

# **Price setting in online markets: Basic facts, international comparisons, and cross-border integration\***

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Abstract

We document basic facts about prices in online markets in the U.S. and Canada, which is a rapidly growing segment of the retail sector. Relative to prices in regular stores, prices in online markets are more flexible and exhibit stronger pass-through (60-75 percent) and faster convergence (half-life less than 2 months) in response to movements of the nominal exchange rate. Multiple margins of adjustment (e.g., frequency of price changes, direction of price changes, size of price changes, exit of sellers) are active in the process of responding to nominal exchange rate shocks. Furthermore, we use the richness of our dataset to show that degree of competition, stickiness of prices, synchronization of price changes, reputation of sellers, and returns to search effort are systematically related to pass-through and the speed of price adjustment for international price differentials.

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## 1. Introduction

E-commerce is a rapidly increasing segment of the retail market. The U.S. Census Bureau estimated that total e-commerce sales for 2013 were \$263.3 billion, which is approximately 5.6 percent of total retail sales in the U.S. economy.<sup>1</sup> This represents an increase of 16.9 percent from 2012, while total retail sales increased by 4.2 percent in 2013; this pattern is consistent with historical trends: online sales have grown much faster (10 or more percent) than sales of brick-and-mortar stores. Forrester Research, an independent technology and market research company, predicts that by 2016, online sales will account for more than 9 percent of total retail sales.<sup>2</sup> While e-commerce is young, its digital presence is a major force revolutionizing retail as we know it: according to Deloitte (2015), the internet is projected to influence 64 percent of in-store retail sales by the end of 2015. To the extent that market valuation reflects prospects of companies, stock market participants believe that Amazon.com has a brighter future than Walmart (even though Amazon.com has only a quarter of Walmart's revenue) and that the future of retail is in online markets.

However, despite a significant and rapidly expanding share of e-commerce, the properties of online prices are still relatively understudied, even though these prices can shed new light on a number of key puzzles. Indeed, online markets have unique characteristics. For example, the physical cost of changing prices is negligible for internet stores, and therefore internet prices can fluctuate every instant (e.g., minute, day, week) in response to shifting demand and supply conditions. Searching for best online prices for very narrowly defined goods is particularly cheap and simple as consumers do not need to travel anywhere, buyers can establish the distribution of prices with just a few clicks, and pressure for price convergence is especially strong with ubiquitous price comparison websites (PCWs). More generally, the geographical location of consumers and stores is largely irrelevant in e-commerce, and therefore administrative borders and similar frictions are likely to play a much more limited role.

These special properties of online markets can help understand why pass-through of exchange rate fluctuations and reversion to the law of one price are generally weak in international data and thus constitute one of the central puzzles in international economics (Obstfeld and Rogoff 2000). In a highly integrated market with low frictions of price adjustment, easy search and price comparisons, and limited influence of geographical barriers, one can rule out some popular explanations of the puzzle and narrow down a set of plausible theories. Using internet prices in the U.S. and Canada for a broad array of products, we try to exploit these insights and provide new

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<sup>1</sup> For the same period, U.S. manufacturers reported e-commerce shipments of \$3.3 trillion, which is 57 percent of all manufacturing shipments. See U.S. Census Bureau (2015).

<sup>2</sup> These patterns are very similar in other developed countries. For example, according to the Centre for Retail Research, online retail sales in Europe jumped 20 percent this year, far outstripping the 1.4 percent growth in store-based sales. Furthermore, the share of online sales in total sales is larger in Europe than in the USA. For instance, the share is 9.5 percent in the U.K.

evidence on the nature and sources of frictions in price adjustment and departures from the law of one price.

To document and study the properties of online prices, we have constructed a unique dataset of price quotes. Specifically, we gathered prices and other relevant information from a leading PCW for a duration of 5 years. The data include each good's unique identifier (similar to barcodes in the scanner price data), each good's description, prices for each seller, each seller's unique identifier, the number of seller reviews, the ranking of seller quality, reviews of goods, etc. The dataset covers a broad range of goods that are sold online, including software, electronics, tools, computer parts, and photo equipment. We have collected information for more than 115,000 goods and nearly 20 million price quotes.

There are several advantages of using our data. First, the time span (almost 5 years) is considerably longer than the time span usually available for researchers studying online prices (typically a year or less). This dimension is important when we study dynamic properties of prices, such as duration of price spells, speed of price convergence, and pass-through. Second, the coverage of goods is much broader than in previous analyses of online prices, which typically have focused on books and CDs. The latter types of goods are easy to compare across sellers or countries, but they also have a number of unusual properties that make generalizations difficult. Our dataset is heavily populated by durable goods that tend to be under-represented in typical scanner price data and that are much more likely to be traded and moved across distant locations. Third, we collected prices for identical goods in the U.S. and Canada so that comparison of prices is direct and simple. Thus, we can avoid a number of pitfalls associated with comparing price indexes or goods that are only broadly similar. Fourth, our data include information on important attributes such as the reputation of sellers and goods as revealed by ratings of sellers and products. We can use these attributes to explore the predictors of pass-through and speed of price adjustment for online prices. In contrast, previous research on basic properties of prices had only very limited (if any) information about characteristics of goods for which prices were available. Fifth, our data include many sellers—most stores in our sample sell goods only online and do not have conventional, brick-and-mortar retail outlets (e.g., Amazon.com)—rather than one retail chain; therefore, we can assess the relative importance of different sources of price variation. This multi-seller dimension is important because branches of a single seller are less likely to engage in competition between each other than with branches of different sellers. Finally, the high frequency of our data allows us to time reactions of prices to other high frequency events such as changes in the exchange rate or natural experiments, thus making identification more clear-cut.

Using this dataset, we report properties of various pricing moments (e.g., the frequency and size of price changes) in e-commerce and thus complement earlier studies (e.g., Nakamura and Steinsson 2008) that present the same information for regular, brick-and-mortar stores. We find that the size of price changes in online stores (approx. 4 percent) is less than half the size of price changes in

regular stores (approx. 10 percent). We also find that price changes occur much more frequently in online stores (approx. once every 3 weeks or less) than in regular stores (once every 4-5 months or more). This evidence is consistent with the view that online prices are much more flexible than prices in regular stores. However, the fact that we still observe some rigidity in online prices suggests that the costs of changing prices are more complex than just physical menu costs and instead are likely to involve costs of gathering and processing information as well as potentially coordinating price changes with customers, suppliers, or other sellers. We also document that price dispersion is substantial and persistent, even for very narrowly defined goods. For example, the average standard deviation of log prices in a given week for a precisely defined good at the bar-code level is between 0.13 and 0.16.

Once these basic facts are established, we study the sensitivity of online prices to fluctuations of the nominal exchange rate. Since adjustment of online prices is unlikely to have any physical costs, and with easy shipping the physical location of the seller is much less important, pass-through could be quick and nearly complete, while it can be slow and partial in the prices of regular stores because of the frictions associated with trade flows and mobility of buyers. We find that, on average, pass-through in online markets is incomplete but large and amounts to approximately 60-75 percent, which is greater than the 20-40 percent pass-through documented for regular markets. The speed of price adjustment to equilibrium levels is substantially faster in online markets (half-life is about 2-2.5 months) than in regular markets (half-life varies from 3 quarters to a few years).

There is significant heterogeneity in pass-through and the speed of price adjustment across goods. Using the richness of our data, we show that for goods with certain characteristics, pass-through can be close to 100 percent. We also document that the size of pass-through and the speed of price adjustment are systematically associated with the degree of price stickiness, turnover of sellers, returns to search, synchronization of price changes, reputation of sellers, and the degree of competition. These results help reconcile the heterogeneity of estimated pass-throughs and the speeds of adjustment across studies and provide new facts for theoretical models to match.

This paper is related to several strands of research. The first strand is focused on assessing whether the law of one price (or its milder versions such as the purchasing power parity (PPP) hypothesis) holds and how quickly deviations from the law of one price are eliminated. The early generation of this literature could use only price indexes collected at the country or regional level, which led to a number of practical and conceptual issues with the interpretation of the results. Rogoff (1996) summarizes this literature as documenting that PPP is likely to hold in the long run, but it takes a long time for prices to converge to the PPP (i.e., the half-life is routinely estimated to be over a year and in most cases multiple years). This literature also found that deviations from PPP can be quite large and heterogeneous across countries and time (e.g., Takhtamanova 2010,

Campa and Goldberg 2005, Barhoumi 2005) which can be only partially explained by sticky prices and exchange rate regimes, constituting the PPP puzzle.

Data limitations of the first strand motivated the second generation of studies, which focused on using micro-level price data to measure pass-through and the speed of price adjustment for goods defined more precisely. Imbs et al. (2005, 2010), Crucini and Shintani (2008), Broda and Weinstein (2008), and others showed that pass-through and the speed of price adjustment are higher when prices for narrowly-defined goods are considered: the half-life of price adjustment falls to about a year. These papers demonstrate that the PPP puzzle observed in price indexes can be explained at least to some extent by aggregation biases. We contribute to this literature by examining the behavior of prices at the level of precisely defined goods sold by multiple stores in different countries in a market with arguably low frictions.

Easier access to micro-level price data also allows the exploration of the predictors of pass-through and the speed of price adjustment. For example, Menon (1996), Kardasz and Stollery (2001), Gaulier et al. (2006), Bachis and Piga (2011), Goldberg and Hellerstein (2013), and Mayoral and Gardea (2011) relate market structure, market power (including adjustment of mark-ups), tariffs, presence of multinationals, and importance of non-traded inputs for price stickiness of final goods and the size of pass-through. We contribute to this literature by exploring the predictors of pass-through and the speed of price adjustment for online markets.

The third strand of research is focused on documenting price rigidities at the micro-level, which can be used later to calibrate macroeconomic models (see, e.g., Nakamura and Steinsson (2008)). Studies in this literature concentrate almost exclusively on prices collected in regular, brick-and-mortar stores. In contrast, we focus on online prices, which describe a rapidly growing part of the retail sector. Online prices will play an increasingly important role in the future; therefore, macroeconomists should incorporate properties of a broader set of goods including goods sold online when they characterize micro-foundations of their macroeconomic models. To this end, we complement Cavallo (2015) by covering a different set of goods (i.e., most durables in our data and mostly grocery items in his).

The fourth strand of research documents basic facts about properties of online prices. In a study representative of this literature, Brynjolfsson and Smith (2000) compare online and conventional-store prices for books and CDs. They find that online prices are 9-16 percent lower than prices in regular stores, and the changes in prices are much smaller for online prices, yet quotes of internet prices are quite dispersed, even for precisely defined goods. Much of the subsequent literature has tried to, mostly theoretically, explain the dramatic dispersion of prices in online markets (e.g., Baye and Morgan 2001, 2004, 2009, Morgan et al. 2006) by information frictions (e.g., bounded rationality), sellers' ability to discriminate consumers (e.g., based on what sellers know about customers; see Deck and Wilson (2006)), and differences in advertisement (e.g., investment in

building brand reputation). We complement this literature by covering a broad set of goods and provide evidence that considerable price dispersion in online markets is a typical characteristic.

The most relevant studies to our paper are Lünnemann and Wintr (2011), Boivin et al. (2012), and Cavallo et al. (2014). Lünnemann and Wintr (2011) document stickiness of online prices in the U.S. and large European markets (Germany, France, Italy, and the U.K.). They find that internet prices are more flexible than their offline counterparts with half of the spells ending within a month. While Lünnemann and Wintr (2011) have online price data for multiple countries, they do not study the behavior of international price differentials. In contrast, Boivin et al. (2012) focus on the dynamics of online price differences across three online book sellers in Canada and the U.S.: Amazon.com (and Amazon.ca), BN.com (Barnes & Noble website), and Chapters.ca. They find that price differentials (or relative quantities) for books *do not* react to fluctuations in the relative price of foreign competitors following exchange rate movement; this is consistent with extensive market segmentation and pervasive violations of the law of one price. Similar to Boivin et al. (2012), Cavallo et al. (2014) collect online prices for four large retailers (Apple, H&M, Zara, and IKEA) in a number of countries and document that the violations of the law of one price—for example, they compare prices for a given IKEA product in IKEA websites in Germany and Sweden—appear only for countries outside currency unions and arise at the time goods are introduced rather than at later stages of product life. We merge these lines by exploring a larger, complementary set of goods (including coverage of generic and branded products) using longer time series and price quotes from multiple sellers, exploiting significant movements in the nominal exchange rate, and investigating predictors of observed pass-through and the speed of price adjustment.

The rest of the paper is structured as follows. In the next section, we describe the dataset and how it was collected. In Section 3, we document the basic properties of online prices. In Section 4, we do extensive international price comparisons and estimate pass-through and the speed of price adjustment for online prices. In addition, we explore the predictors and various margins of price adjustment in response to changes in the nominal exchange rate. In Section 5, we discuss our results and make concluding remarks.

## **2. Data Description**

### ***A. Data collection***

This study uses data collected from a PCW that provides price quotes for two countries: USA (.com domain) and Canada (.ca domain).<sup>3</sup> Styles of pages with price quotes are similar across countries, which simplifies data extraction and identification of exactly identical products listed by Canadian

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<sup>3</sup> The U.S. part of the website was among the top 10 Web portals based on total unique visitors in January 2010. Comscore, January 2010. The website reported in 2012 that tens of millions of people visited it every month.

and U.S. sellers. Identifiers for goods listed on the website are similar to barcodes used in the analysis of scanner price data. For example, manufacturing product number (MPN) 0S03110 uniquely identifies Hitachi Touro Mobile Pro Portable External 750 GB 2.5” Hard Drive. Figure 1 shows screenshots of typical web pages from PCWs.

Although the price comparison platform we use has similar websites in other countries, we limit the set of countries to the U.S. and Canada for several reasons. First, the link between the U.S. and Canadian websites greatly simplifies linking goods across countries. Second, trade flows are more likely to be affected by trans-ocean shipping costs, language differences, etc. if we compare prices in, for instance, Japan and the U.S. Finally, we want to study countries with strong trade ties. The U.S.-Canada pair is ideal in this respect as flows of goods and services between these two countries are strong even for online markets. For example, Statistics Canada (2013) reports that 63 percent of Canadian online shoppers placed an order with a U.S. online store in 2012. This is comparable to the 82 percent share of Canadian online shoppers who placed an order with a Canadian online store.

In contrast to a few previous studies that investigate properties of online prices and typically have up to one year of data (e.g., Lünemann and Wintr 2011), our data cover nearly five years. The data collection was launched on November 16, 2008 and continued until September 2013. Importantly, this timeframe includes a period of significant appreciation of the Canadian dollar against the U.S. dollar from 1.30 in the end of 2008 to 0.95 in the middle of 2011 (see Figure 2). A longer time series combined with significant changes in the exchange rate will help us to obtain precise estimates.

Every Saturday at midnight, a Tcl/python script was triggered to collect webpages with price information. The script has several stages. First, it collects information on the universe of goods available for a given type of goods on the comparison website. For each good, there exists a link to a unique webpage with price quotes. The script constructs a dictionary of goods and associated links. Second, the script follows the links and downloads web pages with price quotes. It usually takes about 24 to 48 hours to download a complete set of pages for all goods in targeted categories. Third, after the web pages are downloaded, the Python part of the script extracts a good’s description, unique manufacturing product number (MPN), prices for each seller, and sellers’ unique ids from every webpage. Our price quotes are net prices (i.e., prices *before* taxes and shipping/handling costs). Figure 3 shows an example of price quotes extracted from the web pages for a good popular in the U.S. and Canada. Whenever possible, we also collected gross prices (i.e., net prices plus taxes and shipping/handling costs) where the destination was an address in Berkeley, CA. Gross prices are available for about one half of net price quotes.

In the end, we obtained information for more than 115,000 goods and nearly 20 million good-seller-week-country quotes. Our price data cover 55 types of goods in four main categories: computers (20 types, e.g., laptops), electronics (13 types, e.g., GPS), software (12 types, e.g., computer games), and cameras (10 types, e.g., digital cameras). Table 1 presents the list of categories and types of goods in our sample.<sup>4</sup> The majority of stores only operate online (Table 2), but there is also a significant presence of stores selling both online and offline. While we have a wide distribution of store sizes, the top 5 percent of sellers by size account for approximately 90 percent of price quotes in our data. Appendix D provides additional details on the properties of the data set. The selection of goods, length of the time sample, and variation in exchange rates in our time sample provide us with a number of advantages relative to what researchers used in previous studies.<sup>5</sup>

First, our dataset covers a relatively diverse set of goods, while the vast majority of papers on online prices almost exclusively focus on books or CDs for which it was relatively easy to ensure that the same good is compared across sellers. Prices of these goods have, however, a number of unusual properties, such as very long spells of constant prices. Furthermore, the market for books and CDs is dominated by a handful of major sellers, such as Amazon.com and Barnes&Noble. Thus, it may be hard to generalize results beyond books and CDs. The diversity of goods in our sample will be essential when we study predictors of the size of exchange rate pass-through and the speed of price adjustment.

Second, a great deal of research on the law of one price has used data on goods for which transaction costs for cross-border purchases are likely to outweigh even large departures from the law of one price. For example, consumers are unlikely to directly take advantage of arbitrage opportunities in grocery products, which are typically available in scanner price data or cost-of-living surveys (e.g., Economist Intelligence Unit). In contrast, we focus on goods for which transaction costs are small and consumers are essentially free to exploit even small arbitrage opportunities. Indeed, goods in our sample are durable, standardized, and easy to ship. Most goods in our sample are produced outside the U.S. or Canada, and marginal cost shocks can be effectively differenced out when we take the ratio of Canadian and U.S. prices. These qualities are also likely

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<sup>4</sup> The price comparison website used in this study has been introducing more detailed categories over time. To ensure consistency in our data, we use the classification of goods available at the time when we started to collect our data. Our choice of product coverage was motivated by several considerations. First, we wanted to cover goods where having sellers in the U.S. and Canada was common. For some categories such as clothes, furniture, etc., it is a tangible restriction because many of these goods are local (e.g., flip-flops for Californians) and are branded or sold exclusively in one country. Second, we had to select categories where goods have an identifier akin to the universal product code (UPC) because we need to link goods over time and across countries. For some categories (e.g., furniture, toys, food), this restriction was a barrier in earlier years because the coding was missing or not sufficiently detailed to ensure that the identifier is unique. Third, we didn't want to cover books, CDs/DVDs because these goods are unusual in many respects.

<sup>5</sup> We have no information on the quantities of goods bought at quoted prices, and some price quotes may be irrelevant for consumers. However, in another dataset with online quotes and clicks associated with these quotes, Gorodnichenko et al. (2014) found that pricing moments are qualitatively similar for equally weighted price quotes and for price quotes weighted by clicks. Because click-weighted moments point to more price flexibility, one may interpret our results as a lower bound on how quickly prices adjust to movements in the exchange rate.

to limit the importance on non-tradables, which often account for a significant share of the cost of selling goods in regular stores.

Third, goods in our data are precisely defined; therefore, one can be more certain that he or she compares prices of the same good when he or she contemplates a purchase. For example, we treat red and blue iPods that otherwise share exactly the same technical characteristics as separate goods. This contrasts with previous research using price indexes or prices for broadly defined goods (e.g., toothpaste).

Fourth, our dataset collects price quotes from multiple sellers while previous research (e.g., Gopinath et al. 2011, Cavallo et al. 2014) typically used micro-level price data from one seller (e.g., because scanner price data are supplied by one retail chain). This aspect is potentially important because branches of the same seller in different countries (e.g., Amazon.com and Amazon.ca) are less likely to compete with each other than outlets of different sellers (e.g., Amazon.com and Rakuten.com). Our data covers a broad spectrum of sellers, such as large general stores (Amazon, Newegg), large specialized or branded stores (B&H or Dell), and niche stores (Memory4less).

Finally, data are collected at weekly frequency; this allows us to study responses of prices at relatively high frequency and makes identification cleaner.

At the same time, one should bear in mind limitations of our data. First, the composition of goods in our sample is skewed towards electronics. While this makes our analysis potentially specific to the electronics market, this market is sufficiently large to be interesting in itself. According to the estimates of the U.S. Census Bureau<sup>6</sup>, 30 percent of revenue in e-commerce retail in 2008-2009 was generated by categories we cover (i.e., computer hardware, computer software, electronics and appliances, office equipment and supplies). The share declined to 20 percent in 2013 as other categories of goods penetrated e-commerce, but goods in our sample continue to be a major market in internet retail. Furthermore, Gorodnichenko et al. (2014) document that properties of online prices relative to offline prices are similar for electronics and other product categories; thus, one may expect our results to generalize.

Second, price quotes listed on the PCW may be not representative of prices offered by online stores. Indeed, competition on PCWs is fierce, and PCWs often charge per click or per listing. As a result, stores may choose to post only their best prices on PCWs. Such behavior can affect some moments of the data (e.g., cross-sectional price dispersion). While this pattern is certainly a valid concern if one is interested in the distribution of *all* price quotes, the issue is likely to be insignificant if one is interested in the behavior of price quotes at which consumers make purchases. There is considerable evidence (e.g., Baye et al. 2009, Chevalier and Kashyap 2011, Gorodnichenko et al. 2014) documenting that transaction prices are heavily concentrated in the

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<sup>6</sup> <http://www.census.gov/econ/estats/2013/all2013tables.html>, Historical Table 5.

competitive (bottom) part of the price distribution so that prices listed on PCW are likely close to transaction prices. As a result, our data are suitable for analyzing international price comparisons but may provide a potentially distorted picture of the micro-level properties of *all* online prices.

Third, most of the sellers in our sample are online-only (see Appendix Table D2); thus, we do not capture the full spectrum of pricing behavior in the internet retail. However, there are advantages of focusing on this type of sellers. For example, sellers with online and offline presence (e.g., Walmart) have to coordinate their online and offline prices to ensure that consumers do not exploit pricing differentials across the retail modes. Because offline prices are rather sticky, they can delay adjustment of online prices. In contrast, online-only stores do not face such a drag and can react to shocks and competitors' prices faster. Thus, an emphasis on online-only stores may offer a better environment to test the predictions of the law of one price in a friction-free setting.

### ***B. Data filters***

Because price data are extraordinarily heterogeneous in our sample, we apply a series of filters to minimize the effects of missing values, extreme observations, etc. Specifically, we drop the top and bottom 1 percent of prices within each category-country. For time series analyses focused on dynamic responses, we keep only goods with at least twenty observations. We remove price quotes for used/refurbished goods, which effectively means excluding many "marketplace" sellers, such as eBay. Finally, because we are interested in international price comparisons, we constrain the sample only to goods that were sold by both U.S. and Canadian online sellers.

This last filter may be fairly restrictive: goods sold in multiple countries typically constitute only a small fraction of goods sold locally. For example, Gopinath et al. (2011) use price data from a large grocery chain prominently present in the U.S. and Canada. Given the universe of approximately 120,000 UPCs sold by the chain, they can match only 3.3 percent of UPCs across the U.S.-Canada border (approx. 4,000 goods). Broda and Weinstein (2008) document a similar effect using a much larger universe of UPCs: only 7.5 percent of the goods are available in both the U.S. and Canada. Fortunately, the overlap in our data is high: the match rate is more than 50 percent.

These filters reduce the number of goods in our sample from 115,000 to about 24,000. We verified that selection into the estimation sample is likely to be random as various pricing moments are approximately the same in the full and estimation samples. For example, the distribution of price levels for the estimation sample is close to the distribution for the full sample. Likewise, the key moments are very similar for the full and estimation samples (see Appendix D).

### ***C. Data quality***

PCWs are convenient and popular aggregators of price information. A major study by the European Commission (2013) reports that 74 percent of *all* shoppers in the E.U. use internet comparison tools

(PCW is the most popular one: 73 percent of comparison tool users) to compare prices (69 percent of users) and find the cheapest price (68 percent of users). Electric/electronic appliances is the product category with the most intensive use of price comparison tools (63 percent of users). 48 percent of users check a PCW before making an online purchase, and 35 percent of users report that the use of a comparison tool results in a purchase. E-commerce merchants use PCWs to attract new customers and increase sales.

PCWs routinely allow automatic export of product feeds so that whenever an online seller changes a good's price, the new price is immediately reflected on PCWs. Online sellers are also interested in keeping their prices as current as possible because they often pay for clicks on PCWs, and if a price is outdated or a good is out of stock, online sellers waste money.<sup>7</sup> However, there could be systematic discrepancies between prices reported on PCWs and prices listed on the websites of sellers because, for example, online sellers may engage in "bait and switch" strategies. To assess the quantitative importance of this concern, we use several approaches.

First, we compare prices from both sources (that is, from the PCW and from a seller listed on the PCW) for a random sample of 100 goods.<sup>8</sup> Specifically, a script clicks on a link for each seller listed on our PCW and collects price information from the seller's webpage (if necessary, this information is checked manually). We find (Figure 4) that while there are some discrepancies, price quotes (Panel A) are remarkably consistent across sources. When we aggregate price quotes across sellers and focus on the average price for a given good (Panel B), the difference between the sources is small. The differences are somewhat larger when we consider dispersion of prices across sellers measured in terms of standard deviation (Panel D) and interquartile range (Panel C). However, even for price dispersion, the PCW provides quite accurate information. If we regress a moment based on prices from sellers' websites on the corresponding moment based on prices from the PCW, we get an estimated slope close to one and an estimated intercept close to zero with  $R^2$  approaching to one. We cannot reject equality of moments across the sources of price information. In a similar spirit, when we compare price quotes for Apple products listed on our PCW and on Apple store website (price quotes for the latter are provided by Cavallo et al. (2014)), we find a high correlation ( $\rho = 0.98$ ) of price quotes across sources (see Appendix E).

Second, we compare the dynamics of prices in our data with the dynamics of prices collected by the Bureau of Labor Statistics (BLS). Specifically, we restrict our sample to product categories that can be matched to disaggregated price indices constructed by the BLS. For example, we can compare the dynamics of "RA01 Televisions" price index constructed by the BLS with the dynamics

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<sup>7</sup> For example, our price comparison website charges between \$0.35 and \$1.15 per click depending on the product category (the website does not charge per listing during the sample period).

<sup>8</sup> We are extremely grateful to Alberto Cavallo for generating price data from websites of online sellers and sharing these data with us.

of an equally weighted price index based on PCW quotes in the Plasma/LCD TV category. Using six matches to the BLS data, we find that the dynamics of prices in our data and the BLS data are similar (see Appendix D for more details).

Third, one may be concerned that PCWs may post outdated price quotes. While it is difficult to establish the lag in price updates, we use a natural experiment to assess the quantitative importance of this potential problem. Specifically, in Appendix A, we explore how price quotes on our PCW responded to the 2011 Thailand floods that had a major impact on the global production of hard drives. We document that prices for hard drives reacted within a week with the peak response within a month. We also observe the significant exit of sellers from the PCW, which is consistent with depleted inventories. These results suggest that price quotes are updated quickly, which is consistent with the assessment in European Commission (2013). We conclude that the quality of price data from the PCW is reasonably high.

### 3. Basic facts about price setting in online markets

Panels A and B of Table 3 show descriptive statistics for our data.<sup>9</sup> Let  $i$ ,  $t$ ,  $s$ ,  $c$  index goods, time (weeks), sellers, and countries, respectively. The average log price  $\log P_{itsc}$  in our sample is 5 (or approx. \$150). This magnitude is significantly larger than the level of prices considered in previous studies (e.g., with scanner price data or online prices of books and CDs), where goods routinely have prices below \$10. It is also not unusual in our sample to observe prices of goods above \$600 (approx. 75<sup>th</sup> percentile) or \$1400 dollars (approx. 90<sup>th</sup> percentile). Since we focus on how quickly cross-border arbitrage opportunities dissipate, the level of prices is important as search effort is likely to be larger for big-price-tag items. The level of prices is approximately the same in the U.S. and Canada.

Goods routinely have multiple sellers in our data. The average number of sellers is approximately 2.4 in Canada and 3.4 in the U.S. This is consistent with the notion that the U.S. market is larger than the Canadian market, but the difference is not as striking as one observes in the numbers of regular, brick-and-mortar stores in two countries. In part, this difference is smaller because online markets tend to be more concentrated. The stability of sellers—we define stability as the ratio of the number of stores selling a good in a given week to the number of stores ever selling this good in the month which covers the given week—is similar in Canada (0.90) than in the U.S. (0.89).

Similar to previous studies of online prices (e.g., Brynjolfsson and Smith 2000, Baye et al. 2006), we observe dramatic cross-sectional dispersion of prices which is calculated as

$$\sigma_{itc} \equiv \left\{ \frac{1}{\#(S_{itc})} \sum_{s \in S_{itc}} \left( \log P_{itsc} - \frac{1}{\#(S_{itc})} \sum_{s \in S_{itc}} \log P_{itsc} \right)^2 \right\}^{0.5},$$

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<sup>9</sup> We present selected statistics by category of goods in Appendix G.

where  $\mathcal{S}_{itc}$  is the set of stores that sell good  $i$  in week  $t$  in country  $c$ . On average, across goods and time periods, the standard deviation of log prices within a country is 0.13-0.16, which is significant but smaller than one can observe for the dispersion of prices across regular stores.<sup>10,11</sup> Given that the levels of prices are large in our sample, these price differentials correspond to significant dollar amounts. In some cases, the differences between cheapest and most expensive prices are in multiple hundreds of dollars, which could be surprising given easy search for the best prices in online markets. However, we do observe that the size of price differentials is negatively correlated with the level of prices. That is, more expensive goods tend to have smaller (log) price dispersion. We also find that the cross-sectional dispersion of prices in any given market is fairly persistent. The serial correlation of the log or level of  $\sigma_{itc}$  is routinely above 0.85.

The frequency of price changes is high: 20 to 30 percent of prices change in a given week, implying that the average duration of price spells is just a few weeks.<sup>12</sup> Price increases and decreases are equally likely in our data. The average price change is slightly negative, which captures the fact that goods in our sample are subject to technical improvements over time; thus, prices of existing goods tend to depreciate with the age of goods. Temporary price cuts (“sales”) are relatively infrequent (approx. 2-3 percent of goods are on sale in a given week) and small (the average size is 5 to 10 percent). In contrast, prices in scanner price data (e.g., Kehoe and Midrigan 2015), in government surveys of prices (e.g., Nakamura and Steinsson 2008), or in online prices for books (e.g., Boivin et al. 2012) have a much lower frequency of price changes, a larger size of price changes, and more prevalent and deeper sales. At the same time, our moments are consistent with Lünemann and Wintr (2011), who analyze a similar set of goods but have data only for one year. Higher frequency and smaller sizes of price changes for online prices are consistent with “menu” costs being smaller for online sellers than for regular stores.

As a final measure of price stickiness, we consider synchronization of price changes across sellers. Specifically, we define synchronization in a given week for a given good as the fraction of price quotes with a price change conditional on at least one price change and having at least two sellers at this point in time:

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<sup>10</sup> For example, Coibion et al. (2015) report that the standard deviation in the log price for a given unique product code (UPC), a given market (metro area), and a given week is 28% on average across periods, markets, and UPCs. Sheremirov (2015) documents similar evidence.

<sup>11</sup> Rating of sellers is a strong predictor of price deviations for a given good; thus, some price dispersion is due to compensating differentials for seller reputation. However, the dispersion remains high even after controlling for store rankings.

<sup>12</sup> We define a price change as a movement in prices larger than one percent in absolute value. We discard very small price changes (less than one percent in absolute value) as these changes are likely to arise from measurement errors (e.g., Eichenbaum et al. 2014).

$$Synchronization_{itc} = \frac{\sum_{s \in \mathcal{S}_{itc}} \mathbf{1}\{P_{itsc} \neq P_{i,t-1,sc}\} - 1}{\sum_{s \in \mathcal{S}_{itc}} \mathbf{1}\{P_{itsc} \neq \text{missing} \cap P_{i,t-1,sc} \neq \text{missing}\} - 1}$$

where we code  $Synchronization_{itc}$  as missing if  $\sum_{s \in \mathcal{S}_{itc}} \mathbf{1}\{P_{itsc} \neq P_{i,t-1,sc}\} < 1$ . The average synchronization is 19 percent in the U.S. and 23 percent in Canada. These magnitudes are very similar to the unconditional frequencies of price changes and hence point to little synchronization of price changes across sellers.

While our results point to greater flexibility of online prices, one may be concerned that this outcome is determined by differences in the composition of goods sold online and in regular stores. To address this concern, we compare moments for narrowly defined categories of goods for price data from our PCW, from a major online shopping platform (Gorodnichenko et al. 2014), and from conventional stores (Nakamura and Steinsson 2008). Consistent with our earlier results, we find (Table 4) that relative to prices in conventional stores, online prices have a higher frequency and smaller size of price changes as well as less frequent and smaller sales. Prices from our PCW have properties (frequency, size, and synchronization of price changes and cross-sectional dispersion of prices) similar to the properties of prices directly provided by a major PCW/shopping platform. Thus, differences in the composition of goods are not a likely explanation for differences in pricing moments in online and offline retail.

## 4. International price differentials

### A. Descriptive statistics

We focus on two popular measures of international price differentials: the relative exchange rate  $\log(P_{it}^{CA}/P_{it}^{US})$  and the real exchange rate  $\log(EX_t^{-1} \times P_{it}^{CA}/P_{it}^{US})$ , where  $i$  and  $t$  index goods and time, respectively,  $P_{it}^{CA}$  ( $P_{it}^{US}$ ) is a price measure for a given good in Canada (U.S.), and  $EX$  is the CAD/USD nominal exchange rate. Since for any given period/good/country there are multiple sellers and hence multiple prices, we consider several measures of prices at the country level: mean price across sellers; median price across sellers; and minimum price across sellers.<sup>13</sup> Each of these measures has pros and cons. For example, while the mean price was often used in previous research, median prices are less sensitive to extreme price quotes. In light of Baye et al. (2009), Chevalier and Kashyap (2011), and Gorodnichenko et al. (2014), one may conjecture that minimum prices are closer to transaction prices and thus are more likely to capture prices relevant for consumers.

Irrespective of which measure of prices we use, international price differentials are moderately large (Panel C, Table 3). The mean of  $\log(P_{it}^{CA}/P_{it}^{US})$  and  $\log(EX_t^{-1} P_{it}^{CA}/P_{it}^{US})$  is about

<sup>13</sup> We also considered mean price weighted by the reputation of sellers, where reputation is measured as the number of stars, from 1 to 5, that consumers assign to sellers. Results for star-weighted moments are similar to the results reported in the paper. We also constrained our sample to include sellers with 4+ star reviews. We found similar results.

5 to 12 percent. Some of the price dispersion across countries can be explained by differences in taxes. For example, the value added tax (federal and provincial) in Canada is about 13 percent, and there is big variation in sales taxes across U.S. states.<sup>14</sup> However, differences in taxes are unlikely to be the whole story. First, there is dramatic variation in price differentials (columns (4) and (5) in Table 2): the 25<sup>th</sup> percentile of the mean price differential is negative, while the 75<sup>th</sup> percentile is between 15 and 25 percent. The AR(1) coefficient for either exchange rate is between 0.80 and 0.92 (at weekly frequency), depending on whether we control for good/type fixed effects so that the implied half-life is 3 to 6 weeks, which is much shorter than half-lives estimated on prices collected in regular stores. If price differentials were mainly determined by taxes, one would expect to see little if any variation in price differentials across goods or over time. Second, for a subsample of goods that we have information for gross prices that include taxes and shipping costs, we observe similar international price differentials (Appendix Table F1).<sup>15</sup>

The standard deviation of price differentials across countries—which ranges from 0.22 to 0.27 see column (2)—is much larger than the standard deviation of price differentials within countries, which is between 0.09 and 0.11. This finding is qualitatively consistent with results reported in the earlier literature comparing price differentials within and across countries (e.g., Engel and Rogers 1996, Gorodnichenko and Tesar 2009). However, moments for the real and relative exchange rates are broadly similar so that fluctuations in the nominal exchange rate are unlikely to be the main factor in cross-border price differentials.

In summary, properties of online price differentials are qualitatively similar to properties of prices in regular markets, but the magnitude and persistence of price differentials are smaller relative to counterparts reported in previous studies for brick-and-mortar stores. Thus, this first pass at the data suggests that frictions are much smaller in online markets, but non-negligible cross-sectional dispersion of prices and some persistence of price differentials are consistent with some border frictions in online markets. In the following sections, we will examine predictors of these persistent and volatile cross-border price differentials in online markets.

### ***B. Pass-through and the speed of price adjustment***

To characterize the dynamics of cross-border price differentials, economists commonly use two metrics: pass-through (i.e., how movements in the nominal exchange rate are translated into

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<sup>14</sup> Although we use an address in Berkeley, CA, online sellers with no physical presence in California do not have to collect sales tax (close to 10 percent) on behalf of the state of California. As a result, Californian consumers often pay no sales tax on their online purchases.

<sup>15</sup> The price comparison web page was redesigned for various goods in various times, and in many versions of the webpages, we could specify the location of the buyer and thus obtain net and gross prices. We used the address of the Department of Economics at UC Berkeley as the shipping destination. Gross prices are available for about half of quotes for which we have net prices.

movements of prices of goods) and the speed of price adjustment to equilibrium levels. While there is a variety of versions of these two metrics, we employ two basic econometric specifications to construct these metrics:

$$\text{Pass-through } \alpha: \log\left(\frac{P_{it}^{CA}}{P_{it}^{US}}\right) = \alpha EX_t + \text{Controls} + \text{error}_{it}, \quad (1)$$

$$\begin{aligned} \text{Speed of price adjustment } \beta: d \log\left(\frac{P_{it}^{CA}}{P_{it}^{US}}\right) &= \beta \left( \log\left(\frac{P_{i,t-1}^{CA}}{P_{i,t-1}^{US}}\right) - \alpha EX_{t-1} \right) \\ &+ \phi_1 d \log\left(\frac{P_{i,t-1}^{CA}}{P_{i,t-1}^{US}}\right) + \lambda_1 d EX_{t-1} + \text{Controls} + \text{error}_{it}, \quad (2) \end{aligned}$$

where *Controls* is a set of control variables, and  $dx_t \equiv x_t - x_{t-1}$  is the first difference operator.<sup>16</sup> Specification (1) estimates the long-run pass-through and is a generic specification estimated in the literature (see Goldberg and Knetter (1997) for a survey). The law of one price predicts that  $\alpha$  should be equal to one and, hence, values of  $\alpha$  closer to one correspond to smaller departures from the law of one price. Specification (2) is set in the error-correction/cointegration form where  $\beta$  quantifies how quickly the deviation from equilibrium is eliminated. More negative values of  $\beta$  mean faster adjustment. In specification (2), equilibrium relationship between relative and the exchange rate (coefficient  $\alpha$ ) is determined according to specification (1). Thus, while the equilibrium relationship nests the law of one price, it also allows deviations from the law of one price (i.e.,  $\alpha$  can be less than one).<sup>17</sup> In our preferred specification, *Controls* include good fixed effects.

A key assumption behind specifications (1) and (2) is that price differentials have a common stochastic trend, which is captured by the nominal exchange rate. Because the error term is almost certainly correlated across goods, and hence standard panel-data unit root tests are not suitable, we use the Bai and Ng (2004) approach to extract a common component from price differentials and test it for a unit root and for cointegration with the nominal exchange rate. The results of these tests (Appendix B) indicate that there is indeed a common stochastic trend cointegrated with the nominal exchange rate. Hence, specifications (1) and (2) are valid.

Table 4 reports estimated specifications (1) and (2) on pooled data. To account for the fact that error terms in specifications (1) and (2) can be correlated across time, goods, and countries as well as the fact that  $EX_t$  is common across goods and countries, we use the Driscoll and Kraay (1998)

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<sup>16</sup> We use BIC to select the number of lags for  $d \log(P_{i,t-1}^{CA}/P_{i,t-1}^{US})$  and  $d EX_{t-1}$ .

<sup>17</sup> Since we use an estimated  $\alpha$  in equation (2), one may be concerned about the consistency of estimated  $\beta$  as well as using standard inference for estimated  $\beta$ . These concerns are unlikely to be quantitatively important for several reasons. First, exchange rates are fairly persistent and approach a unit root so that an estimate of  $\alpha$  in specification (1) can be super-consistent. Second, the error terms in specifications (1) and (2) are essentially uncorrelated; thus, adjustment for the generated regressors is minimal. Hence, we can first estimate specification (1) and then use  $\hat{\alpha}$  to construct the deviation from equilibrium relationship in specification (2).

standard errors. Note that for specification (2) we have fewer observations because we restrict the sample only to goods with at least twenty observations.

The estimated exchange rate pass-through (Panel A) is about 60 to 75 percent, which is considerably larger than 20 to 40 percent pass-through typically reported in previous studies based on prices collected from regular stores (Menon 1996, Kardasz and Stollery 2001, Goldberg and Verboven 2001, Barhoumi 2005, Campa and Goldberg 2005, Gaulier et al. 2006, Takhtamanova 2010, Gopinath and Rigobon 2008, Cao et al. 2012). This increased pass-through is consistent with salient features of online markets: i) prices are more flexible, ii) competition is fierce, iii) consumers can easily buy goods from the U.S. or Canada, iv) distribution/non-tradable costs are small, and v) most goods are produced overseas so that the costs are similar across countries.

Estimated  $\beta$ 's (Panel B) suggest a fast correction of prices toward a long-run equilibrium. If we abstract from the short-run dynamics (i.e.,  $\phi$  and  $\lambda$ ) in specification (2), 7 percent or more of the gap from the long-run relationship is closed in a week (correspondingly about 25 percent of the gap is closed in a month and 60 percent in a quarter), which implies the half-life of 2-2.5 months or less. This speed of adjustment is considerably faster than the speed estimated on price indexes (e.g., Rogoff (1996) estimates a half-life of 3 to 5 years) or scanner price data, where prices of exact same goods sold in regular stores are compared across countries (e.g., Broda and Weinstein (2008) estimate a half-life of 2.9 quarters). This speed of price adjustment, however, would probably not surprise observers of the online markets. For example, Baye et al. (2007) emphasize that i) online customers compare prices within goods, not within stores; ii) the number of sellers and prices changes frequently; and iii) firms need to constantly monitor prices of their rivals. All of these factors are likely to accelerate price adjustment.

One may be concerned that high pass-through and the speed of price adjustment are potentially determined by idiosyncratic, transitory shocks such as sales and measurement errors in our data. To address this concern, we perform several checks. First, we run a series of calibrated Monte Carlo experiments to show that it would take implausibly large measurement errors to drive our results (see Appendix C). Second, we aggregate data to monthly frequency to reduce the importance of transitory shocks in the data. Pass-through and the speed of price adjustment estimated at a monthly frequency (Appendix Table F4) are similar to the estimates at a weekly frequency. Third, we re-estimate specifications (1) and (2) on regular prices (i.e., excluding sales) and find similar results (Appendix Table F7).<sup>18</sup> One should also note that we use prices averaged across sellers so that adverse effects of idiosyncratic shocks on estimated pass-through and the speed of price adjustment are likely attenuated. Thus, we conclude that idiosyncratic, transitory shocks are unlikely to drive our estimates.

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<sup>18</sup> We use  $\wedge$ - and  $\vee$ -shaped filters as in Nakamura and Steinsson (2008) to identify sales.

The speed of adjustment in our data is much higher than the speed estimated by Boivin et al. (2012) for online prices of books or by Cavallo et al. (2014) for online prices of Apple products. The discrepancy in the results for books is likely to reflect the specifics of book markets, which tend to have much stickier prices and higher market power of sellers. While Apple goods are seemingly similar to goods in our sample, there are important differences. Most importantly, Apple has considerable market power and can limit price competition across sellers and its own Apple store. As a result, Apple products have stickier prices, fewer and smaller sales, lower cross-sectional price dispersion as well as lower pass-through and slower speed of price adjustment (see Appendix E). More generally, one may expect that sellers present in both online markets (e.g., Amazon.com and Amazon.ca) can price discriminate consumers in Canada and the U.S. and reduce competition between their branches in different countries. This behavior should reduce pass-through and the speed of price adjustment. Results in Panel C of Table 5 are consistent with this intuition and may explain why previous studies (e.g., Gopinath et al. 2011, Cavallo et al. 2014) using price comparisons across branches of the same seller in different countries tend to find low pass-through.

### ***C. Predictors of pass-through and the speed of price adjustment***

While in the previous section we focus on pooled estimates of pass-through and the speed of price adjustment to present simple summary statistics, there is dramatic heterogeneity of these characteristics across goods (Table 5) when we estimate  $\alpha$  and  $\beta$  at the level of individual goods. A key question is as follows: what factors are systematically related to the size of pass-through and the speed of price adjustment? Usually, it is hard to answer this question because the data are available only at the aggregate level or little is known about the properties of goods and, as a result, previous research (e.g., Yang 1997, Campa and Goldberg 2005) focused on macroeconomic determinants (e.g., exchange rate regime, level of inflation) of pass-through. Fortunately, our dataset contains information about a number of potentially important determinants at the micro level.

To be clear, we have observational data, and, therefore, our results should not be interpreted as causal; they document correlations. However, these correlations are informative about equilibrium relationships in the data, and, therefore, they provide important inputs for theoretical efforts aimed at rationalizing the behavior of international price differentials. In what follows, we discuss several groups of factors that are arguably related to the behavior of international price differentials and then explore if estimated correlations are consistent with theoretical predictions.

First, Head et al. (2010), Richards et al. (2014), and others argue that the degree of pass-through is negatively related to search costs. The return to search effort should be higher for expensive goods. For example, consumers are more likely to search for better deals on computers and plasma TVs than on toothpaste or beer. A higher search intensity should put a larger pressure on price

convergence across sellers and countries. Thus, one may expect that more expensive goods should exhibit a larger pass-through and faster speed of price adjustment. Our dataset has a wide distribution of goods in terms of their prices, and we can exploit this variation to examine and quantify this channel. Specifically, we use log median prices to proxy for returns on search.

Second, a number of studies (Rogoff 1996, Apslund and Friberg 2001, Bergin and Feenstra 2001, Imbs et al. 2005, Mayoral and Gadea 2011, Devereux and Yetman 2010, Takhtamanova 2010) suggest that price stickiness can be an important force in determining how deviations from the law of one price are eliminated. With flexible prices, adjustment can be deep and quick. In contrast, sticky prices can delay price adjustment and make it incomplete. We can measure the degree of price stickiness using the mean frequency of price changes for a given good in our sample. More frequent price changes should be associated with larger pass-through and faster price adjustment. In addition, we use prevalence of convenient prices (e.g., prices like \$199, \$99, \$39.99) and frequency of sales to capture price rigidity more completely. Intuitively, convenient prices create barriers to price adjustment because pricing points ending in, e.g., 9, tend to be far apart; hence, firms may choose to stick to a convenient price even in spite of relatively large shocks. Knotek (2011) documents that high incidence of convenient price is indeed associated with increased price rigidity. On the other hand, sales may be interpreted as a form of price flexibility used by a firm to respond to shocks when the firm cannot change its regular price (Kehoe and Midrigan 2015).

Third, the degree of synchronization in price changes can be important because pass-through and the speed of price adjustment could be affected not only by the degree of price stickiness at the level of individual sellers but also to what extent price setting is staggered (see Neiman 2010). Indeed, in many macroeconomic models, one needs staggered price setting in addition to strategic complementarity to generate gradual adjustment of prices. As argued by Bhaskar (2002) and others, if prices are set simultaneously (i.e., synchronization is high), the reaction of prices to shocks is stronger, and departures from equilibrium levels are quickly eliminated.

Fourth, Feenstra et al. (1996), Atkeson and Burstein (2008), and many others emphasize that market power can affect the magnitude of pass-through. While the theory often stresses market share, we do not have information on sales of individual stores, and we will instead use a proxy for the degree of market power. Specifically, the number of sellers should be indicative of the degree of competition. With more sellers, one should expect a larger pass-through and speed of adjustment.

Fifth, Gust et al. (2010) argue that firm entry can increase exchange rate pass-through. Indeed, an easier entry into selling a good is likely to make competition stronger (e.g., hit-and-run strategy) and, as a result, make pass-through larger and price adjustment faster. A stronger turnover of sellers is likely to be indicative of how easy it is to start selling a given good. We proxy for the turnover using our stability measure (i.e., a more stable set of sellers means a lower turnover), and,

hence, we should expect a negative correlation between stability and pass-through and between stability and the speed of price adjustment.

Finally, reputation of sellers can influence pass-through and speed of price adjustment. Specifically, consumers are more likely to take advantage of price differentials if sellers of a given good have a high reputation because price differentials then likely present a genuine opportunity to have a good deal rather than capture a compensating differential for lack of reputation or heterogeneity in some other dimension (see Imbs et al. 2010 for a discussion). This logic suggests that pass-through and speed should be high if sellers have a high reputation.

To test these predictions, we estimate specifications (1) and (2) for each good separately and then regress estimated  $\hat{\alpha}$  and  $\hat{\beta}$  on the factors we describe above:

$$Outcome_i = \gamma_1 \log(\bar{P}_i) + \gamma_2 [\log(\bar{P}_i)]^2 + \gamma_3 Frequency_i + \gamma_4 \log(Sellers_i) + \gamma_5 [\log(Sellers_i)]^2 + \gamma_6 StabilitySellers_i + \gamma_7 Synchronization_i + \gamma_8 Reputation_i + \gamma_9 Sales_i + \gamma_{10} Convenient_i + T_i + C_i + error_i, \quad (3)$$

where  $i$  indexes goods,  $Outcome_i = \{\hat{\alpha}_i, \hat{\beta}_i\}$ ,  $\bar{P}_i$  is the median price of good  $i$  in the U.S.,  $Frequency_i$  is the average frequency of price changes in Canada and the U.S.,  $Sellers_i$  is the number of sellers in the U.S. and Canada,  $StabilitySellers_i$  is the average stability of sellers in the U.S. and Canada,  $Synchronization_i$  is the average synchronization rate of price changes in the U.S. and Canada,  $Reputation_i$  is the average star rating of U.S. and Canadian sellers,  $Sales_i$  is the average frequency of sales in the U.S. and Canada,  $Convenient_i$  is the average share of convenient prices in the U.S. and Canada,<sup>19</sup>  $T_i$  is a set of fixed effects for periods over which  $\hat{\alpha}_i$  and  $\hat{\beta}_i$  are estimated, and  $C_i$  is a set of fixed effects for categories of goods. Each variable on the right-hand side is calculated as the time series average. Table 6 reports estimated coefficients for specification (3) by least squares for various measures of prices.

We have conjectured a positive relationship between the size of pass-through and returns on search proxied by the price of a good. The estimates suggest a non-linear relationship. For goods with prices less than approximately \$150—which is close to the median price of goods in our data—the relationship is positive, but it turns into a negative one for more expensive goods. This inverted-U relationship suggests that pass-through and search have an interplay that is more complex than often assumed. Indeed, pass-through and search are determined simultaneously in equilibrium, and firms can respond to endogenous search effort by pricing goods in such a way that returns to search are reduced for expensive goods where search is likely to be most intensive and hence the elasticity of demand can be particularly high. For example, a manufacturer can require online stores to sell its good at a price

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<sup>19</sup> We define convenient prices as prices that end with 9 in the \$1-\$100 range (e.g., \$39, \$59.99, \$79.50) or that end with 99, 98, 97, 96, or 95 in the \$100+ range (e.g., \$199, \$399.99, \$999.50). Note that in defining convenient prices, we ignore cents and focus only on dollar amounts. As a result, prices like \$30.99 are not considered convenient.

set by the manufacturer rather than by retailers, thus limiting price dispersion and competition between stores. In addition, manufacturers could be more likely to sell high-price goods (e.g., laptops) directly to customers than low-price goods (e.g., cables), and they may be interested in preserving sales through their websites again by limiting price dispersion. While we are not able to test hypotheses of this type with our data, there is anecdotal evidence consistent with this explanation.<sup>20</sup>

Interestingly, we also find an inverted-U relationship between a good's price and the speed of price adjustment, where the speed is the slowest for goods priced around \$150, which is approximately the price where the estimated pass-through is the highest. Note that  $\hat{\alpha}_i$  and  $\hat{\beta}_i$  are essentially uncorrelated, and, therefore, it is unlikely that this pattern arises mechanically from the way we estimate these parameters. It is more likely that this pattern reflects incentives to adjust prices. Intuitively, if pass-through is close to 100 percent, returns to arbitrage are second-order as the profit function is approximately flat. As a result, the speed of price adjustment is slow. In contrast, when pass-through is low, returns to arbitrage are high (the slope of the profit function is steep), and, thus, the speed is fast.

There is also a non-linear relationship between the number of sellers and pricing dynamics. Specifically, raising the number of sellers from two sellers (the minimum number) to 4-5 sellers (approximately, the average number of sellers) is associated with increased pass-through. Further increases in the number of sellers are associated with decreasing pass-through. The speed of price adjustment is not significantly correlated with the number of sellers.

There is a strong positive relationship between the size of the estimated pass-through and frequency of price changes. Specifically, a one standard deviation increase in the frequency of price changes (approx. 0.17) is associated with a 34 percentage point increase in pass-through. High frequency of price changes is also strongly associated with faster price adjustment. Estimates for other proxies of price stickiness (prevalence of convenient prices) and price flexibility (frequency of sales) paint a similar picture. Overall, consistent with theoretical predictions, goods with stickier prices have a lower speed of price adjustment.

Greater synchronization of price changes is associated with lower pass-through. At the same time, we find weak evidence that synchronization decelerates price adjustment. These results suggest that synchronization likely captures market power, enabling coordination of price changes and limiting the ability of online sellers to eliminate arbitrage opportunities.

The stability of sellers is significantly negatively correlated with the speed of price adjustment: a lower turnover of sellers (higher stability) reduces the speed (i.e.,  $\hat{\beta}$  becomes larger and closer to zero). This finding is consistent with the view that easy entry into a market and limited time-horizons for sellers, which limits the scope for collusion, are likely to eliminate arbitrage

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<sup>20</sup> For example, Apple products sold in a broad array of online stores show little, if any, price dispersion across online stores because Apple apparently coordinates prices across sellers (see an [article](#) on zdnet.net).

opportunities and mis-pricing of goods faster. The quantitative effect of seller stability is large. A one standard deviation increase in stability (approximately 0.05) is associated with a 0.05 reduction in the speed. At the same time, we do not find a significant relationship between pass-through and stability.

In summary, although we cannot establish causal links in our data, estimated correlations shed useful light on the relative roles of potential forces that determine pass-through and the speed of price adjustment. Future work that makes identifying assumptions (i.e., structural approach) or employs (quasi-)experimental design may quantify causal chains in the data. Our results summarizing patterns in the data supply moments to be matched in this future work.

#### **D. Margins of price adjustment**

While the previous section documents that pass-through and the speed of price adjustment are high in online markets, one can learn more about these two objects by exploring what margins of price adjustment are used in response to movements in the nominal exchange rate. We use our specification (1) to construct a measure of the deviation from equilibrium  $EC$ :

$$\widehat{EC}_{it} = \log\left(\frac{P_{it}^{CA}}{P_{it}^{US}}\right) - \hat{\alpha}EX_t. \quad (4)$$

where, as before,  $i$  and  $t$  index goods and time (weeks), respectively,  $P$  is a measure of a price (e.g., median price, mean price, minimum price), and  $EX$  is the nominal exchange rate. Note that  $\alpha$  is estimated for each price measure separately.

We measure the intensive margin of price adjustment as the average price change (conditional on price change) across sellers of good  $i$  in country  $c$  and week  $t$ :

$$\overline{dP}_{ict} = \frac{\sum_{s=1}^{S_{itc}} \log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) \times \mathbf{1}\left\{\left|\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right)\right| > 0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\left|\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right)\right| > 0.01\right\}}. \quad (5)$$

We also calculate the mean size of price increases and price decreases separately:

$$\overline{dP}_{ict}^{decrease} = \frac{\sum_{s=1}^{S_{itc}} \log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) \times \mathbf{1}\left\{\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) < -0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) < -0.01\right\}}, \quad (5')$$

$$\overline{dP}_{ict}^{increase} = \frac{\sum_{s=1}^{S_{itc}} \log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) \times \mathbf{1}\left\{\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) > 0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) > 0.01\right\}}. \quad (5'')$$

The extensive margin of price adjustment—again with the distinction for any price change, price increase, and price decreases—is measured as

$$\Pr(dP \neq 0)_{ict} = \frac{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\left|\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right)\right| > 0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isc,t}}{P_{isc,t-1}}\right) \text{ is not missing}\right\}} \quad (6)$$

$$\Pr(dP > 0)_{ict} = \frac{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isct}}{P_{isc,t-1}}\right) > 0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isct}}{P_{isc,t-1}}\right) \text{ is not missing}\right\}} \quad (6')$$

$$\Pr(dP < 0)_{ict} = \frac{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isct}}{P_{isc,t-1}}\right) < -0.01\right\}}{\sum_{s=1}^{S_{itc}} \mathbf{1}\left\{\log\left(\frac{P_{isct}}{P_{isc,t-1}}\right) \text{ is not missing}\right\}} \quad (6'')$$

and is thus a fraction of sellers that change their prices in the set of sellers that have listed good  $i$  in weeks  $t$  and  $t - 1$ .

Finally, stores with the best prices may run out of inventories faster than other stores; thus, cheap stores can be more likely to exit the market until they replenish their inventories. We calculate the probability of exit as follows:

$$\Pr(exit)_{ict} = \frac{\sum_{s=1}^{S_{itc,t-1}} \mathbf{1}\{P_{isct} \text{ is missing} \cap P_{isc,t-1} \text{ is not missing}\}}{\sum_{s=1}^{S_{itc,t-1}} \mathbf{1}\{P_{isc,t-1} \text{ is not missing}\}}. \quad (7)$$

Using these measures, we estimate the following generic specification with a pricing moment given in (5)-(7) as the dependent variable:

$$Moment_{ict} = \gamma_c + \psi_c \widehat{EC}_{i,t-1} + \kappa_{c1} EX_{t-1} + \kappa_{c2} Moment_{ic,t-1} + \lambda_{ic} + error_{ict}. \quad (8)$$

Note that specification (8) is estimated for each country separately as the direction of the change in the pricing moment can depend on whether equilibrium error  $EC$  is positive or negative; thus, estimated coefficients may move in opposite directions for Canada and the U.S. For example, if  $EC > 0$  (goods in Canada are relatively expensive), one may expect prices in Canada to decrease (i.e.,  $\overline{dP}_{i,CA,t} < 0$ ) and prices in the U.S. to increase (i.e.,  $\overline{dP}_{i,US,t} > 0$ ) and hence  $\psi_{CA} < 0$  and  $\psi_{US} > 0$ .

Table 7 presents estimates of  $\psi_c$ , which is the key parameter in specification (8), for various pricing moments and measures of prices. For the response of the mean price change  $\overline{dP}_{ict}$ , we consistently find (row 1) that if prices in Canada are 10 percentage points above equilibrium level, prices in Canada fall by 0.8 to 1.3 percentage points on impact, while prices in the U.S. increase by 0.4 to 0.7 percentage point on impact. Consistent with our previous findings, these results suggest fast adjustment of prices to equilibrium levels. This pattern also applies to both price increases (row 2) and price decreases (row 3). For example, if we focus on the mean prices in the U.S. and Canada, a positive equilibrium error  $EC$  (i.e., prices are more expensive in Canada), price increases in Canada become smaller, while price decreases become larger (more negative). Likewise, a positive equilibrium error  $EC$  tends to lead to larger price increases and smaller (i.e., less negative) price decreases in the U.S. Hence, we do not observe strong asymmetric effects in the size of price adjustment as prices appear to be equally flexible in terms of increases and decreases. The magnitude of the response is generally larger for Canada than for the U.S., which is consistent with the view that price adjustment is likely to be larger in smaller markets.

The frequency of price adjustment for all price changes (row 4) does not exhibit a robust relationship to equilibrium errors. However, this lack of correlation reflects that movements in frequencies of price increases and frequencies of price decreases roughly offset each other. Once we focus on the frequency of price increases (row 5) and the frequency of price decreases (row 6) separately, the data indicates a strong link between the frequencies of price adjustment and equilibrium errors. Consider the frequency of price increases when we use mean prices. A positive 10 percentage point equilibrium error  $EC$  reduces the frequency of prices increases in Canada by 0.85 percentage points and increases the frequency of price increase in the U.S. by 0.29 percentage points. This finding is in line with the price adjustments along the intensive margin where positive  $EC$  leads to smaller price increases in Canada and larger price increases in the U.S. The effect is in the opposite direction for the frequency of price decreases: a positive 10 percentage point equilibrium error  $EC$  increases the frequency of prices decreases in Canada by 0.76 percentage points and decreases the frequency of price decrease in the U.S. by 0.20 percentage points. One can immediately see that the movements of the frequency of price increases and the frequency of price decreases have similar magnitudes, and thus the effect on the frequency of all price changes becomes weak. Similar to the results for the intensive margin, the response of the extensive margin is stronger for Canada than for the U.S.

The exit of goods with cheap prices is not strongly correlated with equilibrium errors. We only find one case with minimum prices with significant statistical evidence that a positive equilibrium error makes exit of stores less likely in Canada and more likely in the U.S. While one should expect this pattern, we conjecture that we do not find the same patterns for other price measures because the consumer pressure arising from price differentials is likely to be the highest for stores offering lowest prices. Indeed, price sensitive consumers are likely to buy at the cheapest prices and thus are more likely to respond to arbitrage opportunities when relative prices shift. At the same time, given fairly large dispersion of prices within countries, mean or median prices at the level of countries may be too coarse to detect changes in demand arising from shifts in relative prices.

To further explore margins of price adjustment, Figure 5 plots the time series of mean price changes (i.e., all price changes, price increases, and price decreases in Panels A, B, and C) when we aggregate across goods (with equal weights) to the country level. We also report the estimated slope from regressing each series on the nominal exchange rate. In general, price increases (decreases) in Canada are negatively (positively) correlated with the nominal exchange rate (CAD/USD), and the pattern of correlations is reversed for the U.S. One can also observe that the correlation between the size of price decreases in the U.S. and in Canada is negative.

In a similar manner, we aggregate frequencies of price adjustment across goods to the country level (Panels D, E, and F). These aggregate frequencies for the U.S. and especially for Canada tend to be positively correlated with the nominal exchange rate. However, a decomposition

of price changes into price increases (Panel E) and price decreases (Panel F) suggests that the correlation with the nominal exchange rate is the strongest for price increases in Canada and equally weak for price increases and price decreases in the U.S.

The frequency of price increases and decreases in Canada was the highest in late 2008 and early 2009 when the Canadian dollar was strongly appreciating. The fact that the frequency of price changes rose for both price increases and price decreases highlights that the exchange rate movements induced firms to review their prices with possible adjustment in either direction rather than move all Canadian prices in one direction. In other words, firms appeared to be re-optimizing their prices rather than mechanically adjusting their prices by changes in the exchange rate. Obviously, these price adjustments happened during the Great Recession, so perhaps this “churning” of price changes reflects increased intensity of price adjustment in recessions rather than responsiveness of prices to exchange rate fluctuations. However, we observe only a moderate to weak increase in the frequency of price adjustment for U.S. retailers; therefore, it is hard to see the contribution of the Great Recession to increased frequency of price adjustment in Canada.

To explore this issue further, we regress the frequency of price increases and the frequency of price decreases on the CAD/USD exchange rate over the period that excludes the Great Recession; that is, we use data after June 2009. We find that the frequency of price decreases in Canada is not statistically or economically sensitive to the exchange rate, while the frequency of price increases continues to stay highly significant in statistical and economic terms. At the same time, the frequency of price decreases in the U.S. is positively related to the CAD/USD exchange rate (although the sensitivity is smaller than that for Canada), while the frequency of price increases in the U.S. does not exhibit a significant correlation with the exchange rate. This pattern of responses is consistent with the predictions of economic theory on how firms should adjust their prices, and it therefore corroborates our findings in Table 7.

The exit frequency (Figure 6) is positively correlated with the nominal exchange rate for both the U.S. and Canada, but, similar to other margins, the exit margin in Canada is more sensitive to fluctuations in the nominal exchange rate. Some of the positive correlation is determined by the coincidence of high turnover of sellers and goods (i.e., high exit frequency) and depreciation of the Canadian dollar in the Great Recession. If we exclude the Great Recession, the exit frequency in the U.S. shows no sensitivity to the exchange rate, while the exit frequency in Canada is even more strongly positively related to the CAD/USD exchange rate. It appears that when the Canadian dollar depreciates, the U.S. consumers take advantage of cheap Canadian prices and deplete inventories of Canadian stores, while the pool of Canadian customers is unable to exercise the same pressure on U.S. stores when the Canadian dollar appreciates.

## 5. Concluding remarks

While the law of one price is an appealing concept, the vast majority of previous research has emphasized various frictions that prevent the law from holding over relative long periods. These frictions can take a variety of forms, but the most popular barriers leading to violations of the law are search costs, costs of nominal price adjustment, and transportation/distribution costs. Assessing the contribution of these frictions has been remarkably difficult as these frictions are ubiquitous in standard markets with brick-and-mortar stores.

Online markets have unusual characteristics, such as low search costs, irrelevance of physical locations of buyers and sellers, and negligible physical costs of price changes; thus, studying price setting in online markets offers a unique opportunity to rule out the prominent frictions and explore whether the law of one price holds in this close-to-ideal setting.

We construct a new, massive dataset of online price quotes in the U.S. and Canada. This dataset has a number of desirable features, such as long time series, large cross sections, and multiple sellers. We document that, relative to prices in regular stores, prices in online markets are more flexible as well as exhibit stronger pass-through and faster convergence in response to movements of the nominal exchange rate. Multiple margins of adjustment (frequency of price changes, direction of price changes, size of price changes, exit of sellers) are active in the process of responding to nominal exchange rate shocks. Furthermore, we use the richness of our dataset to show that the sensitivity of prices to changes in the nominal exchange rate is systematically correlated with the characteristics of goods and markets (e.g., the degree of competition). To the extent future retail will shift to the internet, one can therefore expect that cross-country price differentials are going to be smaller and less persistent, bringing the law of one price closer to reality.

Scraping online prices is a cheap and fast approach to collecting price quotes at high frequencies; therefore, it is attractive to statistical agencies. While these data open new, unprecedented research opportunities (e.g., the Billion Prices Project run by Alberto Cavallo and Roberto Rigobon), economists should also appreciate limitations of many currently available datasets, including the dataset used in this paper. Perhaps the most important one is the lack of information about volumes of purchases associated with price quotes. Using the number of clicks may provide a simple proxy for quantities of goods sold in online stores, but the quality of this and similar proxies should be verified with alternative information. As information technology progresses and internet retailers become more willing to share transaction data, one may expect major improvements in the quality of data so that one can answer questions that seem currently insurmountable. For example, these new data can help us to understand how stores selling goods online and offline (e.g., Walmart) set prices and conduct sales in these interconnected markets. One

may also be able to trace consumers' history of searches to transactions and, hence, have a better understanding of how searching operates and how it is related to price dispersion and adjustment.

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Figure 1. Screenshots of typical web pages from price comparison websites.

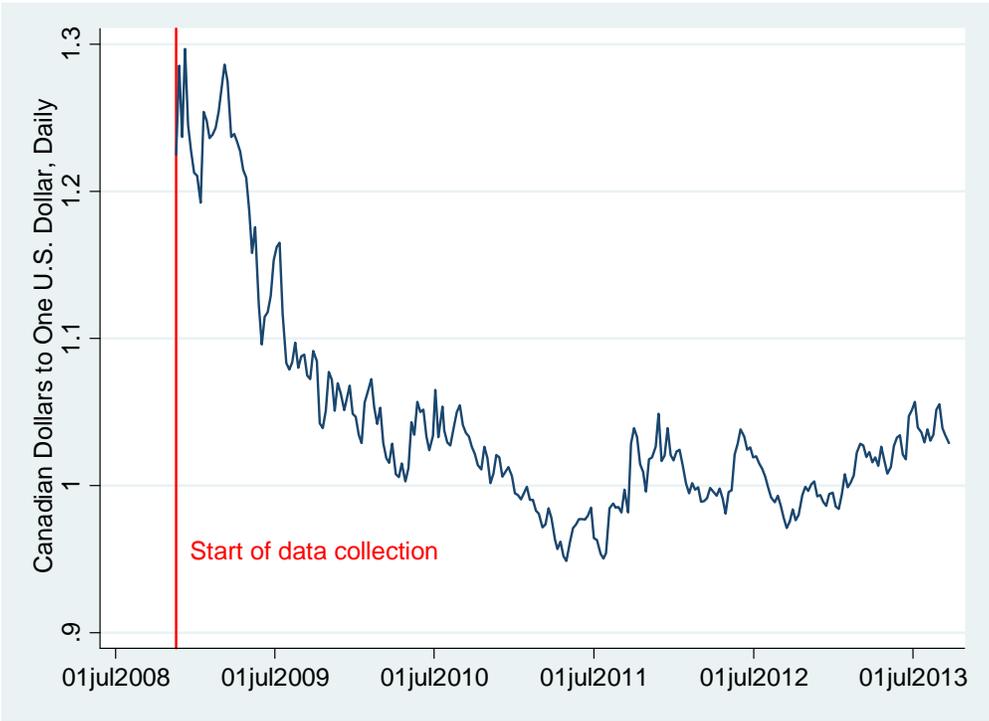
Retailer	Rating	Retailer message	Price	Availability
amazon.co.uk Info on Amazon.co.uk	☆☆☆☆☆ 2 reviews	Samsung NP350V5C 15.6 inch Laptop (Silver) (Intel Core i5...	£ 399.99 + Delivery : £ 0.00 <b>£ 399.99</b>	In stock 13/10/12 <b>Go to store</b>
LASKYS Info on Laskys	☆☆☆☆☆ 1466 reviews CUSTOMER CERTIFIED	SAMSUNG NP350V5C-A02UK Office 2010 for £59.99 when bought with any Laptop at Laskys	£ 412.58 + Delivery : £ 0.00 <b>£ 412.58</b>	In stock 3 - 5 days 13/10/12 <b>Go to store</b>
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ebay.co.uk Info on eBay	☆☆☆☆☆ 0 reviews	Samsung 350v5c 15.6" 6gb Ram 500gb Hdd Webcam Hdmi Dvd Re... eBay is the largest online marketplace. With great offers from big brands or individual sellers, you can be sure to get a great deal here.	£ 436.98 + Delivery : £ 0.00 <b>£ 436.98</b> More product options	Unknown stock 13/10/12 <b>Go to store</b>
WAE Info on WAE +	☆☆☆☆☆ 7 reviews	Samsung NP350V5C-A02UK Free Delivery On This Item	£ 438.18 + Delivery : £ 0.00 <b>£ 438.18</b>	In stock 13/10/12 <b>Go to store</b>
amazon.co.uk Info on Amazon Marketplace UK	☆☆☆☆☆ 285 reviews	Samsung NP350V5C 15.6 inch Laptop (Silver) (Intel Core i5... New, used, refurbished and collectable products at great prices, safely and securely from third parties, at Amazon.co.uk.	£ 469.99 + Delivery : £ 5.69 <b>£ 475.68</b>	In stock 13/10/12 <b>Go to store</b>

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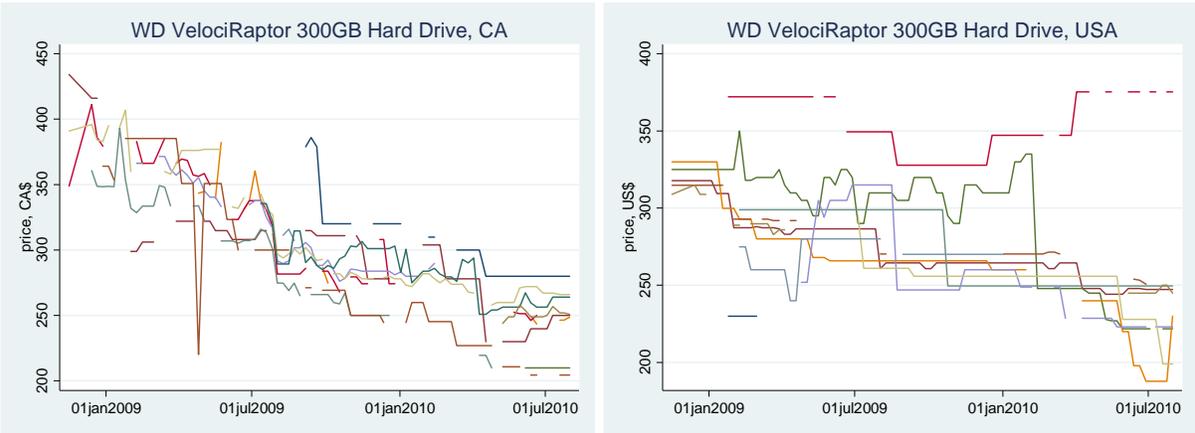
Produktbezeichnung des Shops*	Preis/Versand/Gesamtpreis (jew. inkl. MwSt.)*	Lieferzeit*	Shopmeinungen/Shop
Samsung Serie 3 NP350V5C-S07 39,6cm C17-3610QM 8GB 750GB HD7670 Win7HP	<b>739,00 €</b> Preis gilt nur bei Verwendung des Gutschein-Codes: MSHOP30EUR (30 EUR Rabatt ab 600 EUR Einkaufswert - gültig bis 31.10.12) Vorkasse: <b>versandkostenfrei</b> Nachnahme: 5,00 € inkl. Versand (Gesamtpreis: 744,00 €) Daten vom 13.10.2012 20:07, Preis kann jetzt höher sein.*	sofort lieferbar	★★★★★ 2.276 Meinungen T-Online-Shop <b>WEITER</b>
Samsung 3 Series 350V5C S07	<b>752,37 €</b> Vorkasse: <b>versandkostenfrei</b> Nachnahme: 12,95 € inkl. Versand (Gesamtpreis: 765,32 €) Daten vom 13.10.2012 19:59, Preis kann jetzt höher sein.*	Innerhalb von 2 Werktagen versandfertig	★★★★★ 238 Meinungen XITEDA <b>WEITER</b>
Notebook NP350V5C-S07/Intel Core i5-3210M / 8GB / 39,6 cm (17,3") H / AMD Radeon HD7670M 2,048 MB / 750 GB / Multi / ZHP64	<b>767,21 €</b> Vorkasse: 6,90 € inkl. Versand (Gesamtpreis: 774,11 €) Nachnahme: 12,80 € inkl. Versand (Gesamtpreis: 780,01 €) PayPal: 20,83 € inkl. Versand (Gesamtpreis: 788,04 €) Daten vom 13.10.2012 20:07, Preis kann jetzt höher sein.*	sofort lieferbar	★★★★★ 514 Meinungen Hardwarehouse <b>WEITER</b>
Samsung Notebook Serie 3 350V5C S07	<b>769,00 €</b> Vorkasse: <b>versandkostenfrei</b> Sofortüberweisung: 1,00 € inkl. Versand (Gesamtpreis: 770,00 €) Nachnahme: 5,00 € inkl. Versand (Gesamtpreis: 774,00 €) PayPal: 12,38 € inkl. Versand (Gesamtpreis: 781,38 €) Kreditkarte: 15,38 € inkl. Versand (Gesamtpreis: 784,38 €) Abholung kostenlos möglich in 31157 Sarstedt Daten vom 13.10.2012 20:07, Preis kann jetzt höher sein.*	sofort ab Lager / 24h-Service möglich	★★★★★ 4.326 Meinungen notebooks billiger.de <b>WEITER</b>
Samsung Serie 3 350V5C S07 15,6 Notebook - Core i7 8GB Ram	<b>774,90 €</b> Vorkasse, Kreditkarte, PayPal, giropay: <b>versandkostenfrei</b> Nachnahme: 2,00 € inkl. Versand (Gesamtpreis: 776,90 €) Daten vom 13.10.2012 20:05, Preis kann jetzt höher sein.*	Lieferbar in 2-4 Werktagen	★★★★★ 1.855 Meinungen getgoods.de <b>WEITER</b>
Samsung Serie 3 350V5C S07 15,6 Notebook - Core i7 8GB Ram	<b>774,90 €</b> Vorkasse, Nachnahme, Kreditkarte, Sofortüberweisung, PayPal, giropay: <b>versandkostenfrei</b> Daten vom 13.10.2012 20:11, Preis kann jetzt höher sein.*	Lieferbar in 2-4 Werktagen	★★★★★ 2.859 Meinungen Hohl.de <b>WEITER</b>
	<b>774,98 €</b>		

Figure 2. Time series of CAD/USD exchange rate.



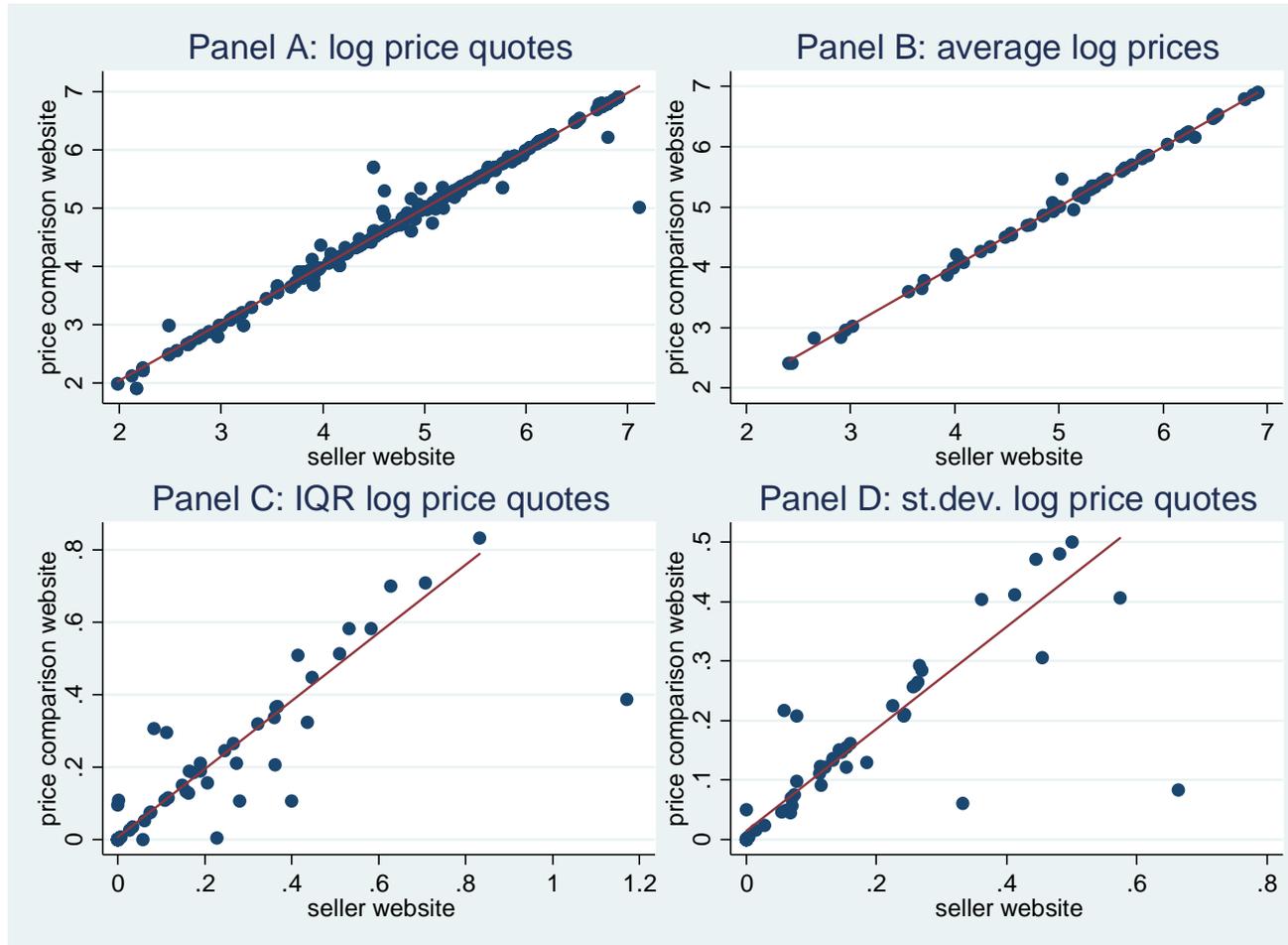
Notes: Source: Board of Governors.

Figure 3. Price quotes.



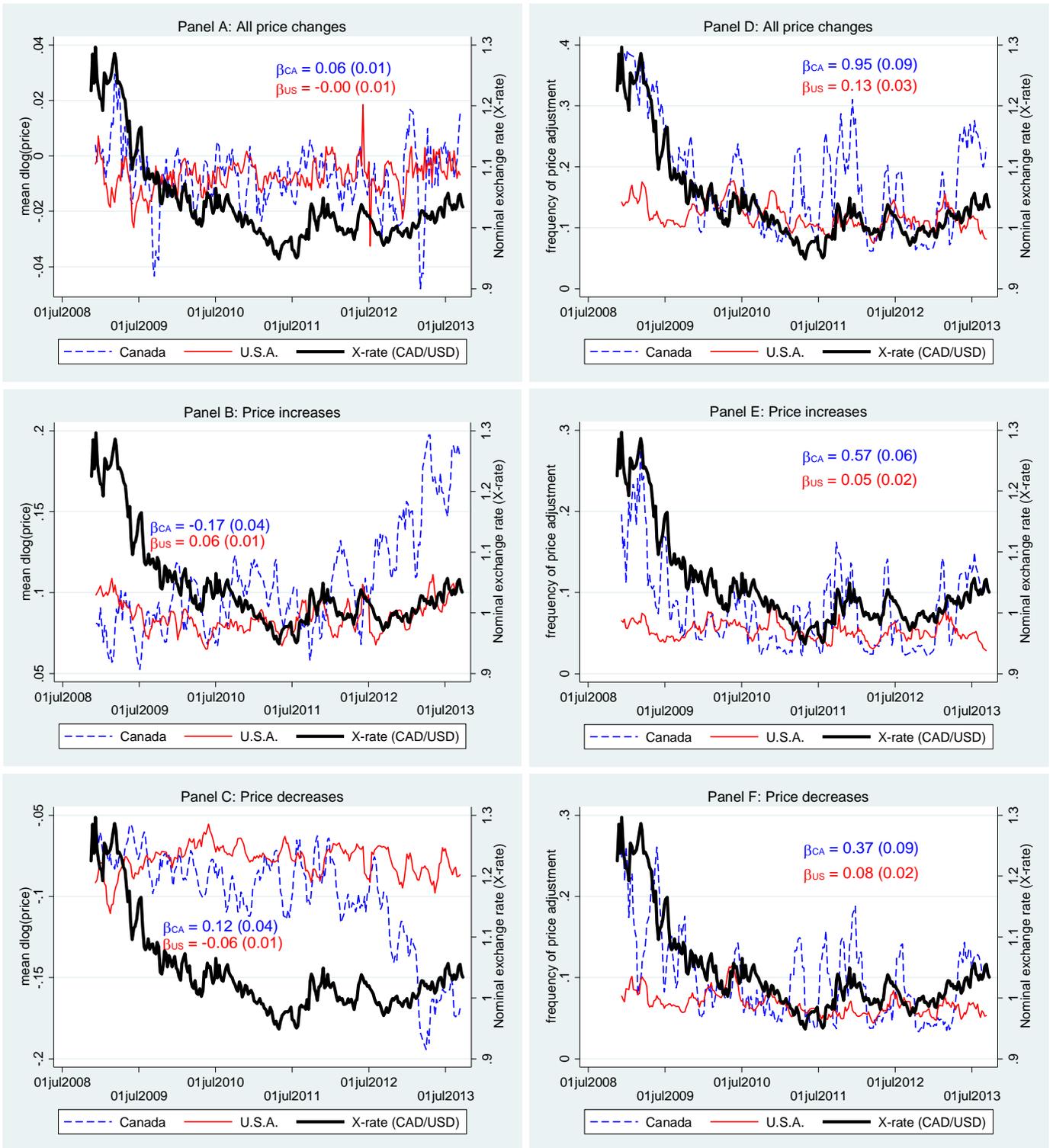
Notes: Each line shows a path of price quotes for a given online seller of the WD VelociRaptor 300Gb hard drive. The left panel is for Canadian sellers. The right panel is for U.S. sellers.

Figure 4. Price quotes listed on the price comparison website and seller websites.



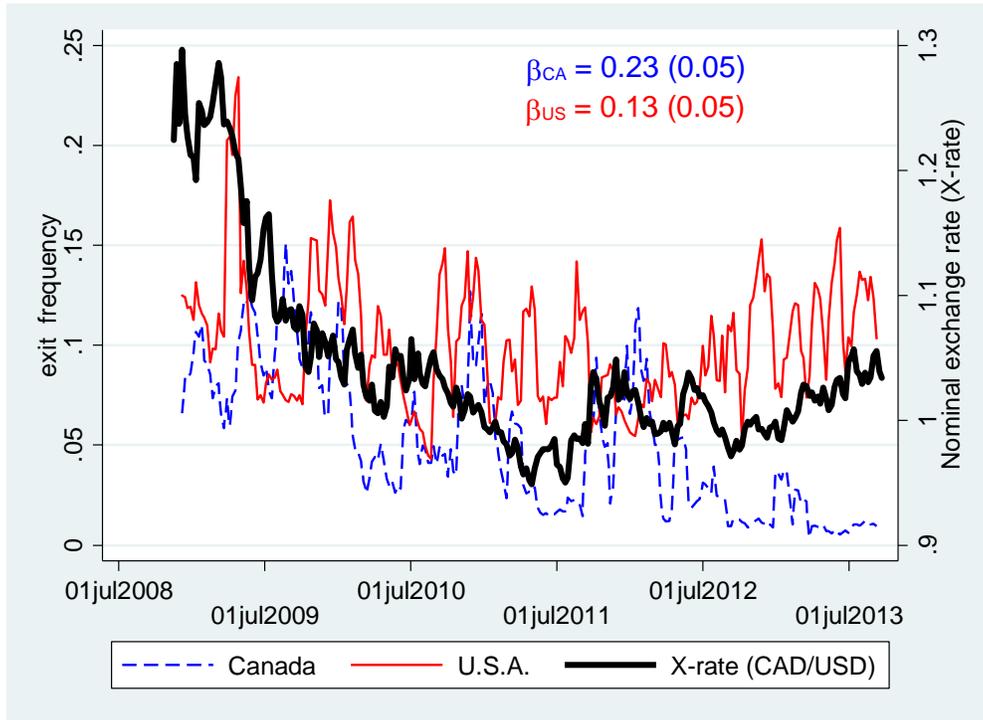
Notes: Panel A shows price quotes listed on the price comparison website and seller websites for each good, that is, each point is a good-seller price quote. In Panel B, average log price quote is calculated for each source of price information, that is, each point shows an average log price for a good. Panel C shows the interquartile range of log prices across sellers for each good in both sources of price information. Panel D shows the standard deviation of log prices across sellers for each good in both sources of price information.

Figure 5. Intensive and extensive margins of price adjustment.



Notes:  $\beta_{CA}$  and  $\beta_{US}$  show estimated slopes of regressing a given variable for Canada and the U.S. on the nominal CAD/USD exchange rate. Newey-West standard errors are in parentheses. See section 4.D for further details.

Figure 6. Exit margin of price adjustment.



Notes:  $\beta_{CA}$  and  $\beta_{US}$  show estimated slopes of regressing a given variable for Canada and the U.S. on the nominal exchange rate. Newey-West standard errors are in parentheses. See section 4.D for further details.

**Table 1. Description of categories.**

Category	Type	Quotes	Goods	Sellers	Goods/Seller
Cameras (10 categories)	35mm SLR lens Accessories, Bags and Cases, Binoculars, Camcorders, Camcorder Batteries, Camcorder Accessories, Dedicated Flashes, Digital Cameras, SLR Lenses, Tripods	1,398,396	12,215	405	62
		(543,587)	(1,197)	(299)	(85)
Computers (20 categories)	Cases, Desktops, Flash Memory, Flat Panel LCD monitors, Hard Drives, Hubs, Keyboards, Laptop, Laptop Memory, Microphones and Headsets, Modems, Motherboards, Network Adapters, Power Supply, Processors, Scanners, Speakers, Storage Media, UPSS, Webcams	11,260,217	50,240	815	69
		(8,368,381)	(12,717)	(694)	(86)
Electronics (13 categories)	Audio Cables, AV Accessories, Calculators, Cash Registers, GPS, Headphones, MP3 players, Portable Device Accessories, Projectors, Projection Screens, Plasma/LCD TV, TV Accessories, Video Cables	4,313,179	38,883	676	60
		(2,704,025)	(8,964)	(509)	(78)
Software (12 categories)	Anti-Virus, Audio/Video Utilities, Computer Games, Engineering and Design, Databases, Financial and Legal Software, Graphics and Publishing, Office Suites, Programming, Security, System Utilities, Windows Operating Systems	1,628,044	16,648	382	100
		(726,704)	(1,315)	(298)	(116)

Notes: The last four columns report the number of unique price quotes, goods, and sellers as well as the median number of goods per seller. Figures in parentheses report the corresponding statistics for the sample of goods used in Table 5.

**Table 2. Composition of sellers in the sample.**

Seller type	Canada	USA	Pooled
Offline-online	11.53	3.21	7.00
Online-only	78.05	76.21	77.05
Marketplace	-	1.52	0.83
Not classified	10.42	19.06	15.13
Total	100.00	100.00	100.00

Notes: “Offline-online” sellers include stores that sell goods online and that have conventional, brick-and-mortar retail outlets (e.g., Walmart). “Online-only” sellers cover stores that sell goods online and that do not have conventional, brick-and-mortar retail outlets (e.g., Amazon.com). “Marketplace” sellers are multi-vendor online shops (e.g., eBay.com). For “not classified” stores, we could not establish if a seller has a conventional retail outlet.

**Table 3. Descriptive statistics.**

	Mean (1)	St.Dev (2)	Median (3)	P25 (4)	P75 (5)
<b>Panel A: Canada</b>					
Cross-sectional distribution of prices					
St.dev. log(Price)	0.128	0.090	0.111	0.066	0.160
IQR log(Price)	0.111	0.083	0.091	0.051	0.158
Median log(Price)	5.403	1.407	5.292	4.448	6.602
Frequency of price changes	0.367	0.169	0.367	0.246	0.462
Size of price changes					
Median dlog(Price)	-0.006	0.019	-0.003	-0.007	-0.002
Median abs(dlog(Price))	0.029	0.044	0.017	0.008	0.031
Sales					
Mean size	0.067	0.101	0.028	0.018	0.071
Frequency	0.027	0.032	0.023	0.000	0.039
Synchronization of price changes	0.231	0.210	0.182	0.037	0.374
Properties of sellers					
Number of sellers	2.426	1.209	1.871	1.585	3.127
Stability	0.899	0.065	0.907	0.850	0.952
Freq. of convenient prices	0.196	0.187	0.137	0.061	0.262
<b>Panel B: USA</b>					
Cross-sectional distribution of prices					
St.dev. log(Price)	0.159	0.113	0.140	0.077	0.220
IQR log(Price)	0.173	0.139	0.142	0.075	0.250
Median log(Price)	5.328	1.415	5.191	4.365	6.541
Frequency of price changes	0.197	0.155	0.191	0.055	0.300
Size of price changes					
Median dlog(Price)	-0.006	0.033	-0.004	-0.011	0.000
Median abs(dlog(Price))	0.042	0.052	0.030	0.017	0.049
Sales					
Mean size	0.071	0.087	0.046	0.026	0.082
Frequency	0.022	0.031	0.010	0.000	0.035
Synchronization of price changes	0.187	0.124	0.176	0.101	0.258
Properties of sellers					
Number of sellers	3.370	1.920	2.870	1.868	4.306
Stability	0.887	0.052	0.887	0.856	0.926
Freq. of convenient prices	0.194	0.203	0.141	0.034	0.280
<b>Panel C: International price differentials</b>					
Mean prices					
Relative exchange rate	0.074	0.225	0.050	-0.035	0.183
Real exchange rate	0.051	0.218	0.034	-0.048	0.142
Median prices					
Relative exchange rate	0.081	0.227	0.056	-0.028	0.189
Real exchange rate	0.058	0.221	0.038	-0.039	0.148
Minimum prices					
Relative exchange rate	0.123	0.272	0.085	-0.007	0.234
Real exchange rate	0.100	0.268	0.069	-0.025	0.196

Notes: P25 and P75 in columns (4) and (5) show 25<sup>th</sup> and 75<sup>th</sup> percentile of the statistics indicated in the first column. Relative exchange rate is calculated as  $\log(P_{it}^{CA}/P_{it}^{US})$  where  $i$  and  $t$  index goods and weeks, respectively,  $P^{CA}$  is the price in Canada, and  $P^{US}$  is the price in the U.S. The real exchange rate is calculated as  $\log(EX_t^{-1} \times P_{it}^{CA}/P_{it}^{US})$  where  $EX_t$  is the nominal CAD/USD exchange rate. See text for further details.

**Table 4. Comparison of pricing moments**

		Price comparison website	Leading shopping platform		Conventional stores
		(1)	no weights	click weighted	(4)
Frequency of posted price changes, per week					
EE011	Personal Computers and Per. Equipment	27.15	16.25	21.94	7.74
EE021	Computer Software	20.32	13.33	24.17	2.60
EE042	Calculators and Adding Machines	10.10	9.81	14.74	1.95
RA011	Televisions	28.80	25.76	23.10	7.02
RA051	Radio and Tape Recorders/Players	14.94	11.35	20.37	5.22
RD012	Still Camera	24.90	11.37	33.28	4.47
Mean $ \Delta \log P $ , percent					
EE011	Personal Computers and Per. Equipment	4.77	11.50	11.57	11.26
EE021	Computer Software	8.00	11.41	11.47	22.65
EE042	Calculators and Adding Machines	11.10	19.67	17.64	19.94
RA011	Televisions	5.00	7.36	8.20	9.71
RA051	Radio and Tape Recorders/Players	8.94	16.72	17.00	12.60
RD012	Still Camera	7.32	13.33	13.37	10.54
Frequency of sales, per week					
EE011	Personal Computers and Per. Equipment	2.80	1.21	1.95	5.87
EE021	Computer Software	2.91	0.66	1.71	6.12
EE042	Calculators and Adding Machines	2.90	0.81	0.98	6.02
RA011	Televisions	2.80	1.51	2.19	12.30
RA051	Radio and Tape Recorders/Players	3.53	1.08	1.84	14.12
RD012	Still Camera	3.86	0.99	2.76	9.73
Mean abs. size of sales, percent					
EE011	Personal Computers and Per. Equipment	5.67	10.23	9.75	9.32
EE021	Computer Software	8.40	7.59	9.65	18.21
EE042	Calculators and Adding Machines	6.40	-	-	14.93
RA011	Televisions	6.70	11.94	13.74	6.61
RA051	Radio and Tape Recorders/Players	9.52	15.12	12.38	9.71
RD012	Still Camera	8.49	10.70	11.74	7.78
Cross-sectional dispersion, <i>st. dev. log P</i> , percent					
EE011	Personal Computers and Per. Equipment	10.63	20.80	14.40	-
EE021	Computer Software	20.03	14.80	13.70	-
EE042	Calculators and Adding Machines	16.70	18.70	22.70	-
RA011	Televisions	8.80	14.10	11.60	-
RA051	Radio and Tape Recorders/Players	17.84	18.80	16.90	-
RD012	Still Camera	8.94	14.70	12.80	-
Within-good price synchronization					
EE011	Personal Computers and Per. Equipment	20.18	15.09	17.69	-
EE021	Computer Software	15.98	8.48	15.41	-
EE042	Calculators and Adding Machines	5.40	12.49	16.13	-
RA011	Televisions	17.40	18.19	20.15	-
RA051	Radio and Tape Recorders/Players	12.02	9.53	17.50	-
RD012	Still Camera	20.08	11.53	23.27	-

Notes. The table compares the frequency and absolute size of price changes and sales, cross-sectional dispersion and price within-good price synchronization for selected narrow categories in online data used in this paper, data used in Gorodnichenko, Sheremirov and Talavera (2014), and data for conventional stores (column 4) are from Nakamura and Steinsson (2008). All data are for the U.S. Only matched categories are shown.

**Table 5. Pass-through and the speed of price adjustment.**

	No Fixed effects	Type Fixed effects	Good Fixed effects	N
	(1)	(2)	(3)	(4)
<b>Panel A: Pass-through</b>				
Mean Price	0.765 (0.100)	0.727 (0.091)	0.670 (0.086)	1,739,845
Median Price	0.747 (0.101)	0.710 (0.092)	0.666 (0.089)	1,739,384
Minimum Price	0.706 (0.071)	0.695 (0.061)	0.620 (0.045)	1,738,222
<b>Panel B: Speed of Adjustment</b>				
Mean Price	-0.062 (0.004)	-0.067 (0.004)	-0.154 (0.007)	1,400,705
Median Price	-0.070 (0.004)	-0.075 (0.004)	-0.168 (0.007)	1,399,840
Minimum Price	-0.069 (0.004)	-0.075 (0.004)	-0.162 (0.007)	1,399,055
<b>Panel C: Intra-seller prices</b>				
Pass-through	0.553 (0.069)	0.240 (0.060)	0.206 (0.060)	84,143
Speed of Adjustment	0.005 (0.017)	-0.055 (0.013)	-0.100 (0.027)	63,496

Notes: Panel A presents estimates of  $\alpha$  in specification (1). Panel B presents estimates of  $\beta$  in specification (2). Panel C reports estimates of  $\alpha$  (the first row) and  $\beta$  (the second row) for the sample of price quotes by the same seller in the U.S. and Canada. Driscoll and Kraay (1998) standard errors are in parentheses.

**Table 6. Determinants of pass-through and the speed of price adjustment.**

	Pass-Through, $\hat{\alpha}$			Speed of Adjustment, $\hat{\beta}$		
	Mean price	Median price	Minimum price	Mean price	Median price	Minimum price
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Median Price)	0.227 (0.088)	0.338 (0.087)	0.566 (0.122)	0.051 (0.008)	0.048 (0.009)	0.022 (0.009)
Log(Median Price) <sup>2</sup>	-0.024 (0.008)	-0.033 (0.008)	-0.053 (0.011)	-0.004 (0.001)	-0.004 (0.001)	-0.002 (0.001)
Freq. of price change	1.947 (0.194)	1.964 (0.183)	2.062 (0.224)	-0.126 (0.017)	-0.132 (0.017)	-0.143 (0.025)
Log(Sellers)	1.287 (0.282)	1.262 (0.299)	1.498 (0.279)	-0.025 (0.030)	-0.016 (0.033)	0.000 (0.037)
Log(Sellers) <sup>2</sup>	-0.421 (0.084)	-0.404 (0.091)	-0.486 (0.087)	0.010 (0.008)	0.006 (0.009)	-0.000 (0.010)
Stability of Sellers	0.296 (0.658)	0.548 (0.586)	-0.969 (0.643)	0.871 (0.074)	0.966 (0.082)	1.014 (0.082)
Synchronization	-0.342 (0.157)	-0.366 (0.152)	-0.356 (0.160)	0.035 (0.017)	0.013 (0.016)	-0.017 (0.015)
Average Reputation	-0.120 (0.057)	-0.127 (0.055)	0.011 (0.064)	-0.015 (0.005)	-0.018 (0.006)	-0.025 (0.007)
Freq. of Sales	1.040 (0.756)	1.157 (0.798)	0.635 (0.616)	-0.402 (0.054)	-0.388 (0.056)	-0.400 (0.065)
Freq. of Convenient Prices	0.111 (0.101)	0.178 (0.097)	0.028 (0.161)	0.024 (0.011)	0.030 (0.014)	-0.018 (0.014)
Observations	21,734	21,667	21,750	22,068	22,118	22,072
R <sup>2</sup>	0.15	0.15	0.25	0.16	0.16	0.18
	Descriptive statistics for dependent variables					
Mean	0.636	0.639	0.904	-0.347	-0.365	-0.491
St.Dev.	1.908	1.951	2.380	0.342	0.347	0.856
Median	0.616	0.608	0.860	-0.223	-0.244	-0.231
P25	-0.091	-0.101	-0.039	-0.472	-0.495	-0.467
P75	1.407	1.406	1.881	-0.106	-0.118	-0.105

Notes: Columns (1)-(3) and (4)-(6) report estimated specification (3) for pass-through and the speed of price adjustment, respectively. Category fixed effects  $C_i$  and time fixed effects  $T_i$  are included but not reported. The regressions are run on samples where top and bottom 1 percent of estimated  $\hat{\alpha}$  and  $\hat{\beta}$  are winsorized. Standard errors are clustered by good type. The last two rows show 25<sup>th</sup> and 75<sup>th</sup> percentiles. The number of goods is 24,129.

**Table 7. Margins of price adjustment.**

	Mean price		Median price		Minimum Price	
	CA	US	CA	US	CA	US
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Mean price change</b>						
Any, $\overline{dP}_{ict}$	-0.128	0.066	-0.109	0.059	-0.081	0.039
	(0.014)	(0.006)	(0.013)	(0.006)	(0.008)	(0.003)
Increase, $\overline{dP}_{ict}^{increase}$	-0.046	0.031	-0.031	0.019	-0.037	0.052
	(0.011)	(0.008)	(0.010)	(0.006)	(0.005)	(0.003)
Decrease, $\overline{dP}_{ict}^{decrease}$	-0.088	0.051	-0.073	0.047	-0.055	0.002
	(0.011)	(0.006)	(0.009)	(0.005)	(0.008)	(0.002)
<b>Probability of price adjustment</b>						
Any, $\Pr(dP \neq 0)$	-0.008	0.009	-0.006	0.005	-0.019	0.010
	(0.015)	(0.006)	(0.015)	(0.005)	(0.013)	(0.003)
Increase, $\Pr(dP > 0)$	-0.085	0.029	-0.079	0.027	-0.061	0.023
	(0.010)	(0.005)	(0.009)	(0.005)	(0.007)	(0.003)
Decrease, $\Pr(dP < 0)$	0.076	-0.020	0.072	-0.022	0.042	-0.013
	(0.011)	(0.004)	(0.011)	(0.004)	(0.010)	(0.002)
<b>Probability of exit</b>						
$\Pr(exit)$	-0.015	-0.001	-0.015	0.004	-0.045	0.034
	(0.009)	(0.007)	(0.008)	(0.007)	(0.005)	(0.005)

Notes: The table reports estimated  $\psi$  in specification (8). Good fixed effects are included but not reported. Newey-West standard errors are in parentheses.

## **ONLINE APPENDIX**

## APPENDIX A: 2011 THAILAND FLOODS

Our price comparison website provides a wealth of information about weekly price quotes for goods sold online. To explore how quickly firms adjust prices in response to shocks, we use a natural experiment that significantly affected prices and availability of hard drives: the 2011 flooding in Thailand.

The floods in Thailand started in late July 2011. By mid-October, they reached the capital, Bangkok. The floods did not recede until January 2012. As of December 2011, the World Bank had estimated US\$ 45 billion in damages for the Thai economy, mostly due to disruptions in manufacturing (US\$ 32 billion). More than 90% of all losses were borne by private owners.<sup>22</sup>

As Thailand hosts major hard-drive producers, the floods took their toll on hard-drives production and prices. For example, Western Digital (WD), the leading manufacturer, had over 60% of its capacity in the affected region. Appendix Figure A1 shows the extent of damages to a WD factory that produces hard drives. Western Digital's Thailand Plant suspended operation on October 21, 2011. Nidec, which produces 75% of hard drive motors—an essential part of hard drives—also had to shut down.<sup>23</sup> This natural disaster created a major shortage of hard drives on the market.

We use our data to study the effects of the flood on prices and availability of hard drives. First, for each good-seller-country price line, we calculate weekly changes in the price. Second, we calculate the average (log) price change for each manufacturer, country, and week. We consider two groups of manufacturers: i) WD and ii) other major brands (Fujitsu, Seagate, Samsung, Toshiba, and Hitachi). While other major brands had significant presence in Thailand, their direct loss due to the flood was less dramatic than WD's. Third, we cumulate weekly average price change starting in July 2011 to show the combined effect of price changes over time. The cumulative change is normalized to start at zero in July 2011. Finally, for each week, country, and group of manufacturers, we calculate the number of price quotes. This number combines the number of hard-drive models and the number of sellers.<sup>24</sup> Appendix Figure A2 shows the time series of weekly price changes, cumulative price change (since July 2011), and the number of price quotes.

While there was a significant inventory of hard drives before the flood, the flood led to a dramatic increase in the price of hard drives. The top panel of Appendix Figure A2 shows that the price of hard drives increased significantly within a week after the floods affected production facilities of WD and other major producers. The cumulative increase in the price of WD hard drives reached nearly 40 percent by the end of November 2011 (see the middle row). Prices for hard drives from other manufacturers also increased quickly and considerably—although the increase was smaller than the increase for WD hard drives—as there is some substitutability across hard drives, and other manufacturers were less affected by the flood. Shortly after the floods, the number of price quotes on our price comparison website declined by more than 50 percent. These dynamics are consistent with rapidly declining inventories of hard drives. The patterns are similar for the U.S. and Canada.

In summary, our findings suggest that price quotes are updated reasonably quickly on the price comparison website. Thus, our price data are suitable for the analysis of pass-through, etc., in the context of exchange rate fluctuations.

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<sup>22</sup>Source:

<http://www.worldbank.or.th/WBSITE/EXTERNAL/COUNTRIES/EASTASIAPACIFICEXT/THAILANDEXTN/0,,contentMDK:23067443~pagePK:141137~piPK:141127~theSitePK:333296,00.html>

<sup>23</sup>Source:

[http://www.pcworld.com/businesscenter/article/242913/thai\\_floods\\_hit\\_q4\\_hard\\_drive\\_production\\_says\\_research\\_firm.html](http://www.pcworld.com/businesscenter/article/242913/thai_floods_hit_q4_hard_drive_production_says_research_firm.html)

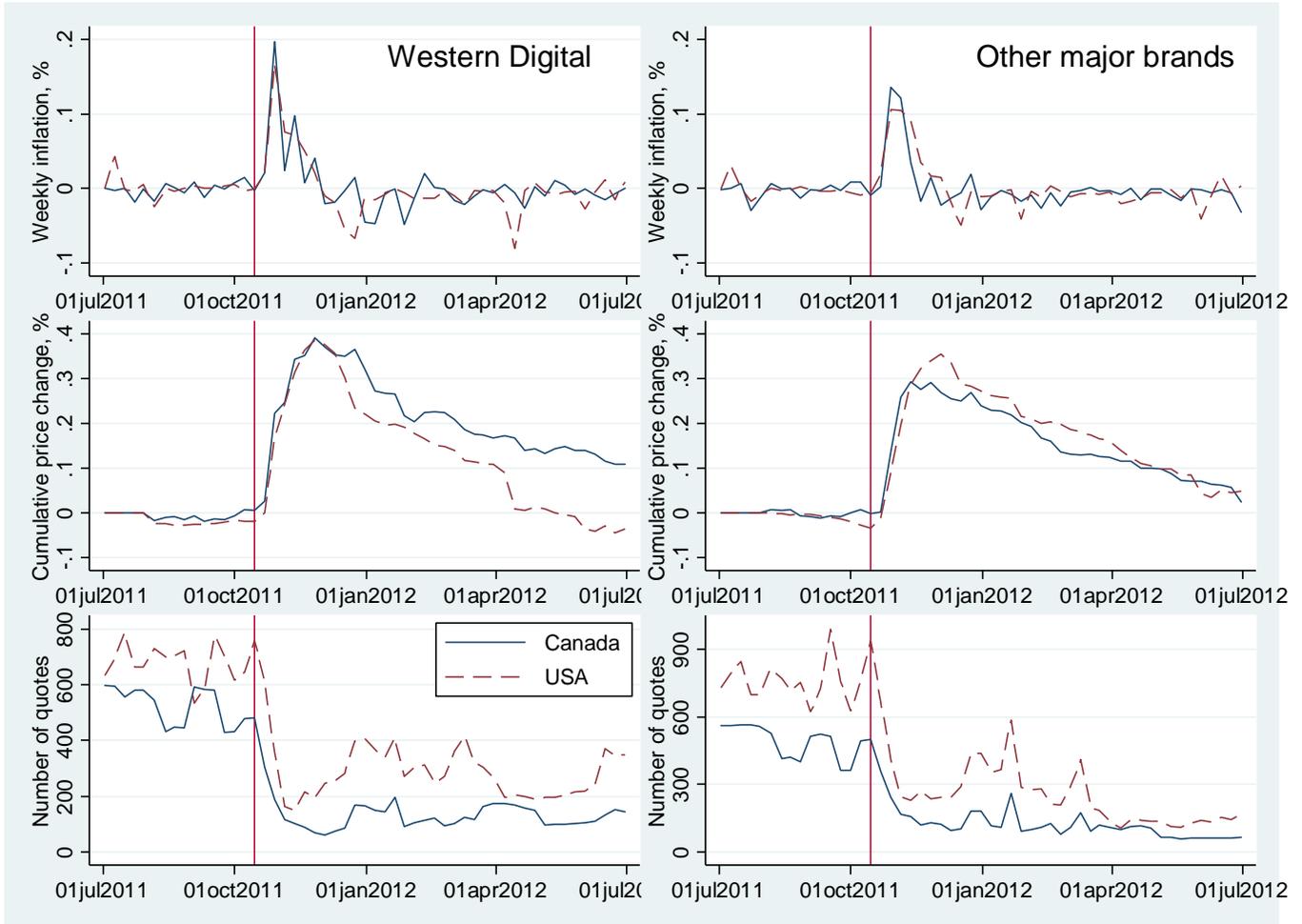
<sup>24</sup> Results are similar if we use the number of sellers, the number of quotes per seller, or the number of quotes per good.

**Appendix Figure A1. Flooded Western Digital facility in Thailand, 2011**



Source: New York Times, Nov. 6, 2011

**Appendix Figure A2. Price change and the number of sellers**



Notes: The vertical line shows the time when WD closed its production facility in Thailand. The left column shows results for Western Digital (WD). The right column shows results for *Other major brands*, which includes Fujitsu, Seagate, Samsung, Toshiba, and Hitachi. The top row shows the time series of weekly average price changes for each group of manufacturers. The middle row shows the cumulative change in the price of hard drives using weekly average price changes shown in the top row. The bottom row shows the number of price quotes on a given week for a given manufacturer in a given country.

## APPENDIX B: UNIT ROOT AND COINTEGRATION IN CROSS-COUNTRY PRICE DIFFERENTIALS

The main specification (1)-(2) in the paper assumes that price differentials  $D_{it} \equiv \log(P_{it}^{US}/P_{it}^{CA})$  are non-stationary and co-integrated with the nominal exchange rate  $EX_t$ . This assumption motivates the error-correction specification where we estimate pass-through from a cointegration vector and the speed of price adjustment from how quickly price differentials return to equilibrium levels given by the cointegration vector.

Testing for unit roots and cointegration in the context of panel data, where shocks are correlated cross-sectionally presents special challenges as the standard panel-data unit root tests, assume that cross-sections are independent. This assumption is clearly violated in our case. Furthermore, standard panel-data unit root tests may be not particularly informative in practice because the null hypothesis is too restrictive: e.g., the null of *all* cross-sections have a unit root vs. the alternative that some cross sections do not have a unit root. To address this challenge, we use the insight of Bai and Ng (2004) to develop a procedure for a joint test of unit root and cointegration in panel data where dependence in the cross-section is allowed.

In a nutshell, the Bai-Ng approach amounts to extracting common factors  $\mathbf{F}_t$  from  $D_{it}$  and then testing if  $\mathbf{F}_t$  have unit roots. That is, the considered data generating process is given by  $D_{it} = \Lambda_i \mathbf{F}_t + u_{it}$ , where  $\Lambda_i$  is a vector of loadings on  $\mathbf{F}_t$ . By construction,  $\mathbf{F}_t$  are the common components across  $D_{it}$ , which is akin to cointegration. If  $f_t$ , a part of  $\mathbf{F}_t$ , has a unit root, then  $D_{it}$  have a common stochastic trend  $f_t$  (and thus  $D_{it}$  are not stationary), and  $D_{it}$  are cointegrated with  $f_t$ . While Bai and Ng (2004) do not give a structural interpretation to extracted  $\mathbf{F}_t$ , we have a natural candidate for  $\mathbf{F}_t$ : the nominal exchange rate  $EX_t$ .

To implement the Bai-Ng approach, we proceed as follows. First, we extract the common component in  $D_{it}$ . While Bai and Ng (2004) use the covariance matrix of first differences of  $D_{it}$  to extract  $\Delta f_t$  (using principal component analysis) and then cumulate the series to  $f_t = \sum_{s=0}^t \Delta f_s$ , we use the approach suggested in Pesaran (2006, 2007). That is, we project  $D_{it}$  on the full set of weekly dummies and estimate  $\bar{D}_t = N^{-1} \sum_{i=1}^N D_{it}$ , which provides us with a measure for  $f_t$ . The key advantage of the Pesaran approach to extracting a common factor is that it does not require us to have non-missing series for  $D_{it}$  for all cross-sections. In other words, one may have a sample of goods where spells of  $D_{it}$  do not necessarily overlap. This is useful in our case because there is a significant turnover of goods in the sample and few goods are sold continuously between 2008 and 2013. Note that we can identify  $f_t$  only up to a scale, but this is not material as the space spanned by  $f_t$  is the same irrespective of the scaling coefficient.

Second, we test if  $\bar{D}_t$  and  $EX_t$  have unit roots. Note that although  $\bar{D}_t$  is estimated, Bai and Ng (2004) show that one can ignore sampling uncertainty in the estimate when the number of cross-sections is large, which is true in our case.

Third, conditional on having unit roots in both series, we test if  $\bar{D}_t$  and  $EX_t$  are cointegrated. If true (i.e.,  $\bar{D}_t - \phi EX_t$  is stationary for some  $\phi$ ), then one may interpret the common component  $\bar{D}_t$  as a proxy for  $EX_t$  as the difference between the two in the cointegration vector is stationary. In other words, if  $\bar{D}_t$  is the common stochastic trend in  $D_{it}$ , then  $EX_t$  captures the same stochastic trend.

The extracted common component  $\bar{D}_t$  and  $EX_t$  are highly correlated ( $\rho = 0.77$ ) and track each other closely (Appendix Figure B1). Both series exhibit behavior typical for series with stochastic trends. Consistent with the visual inspection of the data, Appendix Table B1 shows that the extracted common component  $\bar{D}_t$  has a unit root. So does the nominal exchange rate  $EX_t$ . The last row in the

table documents that  $\bar{D}_t$  and  $EX_t$  are cointegrated: the residual in the estimated cointegration vector, which is estimated by the OLS, is stationary as we can reject the null of a unit root in the residual at 1% level.

We conclude that our error-correction specification (1)-(2) is appropriate in our context.

**References:**

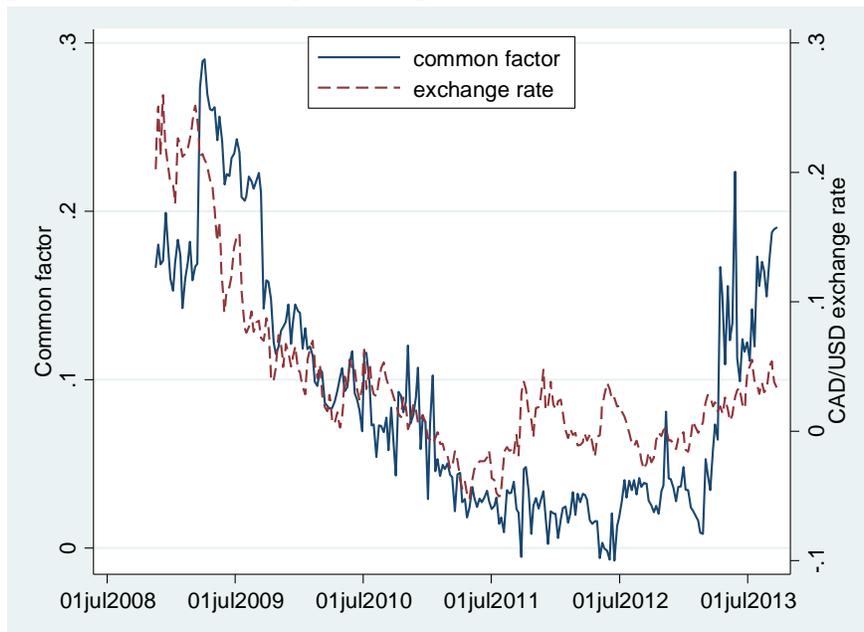
Bai, Jushan, and Serena Ng, 2004. “A PANIC Attack on Unit Roots and Cointegration,” *Econometrica* 72(4), 1127-1177.  
 Pesaran, M. Hashem, 2006. “Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure,” *Econometrica* 74(4), 967-1012.  
 Pesaran, M. Hashem, 2007. “A simple panel unit root test in the presence of cross-section dependence,” *Journal of Applied Econometrics* 22(2), 265-312.

**Appendix Table B1. Phillips-Perron test for unit root**

Variable	Test statistic	p-value
Common component, $\bar{D}_t$	-6.470	0.398
CAD/USD exchange rate (log), $EX_t$	-5.584	0.142
Residual of the estimated cointegration vector: $\bar{D}_t - 0.805EX_t$	-28.160	0.004

Notes: The null hypothesis of the test is that a series has a unit root. The number of lags in the test is set at 12.

**Appendix Figure B1. Common component in price differentials and the nominal exchange rate.**



Notes: The figure plots time series for the common component  $\bar{D}_t$  (left axis) and the CAD/USD exchange rate (log; right axis).

## APPENDIX C: MONTE CARLO EXPERIMENT

This appendix examines the potential role of measurement errors in affecting our estimates of pass-through and the speed of price adjustment.

Suppose that the data-generating process is described by the following system of equations:

$$EX_t = EX_{t-1} + u_t, \quad (C.1)$$

$$\Delta P_{it} = \beta(P_{t-1} - \alpha EX_{t-1}) + b_1 \Delta EX_{t-1} + b_2 \Delta P_{i,t-1} + e_{it}, \quad (C.2)$$

where  $i$  and  $t$  index goods and time, respectively,  $EX_t$  is the exchange rate,  $P_{it}$  is the relative price of good  $i$  in country A relative to country B, and  $u_t$  and  $e_{it}$  are uncorrelated at all leads and lags. Coefficient  $\alpha$  measures the long-term pass-through of the exchange rate. Coefficient  $\beta$  measures the speed of adjustment.

We estimate  $\alpha$  and  $\beta$  using a two-step procedure. In the first step, we estimate  $\alpha$  as a part of the cointegration vector:

$$P_{it} = \alpha EX_t + \epsilon_{it}. \quad (C.3)$$

The error in this regression  $\epsilon_{it}$  is interpreted as the deviation from equilibrium. In the second step, we estimate  $\beta$  using the following specification

$$\Delta P_{it} = \beta \hat{\epsilon}_{it} + b_1 \Delta EX_{t-1} + b_2 \Delta P_{i,t-1} + error. \quad (C.4)$$

Although  $\hat{\epsilon}_{it}$  is a generated regressor, econometric theory shows that one can use standard inference for  $\beta$  in regression (4) because the estimate of  $\alpha$  is superconsistent.

To assess the quantitative importance of measurement errors for the estimates of  $\beta$  and  $\alpha$ , we run the following Monte Carlo experiment. We calibrate parameters of DGP in equations (C.1)-(C.2) to match estimates in the data. Specifically, our empirical estimates are such that  $b_1 = -0.189$ ,  $b_2 = 0.104$ ,  $\alpha = 0.7$ ,  $\beta = -0.162$ . The root mean squared error in regression (C.3) is 0.014, so we set  $\sigma_u = 0.014$ . The root mean squared error in regression (C.4) is 0.0867, so we set  $\sigma_e = 0.085$ .

To model idiosyncratic shocks, we assume that the observed relative price is equal to the true relative price plus measurement error (idiosyncratic shock):

$$P_{it}^* = P_{it} + \eta_{it}, \quad (C.5)$$

where the measurement error is classical. To calibrate the size of measurement error, we use validation data generously provided by Alberto Cavallo. Specifically, we calculate the standard deviation of the log difference between the price reported on the price comparison website and the price reported on the seller website. To scale the size of the measurement error, we calculate the standard deviation of log prices for goods in our validation sample. The ratio of these two standard deviations is 0.0838. The standard deviation of log relative prices in our data is 0.163. Thus, we calibrate the size of measurement error at  $\sigma_\eta = 0.163 * 0.0838 = 0.0137$ . In simulations, we also explore larger values of  $\sigma_\eta$ .

In our simulations, we set sample size to  $N = 20,000$  and  $T = \{100, 250, 400\}$ . With  $T = 250$ , the sample size mimics what we have in the data. For each parameterization, we generate 500 histories (the burn-in period is set to  $T$ ), estimate system (C.3)-(C.4), and report results in Appendix Table C1.

We find that the estimate of  $\alpha$  is insensitive to the size of the measurement error as the error only appears on the left hand side of equation (C.3). While the size of the error can influence the estimate of  $\beta$ , the size of the bias in the base case is small: the estimate of  $\beta$  decreases from -0.162 to -0.166. If we double the size of the error, the estimate decreases further to -0.167, but the difference continues to be small. It takes implausibly large measurement errors to tangibly move the estimate of  $\beta$ .

We conclude that idiosyncratic shocks such as measurement errors are unlikely to determine the fast speed of price convergence in online markets.

**Appendix Table C1. Bias in the estimated pass-through and the speed of price adjustment**

Size of measurement error $\eta$	T=100				T=250				T=400			
	$\hat{\alpha}$		$\hat{\beta}$		$\hat{\alpha}$		$\hat{\beta}$		$\hat{\alpha}$		$\hat{\beta}$	
	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.
0 (no error)	0.632	0.071	-0.162	0.00045	0.669	0.039	-0.162	0.00028	0.681	0.025	-0.162	0.00022
$\sigma_\eta$	0.638	0.066	-0.166	0.00044	0.676	0.028	-0.166	0.00029	0.681	0.025	-0.166	0.00022
$2\sigma_\eta$	0.633	0.072	-0.170	0.00046	0.672	0.032	-0.170	0.00029	0.681	0.025	-0.170	0.00023
$3\sigma_\eta$	0.638	0.073	-0.174	0.00048	0.673	0.030	-0.174	0.00031	0.681	0.025	-0.174	0.00023
$4\sigma_\eta$	0.634	0.087	-0.178	0.00047	0.672	0.032	-0.178	0.00030	0.681	0.025	-0.178	0.00024
$5\sigma_\eta$	0.632	0.071	-0.182	0.00051	0.673	0.030	-0.178	0.00030	0.681	0.025	-0.182	0.00025
$6\sigma_\eta$	0.638	0.066	-0.186	0.00050	0.672	0.032	-0.186	0.00031	0.681	0.026	-0.186	0.00025
$7\sigma_\eta$	0.632	0.071	-0.190	0.00053	0.673	0.030	-0.190	0.00033	0.681	0.025	-0.190	0.00026
$8\sigma_\eta$	0.638	0.065	-0.193	0.00053	0.672	0.031	-0.193	0.00032	0.681	0.027	-0.194	0.00026
$9\sigma_\eta$	0.632	0.071	-0.198	0.00054	0.673	0.029	-0.198	0.00034	0.681	0.025	-0.198	0.00027
$10\sigma_\eta$	0.638	0.066	-0.201	0.00055	0.672	0.032	-0.201	0.00034	0.681	0.027	-0.201	0.00027

## APPENDIX D: DATA DESCRIPTION

In this appendix, we provide additional details about the properties of our dataset. We highlight five aspects of the data. First, our data are dominated by “online-only” sellers. Second, most price quotes are supplied by large stores. Third, we describe the business model of the price comparison platform. Fourth, we discuss how we validate the quality of our data. Fifth, we clarify criteria for selecting product categories.

**Types of sellers:** Appendix Table D1 presents shares for three types of sellers: online-offline sellers (e.g., Walmart, Dell); online-only sellers (e.g., Amazon.com); and marketplace sellers (e.g., Amazon marketplace or Ebay). To classify the sellers into these groups, we *manually* examined every store in the list of stores in our sample and determined into which group each store belongs. In some cases, we could not establish the nature of the sellers because they were merged with other sellers, or they exited the market. Most likely, not-classified type sellers are marketplace-type, but we cannot confirm this. Appendix Figure D1 shows the dynamics of the shares.

The dominant seller type is online-only, and the share of online-only sellers has been increasing over time with the rise of Amazon and similar sellers (see Figure 1 below). Online-offline sellers are common in Canada but less so in the U.S., and marketplace-type sellers have only a modest share in our sample.

The low share of marketplace sellers reflects the fact that we filter out observations that sell goods that are refurbished or used. We exclude used/refurbished goods because then the issues of quality comparison become acute, and we may be comparing “apples” and “oranges”. Many marketplace sellers (esp. on eBay) sell used goods, and so they get excluded. We also filter out observations that i) do not provide price quote on the price comparison website and instead post “see website” or ii) specify that the good is not currently available (e.g., out of stock or needs a pre-order). Finally, we filter out price spells with less than four observations because we use pricings moments such as the frequency of price changes, and four observations is the minimum to calculate such statistics. Again, this filter removes many marketplace sellers because they often appear only for one week or a few weeks.

**Size distribution:** Online retail has many stores that sell only a handful of goods; however, the market is dominated by large stores. The top 5 percent of sellers by size account for 90 percent of price quotes in our data (see Figure 2 for the distribution). This outsized importance of large sellers is also evident in other data for e-commerce. For example, Gorodnichenko, Sheremirov and Talavera (2014) use a representative sample of goods listed on a leading PCW/shopping platform (these data are not scraped; the dataset is provided by the platform directly and thus the quality of the data is extremely high) and document that large online stores (sell more than 100 goods) account for 80 percent of clicks (a proxy for quantities sold) in the U.S. and U.K. Thus, the focus on large sellers may be desirable as it covers price quotes that are most relevant for consumers.

**Business model:** To provide a sense of where price comparison websites stand relative to each other, we use reports compiled by CPC Strategy, an e-commerce consultancy and market research firm. The time series shown in Appendix Figure D3 document that Google Shopping had no cost of listing or per click until 2012. In contrast, our price comparison website (one of the listed platforms) and other main competitors were charging a fee per click consistently in our sample period so that the quality of price quotes was likely to be higher than the quality on Google Shopping. Indeed, incorrect/missing listings not only fail to bring revenue to a seller but also have a direct cost to the seller. Our price comparison website consistently charged between \$0.35 and \$1.15 per click depending on the product category (the website does not charge per listing during the sample period). Thus, there is great pressure to list only current, competitive prices on the price comparison website. In our sample period, the platform did not charge regular customers (that is, merchants with an e-commerce website) per listing. To serve small-scale sellers, our shopping

platform introduced a “storefront” program to target marketplace-type customers. Sellers in this program pay no listing fee for the first 100 products listed and a \$0.25 service fee on all items afterward. In addition to the listing fee, sellers in this program pay a commission of \$1.50 + 9% of the purchase price.

Appendix Figure D4 documents that while Google Shopping is the dominant platform now, other platforms continue to generate significant revenue and traffic. Their conversion rates are somewhat lower than Google’s, but the magnitudes are quite close.

**Validation:** To validate the quality of our data, we group categories of goods in our sample of quotes from the price comparison website (PCW) to match category-level consumer price indices (CPI) constructed by the Bureau of Labor Statistics (BLS). Specifically, we make the following groupings:

- *Television* uses CPI sub-index “RA01 Televisions” for the BLS series and covers the following categories on PCW: Plasma/LCD TV.
- *Photographic equipment* uses CPI sub-index “R18 Cameras or other photographic equipment, excluding film” for the BLS series and covers the following categories on PCW: SLR lenses, 35mm SLR lens accessories, camcorders, camcorder accessories, camcorder batteries power, digital cameras, dedicated flashes, tripods, bags/cases.
- *Computer and periphery* uses CPI sub-index “EE01 Personal computers and peripheral equipment” for the BLS series and covers the following categories on PCW: desktop, hard drives, hubs, keyboards, laptops, laptop memory, modems, motherboards, network adapters, power supplies, processors-retail-box, scanners, UPSs, webcams.
- *Software* uses CPI sub-index “EE02 Computer software and accessories” for the BLS series and covers the following categories on PCW: anti-virus software, database management software, engineering/home design software, financial/legal software, flash memory, graphics/publishing software, miscellaneous programming software, office suites software, security software, storage media, system utilities, windows operating system, computer games.
- *Calculators* uses CPI sub-index “E15 Calculators, typewriters, or other information-processing equipment” for the BLS series and covers the following categories on PCW: calculators.
- *Audio equipment* uses CPI sub-index “RA051 Audio Components, Radios, Tape Recorders/Players, and Other Equipment” for the BLS series and covers the following categories on PCW: headphones, microphones-headsets, mp3-players, speakers.

Appendix Figure D5 shows that price indices constructed on our data follow price indices published by the BLS closely. Thus, while there are certainly potential errors in our data and some moments may be affected, results based on aggregate moments of the data (e.g., pass-through) are unlikely to be materially affected by such errors.

**Selection of goods and categories:** We used the following criteria to choose categories in 2008 when we started the project. First, the four main categories of goods in our sample were the most popular ones at the time. According to the estimates of the U.S. Census Bureau<sup>1</sup>, 30% of revenue in e-commerce retail in 2008-2009 was generated by categories we cover (computer hardware, computer software, electronics and appliances, office equipment, and supplies). Second, we wanted to cover goods where having sellers in the U.S. and Canada was common. For some categories such as clothes, furniture, etc., it is a tangible restriction because many of these goods are local (e.g., flip-flops for Californians) and are branded or sold exclusively in one country. Third, we had

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<sup>1</sup> <http://www.census.gov/econ/estats/2013/all2013tables.html>, Historical Table 5.

to select categories where goods have an identifier akin to the universal product code (UPC) because we need to link goods over time and across countries. For some categories (e.g., furniture, toys, food), this restriction was a barrier in earlier years because the coding was missing or not sufficiently detailed to ensure that good ID is unique. For example, a bed may have MPN (manufacturer product number) of “613”, but this number can be used for other goods by another manufacturer. Fourth, we did not want to cover books, CDs, and DVDs because these goods are unusual in many respects: the market is dominated by Amazon, and prices tend to be extremely sticky.

As of 2008, our platform had fewer categories than it has now. The platform shifted some subcategories over time. To ensure consistency of our data, we collected the same set of product categories as we had in 2008.

While the selection of categories is not random, we believe it represents a large fraction of retail e-commerce. As we already mentioned, these goods accounted for a third of retail e-commerce in 2008-2009. The share declined to 20% in 2013 as other categories of good penetrated e-commerce. Gorodnichenko, Sheremirov, and Talavera (2014) also document that these goods are very popular in terms of the number of goods sold and the number of clicks.

As we discuss in the paper, we apply several filters to improve the quality of the data used in estimation of pass-through and the speed of price adjustment. The distribution of pricing moments is similar across the full and estimation samples (Appendix Table D3). We also find that the distribution of prices for goods selected into the estimation sample is similar to the distribution of prices for the full sample (Appendix Figure D6). Thus, draws into the estimation sample appear to be distributed in a balanced fashion.

**Appendix Table D1. Composition of stores.**

Seller type	Canada	USA	Pooled
Offline-online	11.53	3.21	7.00
Online only	78.05	76.21	77.05
Marketplace	-	1.52	0.83
Not classified	10.42	19.06	15.13
<b>Total</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>

**Appendix Table D2. Largest sellers in the sample.**

U.S.		Canada	
Name	Goods/week	Name	Goods/week
1 TheNerds.net	5,754	Agile Electronics	22,698
2 Rakuten.com	5,595	PC-Canada	7,053
3 NextWarehouse.com	5,208	Cendirect.com	5,612
4 SeaBoom.com	4,429	OnHop	5,317
5 TechLoops.com	4,218	Mostly Digital	5,131
6 CompSource Inc.	3,018	FrontierPC.com	4,656
7 LACC.com	3,016	Ashlin.ca	4,426
8 ValleySeek Store	3,012	DirectDial Canada	3,888
9 PROVANTAGE	2,657	Computer Valley	3,632
10 TigerDirect	1,903	Comtron	3,457
11 TechOnWeb.com	1,900	B&H Photo Video	3,267
12 Dell	1,730	Newegg.ca	2,916
13 PCNation.com	1,636	Can Leaf Mart	2,641
14 PC Connection	1,555	100DIRECT	2,638
15 Datavision	1,443	Shark Systems	2,538
16 TheTwisterGroup.com	1,392	TigerDirect.ca	2,375
17 HardwareNation.com	1,184	Dell E&A	1,497
18 Amazon.com	1,026	Amazon.ca	1,287
19 CtiStore	920	Canada Computers	1,027
20 CompUSA	793	Expansys CA	970
21 CostCentral.com	782	SoftwareMedia	876
22 B&H Photo-Video	744	newoemtoners.com	752
23 Mwave.com	712	beDirectT	717
24 iUnitek	710	PCCZone	700
25 Kingston	683	SIG Electronics	682
26 Memory4Less.com	631	LuComputers	633
27 pcRUSH.com	581	IT Yuda	278
28 J&R	568	iBuyOfficeSupply.ca	273
29 Newegg.com	555	Computer Systems Centre	239
30 California Computer	548	SonicElectronix	198
31 SoftwareMedia.com	538	Dytronix	163
32 ServerSupply.com	516	Dell.ca	160
33 Amazon.com Marketplace	498	BuyOnlineNow.ca	143
34 Unistorage	410	Scionex Systems	140
35 Directron	400	Lenovo	137
36 VioSoftware.com	392	RoyalDiscount	132
37 Gemini Computers	390	Canon Canada	127
38 CDW.com	367	KooyaComputers.ca	111
39 OutletPC.com	347	MDG Computers Canada Inc.	91
40 Compuvest	337	ITFactory.ca	91

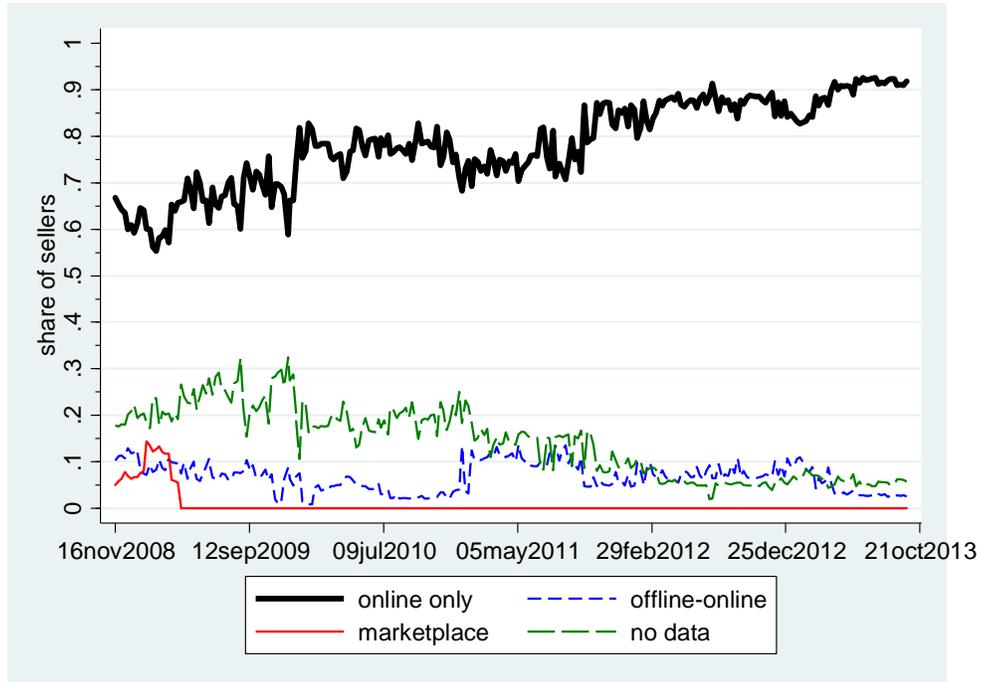
Notes: The table provide median (across weeks) number of goods by seller for largest sellers on the price comparison website.

**Appendix Table D3. Pricing moments for the full and estimation sample.**

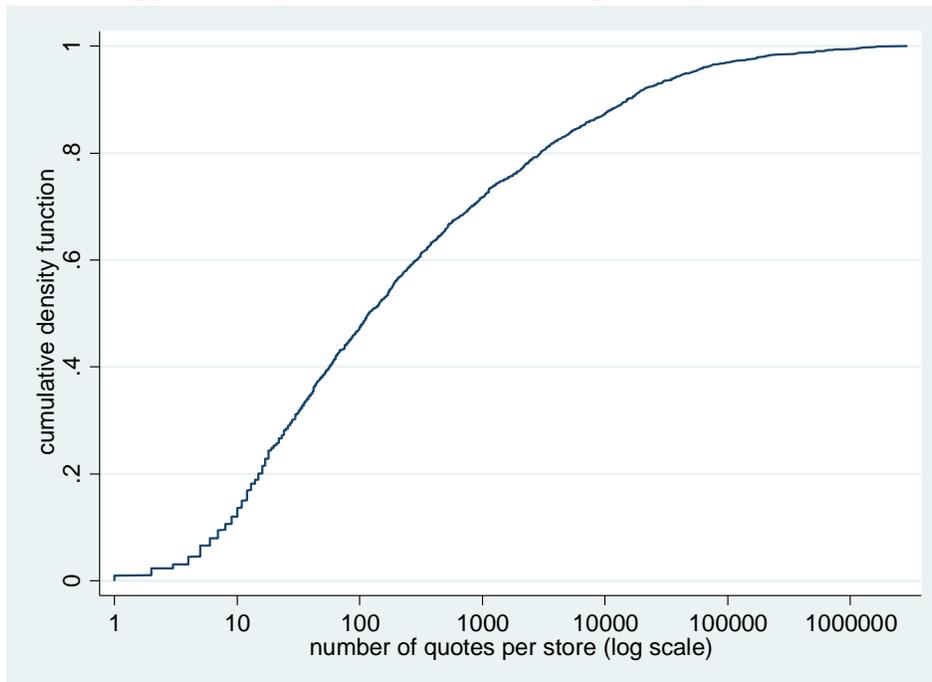
Moment	U.S.A.		Canada	
	Estimation sample	Full sample	Estimation sample	Full sample
	(1)	(2)	(3)	(4)
Mean price	5.30	5.20	5.21	5.14
Average cross-sectional st.dev. log price	0.16	0.16	0.12	0.12
Average freq. of price changes	0.22	0.23	0.38	0.39
Average absolute size of price change	0.07	0.06	0.05	0.05
Average turnover of sellers	0.90	0.90	0.91	0.89
Average seller rating	4.46	4.47	4.30	4.28
Number of sellers	5.40	5.84	3.29	4.02

Notes: The table reports pricing moments for the full sample and the estimation sample (i.e., data after applying filters).

**Appendix Figure D1. Dynamics of the types of sellers.**

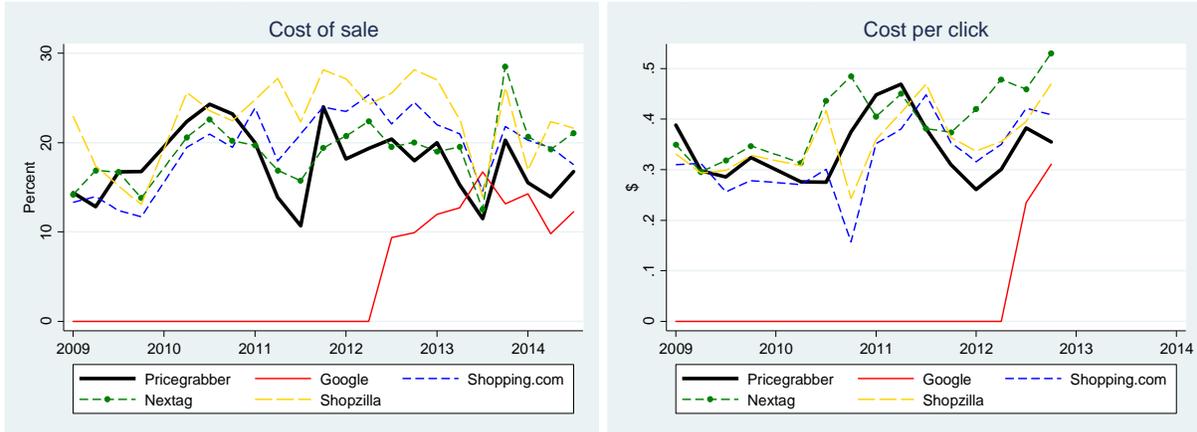


**Appendix Figure D2. Distribution of quotes by store size.**

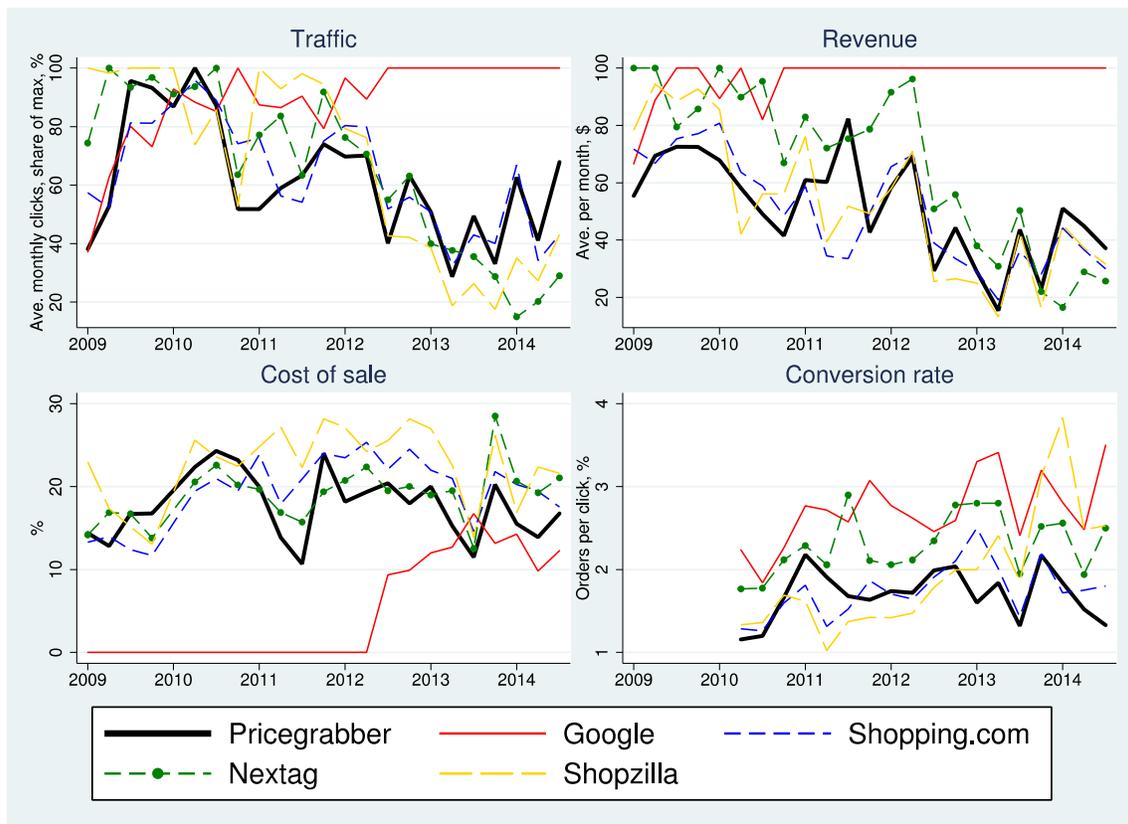


Notes: The figure shows cumulative distribution for the number of price quotes by store size, which is measures the number of quotes per store. The horizontal axis is on log scale.

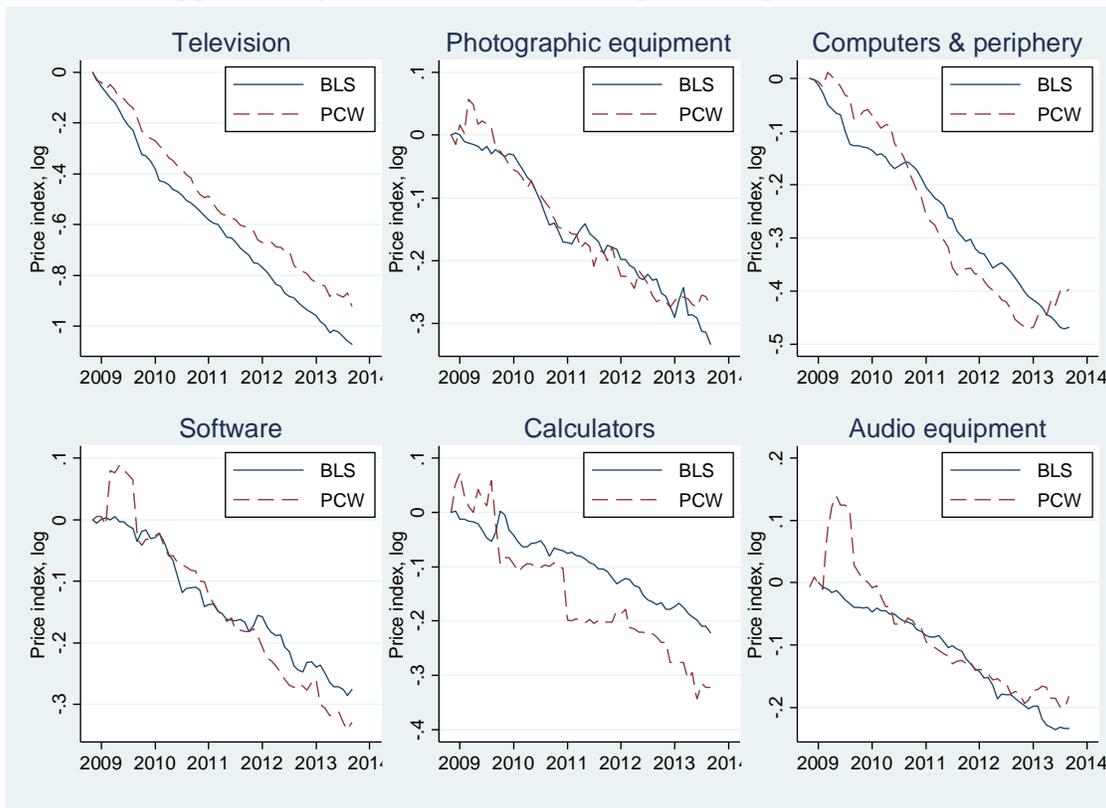
**Appendix Figure D3. Cost of sales by price comparison website.**



**Appendix Figure D4. Comparison of price comparison websites**

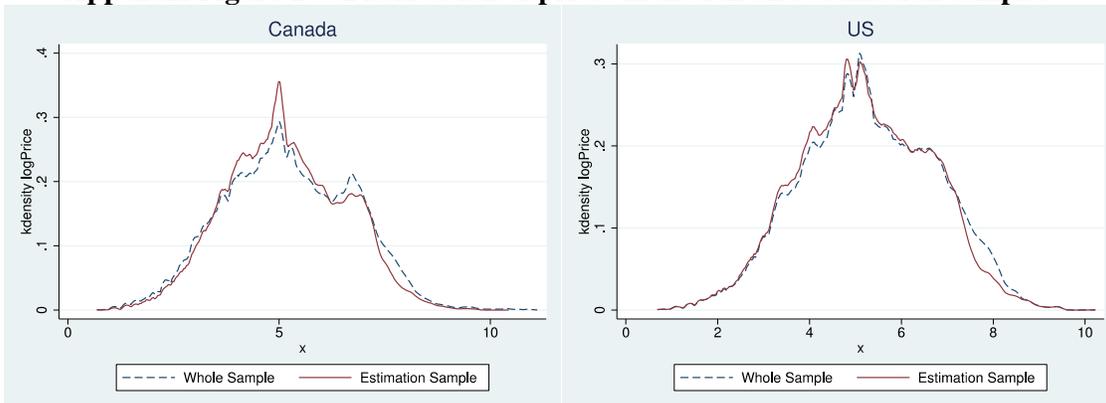


**Appendix Figure D5. Cost of sales by price comparison website.**



Notes: The figure plots time series of (log) price indices for selected categories of goods. The blue, solid line shows series from the Consumer Price Index (CPI) by Bureau of Labor Statistics (BLS). The red, dashed line show series constructed from price quotes on the price comparison website (PCW). Each series is normalized to zero at the start of the sample.

**Appendix Figure D6. Distribution of prices in the full and estimation samples.**



Notes: The figures show kernel densities for the distribution of prices (Epanechnikov kernel with optimal width). Log price is on the horizontal axis.

## APPENDIX E: APPLE PRODUCTS

In a prominent study, Cavallo et al. (2014) examine properties of online prices for four major sellers. While three sellers are in fashion/clothing industry, one of the sellers is Apple, which has a coverage of goods similar to what we have in our data. Cavallo et al. (2014) scrape price quotes directly from the websites of the manufacturers (in contrast, we scrape price quotes from a price comparison website). Recently, Cavallo et al. (2014) made their data publicly available. Fortunately, their dataset has a description of products so that we can merge the two datasets and, hence, shed additional light on properties of online prices and reconcile some differences in the results. First, we use this alternative source of information from Cavallo et al. to validate the quality of our data. Second, we explore differences (if any) in the behaviour of prices of “generic” and “branded” goods.

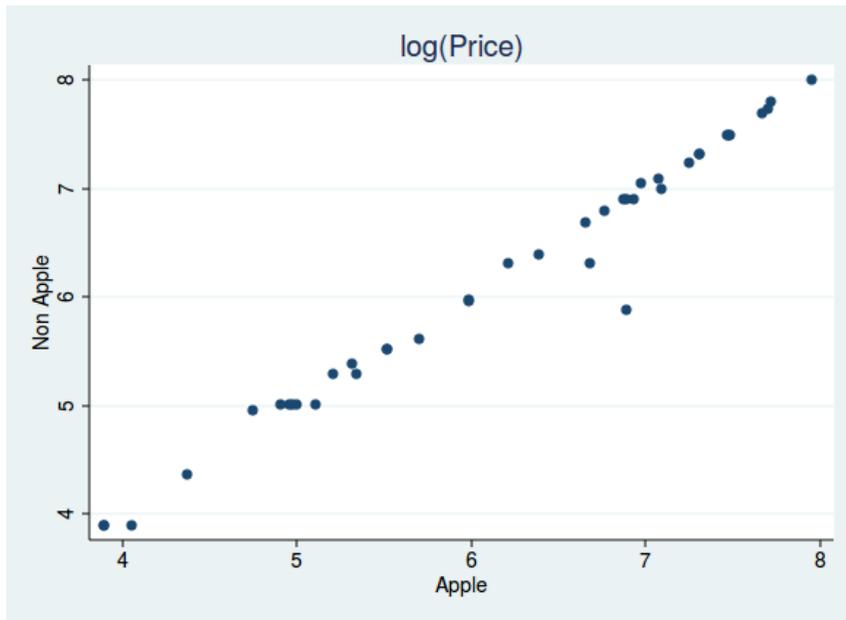
Using the description of goods and manufacture product numbers (MPNs), we identify exact matches in the Cavallo et al. data and our data. For example, MPN “MA623” and other information indicate that the product is “Apple iPod touch”. Likewise, MPN “M9179L” and other information indicate that the product is “Cinema HD Display LCD Monitor, M9179”. We matched 40 products exactly. The types of goods matched across the two dataset is fairly broad and ranges from iPods to monitors to iMacs to batteries. For each matched pair, we calculate the average price over the period where our data overlap with the Cavallo et al. data. Appendix Figure E1 shows that the correlation between the level of prices across the datasets is extremely high ( $\rho = 0.98$ ). Because price data are consistent across the two datasets, we conclude that the quality of our data is reasonably high.

While the average prices are very similar across goods, the dynamics of price adjustment is different. Prices on Apple store tend to be much more inflexible than prices on the price comparison website. Appendix Figure E2 plots price paths for Mac Mini Core i7 2.0GHz (MPN MC936) sold on Apple store and via the price comparison website. The price on the Apple store website was fixed for over a year (from mid 2011 to mid 2012), while price quotes on the price comparison website had a series of price cuts so that the duration of price spells is considerably shorter in our data than in the price data scraped from the Apple store website. However, even these more flexible prices are fairly rigid when compared to similar but “generic” products.

Using data from the price comparison website, we calculate basic pricing moments for identified Apple products and non-Apple products sold in the same product category. For example, prices for Apple’s iPods are compared to prices of other MP3 players. Appendix Table E1 documents that Apple prices tend to be stickier, have fewer sales, and show much less cross-sectional price dispersion. As a result, one may expect that adjustment of prices may be more incomplete and sluggish for Apple product than for non-Apple products.

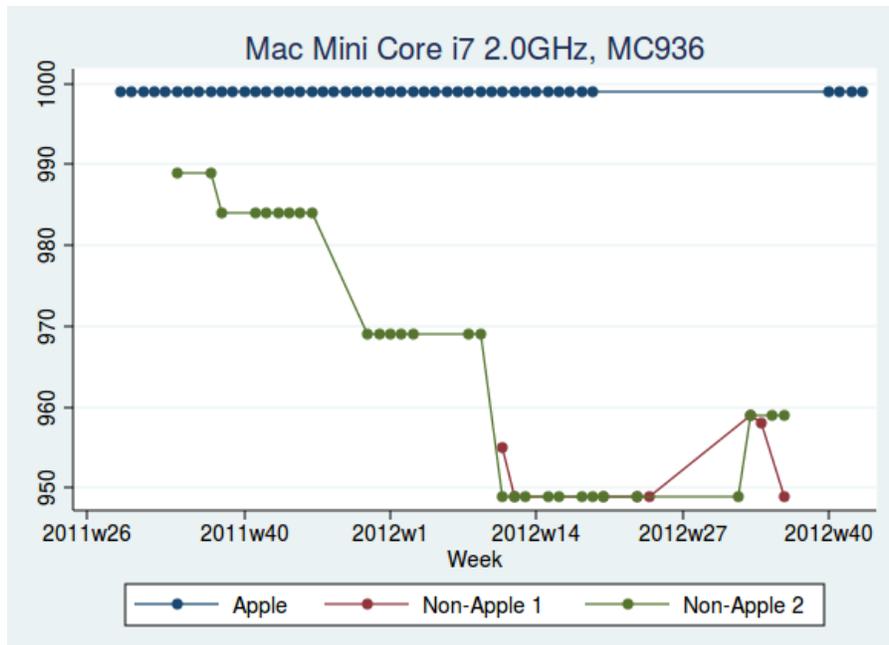
This conjecture is confirmed in Appendix Table E2. The estimated pass-through for Apple products is close to 0.2, while the non-Apple counterpart is between 0.7 and 0.8. Likewise, the speed of price adjustment is smaller for Apple products than for non-Apple products, although the difference is not as large as one observes for pass-through. We conclude that differences between results in Cavallo et al. (2014) and our results are likely to arise from differences in the coverage of goods (specifically, “branded” vs “generic”) and our focus on online-only sellers (rather than on online-offline sellers).

**Appendix Figure E1. Comparison of average prices in Cavallo et al. (2014) and price comparison website.**



Notes: The horizontal axis shows the average price on the Apple store. The vertical axis shows the average price on the price comparison website. Each point corresponds to a unique product manufactured by Apple.

**Appendix Figure E2. Price paths for a selected product**



Notes: The figure plots time series of prices for Apple’s Mac Mini Core i7 2.0Ghz (MPN MC936). Prices are scraped from Apple store and from a price comparison website. The horizontal axis shows calendar time (weeks). The vertical axis shows the price in US dollars.

**Appendix Table E1. Selected pricing moments for Apple and non-Apple products**

	Non-Apple products		Apple products	
	mean	st.dev.	mean	st.dev.
Price changes				
Frequency, per week	0.341	(0.143)	0.147	(0.100)
Median abs. size	0.057	(0.043)	0.065	(0.068)
Sales				
Frequency	0.028	(0.032)	0.008	(0.018)
Mean abs. size	0.045	(0.066)	0.066	(0.066)
Cross-sectional distribution of prices				
St.dev. log(Price)	0.061	(0.072)	0.029	(0.050)
IQR log(Price)	0.078	(0.120)	0.036	(0.089)
Number of goods	8,692		117	

Notes: moments are calculated on data from the price comparison website.

**Appendix Table E2. Price adjustment for Apple and non-Apple products.**

	Non-Apple products			Apple products		
	No Fixed effects	Type Fixed effects	Good Fixed effects	No Fixed effects	Type Fixed effects	Good Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Pass-through</b>						
Mean Price	0.778 (0.052)	0.775 (0.051)	0.722 (0.047)	0.277 (0.111)	0.243 (0.124)	0.223 (0.061)
Median Price	0.791 (0.055)	0.788 (0.053)	0.727 (0.049)	0.274 (0.106)	0.233 (0.119)	0.187 (0.066)
Minimum Price	0.777 (0.042)	0.774 (0.038)	0.609 (0.038)	0.334 (0.119)	0.290 (0.146)	0.353 (0.073)
N obs	314,076			2,462		
<b>Panel B: Speed of Adjustment</b>						
Mean Price	-0.066 (0.004)	-0.066 (0.004)	-0.179 (0.008)	-0.089 (0.020)	-0.091 (0.020)	-0.185 (0.046)
Median Price	-0.074 (0.004)	-0.074 (0.004)	-0.187 (0.007)	-0.090 (0.020)	-0.091 (0.020)	-0.192 (0.045)
Minimum Price	-0.056 (0.004)	-0.057 (0.004)	-0.177 (0.006)	-0.107 (0.029)	-0.109 (0.029)	-0.234 (0.051)
N obs	236,561			1,789		

Notes: *Non-Apple products* includes only goods in the categories where *Apple products* are present (desktops, flat panel LCD monitors, hard-drives, laptops, mp3 players). Panel A reports the estimated pass-through,  $\alpha$  in specification (1). Panel B reports the estimated speed of adjustment,  $\beta$  in specification (2). Driscoll and Kraay (1998) standard errors are in parentheses. See the note for Table 4 for more details.

## APPENDIX F: ADDITIONAL TABLES

**Appendix Table F1. Descriptive statistics for gross prices that include taxes and shipping costs.**

	Mean	St.Dev.	Median	P25	P75	N
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: Mean prices</b>						
Relative exchange rate	0.067	0.190	0.051	-0.027	0.144	996,033
Real exchange rate	0.067	0.191	0.053	-0.026	0.147	996,033
<b>Panel B: Median prices</b>						
Relative exchange rate	0.071	0.191	0.054	-0.022	0.147	996,125
Real exchange rate	0.072	0.192	0.056	-0.021	0.151	996,125
<b>Panel C: Minimum prices</b>						
Relative exchange rate	0.117	0.243	0.082	-0.008	0.230	996,146
Real exchange rate	0.118	0.243	0.082	-0.008	0.231	996,146

Notes: Relative exchange rate is calculated as  $\log(P_{it}^{CA}/P_{it}^{US})$  where  $i$  and  $t$  index goods and weeks, respectively,  $P^{CA}$  is the price in Canada, and  $P^{US}$  is the price in the U.S. The real exchange rate is calculated as  $\log(EX_t^{-1} \times P_{it}^{CA}/P_{it}^{US})$  where  $EX_t$  is the nominal CAD/USD exchange rate. P25 and P75 in columns (4) and (5) show 25<sup>th</sup> and 75<sup>th</sup> percentile of the statistics indicated in the first column. The sample of goods is the same as in Table 2. See text for further details.

**Appendix Table F2. Pass-through and the speed of price adjustment for gross and net prices.**

<b>Panel A: Pass-through</b>				
	Gross Prices		Net Prices	
	Good Fixed effects	N	Good Fixed effects	N
	(1)	(2)	(3)	(4)
Mean Price	0.195 (0.097)	996,033	0.227 (0.105)	996,056
Median Price	0.200 (0.086)	996,125	0.240 (0.094)	996,038
Minimum Price	0.249 (0.113)	996,146	0.276 (0.102)	996,165

<b>Panel B: Speed of Adjustment</b>				
	Gross Prices		Net Prices	
	Good Fixed effects	N	Good Fixed effects	N
	(1)	(2)	(3)	(4)
Mean Price	-0.270 (0.018)	815,279	-0.258 (0.017)	815,519
Median Price	-0.290 (0.017)	814,640	-0.278 (0.016)	814,567
Minimum Price	-0.305 (0.023)	813,822	-0.292 (0.021)	814,399

Notes: The table presents estimates of pass-through and the speed of price adjustment for gross prices (net price + shipping/handling costs) in column (1). The specification reported in the table corresponds to column (3) in Table 4. Column (3) presents results for net prices where the estimation sample of goods is identical to the sample in column (1). All data are at weekly frequency. Driscoll and Kraay (1998) standard errors are in parentheses.

**Appendix Table F3. Pass-through and the speed of price adjustment for gross and net prices, monthly frequency.**

<b>Panel A: Pass-through</b>				
	Gross Prices		Net Prices	
	Good Fixed effects	N	Good Fixed effects	N
	(1)	(2)	(3)	(4)
Mean Price	0.386 (0.140)	277,914	0.419 (0.148)	277,921
Median Price	0.390 (0.127)	277,916	0.429 (0.137)	277,915
Minimum Price	0.637 (0.196)	277,936	0.652 (0.186)	277,923

<b>Panel B: Speed of Adjustment</b>				
	Gross Prices		Net Prices	
	Good Fixed effects	N	Good Fixed effects	N
	(1)	(2)	(3)	(4)
Mean Price	-0.389 (0.034)	219,989	-0.376 (0.033)	220,091
Median Price	-0.429 (0.034)	219,909	-0.416 (0.033)	219,929
Minimum Price	-0.446 (0.044)	219,501	-0.438 (0.043)	219,503

Notes: The table replicates results of Appendix Table F2 on data aggregated to monthly frequency (instead of weekly). See notes to Appendix Table F2 for more details.

**Appendix Table F4. Pass-through and the speed of price adjustment, net prices, monthly frequency.**

	No Fixed effects	Type Fixed effects	Good Fixed effects	N
	(1)	(2)	(3)	(4)
<b>Panel A: Pass-through</b>				
Mean Price	0.894 (0.150)	0.791 (0.132)	0.723 (0.116)	486,456
Median Price	0.869 (0.151)	0.767 (0.135)	0.707 (0.123)	486,461
Minimum Price	0.762 (0.087)	0.672 (0.062)	0.648 (0.055)	486,475
<b>Panel B: Speed of Adjustment</b>				
Mean Price	-0.099 (0.011)	-0.111 (0.011)	-0.264 (0.013)	390,145
Median Price	-0.115 (0.011)	-0.128 (0.011)	-0.288 (0.015)	389,967
Minimum Price	-0.114 (0.008)	-0.130 (0.008)	-0.292 (0.017)	389,506

Notes: The table replicates the results of Table 5 on data aggregated to monthly frequency (instead of weekly). See notes to Table 4 for more details.

**Appendix Table F5. Pass-through and the speed of price adjustment, large stores (top 10 percent).**

	No Fixed effects	Type Fixed effects	Good Fixed effects	N
	(1)	(2)	(3)	(4)
<b>Panel A: Pass-through</b>				
Mean Price	0.989 (0.096)	0.829 (0.082)	0.712 (0.074)	1,406,723
Median Price	0.953 (0.099)	0.787 (0.085)	0.682 (0.079)	1,406,756
Minimum Price	0.870 (0.072)	0.660 (0.045)	0.588 (0.041)	1,406,814
<b>Panel B: Speed of Adjustment</b>				
Mean Price	-0.077 (0.005)	-0.087 (0.006)	-0.191 (0.011)	1,079,612
Median Price	-0.085 (0.005)	-0.095 (0.005)	-0.203 (0.010)	1,079,471
Minimum Price	-0.083 (0.006)	-0.092 (0.006)	-0.195 (0.010)	1,079,293

Notes: The table replicates the results of Table 5 on data constrained to stores with the largest number of goods per store (top 10 percent). See notes to Table 5 for more details.

**Appendix Table F6. Pass-through and the speed of price adjustment by type of store.**

	Online-only stores			Online-offline stores		
	No Fixed effects	Type Fixed effects	Good Fixed effects	No Fixed effects	Type Fixed effects	Good Fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Price	0.769 (0.091)	0.662 (0.086)	0.594 (0.080)	0.949 (0.084)	0.900 (0.051)	0.853 (0.044)
Median Price	0.793 (0.093)	0.684 (0.087)	0.624 (0.083)	0.956 (0.084)	0.908 (0.051)	0.863 (0.044)
Minimum Price	0.608 (0.071)	0.474 (0.061)	0.441 (0.058)	1.075 (0.077)	1.022 (0.052)	0.977 (0.050)
N obs	1,566,189			48,320		
Mean Price	-0.056 (0.004)	-0.063 (0.005)	-0.147 (0.006)	-0.034 (0.010)	-0.050 (0.011)	-0.163 (0.020)
Median Price	-0.064 (0.004)	-0.072 (0.004)	-0.160 (0.006)	-0.035 (0.010)	-0.051 (0.011)	-0.167 (0.021)
Minimum Price	-0.059 (0.004)	-0.068 (0.004)	-0.152 (0.005)	-0.060 (0.017)	-0.084 (0.019)	-0.246 (0.039)
N obs	1,228,732			15,267		

Notes: The table replicates the results of Table 5 on data constrained to stores that sell only online (columns 1-3) and that sell both online and offline (columns 4-6). See notes to Table 5 for more details.

**Appendix Table F7. Pass-through and the speed of price adjustment, regular prices.**

	No Fixed effects	Type Fixed effects	Good Fixed effects	N
	(1)	(2)	(3)	(4)
<b>Panel A: Pass-through</b>				
Mean Price	0.887 (0.103)	0.751 (0.092)	0.663 (0.083)	1,725,138
Median Price	0.872 (0.104)	0.738 (0.093)	0.658 (0.087)	1,725,184
Minimum Price	0.793 (0.067)	0.661 (0.047)	0.618 (0.044)	1,725,211
<b>Panel B: Speed of Adjustment</b>				
Mean Price	-0.064 (0.004)	-0.072 (0.004)	-0.155 (0.008)	1,386,187
Median Price	-0.074 (0.004)	-0.083 (0.004)	-0.171 (0.008)	1,385,728
Minimum Price	-0.070 (0.003)	-0.078 (0.003)	-0.161 (0.007)	1,385,782

Notes: The table replicates the results of Table 5 on regular prices that exclude sales. Sales are identified with filters as in Nakamura and Steinsson (2008). See notes to Table 5 for more details.

# APPENDIX G: DESCRIPTIVE STATISTICS BY PRODUCT CATEGORY

Appendix Table G1. Descriptive statistics for standard deviation log(Price).

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.184	0.111	21	0.103	0.059	21
AV accessories	0.110	0.051	2,838	0.207	0.060	2,726
Antivirus software	0.187	0.095	20	0.183	0.139	20
Audio cables	0.275	0.178	100	0.364	0.189	100
Audio video utilities	0.149	0.114	73	0.094	0.062	72
Bags cases	0.158	0.091	91	0.147	0.129	82
Binoculars	0.256	0.116	35	0.169	0.098	34
Calculators	0.163	0.113	61	0.167	0.095	61
Camcorder accessories	0.220	0.122	24	0.130	0.073	24
Camcorder batteries power	0.282	0.154	25	0.193	0.128	25
Camcorders	0.125	0.090	227	0.087	0.054	225
Cases	0.106	0.068	344	0.135	0.066	340
Cash registers pos equipment	0.085	0.052	214	0.087	0.082	212
Computer games	0.489	0.316	47	0.261	0.201	32
Database management software	0.116	0.054	56	0.057	0.070	56
Dedicated flashes	0.169	0.108	23	0.079	0.026	22
Desktop computers	0.047	0.023	497	0.047	0.019	487
Digital cameras	0.109	0.084	538	0.081	0.040	532
Engineering and home design software	0.187	0.163	9	0.103	0.063	8
Financial and legal software	0.218	0.263	10	0.177	0.172	9
Flash memory	0.180	0.093	966	0.249	0.144	949
Flat panel and LCD monitors	0.080	0.074	757	0.070	0.028	753
GPS	0.116	0.072	156	0.129	0.073	156
Graphics and publishing software	0.122	0.097	606	0.120	0.096	581
Hard drives	0.110	0.071	1,629	0.143	0.085	1,622
Headphones	0.200	0.135	263	0.203	0.180	258
Hubs	0.094	0.078	715	0.129	0.081	714
Keyboards	0.121	0.069	526	0.159	0.084	522
Laptop memory	0.145	0.071	2,422	0.174	0.112	2,378
Laptops	0.052	0.026	549	0.043	0.019	547
Microphones and headsets	0.162	0.071	73	0.215	0.137	73
Miscellaneous programming software	0.171	0.125	99	0.074	0.084	97
Modems	0.159	0.170	89	0.183	0.148	89
Motherboards	0.093	0.081	648	0.091	0.073	642
Mp3 players	0.143	0.089	131	0.139	0.104	128
Network adapters	0.121	0.119	240	0.217	0.158	240
Office suites software	0.187	0.129	76	0.143	0.121	72
Plasma and LCD televisions	0.108	0.068	164	0.088	0.034	158
Portable device accessories	0.195	0.127	262	0.237	0.173	248
Power supplies	0.101	0.065	423	0.124	0.070	417
Processors in retail box	0.063	0.049	520	0.129	0.087	516
Projection screens	0.166	0.037	3,402	0.185	0.044	3,401
Projectors	0.086	0.070	604	0.086	0.053	599
SLR lenses	0.096	0.055	180	0.067	0.041	178
Scanners	0.067	0.044	614	0.082	0.052	614
Security software	0.093	0.079	117	0.160	0.089	115
Speakers	0.133	0.085	166	0.154	0.094	163
Storage media	0.172	0.124	806	0.258	0.171	799
System utilities software	0.110	0.101	49	0.111	0.081	23
TV accessories and mounts	0.143	0.103	92	0.152	0.088	89
Tripods	0.202	0.077	33	0.113	0.079	29
UPSS	0.067	0.039	661	0.101	0.051	658
Video cables	0.232	0.145	677	0.348	0.194	673
Webcams	0.151	0.099	72	0.146	0.087	68
Windows operating system software	0.135	0.132	153	0.101	0.090	153

**Appendix Table G2. Descriptive statistics for median log(Price).**

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	4.742	0.841	21	4.555	0.958	21
AV accessories	5.571	1.067	2,838	5.557	1.101	2,838
Antivirus software	4.531	1.125	20	4.410	1.085	20
Audio cables	2.960	0.845	100	3.020	0.747	100
Audio video utilities	5.069	0.789	73	4.984	0.798	73
Bags cases	4.528	0.994	91	4.383	0.979	91
Binoculars	4.767	0.678	35	4.741	0.649	35
Calculators	3.677	0.968	61	3.324	0.986	61
Camcorder accessories	4.656	0.770	24	4.493	0.838	24
Camcorder batteries power	4.494	0.371	25	4.210	0.349	25
Camcorders	5.859	0.832	227	5.749	0.814	227
Cases	4.952	0.856	344	4.849	0.858	344
Cash registers pos equipment	5.182	0.682	214	5.161	0.674	214
Computer games	2.930	0.801	47	2.688	1.058	47
Database management software	6.811	1.706	56	6.672	1.720	56
Dedicated flashes	5.546	0.723	23	5.388	0.675	23
Desktop computers	6.802	0.524	497	6.712	0.492	497
Digital cameras	5.503	0.674	538	5.385	0.659	538
Engineering and home design software	5.405	1.461	9	5.436	1.307	9
Financial and legal software	5.174	1.048	10	5.034	1.041	10
Flash memory	3.677	0.873	966	3.643	0.835	966
Flat panel and LCD monitors	5.974	0.839	757	5.887	0.832	757
GPS	5.386	0.623	156	5.266	0.644	156
Graphics and publishing software	5.903	1.017	606	5.802	0.981	606
Hard drives	5.223	0.749	1,629	5.147	0.685	1,629
Headphones	4.054	0.964	263	3.791	1.067	263
Hubs	6.357	1.697	715	6.236	1.678	715
Keyboards	4.173	0.698	526	4.087	0.697	526
Laptop memory	4.481	0.900	2,422	4.366	0.845	2,422
Laptops	6.803	0.617	549	6.729	0.581	549
Microphones and headsets	3.908	0.885	73	3.724	0.887	73
Miscellaneous programming software	7.027	1.154	99	6.826	1.167	99
Modems	4.198	1.319	89	4.160	1.223	89
Motherboards	5.163	0.671	648	5.106	0.677	648
Mp3 players	4.402	0.769	131	4.363	0.756	131
Network adapters	5.045	1.302	240	4.892	1.244	240
Office suites software	5.450	0.640	76	5.262	0.632	76
Plasma and LCD televisions	6.695	0.764	164	6.585	0.720	164
Portable device accessories	3.547	0.982	262	3.564	0.916	262
Power supplies	4.899	0.859	423	4.804	0.820	423
Processors in retail box	6.141	0.911	520	5.946	0.818	520
Projection screens	6.718	0.663	3,402	6.739	0.655	3,402
Projectors	6.946	0.720	604	6.847	0.715	604
SLR lenses	6.634	0.806	180	6.521	0.823	180
Scanners	5.741	0.887	614	5.651	0.870	614
Security software	3.962	1.167	117	3.880	1.056	117
Speakers	4.265	0.881	166	4.172	0.873	166
Storage media	3.643	1.093	806	3.419	1.138	806
System utilities software	5.893	1.763	49	5.834	1.798	49
TV accessories and mounts	5.027	0.772	92	4.877	0.722	92
Tripods	5.143	1.005	33	4.999	1.011	33
UPSS	6.137	1.141	661	6.021	1.147	661
Video cables	3.129	0.866	677	3.091	0.776	677
Webcams	4.117	0.674	72	4.010	0.671	72
Windows operating system software	6.095	1.094	153	5.967	1.108	153

**Appendix Table G3. Descriptive statistics for frequency of price chance, per week.**

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.266	0.214	21	0.111	0.070	21
AV accessories	0.363	0.093	2,838	0.042	0.089	2,838
Antivirus software	0.294	0.184	20	0.171	0.108	20
Audio cables	0.206	0.103	100	0.135	0.052	100
Audio video utilities	0.321	0.160	73	0.193	0.110	73
Bags cases	0.290	0.291	91	0.124	0.097	91
Binoculars	0.564	0.215	35	0.139	0.049	35
Calculators	0.236	0.086	61	0.101	0.053	61
Camcorder accessories	0.353	0.234	24	0.169	0.113	24
Camcorder batteries power	0.309	0.177	25	0.192	0.078	25
Camcorders	0.342	0.203	227	0.291	0.154	227
Cases	0.322	0.152	344	0.212	0.093	344
Cash registers pos equipment	0.563	0.110	214	0.107	0.045	214
Computer games	0.268	0.164	47	0.150	0.091	47
Database management software	0.216	0.194	56	0.158	0.094	56
Dedicated flashes	0.262	0.212	23	0.128	0.067	23
Desktop computers	0.333	0.141	497	0.454	0.142	497
Digital cameras	0.280	0.167	538	0.307	0.132	538
Engineering and home design software	0.384	0.277	9	0.180	0.093	9
Financial and legal software	0.145	0.078	10	0.196	0.133	10
Flash memory	0.342	0.158	966	0.252	0.115	966
Flat panel and LCD monitors	0.419	0.159	757	0.304	0.114	757
GPS	0.332	0.170	156	0.161	0.078	156
Graphics and publishing software	0.371	0.170	606	0.197	0.098	606
Hard drives	0.418	0.179	1,629	0.301	0.094	1,629
Headphones	0.237	0.180	263	0.119	0.082	263
Hubs	0.380	0.201	715	0.245	0.085	715
Keyboards	0.378	0.186	526	0.197	0.076	526
Laptop memory	0.500	0.186	2,422	0.357	0.118	2,422
Laptops	0.362	0.135	549	0.405	0.149	549
Microphones and headsets	0.281	0.128	73	0.167	0.069	73
Miscellaneous programming software	0.289	0.202	99	0.240	0.143	99
Modems	0.376	0.186	89	0.205	0.080	89
Motherboards	0.353	0.169	648	0.265	0.098	648
Mp3 players	0.403	0.216	131	0.138	0.068	131
Network adapters	0.372	0.175	240	0.248	0.095	240
Office suites software	0.208	0.113	76	0.214	0.105	76
Plasma and LCD televisions	0.287	0.205	164	0.288	0.146	164
Portable device accessories	0.291	0.159	262	0.153	0.089	262
Power supplies	0.325	0.157	423	0.216	0.084	423
Processors in retail box	0.331	0.147	520	0.253	0.089	520
Projection screens	0.373	0.071	3,402	0.012	0.037	3,402
Projectors	0.317	0.185	604	0.262	0.110	604
SLR lenses	0.362	0.228	180	0.158	0.066	180
Scanners	0.514	0.175	614	0.173	0.099	614
Security software	0.311	0.114	117	0.126	0.095	117
Speakers	0.308	0.153	166	0.199	0.080	166
Storage media	0.241	0.137	806	0.166	0.084	806
System utilities software	0.148	0.159	49	0.092	0.123	49
TV accessories and mounts	0.413	0.246	92	0.135	0.080	92
Tripods	0.356	0.121	33	0.129	0.116	33
UPSS	0.356	0.149	661	0.245	0.070	661
Video cables	0.198	0.130	677	0.176	0.067	677
Webcams	0.316	0.148	72	0.237	0.087	72
Windows operating system software	0.290	0.169	153	0.221	0.096	153

Appendix Table G4. Descriptive statistics for median  $\text{abs}(\text{dlog}(\text{Price}))$ .

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.018	0.038	21	0.052	0.030	20
AV accessories	0.010	0.018	2,838	0.045	0.084	721
Antivirus software	0.071	0.095	20	0.033	0.020	20
Audio cables	0.062	0.070	100	0.056	0.102	100
Audio video utilities	0.032	0.051	73	0.032	0.023	73
Bags cases	0.034	0.053	91	0.051	0.047	88
Binoculars	0.012	0.006	35	0.069	0.046	35
Calculators	0.059	0.059	61	0.080	0.098	61
Camcorder accessories	0.019	0.022	24	0.050	0.043	24
Camcorder batteries power	0.013	0.008	25	0.042	0.020	25
Camcorders	0.039	0.035	227	0.059	0.041	226
Cases	0.044	0.056	344	0.036	0.024	342
Cash registers pos equipment	0.014	0.004	214	0.025	0.024	212
Computer games	0.098	0.088	47	0.141	0.120	45
Database management software	0.027	0.018	56	0.028	0.018	56
Dedicated flashes	0.019	0.019	23	0.038	0.034	22
Desktop computers	0.019	0.022	497	0.017	0.009	497
Digital cameras	0.052	0.040	538	0.058	0.038	538
Engineering and home design software	0.032	0.019	9	0.086	0.135	9
Financial and legal software	0.138	0.305	10	0.063	0.066	10
Flash memory	0.047	0.054	966	0.053	0.044	963
Flat panel and LCD monitors	0.021	0.015	757	0.022	0.020	757
GPS	0.035	0.036	156	0.055	0.037	156
Graphics and publishing software	0.019	0.020	606	0.024	0.028	587
Hard drives	0.031	0.030	1,629	0.039	0.022	1,627
Headphones	0.117	0.134	263	0.080	0.085	261
Hubs	0.037	0.065	715	0.025	0.020	715
Keyboards	0.037	0.043	526	0.040	0.030	526
Laptop memory	0.034	0.028	2,422	0.049	0.026	2,422
Laptops	0.019	0.015	549	0.017	0.014	549
Microphones and headsets	0.051	0.051	73	0.051	0.044	73
Miscellaneous programming software	0.023	0.019	99	0.020	0.013	98
Modems	0.040	0.045	89	0.033	0.024	89
Motherboards	0.035	0.047	648	0.026	0.021	648
Mp3 players	0.030	0.052	131	0.047	0.031	127
Network adapters	0.031	0.039	240	0.032	0.033	240
Office suites software	0.033	0.025	76	0.036	0.033	74
Plasma and LCD televisions	0.059	0.047	164	0.034	0.024	164
Portable device accessories	0.050	0.057	262	0.062	0.069	255
Power supplies	0.042	0.033	423	0.036	0.033	420
Processors in retail box	0.022	0.022	520	0.033	0.051	520
Projection screens	0.007	0.006	3,402	0.095	0.142	969
Projectors	0.025	0.032	604	0.019	0.017	603
SLR lenses	0.016	0.008	180	0.046	0.033	179
Scanners	0.019	0.016	614	0.019	0.014	608
Security software	0.014	0.012	117	0.079	0.050	115
Speakers	0.042	0.038	166	0.050	0.036	165
Storage media	0.065	0.076	806	0.055	0.053	802
System utilities software	0.019	0.017	49	0.019	0.015	39
TV accessories and mounts	0.043	0.089	92	0.044	0.039	91
Tripods	0.020	0.033	33	0.076	0.064	31
UPS	0.020	0.018	661	0.020	0.015	661
Video cables	0.075	0.073	677	0.044	0.033	677
Webcams	0.046	0.040	72	0.051	0.032	71
Windows operating system software	0.029	0.038	153	0.032	0.060	153

Appendix Table G5. Descriptive statistics for synchronization of price changes.

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.044	0.152	21	0.070	0.089	19
AV accessories	0.077	0.128	2,838	0.117	0.100	660
Antivirus software	0.335	0.253	20	0.192	0.069	20
Audio cables	0.172	0.122	100	0.090	0.075	100
Audio video utilities	0.238	0.171	73	0.131	0.089	72
Bags cases	0.069	0.102	91	0.097	0.103	79
Binoculars	0.014	0.045	35	0.071	0.086	34
Calculators	0.154	0.140	61	0.054	0.063	60
Camcorder accessories	0.078	0.100	24	0.123	0.084	24
Camcorder batteries power	0.081	0.109	25	0.140	0.083	25
Camcorders	0.163	0.156	227	0.235	0.149	223
Cases	0.276	0.207	344	0.167	0.092	338
Cash registers pos equipment	0.494	0.180	214	0.071	0.062	210
Computer games	0.195	0.203	47	0.094	0.083	26
Database management software	0.250	0.247	56	0.142	0.123	56
Dedicated flashes	0.060	0.105	23	0.104	0.055	20
Desktop computers	0.273	0.139	497	0.335	0.132	485
Digital cameras	0.155	0.130	538	0.245	0.136	529
Engineering and home design software	0.288	0.319	9	0.120	0.091	8
Financial and legal software	0.113	0.100	10	0.180	0.108	9
Flash memory	0.277	0.179	966	0.194	0.104	939
Flat panel and LCD monitors	0.292	0.185	757	0.232	0.105	751
GPS	0.347	0.221	156	0.127	0.099	154
Graphics and publishing software	0.326	0.205	606	0.148	0.084	565
Hard drives	0.332	0.173	1,629	0.237	0.093	1,620
Headphones	0.130	0.164	263	0.099	0.113	252
Hubs	0.302	0.241	715	0.182	0.082	713
Keyboards	0.287	0.214	526	0.156	0.079	521
Laptop memory	0.424	0.185	2,422	0.296	0.127	2,373
Laptops	0.269	0.134	549	0.298	0.124	546
Microphones and headsets	0.242	0.158	73	0.118	0.058	73
Miscellaneous programming software	0.239	0.235	99	0.211	0.145	95
Modems	0.294	0.235	89	0.146	0.076	89
Motherboards	0.310	0.210	648	0.196	0.099	641
Mp3 players	0.215	0.182	131	0.110	0.072	125
Network adapters	0.347	0.213	240	0.177	0.079	238
Office suites software	0.181	0.162	76	0.178	0.098	72
Plasma and LCD televisions	0.190	0.201	164	0.174	0.135	158
Portable device accessories	0.192	0.188	262	0.115	0.077	244
Power supplies	0.269	0.203	423	0.167	0.097	412
Processors in retail box	0.274	0.186	520	0.183	0.083	513
Projection screens	0.049	0.061	3,402	0.021	0.057	967
Projectors	0.245	0.208	604	0.199	0.098	596
SLR lenses	0.072	0.145	180	0.135	0.091	176
Scanners	0.457	0.210	614	0.126	0.082	608
Security software	0.170	0.161	117	0.173	0.097	114
Speakers	0.234	0.176	166	0.162	0.095	162
Storage media	0.227	0.144	806	0.120	0.078	792
System utilities software	0.097	0.175	49	0.075	0.092	23
TV accessories and mounts	0.248	0.230	92	0.095	0.071	86
Tripods	0.043	0.068	33	0.078	0.072	28
UPS	0.332	0.190	661	0.188	0.063	656
Video cables	0.117	0.132	677	0.112	0.067	670
Webcams	0.196	0.152	72	0.206	0.089	68
Windows operating system software	0.237	0.177	153	0.176	0.096	153

**Appendix Table G6. Descriptive statistics for number of sellers.**

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	1.473	0.291	21	1.909	0.899	21
AV accessories	1.694	0.391	2,838	2.130	0.998	2,838
Antivirus software	1.895	1.450	20	3.832	2.191	20
Audio cables	2.007	0.724	100	2.470	0.759	100
Audio video utilities	2.190	1.058	73	3.424	1.893	73
Bags cases	1.570	0.498	91	2.347	1.369	91
Binoculars	1.428	0.812	35	2.176	0.942	35
Calculators	1.793	0.938	61	2.769	1.148	61
Camcorder accessories	1.925	0.909	24	2.264	0.819	24
Camcorder batteries power	2.189	0.893	25	2.778	0.862	25
Camcorders	2.520	1.275	227	3.109	2.100	227
Cases	2.426	1.296	344	3.470	1.352	344
Cash registers pos equipment	1.564	0.331	214	3.195	0.978	214
Computer games	1.513	0.650	47	1.919	1.261	47
Database management software	2.182	1.653	56	2.594	1.237	56
Dedicated flashes	1.820	0.628	23	2.664	1.383	23
Desktop computers	3.250	1.273	497	3.844	1.350	497
Digital cameras	2.506	1.184	538	3.349	1.984	538
Engineering and home design software	3.116	2.528	9	3.034	1.735	9
Financial and legal software	2.826	1.752	10	3.401	1.865	10
Flash memory	2.632	1.196	966	3.137	1.300	966
Flat panel and LCD monitors	2.975	1.514	757	4.022	1.342	757
GPS	2.883	1.484	156	4.392	2.152	156
Graphics and publishing software	2.985	1.629	606	4.519	2.743	606
Hard drives	3.010	1.268	1,629	4.837	2.425	1,629
Headphones	1.913	1.075	263	2.967	1.343	263
Hubs	2.406	1.082	715	5.985	2.819	715
Keyboards	2.493	1.302	526	3.755	1.415	526
Laptop memory	3.074	1.071	2,422	3.019	1.343	2,422
Laptops	3.512	1.218	549	4.277	1.721	549
Microphones and headsets	3.006	1.908	73	3.529	1.212	73
Miscellaneous programming software	2.617	2.100	99	3.885	3.296	99
Modems	2.316	1.246	89	3.440	1.274	89
Motherboards	2.959	1.480	648	3.241	1.244	648
Mp3 players	2.062	0.936	131	3.250	1.402	131
Network adapters	2.831	1.058	240	4.705	2.350	240
Office suites software	2.552	1.868	76	4.029	2.625	76
Plasma and LCD televisions	2.123	1.161	164	2.667	1.019	164
Portable device accessories	2.072	0.890	262	3.141	1.392	262
Power supplies	2.526	1.256	423	3.160	1.412	423
Processors in retail box	2.707	1.258	520	3.875	1.750	520
Projection screens	1.674	0.192	3,402	2.027	0.536	3,402
Projectors	2.918	1.444	604	4.381	2.043	604
SLR lenses	1.598	0.430	180	2.960	1.459	180
Scanners	2.126	1.106	614	4.397	1.923	614
Security software	1.555	0.687	117	2.458	1.646	117
Speakers	2.953	1.776	166	3.287	1.324	166
Storage media	2.625	0.997	806	4.344	2.322	806
System utilities software	1.431	0.736	49	1.640	1.288	49
TV accessories and mounts	1.920	0.943	92	3.586	2.016	92
Tripods	1.800	0.569	33	1.720	0.695	33
UPS	2.949	1.306	661	4.901	1.890	661
Video cables	2.202	0.826	677	3.560	1.123	677
Webcams	2.371	1.406	72	4.000	1.732	72
Windows operating system software	2.160	1.158	153	3.445	1.888	153

**Appendix Table G7. Descriptive statistics for stability of sellers.**

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.948	0.021	21	0.882	0.055	21
AV accessories	0.950	0.035	2,838	0.928	0.033	2,838
Antivirus software	0.912	0.053	20	0.923	0.046	20
Audio cables	0.916	0.047	100	0.914	0.039	100
Audio video utilities	0.894	0.054	73	0.887	0.062	73
Bags cases	0.944	0.037	91	0.914	0.051	91
Binoculars	0.964	0.034	35	0.872	0.066	35
Calculators	0.906	0.048	61	0.934	0.037	61
Camcorder accessories	0.926	0.046	24	0.887	0.058	24
Camcorder batteries power	0.911	0.043	25	0.856	0.041	25
Camcorders	0.896	0.056	227	0.857	0.064	227
Cases	0.896	0.061	344	0.886	0.044	344
Cash registers pos equipment	0.893	0.041	214	0.928	0.035	214
Computer games	0.947	0.049	47	0.940	0.061	47
Database management software	0.915	0.067	56	0.928	0.055	56
Dedicated flashes	0.924	0.035	23	0.868	0.061	23
Desktop computers	0.860	0.057	497	0.856	0.058	497
Digital cameras	0.895	0.061	538	0.854	0.066	538
Engineering and home design software	0.906	0.091	9	0.867	0.069	9
Financial and legal software	0.908	0.058	10	0.881	0.087	10
Flash memory	0.864	0.059	966	0.891	0.045	966
Flat panel and LCD monitors	0.871	0.058	757	0.871	0.047	757
GPS	0.884	0.066	156	0.857	0.054	156
Graphics and publishing software	0.885	0.063	606	0.905	0.052	606
Hard drives	0.857	0.061	1,629	0.848	0.050	1,629
Headphones	0.924	0.064	263	0.883	0.056	263
Hubs	0.889	0.072	715	0.887	0.039	715
Keyboards	0.888	0.054	526	0.890	0.045	526
Laptop memory	0.850	0.050	2,422	0.863	0.056	2,422
Laptops	0.848	0.062	549	0.846	0.062	549
Microphones and headsets	0.876	0.061	73	0.884	0.042	73
Miscellaneous programming software	0.898	0.074	99	0.899	0.059	99
Modems	0.896	0.062	89	0.880	0.044	89
Motherboards	0.873	0.065	648	0.875	0.052	648
Mp3 players	0.914	0.061	131	0.888	0.046	131
Network adapters	0.873	0.052	240	0.878	0.036	240
Office suites software	0.912	0.050	76	0.908	0.054	76
Plasma and LCD televisions	0.902	0.060	164	0.869	0.058	164
Portable device accessories	0.905	0.057	262	0.906	0.051	262
Power supplies	0.889	0.054	423	0.891	0.047	423
Processors in retail box	0.889	0.052	520	0.869	0.044	520
Projection screens	0.966	0.029	3,402	0.894	0.035	3,402
Projectors	0.879	0.064	604	0.875	0.043	604
SLR lenses	0.943	0.032	180	0.837	0.047	180
Scanners	0.880	0.047	614	0.904	0.039	614
Security software	0.925	0.055	117	0.951	0.041	117
Speakers	0.882	0.058	166	0.874	0.047	166
Storage media	0.872	0.049	806	0.900	0.042	806
System utilities software	0.942	0.056	49	0.963	0.059	49
TV accessories and mounts	0.926	0.056	92	0.897	0.047	92
Tripods	0.936	0.055	33	0.885	0.062	33
UPSS	0.881	0.049	661	0.878	0.037	661
Video cables	0.911	0.049	677	0.918	0.032	677
Webcams	0.905	0.056	72	0.882	0.053	72
Windows operating system software	0.892	0.062	153	0.907	0.038	153

Appendix Table G8. Descriptive statistics for the frequency of sales, per week.

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.037	0.042	21	0.011	0.019	21
AV accessories	0.021	0.018	2,838	0.007	0.026	2,838
Antivirus software	0.020	0.017	20	0.019	0.031	20
Audio cables	0.029	0.027	100	0.014	0.020	100
Audio video utilities	0.034	0.034	73	0.045	0.052	73
Bags cases	0.020	0.027	91	0.025	0.042	91
Binoculars	0.038	0.026	35	0.017	0.030	35
Calculators	0.029	0.028	61	0.029	0.040	61
Camcorder accessories	0.021	0.015	24	0.022	0.030	24
Camcorder batteries power	0.028	0.018	25	0.031	0.031	25
Camcorders	0.045	0.042	227	0.046	0.052	227
Cases	0.043	0.042	344	0.029	0.029	344
Cash registers pos equipment	0.042	0.021	214	0.018	0.029	214
Computer games	0.049	0.038	47	0.042	0.060	47
Database management software	0.017	0.025	56	0.018	0.036	56
Dedicated flashes	0.029	0.015	23	0.012	0.025	23
Desktop computers	0.029	0.030	497	0.029	0.026	497
Digital cameras	0.059	0.054	538	0.050	0.046	538
Engineering and home design software	0.034	0.033	9	0.060	0.100	9
Financial and legal software	0.010	0.017	10	0.015	0.020	10
Flash memory	0.033	0.033	966	0.024	0.029	966
Flat panel and LCD monitors	0.026	0.021	757	0.030	0.030	757
GPS	0.049	0.041	156	0.027	0.034	156
Graphics and publishing software	0.026	0.028	606	0.027	0.037	606
Hard drives	0.030	0.030	1,629	0.028	0.025	1,629
Headphones	0.068	0.071	263	0.031	0.042	263
Hubs	0.025	0.028	715	0.033	0.027	715
Keyboards	0.044	0.035	526	0.032	0.031	526
Laptop memory	0.036	0.025	2,422	0.020	0.021	2,422
Laptops	0.030	0.028	549	0.024	0.025	549
Microphones and headsets	0.054	0.048	73	0.043	0.032	73
Miscellaneous programming software	0.023	0.026	99	0.025	0.025	99
Modems	0.032	0.025	89	0.023	0.027	89
Motherboards	0.038	0.040	648	0.028	0.032	648
Mp3 players	0.031	0.037	131	0.036	0.036	131
Network adapters	0.029	0.024	240	0.027	0.023	240
Office suites software	0.024	0.030	76	0.026	0.023	76
Plasma and LCD televisions	0.050	0.062	164	0.028	0.039	164
Portable device accessories	0.028	0.032	262	0.029	0.034	262
Power supplies	0.043	0.035	423	0.031	0.034	423
Processors in retail box	0.029	0.025	520	0.026	0.025	520
Projection screens	0.001	0.007	3,402	0.005	0.026	3,402
Projectors	0.024	0.025	604	0.023	0.022	604
SLR lenses	0.035	0.023	180	0.016	0.020	180
Scanners	0.029	0.021	614	0.021	0.025	614
Security software	0.013	0.023	117	0.061	0.038	117
Speakers	0.048	0.045	166	0.038	0.038	166
Storage media	0.024	0.028	806	0.034	0.030	806
System utilities software	0.014	0.025	49	0.018	0.033	49
TV accessories and mounts	0.049	0.060	92	0.029	0.030	92
Tripods	0.023	0.016	33	0.015	0.026	33
UPSS	0.026	0.021	661	0.028	0.022	661
Video cables	0.028	0.038	677	0.020	0.026	677
Webcams	0.051	0.042	72	0.058	0.046	72
Windows operating system software	0.026	0.026	153	0.027	0.028	153

Appendix Table G9. Descriptive statistics for mean size of sales.

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.032	0.046	18	0.071	0.057	6
AV accessories	0.028	0.063	2,059	0.077	0.092	370
Antivirus software	0.057	0.046	13	0.108	0.137	12
Audio cables	0.159	0.175	74	0.128	0.155	49
Audio video utilities	0.056	0.061	53	0.057	0.045	55
Bags cases	0.077	0.121	58	0.088	0.069	37
Binoculars	0.028	0.028	32	0.080	0.072	12
Calculators	0.136	0.127	39	0.064	0.069	32
Camcorder accessories	0.051	0.069	21	0.077	0.071	10
Camcorder batteries power	0.082	0.123	25	0.124	0.134	16
Camcorders	0.103	0.088	184	0.092	0.055	158
Cases	0.084	0.095	273	0.069	0.050	241
Cash registers pos equipment	0.023	0.011	210	0.069	0.089	100
Computer games	0.276	0.261	39	0.120	0.114	21
Database management software	0.068	0.094	23	0.079	0.105	23
Dedicated flashes	0.045	0.053	20	0.089	0.056	7
Desktop computers	0.043	0.054	342	0.042	0.047	378
Digital cameras	0.112	0.089	422	0.086	0.064	426
Engineering and home design software	0.050	0.054	6	0.041	0.015	6
Financial and legal software	0.027	0.001	3	0.033	0.021	5
Flash memory	0.095	0.107	755	0.095	0.108	650
Flat panel and LCD monitors	0.045	0.045	627	0.048	0.043	601
GPS	0.108	0.101	130	0.095	0.068	93
Graphics and publishing software	0.047	0.071	449	0.056	0.057	420
Hard drives	0.085	0.098	1,271	0.063	0.060	1,328
Headphones	0.200	0.203	212	0.123	0.146	146
Hubs	0.070	0.120	491	0.062	0.064	604
Keyboards	0.091	0.127	447	0.075	0.065	363
Laptop memory	0.042	0.052	2,123	0.071	0.082	1,621
Laptops	0.048	0.073	415	0.040	0.053	396
Microphones and headsets	0.112	0.100	67	0.087	0.109	59
Miscellaneous programming software	0.043	0.041	62	0.051	0.046	67
Modems	0.074	0.114	72	0.093	0.112	61
Motherboards	0.059	0.075	503	0.046	0.043	423
Mp3 players	0.091	0.098	103	0.074	0.077	89
Network adapters	0.079	0.130	209	0.086	0.097	202
Office suites software	0.102	0.170	44	0.095	0.108	57
Plasma and LCD televisions	0.089	0.068	103	0.067	0.062	94
Portable device accessories	0.134	0.159	167	0.107	0.145	148
Power supplies	0.084	0.081	358	0.067	0.060	294
Processors in retail box	0.069	0.113	399	0.063	0.086	390
Projection screens	0.040	0.098	169	0.188	0.299	177
Projectors	0.046	0.045	441	0.055	0.069	459
SLR lenses	0.031	0.027	170	0.066	0.058	106
Scanners	0.034	0.047	555	0.046	0.054	367
Security software	0.062	0.100	40	0.111	0.059	99
Speakers	0.104	0.091	140	0.081	0.056	119
Storage media	0.114	0.156	571	0.089	0.099	622
System utilities software	0.082	0.124	14	0.081	0.061	13
TV accessories and mounts	0.071	0.115	79	0.078	0.060	62
Tripods	0.058	0.057	33	0.066	0.024	12
UPS	0.049	0.068	564	0.053	0.064	568
Video cables	0.154	0.208	392	0.100	0.118	397
Webcams	0.113	0.083	59	0.092	0.073	60
Windows operating system software	0.065	0.094	110	0.085	0.133	109

**Appendix Table G10. Descriptive statistics for the frequency of convenient prices.**

Category	Canada			US		
	Mean	SD	N	Mean	SD	N
35mm SLR lens accessories	0.291	0.292	21	0.350	0.346	21
AV accessories	0.118	0.153	2,838	0.078	0.183	2,838
Antivirus software	0.190	0.171	20	0.210	0.170	20
Audio cables	0.066	0.097	100	0.085	0.122	100
Audio video utilities	0.368	0.255	73	0.380	0.258	73
Bags cases	0.184	0.227	91	0.211	0.244	91
Binoculars	0.334	0.245	35	0.366	0.249	35
Calculators	0.141	0.176	61	0.112	0.124	61
Camcorder accessories	0.230	0.167	24	0.278	0.227	24
Camcorder batteries power	0.309	0.241	25	0.183	0.124	25
Camcorders	0.400	0.235	227	0.504	0.278	227
Cases	0.284	0.192	344	0.211	0.181	344
Cash registers pos equipment	0.130	0.082	214	0.152	0.134	214
Computer games	0.108	0.134	47	0.193	0.254	47
Database management software	0.232	0.178	56	0.251	0.178	56
Dedicated flashes	0.393	0.280	23	0.484	0.271	23
Desktop computers	0.155	0.114	497	0.180	0.112	497
Digital cameras	0.411	0.235	538	0.456	0.252	538
Engineering and home design software	0.224	0.163	9	0.286	0.171	9
Financial and legal software	0.429	0.309	10	0.445	0.270	10
Flash memory	0.145	0.149	966	0.139	0.129	966
Flat panel and LCD monitors	0.216	0.142	757	0.203	0.143	757
GPS	0.405	0.234	156	0.441	0.208	156
Graphics and publishing software	0.286	0.183	606	0.331	0.219	606
Hard drives	0.270	0.177	1,629	0.234	0.147	1,629
Headphones	0.393	0.315	263	0.341	0.334	263
Hubs	0.193	0.151	715	0.188	0.111	715
Keyboards	0.176	0.146	526	0.167	0.150	526
Laptop memory	0.156	0.104	2,422	0.141	0.105	2,422
Laptops	0.193	0.145	549	0.271	0.154	549
Microphones and headsets	0.185	0.178	73	0.199	0.192	73
Miscellaneous programming software	0.251	0.191	99	0.326	0.206	99
Modems	0.162	0.129	89	0.137	0.139	89
Motherboards	0.302	0.199	648	0.190	0.139	648
Mp3 players	0.356	0.271	131	0.280	0.245	131
Network adapters	0.155	0.110	240	0.152	0.103	240
Office suites software	0.290	0.156	76	0.254	0.169	76
Plasma and LCD televisions	0.677	0.320	164	0.375	0.237	164
Portable device accessories	0.158	0.182	262	0.171	0.219	262
Power supplies	0.238	0.160	423	0.204	0.174	423
Processors in retail box	0.194	0.145	520	0.194	0.131	520
Projection screens	0.140	0.171	3,402	0.166	0.245	3,402
Projectors	0.263	0.202	604	0.369	0.168	604
SLR lenses	0.336	0.216	180	0.649	0.213	180
Scanners	0.173	0.113	614	0.192	0.133	614
Security software	0.127	0.143	117	0.130	0.145	117
Speakers	0.217	0.177	166	0.254	0.221	166
Storage media	0.107	0.107	806	0.106	0.109	806
System utilities software	0.332	0.323	49	0.264	0.332	49
TV accessories and mounts	0.294	0.286	92	0.334	0.252	92
Tripods	0.249	0.224	33	0.446	0.325	33
UPS	0.193	0.120	661	0.174	0.086	661
Video cables	0.109	0.151	677	0.090	0.116	677
Webcams	0.212	0.163	72	0.179	0.155	72
Windows operating system software	0.298	0.204	153	0.296	0.185	153