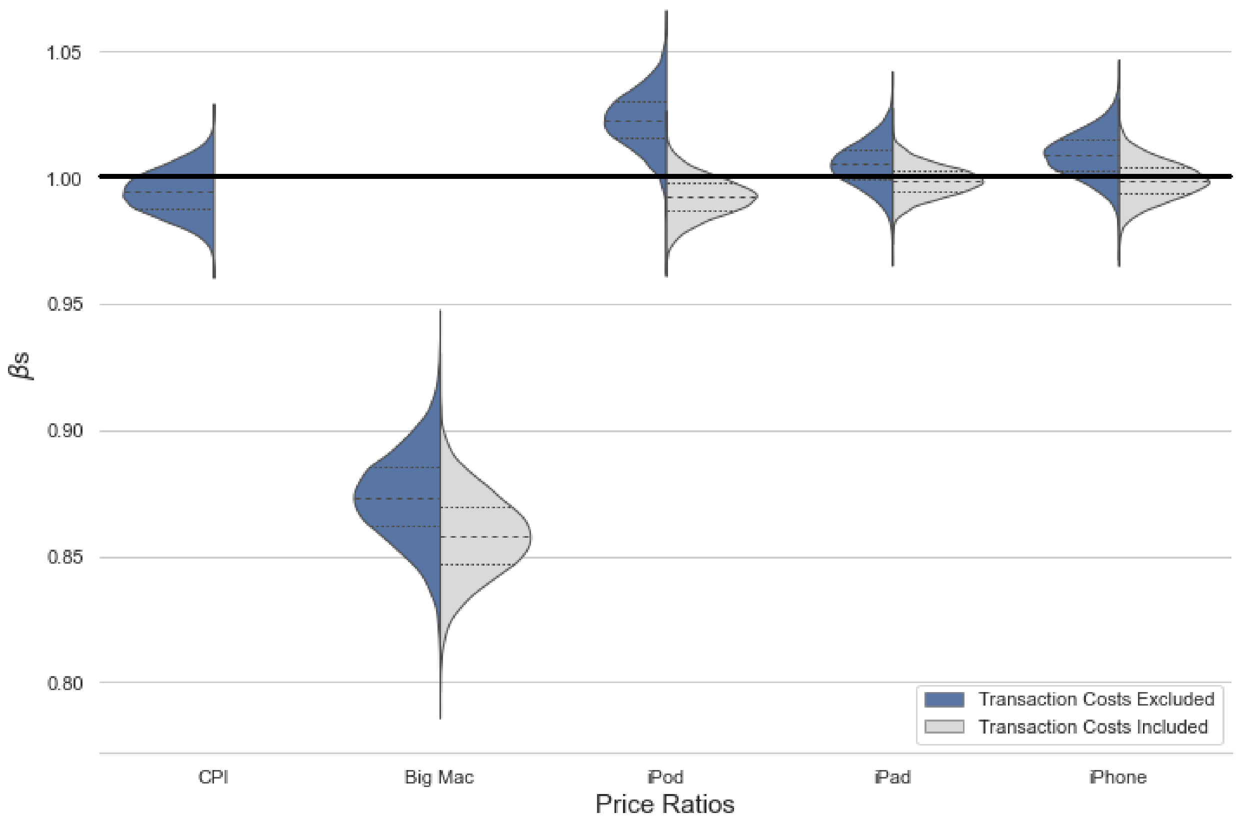
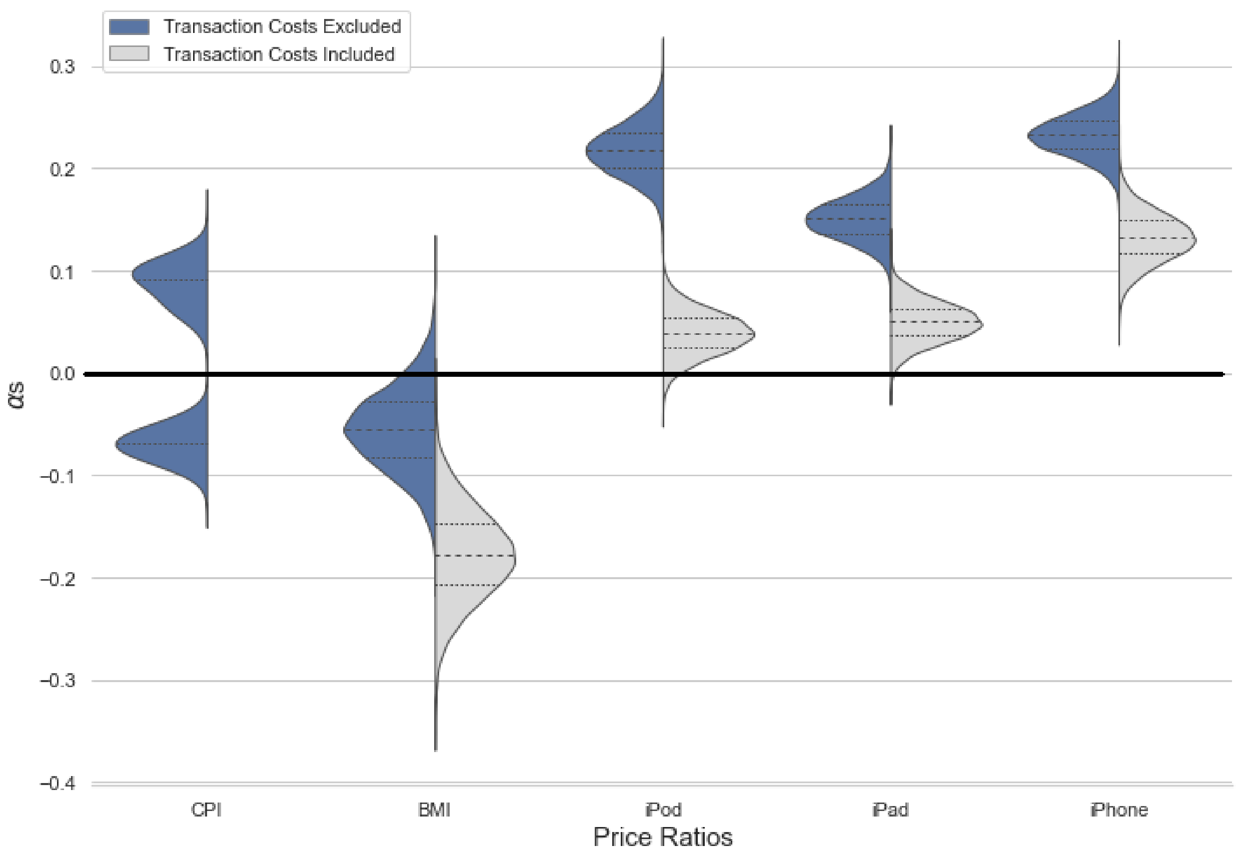
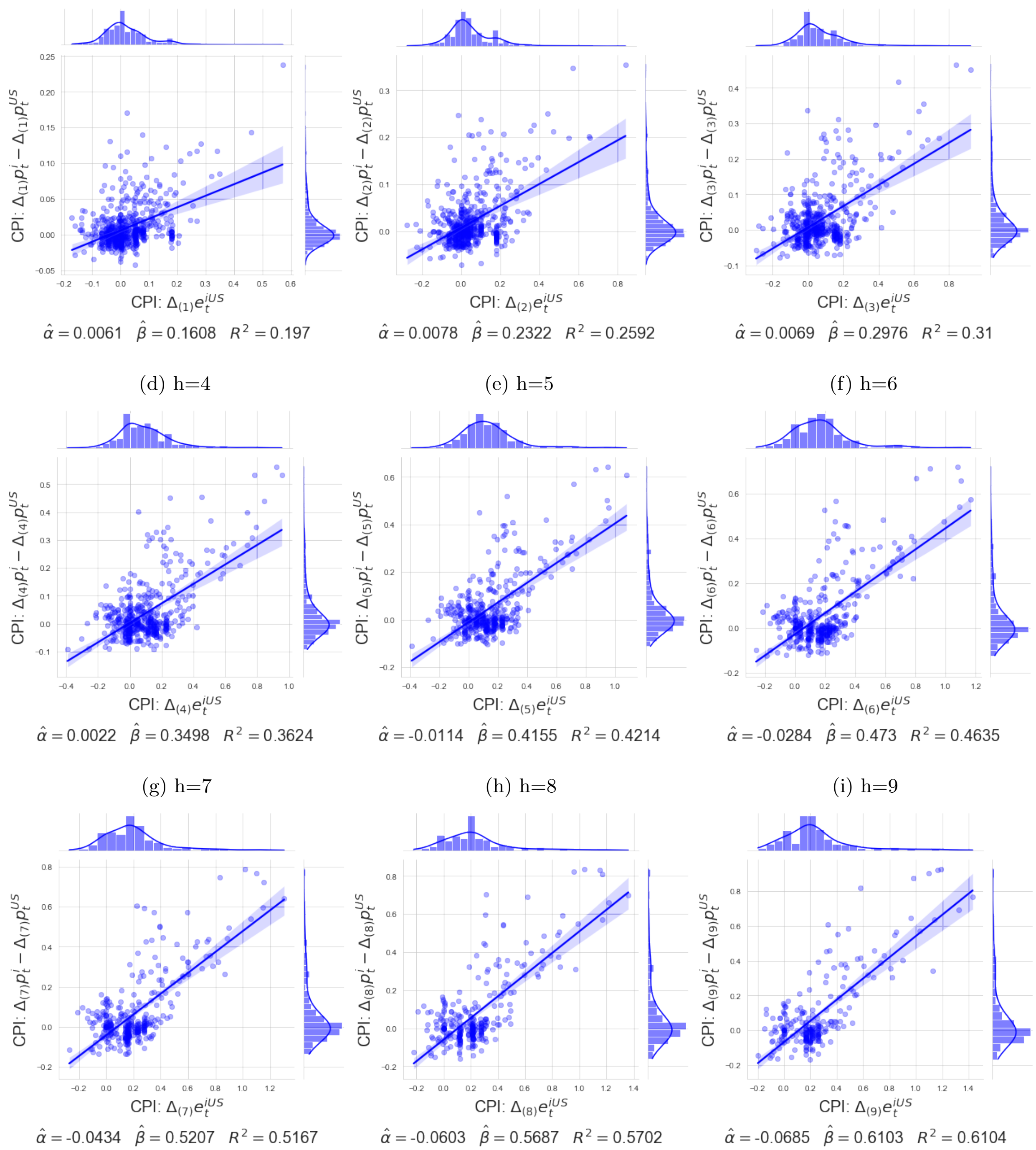


Figure B.24: Violin Plots of MCMC Generated αs



B.3 H-PERIOD CHANGE ANALYSES

Figure B.25: CPI Price Data over h Period Changes



(a) h=1 — $\hat{\alpha} = 0.0061$ $\hat{\beta} = 0.1608$ $R^2 = 0.197$

(b) h=2 — $\hat{\alpha} = 0.0078$ $\hat{\beta} = 0.2322$ $R^2 = 0.2592$

(c) h=3 — $\hat{\alpha} = 0.0069$ $\hat{\beta} = 0.2976$ $R^2 = 0.31$

(d) h=4 — $\hat{\alpha} = 0.0022$ $\hat{\beta} = 0.3498$ $R^2 = 0.3624$

(e) h=5 — $\hat{\alpha} = -0.0114$ $\hat{\beta} = 0.4155$ $R^2 = 0.4214$

(f) h=6 — $\hat{\alpha} = -0.0284$ $\hat{\beta} = 0.473$ $R^2 = 0.4635$

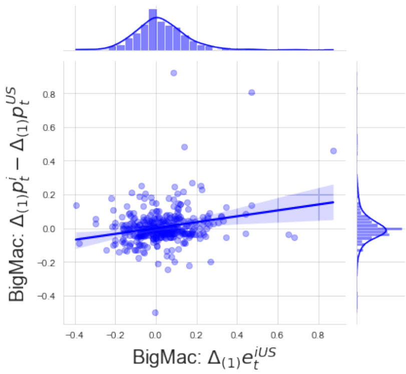
(g) h=7 — $\hat{\alpha} = -0.0434$ $\hat{\beta} = 0.5207$ $R^2 = 0.5167$

(h) h=8 — $\hat{\alpha} = -0.0603$ $\hat{\beta} = 0.5687$ $R^2 = 0.5702$

(i) h=9 — $\hat{\alpha} = -0.0685$ $\hat{\beta} = 0.6103$ $R^2 = 0.6104$

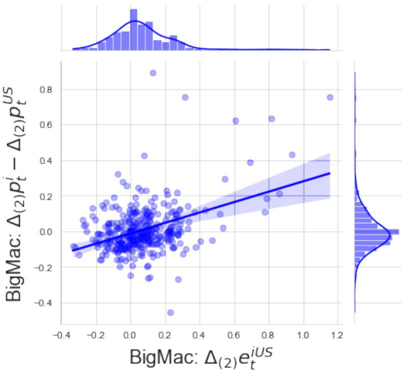
Figure B.26: Big Mac Price Data over h Period Changes

(a) h=1



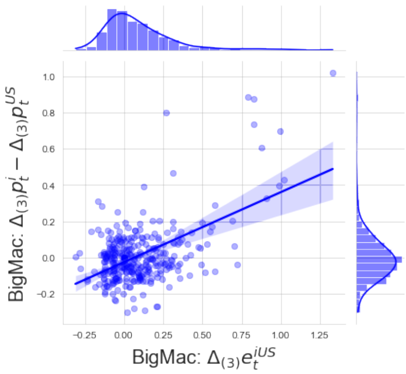
$\hat{\alpha} = 0.0003 \quad \hat{\beta} = 0.1743 \quad R^2 = 0.0527$

(b) h=2



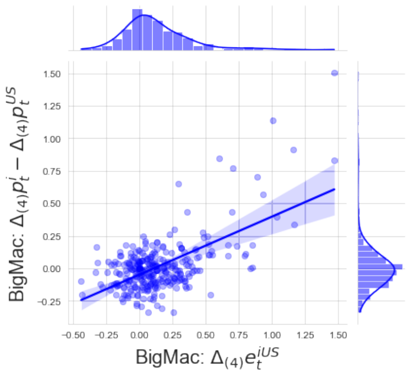
$\hat{\alpha} = -0.012 \quad \hat{\beta} = 0.2916 \quad R^2 = 0.163$

(c) h=3



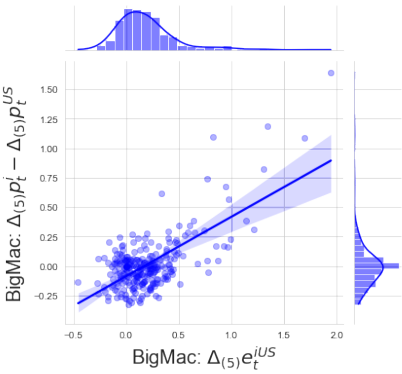
$\hat{\alpha} = -0.0261 \quad \hat{\beta} = 0.3864 \quad R^2 = 0.2869$

(d) h=4



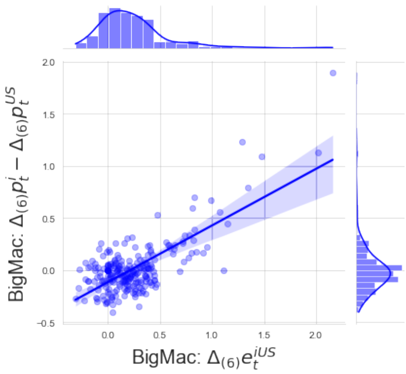
$\hat{\alpha} = -0.049 \quad \hat{\beta} = 0.446 \quad R^2 = 0.3679$

(e) h=5



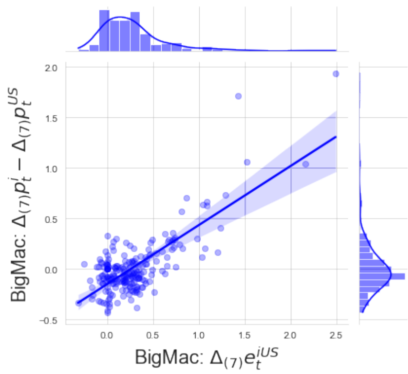
$\hat{\alpha} = -0.0849 \quad \hat{\beta} = 0.5041 \quad R^2 = 0.457$

(f) h=6



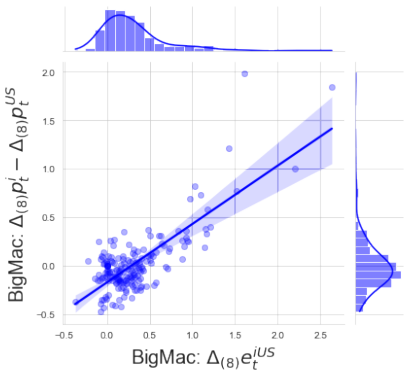
$\hat{\alpha} = -0.1141 \quad \hat{\beta} = 0.5432 \quad R^2 = 0.5332$

(g) h=7



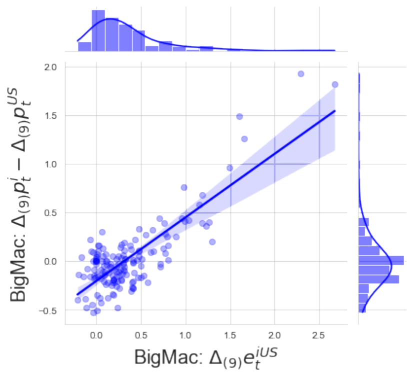
$\hat{\alpha} = -0.1503 \quad \hat{\beta} = 0.5848 \quad R^2 = 0.5826$

(h) h=8



$\hat{\alpha} = -0.1705 \quad \hat{\beta} = 0.6016 \quad R^2 = 0.5974$

(i) h=9



$\hat{\alpha} = -0.2042 \quad \hat{\beta} = 0.6522 \quad R^2 = 0.6588$

Figure B.27: iPod Price Data over h Period Changes

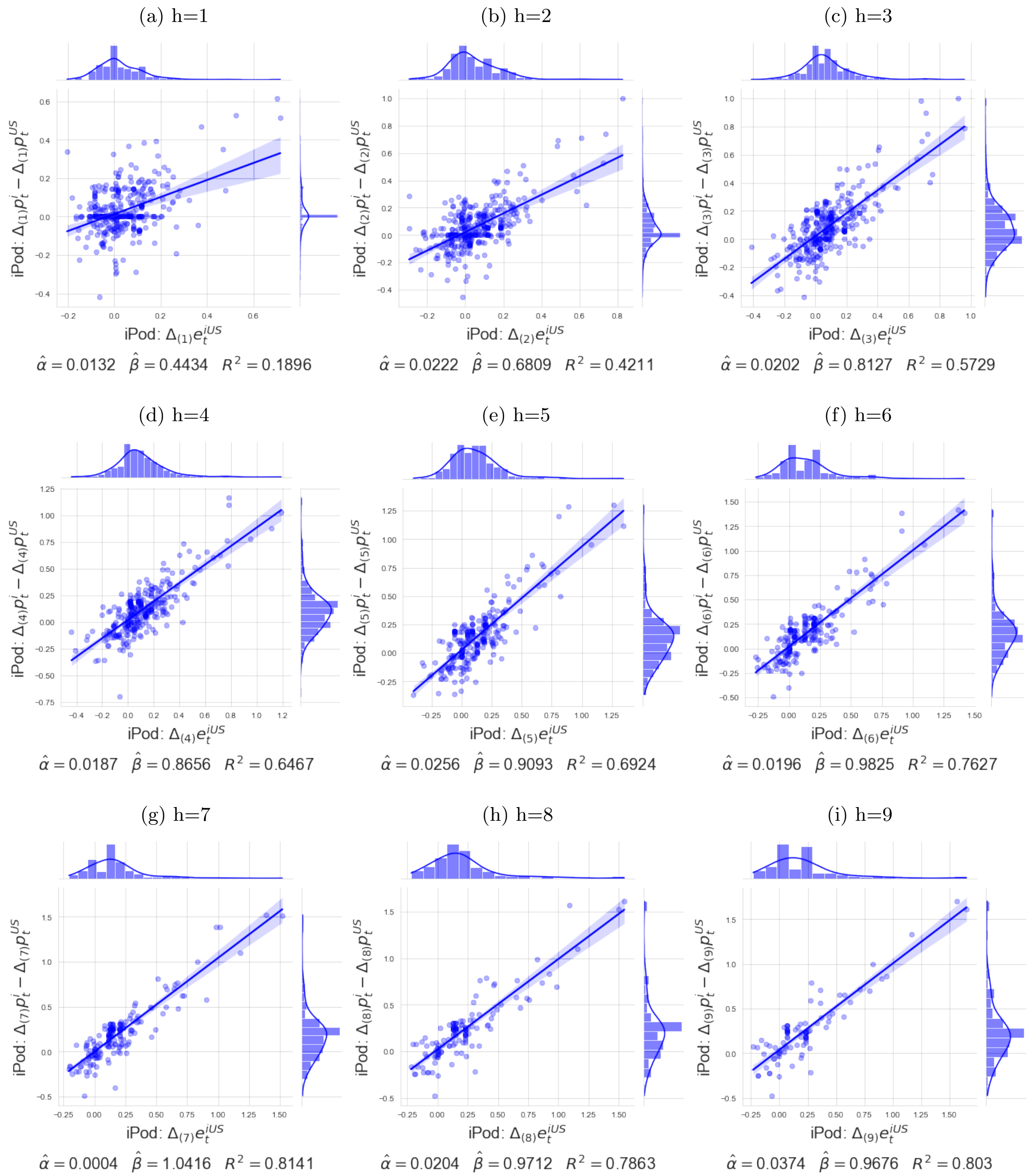
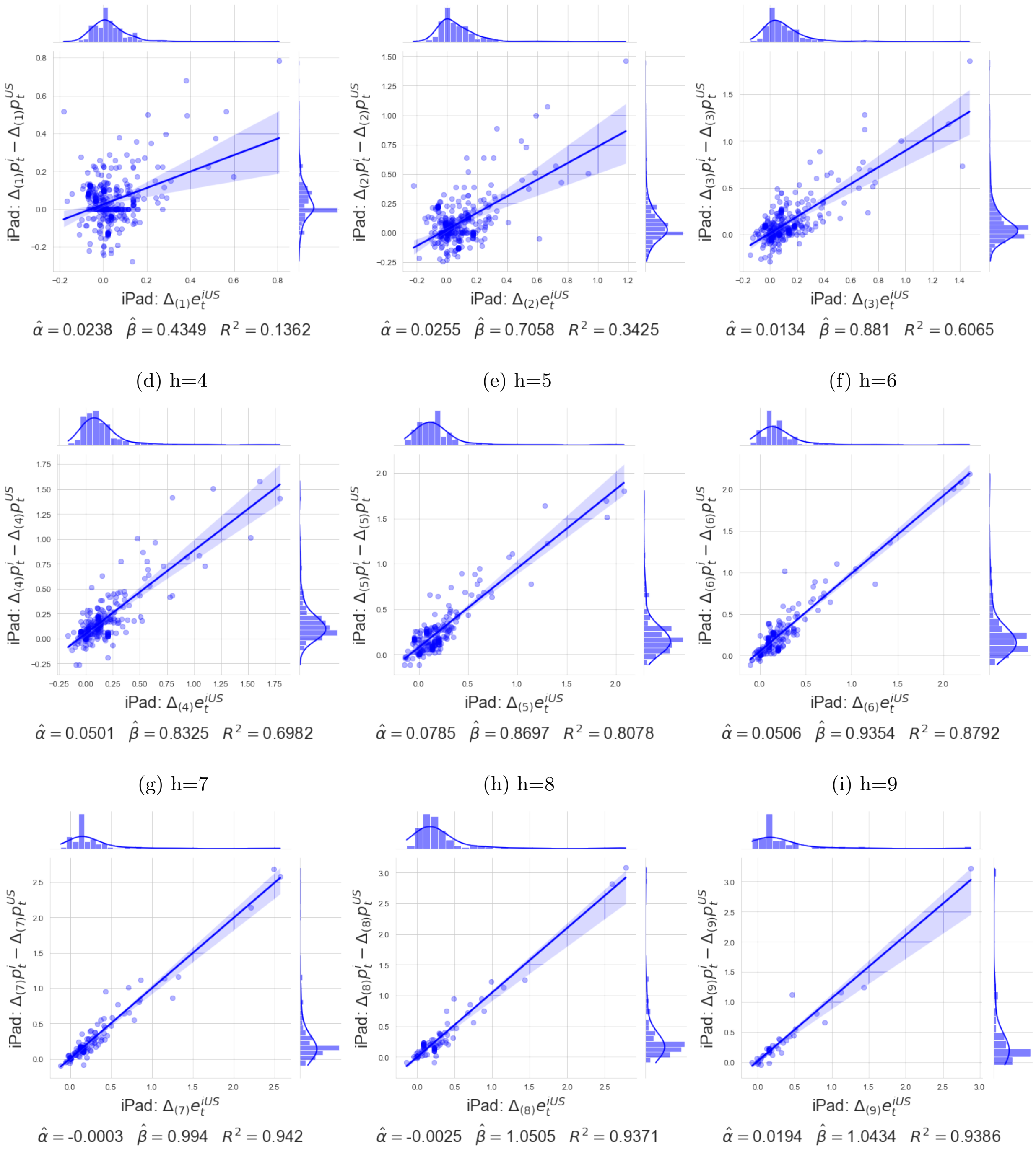


Figure B.28: iPad Price Data over h Period Changes



(a) h=1 — $\hat{\alpha} = 0.0238 \quad \hat{\beta} = 0.4349 \quad R^2 = 0.1362$

(b) h=2 — $\hat{\alpha} = 0.0255 \quad \hat{\beta} = 0.7058 \quad R^2 = 0.3425$

(c) h=3 — $\hat{\alpha} = 0.0134 \quad \hat{\beta} = 0.881 \quad R^2 = 0.6065$

(d) h=4 — $\hat{\alpha} = 0.0501 \quad \hat{\beta} = 0.8325 \quad R^2 = 0.6982$

(e) h=5 — $\hat{\alpha} = 0.0785 \quad \hat{\beta} = 0.8697 \quad R^2 = 0.8078$

(f) h=6 — $\hat{\alpha} = 0.0506 \quad \hat{\beta} = 0.9354 \quad R^2 = 0.8792$

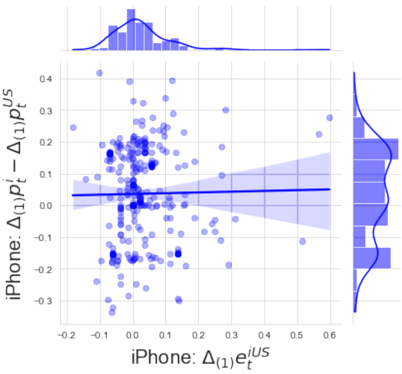
(g) h=7 — $\hat{\alpha} = \text{-}0.0003 \quad \hat{\beta} = 0.994 \quad R^2 = 0.942$

(h) h=8 — $\hat{\alpha} = \text{-}0.0025 \quad \hat{\beta} = 1.0505 \quad R^2 = 0.9371$

(i) h=9 — $\hat{\alpha} = 0.0194 \quad \hat{\beta} = 1.0434 \quad R^2 = 0.9386$

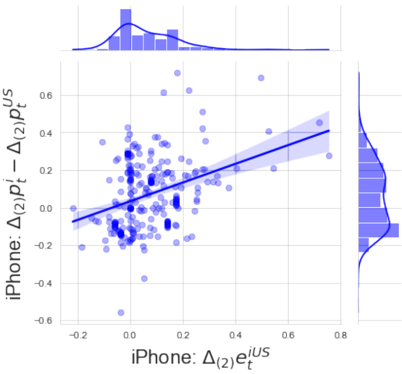
Figure B.29: iPhone Price Data over h Period Changes

(a) h=1



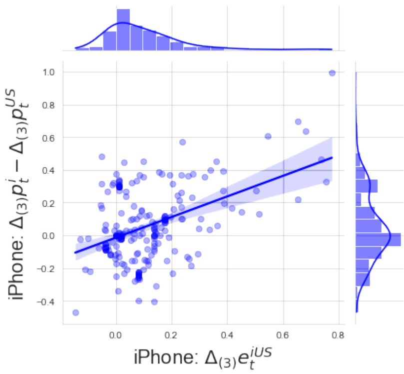
$\hat{\alpha} = 0.0353$ $\hat{\beta} = 0.024$ $R^2 = 0.0002$

(b) h=2



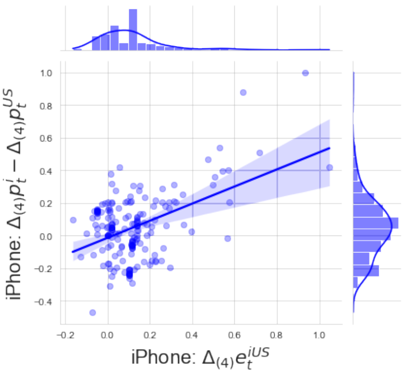
$\hat{\alpha} = 0.0338$ $\hat{\beta} = 0.4973$ $R^2 = 0.1179$

(c) h=3



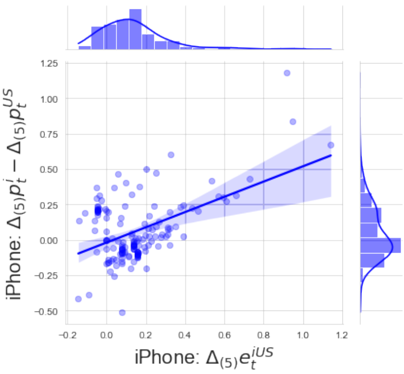
$\hat{\alpha} = -0.0143$ $\hat{\beta} = 0.6289$ $R^2 = 0.2032$

(d) h=4



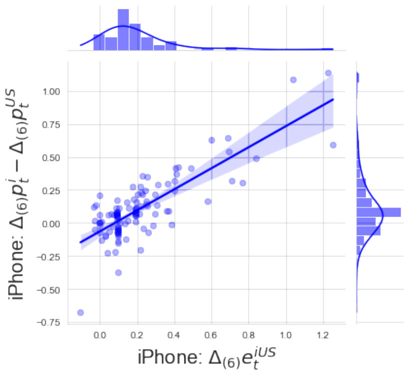
$\hat{\alpha} = -0.0141$ $\hat{\beta} = 0.5241$ $R^2 = 0.2123$

(e) h=5



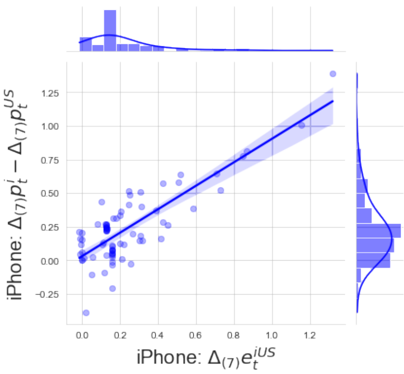
$\hat{\alpha} = -0.0198$ $\hat{\beta} = 0.5393$ $R^2 = 0.232$

(f) h=6



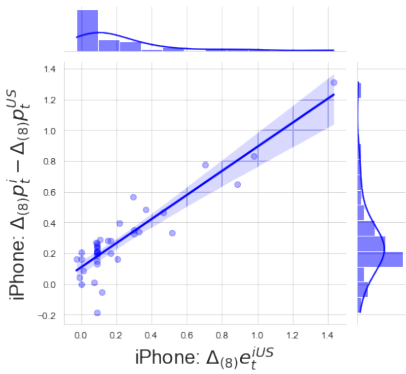
$\hat{\alpha} = -0.0638$ $\hat{\beta} = 0.7954$ $R^2 = 0.6487$

(g) h=7



$\hat{\alpha} = 0.0307$ $\hat{\beta} = 0.8722$ $R^2 = 0.6757$

(h) h=8

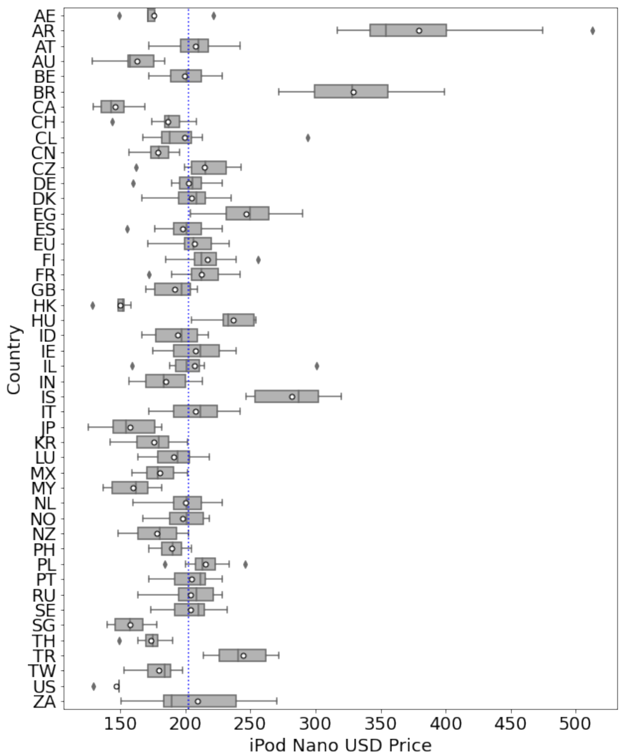


$\hat{\alpha} = 0.1076$ $\hat{\beta} = 0.7828$ $R^2 = 0.8218$

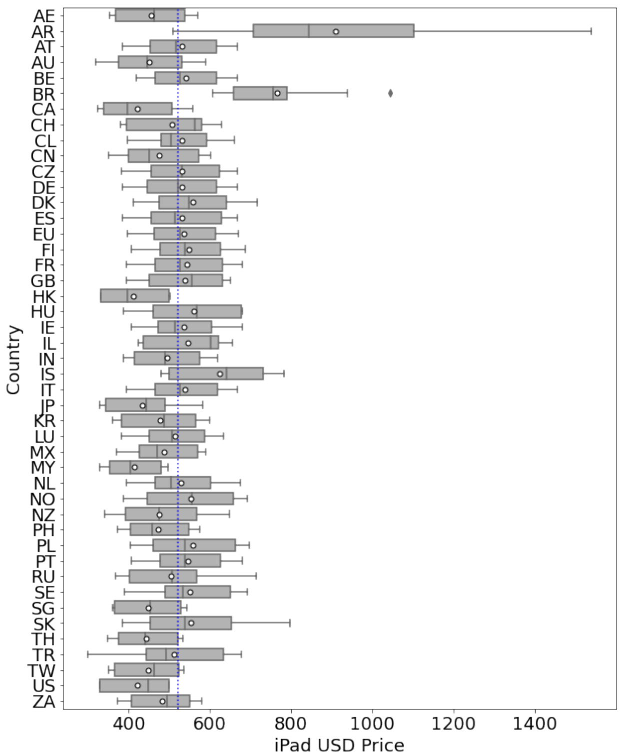
B.4 BOX PLOTS OF USD APPS PRICES

Figure B.30: Annual Dataset: Box Plots of USD Converted Prices of iPods, iPads and iPhones for Various Countries

(a) iPod Nanos Over 2007 to 2017



(b) iPads Over 2010 to 2020



(c) iPhones Over 2012 to 2020

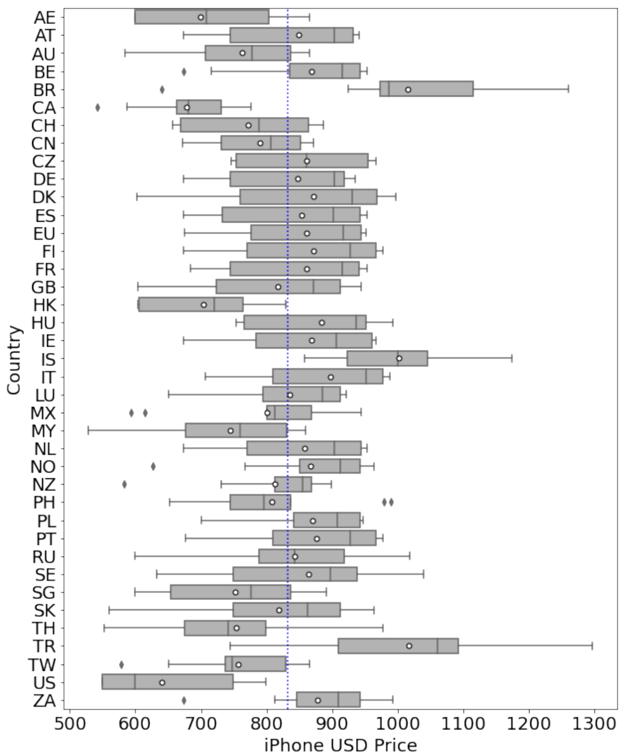


Figure B.31: High Frequency Dataset: Box Plots of USD Converted Prices of iPads in 35 Countries from 2016 to 2021

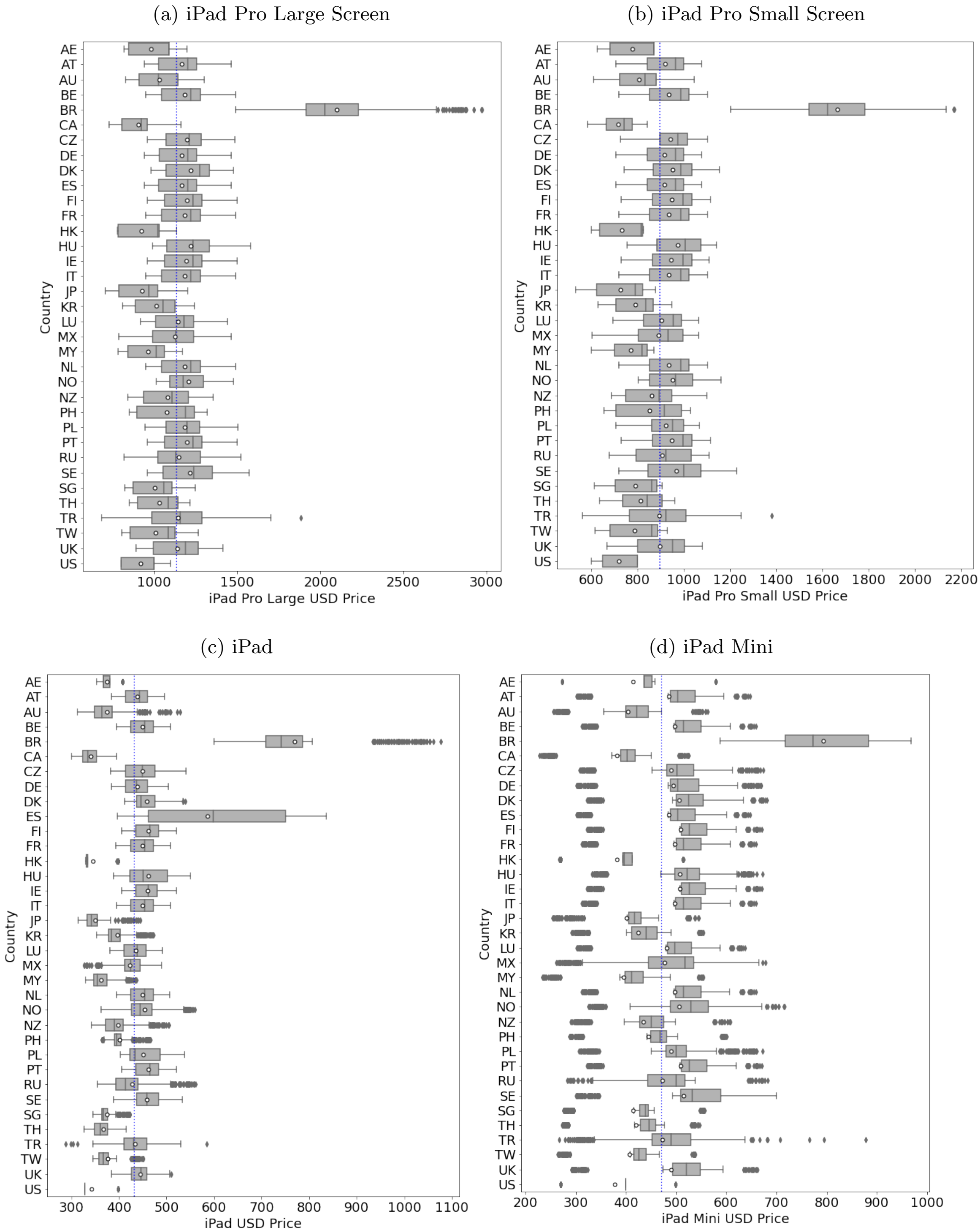
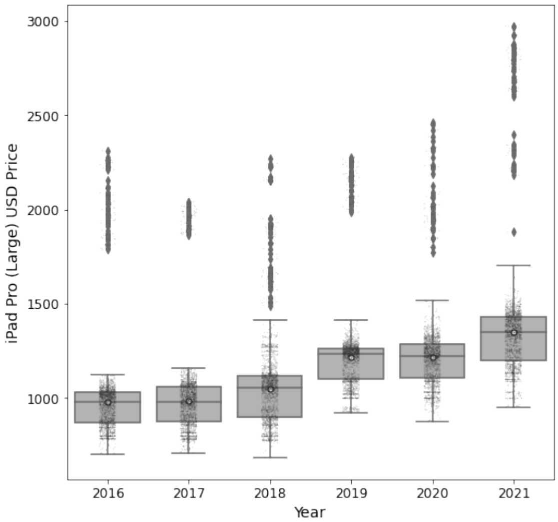
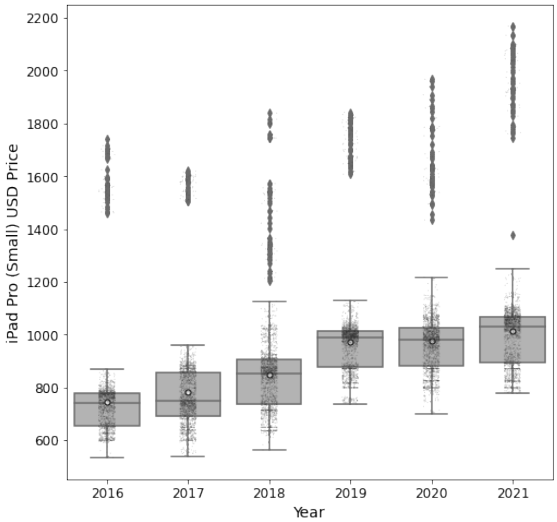


Figure B.32: Box Plots of USD Prices of iPad Devices in 35 Countries from 2016 to 2021

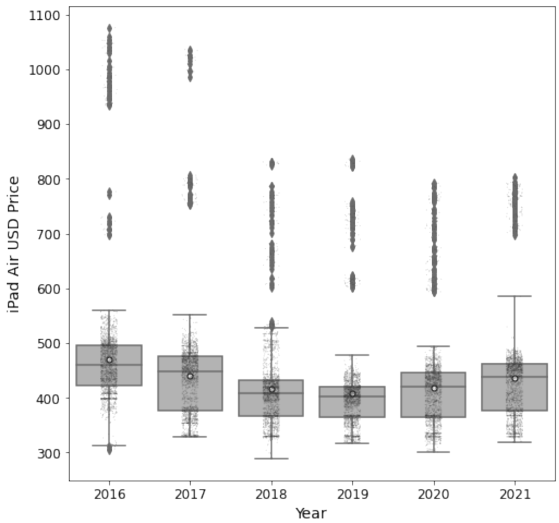
(a) iPad Pro Large Screen



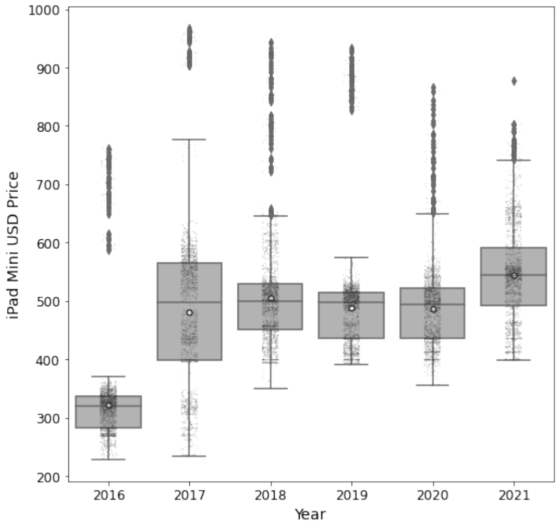
(b) iPad Pro Small Screen



(c) iPad Pro Air



(d) iPad Mini



B.5 LOWESS SCATTERPLOTS

Figure B.33: LOWESS Scatterplots on iPad Pro Large Screen Devices Lagged RERs vs Subsequent Change in RERs Over Different Horizons (d)

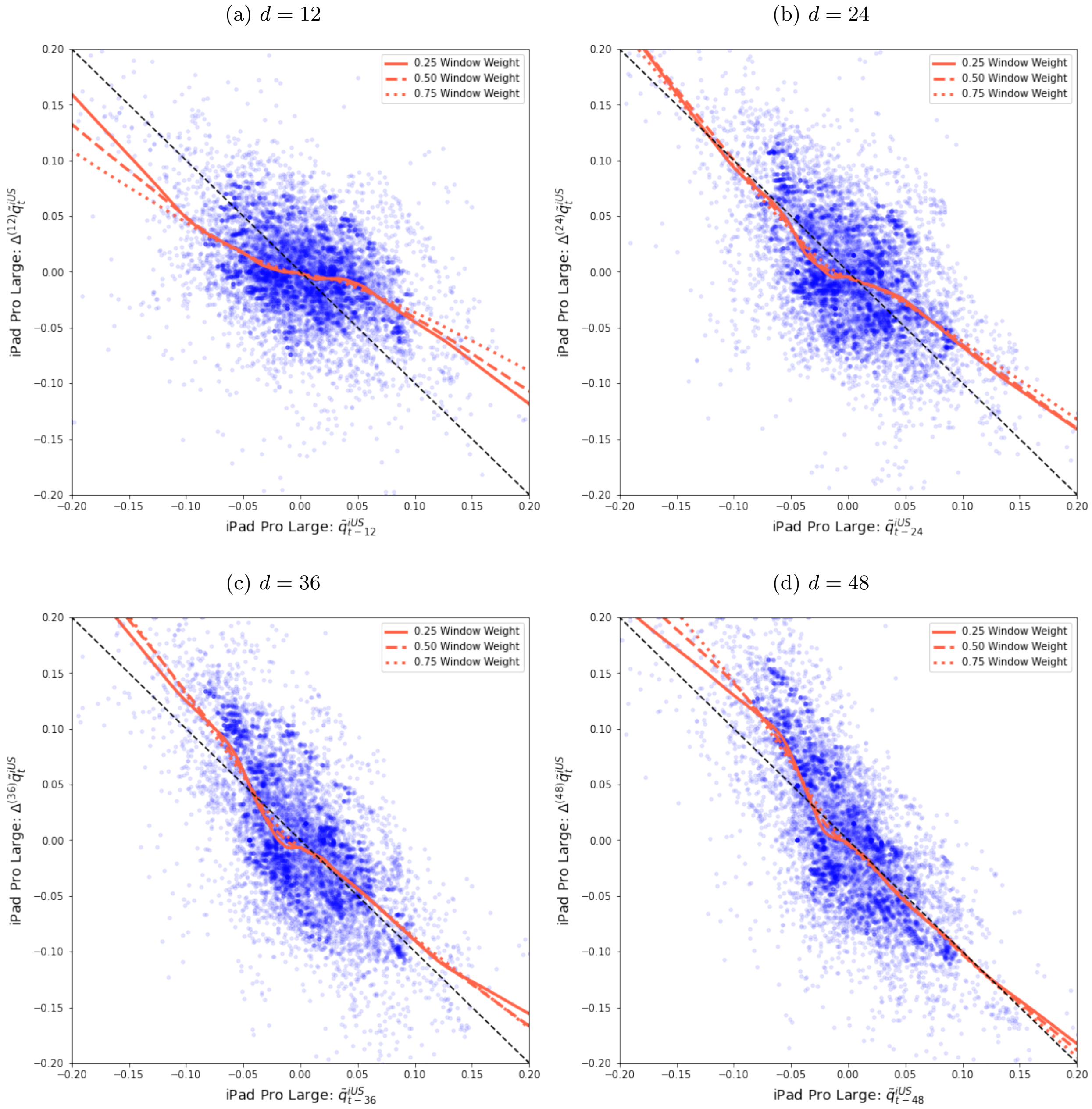
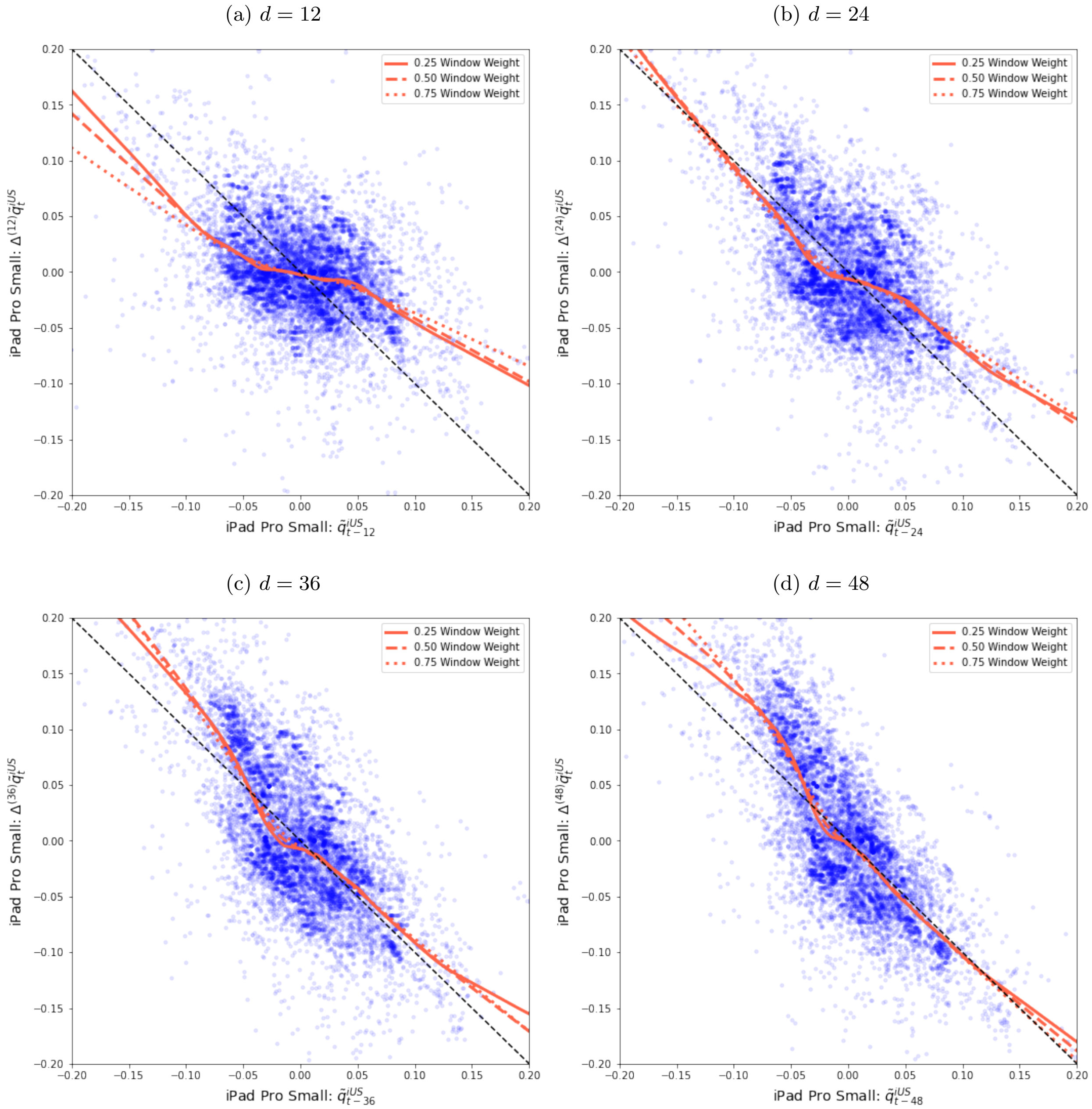


Figure B.34: LOWESS Scatterplots on iPad Pro Small Screen Devices Lagged RERs vs Subsequent Change in RERs Over Different Horizons (d)



(a) $d = 12$

(b) $d = 24$

(c) $d = 36$

(d) $d = 48$

Figure B.35: LOWESS Scatterplots on iPad Air Devices Lagged RERs vs Subsequent Change in RERs Over Different Horizons (d)

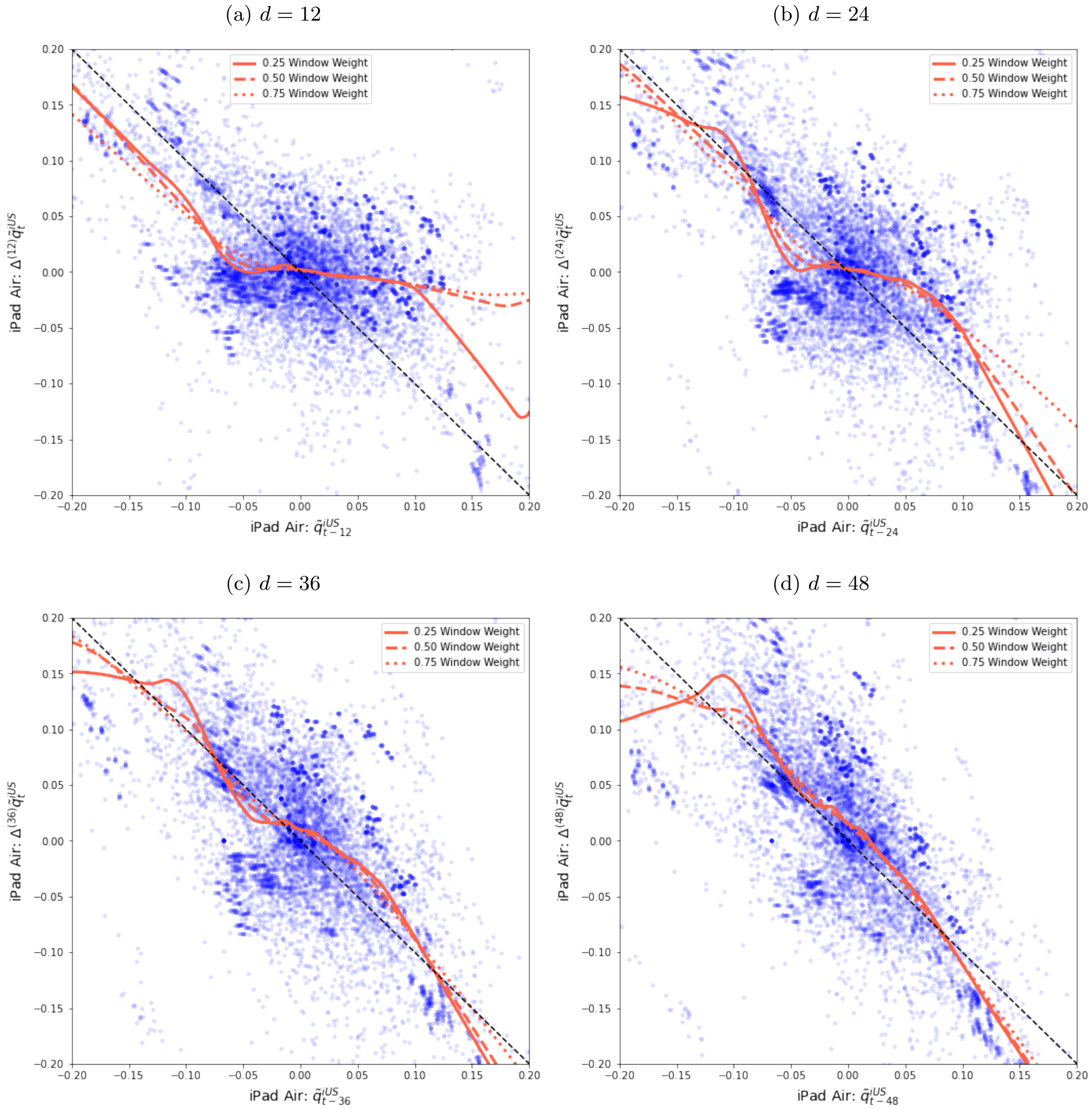
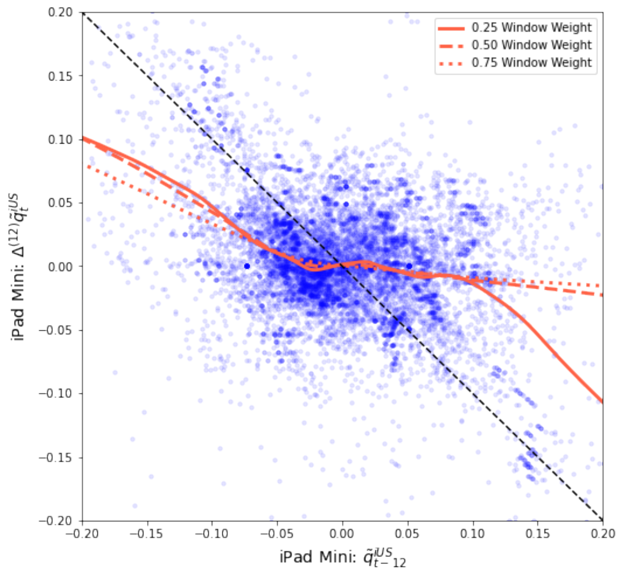
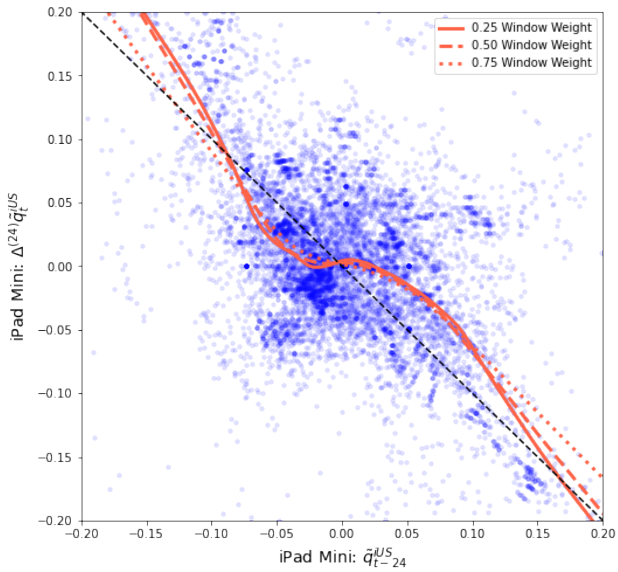


Figure B.36: LOWESS Scatterplots on iPad Mini Devices Lagged RERs vs Subsequent Change in RERs Over Different Horizons (d)

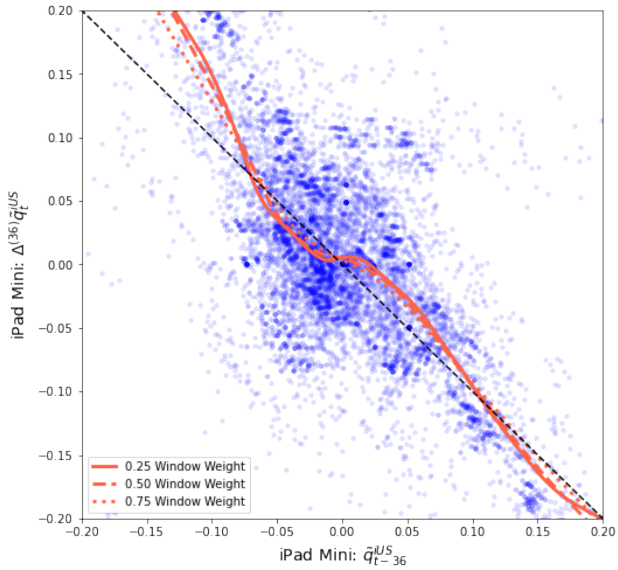
(a) $d = 12$



(b) $d = 24$



(c) $d = 36$



(d) $d = 48$

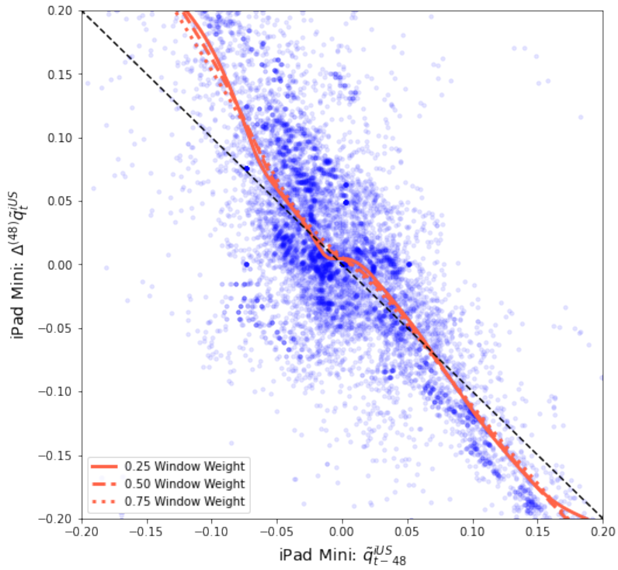


Figure B.37: Box Plots of Country Adjustment Parameter Estimates from Piecewise Linear Regressions on iPad Pro Large Screen Devices over Various Deltas (d)

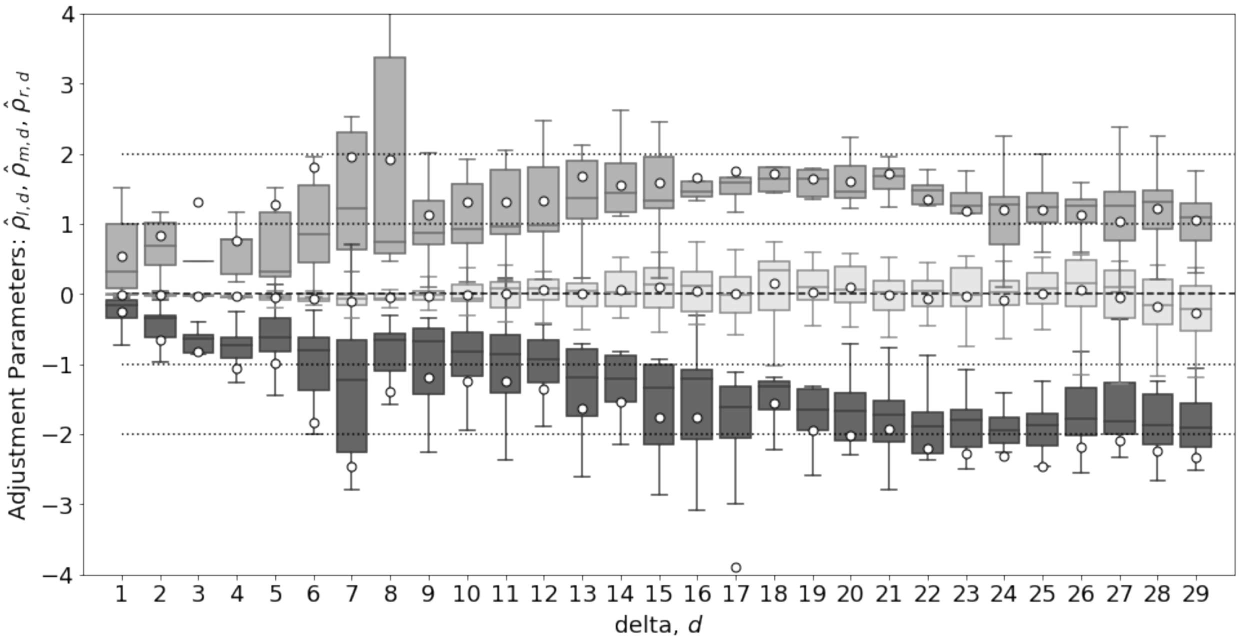


Figure B.38: Box Plots of Country Adjustment Parameter Estimates from Piecewise Linear Regressions on iPad Pro Small Screen Devices over Various Deltas (d)

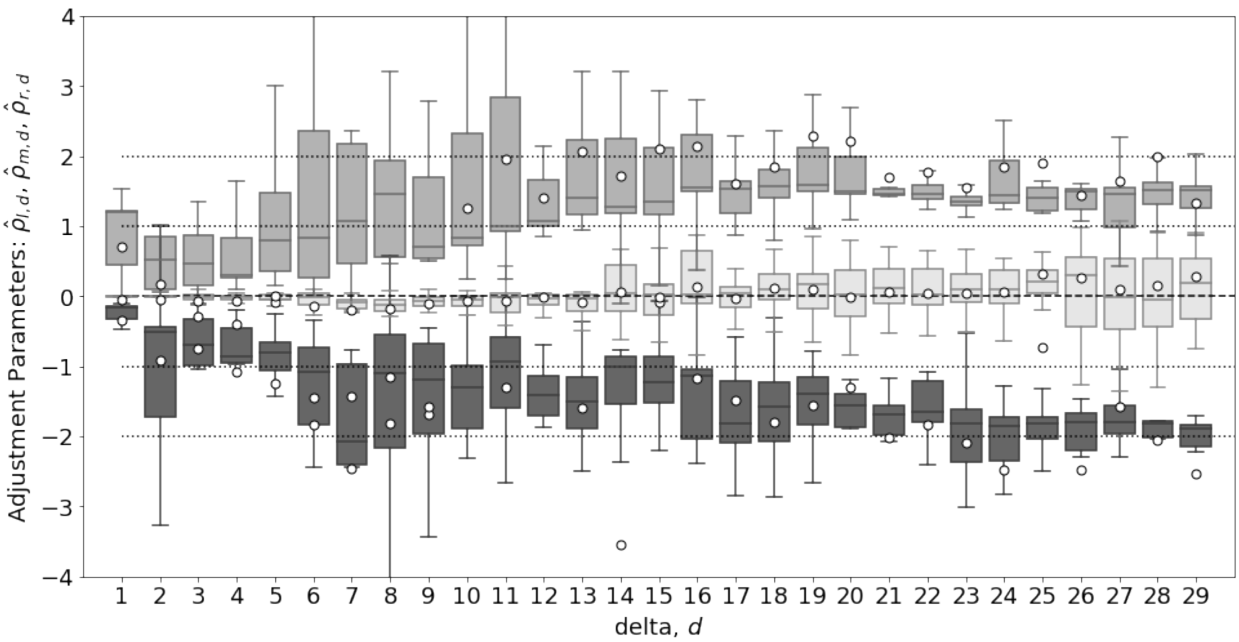


Figure B.39: Box Plots of Country Adjustment Parameter Estimates from Piecewise Linear Regressions on iPad Air Devices over Various Deltas (d)

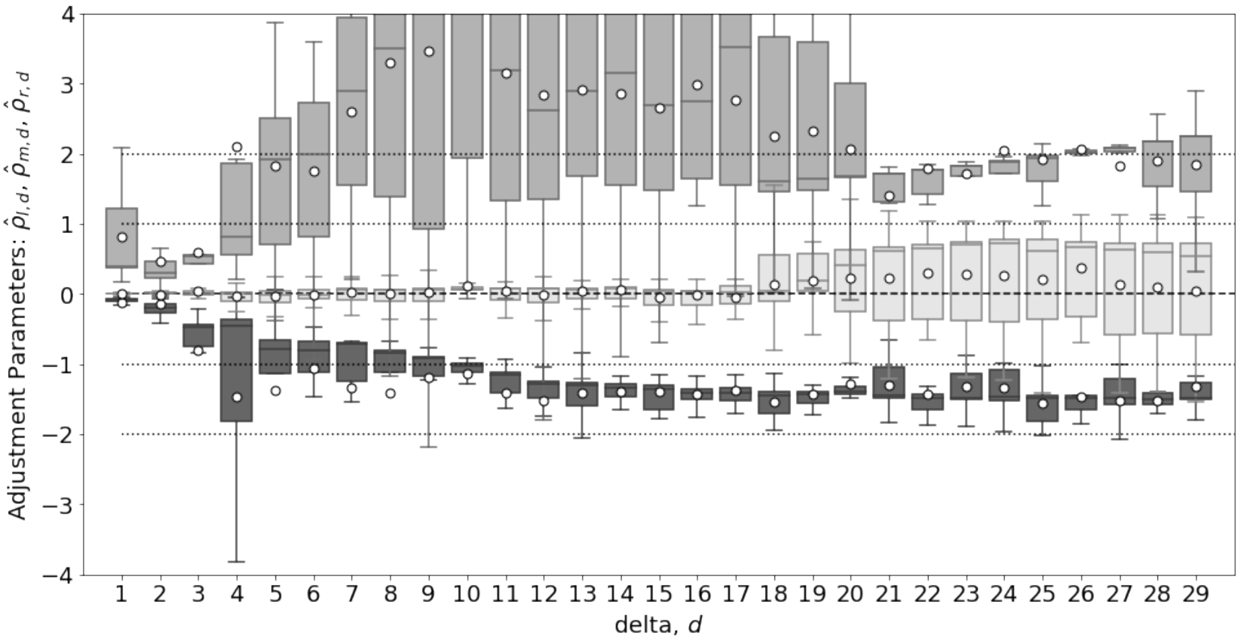


Figure B.40: Box Plots of Country Adjustment Parameter Estimates from Piecewise Linear Regressions on iPad Mini Devices over Various Deltas (d)