Exchange Rate Pass-Through on eBay

May 2013

Zachariah Lott

Department of Economics
Stanford University
Stanford, CA 94305
zlott13@stanford.edu

under the direction of
Professor Liran Einav

ABSTRACT

In this paper, I measure exchange rate pass-through based on eBay transactions. I focus on “seller experiments,” exploiting situations in which a seller lists an item multiple times. I start with U.S. import pass-through from Australia, Canada, Germany, Japan, and the United Kingdom. I calculate an average short-run pass-through of 0.2, which is comparable to estimates in the literature. I then measure pass-through at the monthly, weekly, and daily level. I find monthly pass-through decreases over time, while daily pass through peaks after about seven days before decreasing. Next, I examine how an item’s uniqueness, its seller volume, and its price affect pass-through. I find that unique items garner a higher pass-through than mainstream, that items from high-volume sellers have a higher pass-through than from low, and that item price has no effect on pass-through. Finally, I measure both import and export pass-through for a variety of OECD countries. I find weak evidence that the two are inversely related, and that the greater a country’s currency’s influence on the world or other countries, the lower its import pass-through and higher its export pass-through. I examine pass-through between country pairs and find similar pass-through estimates between a country and a group of countries similar to each other.

Keywords: pass-through, pricing to market, internet markets

Acknowledgements: I would like to thank Professors Einav, Levin, and Rothwell, Dr. Sundarasen, and Messrs. Knoepfle and Popov. Professor Einav inspired my topic, connected me with eBay, and guided me throughout the process. Professor Levin read a late draft of the paper and provided advice as an outsider to the topic. Professor Rothwell helped me think about a thesis early in Econ 198. Dr. Sundarasen directed me at eBay. Finally, Messrs. Knoepfle and Popov instructed me in eBay’s data software, and provided insight into both my thesis and my future plans in economics.
1 Introduction

Exchange rate pass-through is the percentage change of an import price due to a one percent change in the exchange rate between the importing and exporting country. The import price is measured in local currency and the exchange rate in local currency per unit of foreign currency. For example, consider an item the United States imports from Germany. Suppose the exchange rate of dollars per Euro increases by 10 percent (the dollar depreciates by 10 percent) and the item’s price in dollars subsequently increases by 4 percent. Then the exchange rate pass-through is 0.4, that is, 40 percent of the change in the exchange rate has passed through the item’s price in local currency.

Exchange rate pass-through has an important impact on both micro and macroeconomics. On the micro side, pass-through informs theory on competition and the law of one price (LOP), which states that prices across countries should be identical once adjusted by the exchange rate. Competition, however, works against the LOP: if the exchange rate changes, local competition may prevent a foreign producer from changing its price. On the macro side, pass-through is intertwined with sticky prices and monetary economics. Beside local competition, sticky prices may also lower pass-through. Indeed, many papers have tried to isolate either effect. Furthermore, because pass-through affects import prices, it affects net exports, in turn part of a country’s aggregate demand. So policy makers must take pass-through into account when changing the interest rate with monetary economics. In total, exchange rate pass-through plays an important role in micro and macroeconomics. Measuring its size and trends across countries, item type, and other variables provides empirical evidence for theories on competition, the LOP, sticky prices, and monetary economics.
Previous researchers have used macro variables to study pass-through. Specifically, they calculate how an aggregate quarterly measure of a country’s prices varies with its average quarterly exchange rates. They measure pass-through over several years, and include control variables to adjust for macroeconomic factors like commodity prices and a country’s economic health. These studies excel at examining pass-through across several countries over long periods of time. However, they mask pass-through variation within a quarter and within divisions finer than an entire country. Papers have made some progress toward the latter, for example splitting imports to a country into categories like energy and manufactured items. But all must work within the aggregate level of their data.

In this paper, I measure pass-through at the micro level. My data come from eBay, which is one of the world’s largest online retail platforms. eBay collects a vast amount of information from its users, including details of every transaction they undertake. Einav, Kuchler, Levin, and Sundaresan (2011) discuss that the eBay data is incredibly useful because many sellers perform experiments in which they post different listings for the same item. Such experiments are ideal to measure economic phenomena because they resemble a controlled environment where a particular seller offers a particular item under different conditions. In my case, I consider experiments where a user from one country sells to buyers in another country, often at different prices. I then measure if the changes in price have any correlation with changes in the exchange rate. My study relies on the worldwide phenomena of “big data,” where institutions collect ever more data about their participants. My study provides an example of big data’s promising role in future research by exploring a macro-level question on a smaller scale than anyone has done before.
To find avenues for my research, I examined the pass-through literature. Researcher’s first step is to measure pass-through. There is general consensus that pass-through across countries is incomplete, that is, less than 1. Furthermore it has been declining over time in the United States, and is smaller in the United States than in the rest of the OECD countries. Next, it has been measured over the short-run and long-run. The short-run estimate is based on how quarterly prices change due to the average exchange rate of that quarter, while the long-run estimate includes pass-through due to the quarter-of exchange rate as well as quarterly lags of the exchange rate. The literature finds long-run pass-through is greater than short-run but is still incomplete. Its short-run estimate of U.S. import pass-through is between 0.2 and 0.25.

These results inspire the first part of my research. In section 4.1 I examine the magnitude and timing of pass-through. I focus on U.S. import pass-through from the five countries with the greatest volume of eBay sales to the United States: Australia, Canada, Germany, Japan, and the United Kingdom. I find pass-through estimates comparable to the literature’s, with Germany’s higher at 0.3 and Canada’s lower at essentially zero. Following my micro approach, I then dive into the literature’s short-run estimate of pass-through and explore it at the monthly, weekly, and daily level. I find that pass-through is generally highest within the first month and then decreases, while pass-through due to daily changes in the exchange rate peaks about one week after the change. My results reveal interesting heterogeneity in the data, however.

After capturing the short-run and sometimes long-run estimates of pass-through, studies go on to explore the fundamental question, what causes differences in pass-through? The theories generally fall under either micro or macro phenomena. The micro theories explore the pricing decision of individual companies, and how attributes like their productivity or product type affect pass-through. The macro theories explore pricing differences at a country level, and
posit how sticky prices or inflation affect pass-through. I follow a similar division, and explore micro factors that affect pass-through in section 4.2 and macro in section 4.3.

In section 4.2 I examine how three sales attributes affect U.S. import pass-through: an item’s uniqueness, its seller volume, and its price. I find that unique items garner a significantly higher pass-through than mainstream, that items from high-volume sellers have a higher pass-through than from low, and that item price has no effect on pass-through.

In section 4.3, I construct pass-through estimates at the country-wide, macro level while maintaining a micro approach. Specifically, I expand my data set to examine import and export pass-through involving a variety of OECD countries. My data is scant, but I provide evidence that import and export pass-through are inversely related. I posit that the greater a country’s currency’s influence on other countries or the world, the lower its import pass-through and higher its export pass-through. Finally I find similar pass-through estimates between a country and a group of countries similar to each other.

2 Literature Review

2.1 Background and Measuring Pass-Through

2.1.1 Background

Economists have studied exchange rate pass-through for over 40 years, and the topic only grows in importance as the world becomes more globalized. The starting point for exchange rate pass-through is the law of one price (LOP). Rogoff (1996) describes what I will call the strict LOP as $P_i = E P_i^*$, where $P_i$ is the price of an item in local currency, $P_i^*$ is the price of the item in foreign currency, and $E$ is the exchange rate in local currency per unit of foreign currency. This expression states that the price of an item should be the same in every country once adjusted for
the exchange rate. Goldberg and Knetter (1996) allow for friction between borders, and expand the model to what I will call the relaxed LOP:

\[ P_i = \alpha E P_i^* , \]  

(1)

where \( \alpha \) represents costs such as transportation and trade barriers. In both cases however, the percentage change of \( P_i \) equals the percentage change of \( E \), all else equal. From here the research follows two paths. The first is to measure the “border effect,” or the price differentials for identical items across national borders (Parsley and Wei 2001); the second to measure the elasticity of \( P_i \) with respect to \( E \), or the exchange rate pass-through. The border effect provides a broader context for exchange rate pass-through so is worth briefly discussing.

It has long been understood that the strict LOP does not hold. For example, Engels and Rogers (1996) show that price differentials between Canadian cities and US cities are much larger than those between two comparable US cities. Crossing the border is equivalent to adding 75,000 miles between them. Parsley and Wei (2001) find an even larger variation between price differentials in cities within Japan and the United States versus cities between the two countries. Finally, Bergin and Glick (2007) gather data worldwide. They measure price dispersion as the mean squared error of the logs of prices between two city-pairs and find that it started at about 0.7 in 1990, bottomed out at 0.4 in 1997, and increased to 0.55 by 2005, in a quadratic shape. Thus prices converged in the 1990s but have diverged since. If the relaxed LOP was true, \( \alpha \) could be elucidated from the border effect and this would be the end of the story. However, research on exchange rate pass-through has shown the relaxed LOP also fails to hold.

### 2.1.2 Measuring Pass-Through
Goldberg and Knetter (1996) define exchange rate pass-through as “the percent change in local currency import prices resulting from a one percent change in the exchange rate between the exporting and importing country.” In other words, it is the elasticity of $P_i$ with respect to $E$. A pass-through coefficient can be found by including exponents on the right hand side variables in the relaxed LOP equation: $P_i = \alpha E^\gamma P_i^\delta$, or taking logs, $\log(P_i) = \log(\alpha) + \gamma \log(E) + \delta \log(P_i^*)$, and using lowercase to denote logs, $p_i = \alpha + \gamma e + \delta p_i^*$. $\gamma$ then, is the exchange rate pass-through coefficient. Campa and Goldberg (2005) caution from following this approach because it is not derived from more basic principles, and using a microeconomic framework they obtain:

$$p_i = \alpha + \delta x_i + \gamma e_i + \phi Z_i + \epsilon_i,$$

(2)

where $p_i$ is the local currency import price, $x_i$ represents the exporter’s costs, $e_i$ is the nominal exchange rate, and $Z_i$ is a vector of controls for the importer like its GDP, with all variables expressed in logs. Goldberg and Knetter (1996) offer an identical model.

Marazzi, Sheets, and Vigfusson (2005) and Marazzi and Sheets (2007) take a slightly different approach. A simplified version of their model expressed in the same terms as above is $\Delta p_i = \alpha + \gamma \Delta x_i + \gamma \Delta e_i + \epsilon_i$. Here they use difference notation, which does not change the estimates, and exclude $Z_i$, which changes them slightly. More importantly, however, they assume the same coefficient in front of $x_i$ and $e_i$. This is equivalent to raising $EP_i^*$ from equation 1 to a single power rather than both individually: $P_i = \alpha(EP_i^*)^\gamma$. Marazzi and Sheets write that $\gamma$ is the pass-through coefficient and captures “the direct effects of exchange rate adjusted foreign production costs on import prices.” They consider pass-through to be the elasticity of import prices with respect to the exchange-rate-adjusted export costs, rather than to the exchange rate alone. They further explain that the constraint is “typically not rejected in the data.” Equating $\gamma$ and $\delta$ makes some sense, because a currency depreciating by 10 percent is theoretically
equivalent to costs increasing by 10 percent, which would lead the producer to increase the price by 10 percent if it had complete control over the price. Whether a producer sets prices is an empirical question, which Goldberg and Knetter’s model ignores.

The authors also experiment with lags in the regression to account for a delayed response of import prices to the explanatory variables. Campa and Goldberg (2005) first run their regression using data from the same quarter, with no lags, and call the resulting $\gamma$ the short-run pass-through. They include lags one-by-one, and find only the first two affect the cumulative pass-through coefficient. They call the coefficient that involves exchange rates over three quarters the long-run pass-through. Marazzi, Sheets, and Vigfusson (2005) agree, and find that the lags have no effect after about two periods.

From a first look then, cumulative exchange rate pass-through increases over time as sellers incorporate changes in the exchange rate into prices over a period of about nine months. The literature reveals this trend through only two estimates: short-run pass-through, which involves exchange rate changes within one quarter, and long-run pass-through, which incorporates exchange rate changes over at least three quarters. While one quarter is short relative to the macro economy, it hides rich variation at a more micro level. One goal of my research is to provide an in-depth analysis of pass-through at time intervals shorter than the literature considers.

So far I have framed exchange rate pass-through in the context of the LOP and cross-country price differentials. I have explained how the literature has thought about pass-through, has measured it, and one area my micro data can increase our knowledge of it. Now it is time for the numbers.
2.2 General Pass-Through Estimates and Theory

2.2.1 General Pass-Through Estimates

Pass-through takes two forms: either import pass-through or export pass-through. Import pass-through is the change in price of a country’s imported goods due to a change in the exchange rate, while export pass-through is the change in price for exported goods. The early literature focuses on import pass-through. Goldberg and Knetter (1996) provide a thorough review for the studies, which estimate a short-run U.S. import pass-through of about 0.55 in the 1980s. Marazzi, Sheets, and Vigfusson (2005) extend the data. Their estimate is 0.5 in the 1980s and about 0.2 from 1995-2005. Gopinath and Rigobon (2008) offer an estimate of 0.22. Campa and Goldberg (2005) concur, and measure both short-run and long-run pass through. They find that across the OECD, the average short run pass-through is 0.61 and long-run 0.77. The United States is an unusual case in that its short-run pass-through is 0.26 and long-run is 0.41. In total, U.S. import pass-through has decreased in the past 30 years and is lower than the OECD average.

Within the past year, researchers have started to measure export pass-through. Amiti, Itskhoki, and Konings (2012) use Belgian firm-level data from 2000-2008 to examine different factors that affect export pass-through. The authors report pass-through by sector rather than for the country as a whole, but weighting the sector estimates by their export shares yields a Belgian export pass-through estimate of 0.31. Berman, Martin, and Mayer (2012), meanwhile, use French firm data and estimate French export pass-through to be 0.92. These numbers are difficult to analyze without comparing them to a corresponding import pass-through calculated in the same way. To my knowledge, only one paper has done so. Choudhri and Hakura (2012) use data from the OECD’s Monthly International Statistics database and the IMF’s International
Financial Statistics database from 1979-2010. They estimate U.S. import pass-through at 0.38 and export at 0.17, Belgian import pass-through at 0.50 and export at 0.48, and French import pass-through at 0.30 and export at 0.11. Their estimates for U.S. import pass-through differ substantially from the previous literature’s, and their estimates for Belgian and especially French export pass-through are quite different than those in the other two papers that examined export pass-through. Measuring export pass-through is a very recent endeavor and the literature has yet to reach a consensus on country-level estimates. Most important in this line of literature is that researchers recognize a country’s import and export pass-through estimates are not equal empirically. Berman, Martin, and Mayer (2012) note that previous “papers find a low level of exchange rate pass-through into import prices, whereas we find a high pass-through into export prices.” Furthermore, Amiti, Itskhoki, and Konings (2012) estimate average import pass-through in the OECD to be 0.60 and export 0.39, and conclude the numbers are statistically different.

2.2.2. General Pass-Through Theory

The literature’s pass-through estimates bring up many interesting questions. Two are intrinsically linked: what is the difference between import and export pass-through, and why are their estimates less than one? Starting at the second question, Campa and Goldberg (2005) explain there is a debate in the literature over whether incomplete pass-through is due to micro or macroeconomic causes. The most important from the former is pricing to market. Krugman (1987) wrote the seminal paper on pricing to market, which means a firm in a foreign market does not adjust prices when its costs change as much as expected under the LOP. The main explanation is that if it is competing with domestic firms, it may be unable to raise the price without losing market share. Campa and Goldberg (2005) call this “local currency pricing”
If a firm follows LCP, then as Goldberg and Knetter (1996) explain, \( \delta=1 \) and \( \gamma=0 \) in equation 2. In the alternative case, producers following “producer currency pricing” (PCP) perfectly pass changes in the exchange rate through the price, which implies \( \delta=\gamma=1 \). In general actual pricing depends both on local competition and the exchange rate, so \( \gamma \) is between 0 and 1, or pass-through is incomplete. This result reveals the danger of Marazzi, Sheets, and Vigfusson’s assumption that \( \delta=\gamma \). Finally, Gopinath, Itskohiki, and Rigobon (2010) show the dichotomy between LCP and PCP by splitting imports based on whether the items are priced in the local or producer currency. They find that pass-through of items priced in the local currency is 25%, while in producer currency is 95%. The former essentially implies LCP while the latter PCP, with drastic differences in the pass-through coefficients.

LCP and PCP are critical to explain the difference between import and export pass-through. In Choudhri and Hakura’s (2012) model, countries have many firms, some of which engage in LCP and some in PCP. The percentage of a country’s firms using each dictates its pass-through. Further, import pass-through is directly related to foreign countries’ share of PCP firms. Conversely, export pass-through is inversely related to the home country’s share of PCP firms. Amiti, Itskohiki, and Konings’ paper contradicts this second tenant of Choudhri and Hakura’s model. They claim that the more a firm’s marginal costs depend on a foreign country’s currency, the lower its export pass-through to that country. Thus the higher a firm’s LCP, the lower its export pass-through, or equivalently, the higher its PCP, the higher its export pass-through. Thus low home PCP leads to low export pass-through, not high. Based on the meaning of PCP, Amiti, Itskohiki, and Konings’ argument is correct. By definition, the more a firm engages in PCP, the more it passes changes in the exchange rate through its prices. Combining the two papers with the correct concept of PCP, higher foreign PCP is correlated with higher
import pass-through while higher home PCP is correlated with higher export pass-through. Neither paper mentions a link between import and export pass-through, however, which I later claim exists.

On the other side of the debate, some authors maintain that macroeconomic causes lead to incomplete pass-through. Devereux and Yetman (2010) conclude that sticky prices are the most important factor. The idea is that if prices do not change often, they cannot adjust to the exchange rate very well. Price stickiness is a documented macroeconomic phenomenon, for example Gopinath and Rigobon (2008) find that the average price duration for imports is 10.6 months, while Fitzgerald and Haller (2008) find it to be 6.6 months. But Gopinath and Rigobon measure pass-through conditioned on a price change and find a rate just as low as in the literature, so conclude price stickiness does not affect exchange rate pass-through.

Inflation is another macro factor that may affect pass-through. For example, Taylor (2000) posits that pass-through has recently been low because most countries have experienced a long period of low inflation. This relates to the issue of price stickiness and Devreux and Engel’s argument: if producers are already changing prices often due to inflation, it is easier for them to pass changes in the exchange rate through the price as well. Campa and Goldberg (2005) show Taylor’s hypothesis does appear to be the case but that the inflation rate has little explanatory power. Gagnon and Ihrig (2004) and Bailiu and Fuji (2004) find greater power, and researchers generally agree the inflationary environment is an important factor that helps determine exchange rate pass-through. In this case pass-through and inflation are intertwined. While the inflation rate affects pass-through, Cunningham and Haldane (2001) explain that pass-through affects inflation through changes in consumer and producer spending based on the new
interest rate. Thus pass-through not only informs theories on international competition and trade but also has an important impact on monetary policy.

To summarize, U.S. import pass-through has decreased from about 0.5 in the 1980s to 0.25 now, and averages 0.6 in the OECD countries. Recent papers have also measured countries’ export pass-through and the estimates vary widely, but are consistently different than their import pass-through estimates. These numbers bring up the questions: what is the difference between import and export pass-through, and why are they incomplete? Explanations to the first are rooted in microeconomic theory around competition and price-setting, specifically the degree to which a country’s firms engage in LCP and PCP. Explanations for the second lie in the same micro theory as well as macro theory, specifically price stickiness and inflation. In this paper I focus on micro phenomenon, although I later extend my data to a larger scale.

2.3 Specific Topics Related to my Research

Following papers about general pass-through estimates and theory, studies has exploded around more specific details of pass-through to test and refine the theory. I mention those related to my research. In section 4.1, I explore how three factors affect pass-through: an item’s uniqueness, the trade volume of the item’s seller, and an item’s price. Several researchers have performed studies in these domains. Two papers that split the data into categories are Campa and Goldberg (2005) and Gopinath and Rigobon (2008). The former divides its data into categories like energy and manufactured items. Unfortunately, eBay users almost exclusively sell manufactured items, so it is difficult to compare the two data sets. Gopinath and Rigobon (2008) is more promising: the authors split their data by the 6-digit harmonized trade code. They show that sellers adjust the price of homogenous products more frequently than that of differentiated. They explain,
since differentiated items sectors “are sectors where elasticity of demand is arguably less affected by the price the firm sets, we should expect to see higher pass-through in those sectors.” This boils back down to the idea that less competition for an item means higher pass-through. In my study, I test the theory by dividing items based on the categories offered on eBay.

I have not found any papers relating prices or a seller’s trade volume to pass-through. However, one does offer results related to trade volume. Berman, Martin and Meyer (2012) show that higher-performance firms exhibit higher pass-through, where performance is measured through labor productivity or total factor productivity. It makes some sense to consider high-volume sellers on eBay as high-performers, so based on Berman, Martin, and Mayer’s study they should exhibit higher pass-through.

Another issue I explore is why the United States’ pass-through rate is lower than that of the other OECD countries. Goldberg and Knetter (1996) hypothesize that the US has a lower pass-through because the dollar is a global currency, so many foreign firms’ costs depend on it. The more that costs depend on the dollar, the less they depend on the local currency and its exchange rate with the dollar, so the lower the exchange rate’s impact on prices. To put it in the context of Amiti, Itskhoki, and Konings (2012) and Choudhri and Hakura (2012), because the dollar is an influential worldwide currency, foreign firms selling to the United States are more likely to exhibit LCP than PCP, causing low U.S. import pass-through.

The papers about low U.S. pass-through complete my survey of the pass-through literature. I briefly turn to a study related to the other aspect of my research: online markets. To my knowledge no one has explored pass-through in an online market. One paper does use an online market to study the LOP, however. Maier (2009) examines price differentials between countries in the European Union. He tracks 16 high-turnover items on eBay over time and
gathers observations on 5,600 transactions, distributed over eight countries. These items include cameras, shoes, printers, and a Harry Potter book. Like the rest of the literature, he finds systematic price differentials across different countries. He complements previous research by showing price differentials exist even between two different countries using the same currency, the Euro. Maier (2009) produces a fruitful study that explores international trade through eBay. This is exactly my goal.

3 Data and Model

3.1 Data

My data comes from eBay, which is one of the world’s largest online retail platforms. According to its website, in 2011 it harbored over 100 million users and $68 billion in sales. Items sold on eBay are very heterogeneous, from $1 trinkets to $10,000 cars. Because of the heterogeneity, items are less standardized than those on sites like Amazon, and most don’t have a product code. Instead they are divided into categories of increasing granularity, from 33 of what the company calls meta categories, to 38,000 leaf categories. Sellers name their items with a title and optional subtitle if they want to provide more information. eBay has also become increasingly international, with separate sites in major countries like Germany and Canada.

My data range from January 1, 2004 to June 30, 2012. Before 2004 eBay did not systematically collect transaction information. I follow the protocol from Einav, Kuchler, Levin, and Sundaresan (2011), which explores auction theory using listings from “seller experiments.” The authors define a seller experiment as a group of listings from the same seller in the same leaf category with identical auction title and subtitle. Then the seller is listing an item multiple times, often with different auction parameters like auction type, or in the case I’m interested in, price. I
use seller experiments but further divide them into mini-experiments lasting at most two months. The idea is that seller attributes like reputation and experience, and macro variables like GDP growth, do not change much over a two-month period. Then the mini-experiments are essentially controlled experiments and do not need control variables in the regression.

Figure 1 provides an example. It represents an experiment with ten observations from January 8 to June 16 of the same year. I cut the two-month tranches starting on an experiment’s first day. So I divide the example into one mini-experiment with four observations from January 8 to March 7, one with four observations from March 8 to May 7, and one with two observations from May 8 to July 7.

To populate experiments I use buyer and seller location, which eBay members enter when they create an account. To measure a country’s import pass-through, I consider transactions between buyers from that country and sellers from other countries, which is analogous to imports. For any specific country, I only analyze transactions in that country’s currency and on its site. With the United States, for example, I recorded experiments from transactions where U.S. users buy in U.S. dollars on the U.S. site. The latter constraint turns out to be important because eBay’s Canada site allows users to sell in dollars. All other sites, however, only allow users to sell in their home currency.

Three caveats come into play. First, I focus only on fixed-price listings, where the seller sets the price the buyer pays. I do so to isolate the price set by the seller, to avoid the effects that auction format might have on the price, and to choose the type of transactions that are more typical offline. Second, listings on eBay contain both a price and shipping fee. I only include listings with a uniform shipping fee rather than one that changes with distance, again to isolate the seller’s price decision rather than worrying about how the buyer’s distance from the seller
affects the price. Third, I only consider listings that resulted in a sale. The constraint eliminates about 30% of my data, but is necessary to reflect actual sales rather than unsuccessful tests. The final piece of the puzzle is the exchange rate data. Luckily eBay stores this as well: it receives daily exchange rates between the United States and major countries from Bloomberg.

In total, I collect mini-experiments consisting of fixed-price sales within a two-month interval of a particular product by a particular user. The sales are in the importing country’s currency and on its eBay site. Finally, I gather daily exchange rate data from eBay, which in turn receives them from Bloomberg.

3.2 The Model

The model is the bare-bones version of the Goldberg and Knetter (1996) and Campa and Goldberg (2005) models: \( p_i = \alpha_i + \gamma e_i + \epsilon_i \). It is simple because the mini-experiments eliminate the need for control variables. It is the bare-bones version of the Goldberg and Knetter (1996) and Campa and Goldberg (2005) models: \( p_i = \alpha_i + \gamma e_i + \epsilon_i \). Within my data, I index mini-experiments with “i” and listings within a mini-experiment with “t”. The actual regression I estimate is:

\[
p_{it} = \alpha_i + \gamma e_{it} + \epsilon_{it},
\]

where \( p_{it} \) is the total price of an item in the home currency (the sum of the item price and shipping fee), \( e_{it} \) is the exchange rate in home currency per unit of foreign currency, and \( \alpha_i \) is the mini-experiment fixed effect. \( p_{it} \) and \( e_{it} \) are expressed in logs. \( \gamma \) then, is the exchange rate pass-through. The regression essentially measures the pass-through coefficient within each mini-experiment and averages them together. The model approaches pass-through differently than previous studies, and its advantages are clear: it is simple, and isolates sales of a product from a
particular user in a short time interval. It avoids noise created by macro variables, to measure the average pass-through of individual items rather than the pass-through of an average bundle of items. It is a micro approach to a phenomenon traditionally examined through macro variables.

The model deserves one qualification. As I do, other studies measure $p_i$ as the price of items in the home currency. This means they include both items sold domestically by foreigners in the home currency as well as items sold domestically by foreigners in the foreign currency, whose prices they convert to domestic currency via the exchange rate. I do not consider the latter set of items. My omission is noteworthy because Gopinath, Itskhoki, and Rigobon (2010) find that pass-through is higher for items sold in the foreign currency. However, the argument is unimportant for items sold to U.S. buyers because as Gopinath and Rigobon (2008) explain, 90% of U.S. imports are listed in dollars. Even when I expand to other countries, my omission is not grave because the sites force users to sell in their home currency. To sell in the foreign currency, producers must sell to home users on the foreign site, which is rare. Gopinath, Itskhoki, and Rigobon explain that producers decide the currency of an item’s price based on which will make it easier to achieve their desired pass-through. But if sellers are forced to sell in the home currency, they should still exhibit their desired pass-through. While the qualification is interesting to think about, it should not affect my results.

4 Results

4.1 Timing of Pass-Through

4.1.1 Monthly Pass-Through

I first measure U.S. import pass-through from the five countries with the largest number of sales on eBay to the United States: Australia, Canada, Germany, Japan, and the United Kingdom,
using all observations from January 1, 2004 to June 30, 2012 that are part of a seller experiment. Table 1 summarizes the data set. The largest number of observations comes from Canada, with nearly 5 million in 800,000 mini-experiments. Germany’s has the smallest, with almost 250,000 observations in 50,000 mini-experiments. For reference, France has the next-largest number of observations from the OECD countries, at 60,000. The average experiment length was about 18 days, with an average of six observations per mini-experiment. Then on average mini-experiments span one-third of the possible 62 days and contain six observations. The medians indicate that the majority of mini-experiments have even lower numbers. Such mini-experiments offer sparse information, which implies that the majority of my results come from a relatively small number of mini-experiments that have a large number of observations.

For the first step of the analysis I divide the literature’s short-run, quarter-long pass-through by month. Specifically, I regress an item’s total price with the average exchange rate for the month in which it was sold, as well as for the two previous months. In the same way the literature measures long-run pass-through by calculating pass-through from the first quarter and two quarterly lags, I measure short-run pass-through by calculating pass-through from the first month and two monthly lags.

To show how I calculated the average monthly exchange rate, suppose a mini-experiment lasts from January 8th to March 7th. I start all my time divisions in the paper on the first day of the mini-experiment. In this case, I divide the mini-experiment into the two months. The monthly lag 0 exchange rate for observations between January 8th and February 7th is the average of the daily exchange rates for that month, and similarly for observations between February 8th and March 7th. Then the only monthly exchange rate variation in a mini-experiment occurs at the divide between the experiment’s first and second month. Next, the monthly lag 1 exchange rate
for observations between January 8th and February 7th is the average of the daily exchange rates between the previous December 8th and January 7th, and so on.

The results from this first regression appear in Table 2. The row with the sum of the pass-through coefficients on the monthly lags of the exchange rate bridges the results with those in the literature. The estimates in it are equivalent to the literature’s short-run U.S. import pass-through. Pass-through from Australia, Japan, and the United Kingdom are about 0.2, while from Canada is essentially zero and from Germany 0.3. Their average is 0.18, and excluding Canada and Germany it is 0.19. These numbers are comparable to the literature’s estimates of about 0.2 to 0.25. Though I’m measuring something difficult to compare directly to the literature’s concept of pass-through, my results are reasonable. That is, on a high level, eBay sellers respond to changes in the exchange rate in a similar way as offline sellers. Then insights I gain from pass-through on eBay are applicable to pass-through in a broader context.

The first insight arises from Canada’s outlier pass-through estimate, which is not significantly different than zero. Why is it so low? One possible answer comes from Goldberg and Knetter (1996). The authors posit that import pass-through is relatively low in the United States compared to other countries because the dollar is a universal currency that affects their costs. Thus a greater dependence on the dollar could lead to lower pass-through. Because Canada is geographically and culturally similar to the United States, it relies heavily on the dollar. In fact, as I mentioned the Canada eBay site is the only foreign site where sellers can list prices in dollars. Perhaps U.S. import pass-through from Canada is so low because Canada’s fate is intertwined with the dollar. As far as I know, this is the first time anyone has mentioned low pass-through into the United States from Canada. I mention a similar occurrence between the United Kingdom and Ireland in the last part of the data section. On the flip side, I cannot
explain the relatively high pass-through from Germany from the data in Table 1. However, I offer a theory in the next section.

Moving from the sum of the monthly pass-through estimates, consider the coefficients on the individual lagged monthly exchange rates. Canada’s are not significantly different from zero in all three months. Australia and Germany’s pass-through starts high in the first month and then declines, while the opposite occurs for Japan and the United Kingdom. Behind the literature’s monolithic estimate of short-run pass-through lies rich variation.

To my knowledge, my monthly pass-through measurement is the first on such a small time scale. But I want to dive in further. Unfortunately, I cannot expand my current method to intervals longer than one month because I would have to expand the mini-experiment length beyond two months, and macro variables would come into play. I also cannot expand it to intervals less than one month because the average exchange rates become highly correlated and my standard errors skyrocket. I can, however, measure pass-through over shorter intervals if I regress total price against only one average exchange rate.

4.1.2 Lag Graphs

I start by considering pass-through due to monthly lags of the exchange rate once again. However, instead of regressing the total price on all the lagged exchange rates at once, I regress the total price against each lagged exchange rate separately. An immediate advantage of this method is that I can include pass-through coefficients from more lags without worrying about standard errors. Figure 2(a) contains the results, along with two more lags than in the initial regression.
First note that the pass-through coefficients on the lags from the individual regressions are higher than from the single regression. This makes sense because the exchange rate between nearby months is correlated. For example, the pass-through coefficient on Germany’s monthly lag 1 exchange rate is about 0.16 from its corresponding individual regression and 0.12 in the single regression. The first number is higher because the individual regression attributes some of the pass-through effect of the first month onto the second. In this way the magnitude of the pass-through estimates in the lag graphs are inaccurate, because they do not represent the change in an item’s price due solely to a change in the relevant lagged exchange rate. This is exactly the reason I switched to individual regressions, because high correlation makes it difficult to weed out the effect of the exchange rate of two nearby periods. It is only the trends I am after.

While the magnitude of pass-through estimates in the individual regressions are inaccurate, the trends are not. For example, consider Germany again. According to the single regression, pass-through starts high and decreases for about two lags of the exchange rate. The lag graph shows the same pattern. Now consider Japan. The single regression shows that pass-through starts low and increases up to the coefficient on the monthly lag 2 exchange rate. But the lag graph shows more: it shows that the coefficient peaks at monthly lag 2 before dropping to zero for the subsequent months. In fact, for all the countries other than the United Kingdom, pass-through reaches zero within the margin of error by monthly lag 4. Matching the literature, pass-through is generally strongest in the first quarter and then decreases. But the literature’s sole estimates of short-run and long-run pass-through mask heterogeneity in the data, and U.S. import pass-through from the United Kingdom is strong even based on the exchange rate four months prior. Note in this case that a pass-through estimate of zero from an individual
regression is meaningful because the pass-through due to the lagged exchange rates around the particular month must be near zero.

Now that I’ve introduced the concept through the monthly version, consider the lag graphs of pass-through based on the average weekly and the daily exchange rates. The graphs are in figures 2(b) and (c). I’ve included lags up to eight weeks in the weekly graph and 28 days in the daily. To calculate the average weekly exchange rates, I divided mini-experiments into weeks as I did months, except into nine 7-day weeks rather than two months. For the daily results I took no averages and simply used the exchange rate for the relevant day.

The weekly lag graph serves as a gateway to the daily version. For example, examine weeks four to eight in the weekly Japan graph. Pass-through actually increases over this period. This increase coincides with the spike in the monthly Japan graph at monthly lag 2. Now consider the weekly Canada graph. Pass-through peaks around the second or third week. This corresponds to the peak in the daily Canada graph between about days 12 to 20. Then the first month in the weekly graphs summarizes the shape of the daily graphs, while the second hints at the trend in the monthly graphs.

The daily graph for each country is distinctive, but each contains a general pattern. First, the correlation between total price and the exchange rate is generally not highest on the day the exchange rate changed. The peak pass-through ranges from day 0 in Germany to day 16 in Canada, with an average of 7. Thus it appears prices react the strongest to daily changes in the exchange rate about one week after it changes. This pattern offer insight into how people behave on eBay, and perhaps in general. It takes time to recognize and respond to a change, and the delay suggests that sellers run through their wares in a cycle, about once per week. It is interesting because even though the length of a week is arbitrary, people seem to use it to form
their habits. The second discernible pattern is that the lagged pass-through diminishes over time. This makes sense, because after a few weeks, daily changes in the exchange rate should have little effect on the price. Pass-through does not necessarily drop to zero, however, because the daily exchange rate is still correlated with the weekly and monthly rates that subsume it.

To summarize, I started this section by taking a closer look at the literature’s short-run pass-through by measuring the pass-through coefficients due to the exchange rates of each month within the first quarter of a price change. I found short-run pass-through estimates comparable to those in the literature as well as rich variation in the pattern of pass-through within the first three months. The estimates for U.S. import pass-through from Australia and Germany decreased then increased, and for Japan and the United Kingdom increased then decreased. The estimate from Canada stayed at zero throughout, which I posited was due to the dollar’s strong influence on its firms’ costs. Next I moved away from a single regression involving lagged exchange rate averages to individual regressions for each lagged exchange rate in order to graph trends in the monthly, weekly, and daily data. At the monthly level I found U.S. import pass-through decreased to zero from all countries but the United Kingdom by the fourth monthly lag of the exchange rate. I generated weekly lag graphs which served as a bridge to the daily graphs. With the latter I found pass-through due to daily changes in the exchange rate peaked around the seventh day, and then diminished as the day-to-day changes became less important than the long-term trends. My daily lag graphs lead me to the baseline I use to explore pass-through beyond the time trends. I introduce the baseline as my standard pass-through measurement in the next section, and use the baseline to answer new questions about pass-through in sections 4.2 and 4.3.

4.1.3 A Baseline Measurement of Pass-Through
The purpose of my baseline is to generate a standard pass-through measure that I can use to compare different sets of data. For the baseline I use the daily lag 0 pass-through presented in Figure 3(c). The reasons are two-fold: first, this estimate sports the lowest standard error of the pass-through measures I’ve introduced. This becomes especially important when I use the baseline to examine smaller data sets. Second, the baseline is also the simplest of my measures because it only uses estimates eBay provides and involves no extra calculations. The main disadvantage is that the numbers are less meaningful than the ones from my initial single regression, but this is less important because I only plan to compare relative magnitudes. The baseline results are in Table 3(a). The U.S. import pass-through is 0.083 from Australia, 0.017 from Canada, 0.198 from Germany, 0.063 from Japan, and 0.095 from the United Kingdom. All are significantly different than zero at the one percent confidence level.

Before I use it to analyze new data, I confirm the baseline technique is unbiased. First I considered two other ways to divide mini-experiments. For the first alternative I followed the same protocol as the baseline but split experiments into one-month-long mini-experiments rather than two. This method could lead to a different result with statistical significance if macro variables and other long-term factors creep into the longer mini-experiments, which would affect those in the baseline more than in the one-month partition. However, none of the results between the one-month partition and baseline are statistically different at the 5% level, so macro variables do not seem to affect the baseline. In the second alternative, I split the 8.5-year sample region into 8-week blocks by calendar week. Instead of dividing seller experiments into mini-experiments starting on the first day of the experiment, I divided them by the 8-week blocks. I did this to ensure I was not splitting mini-experiments in a biased way. Again, none of the results between the 8-week partition and the baseline are statistically different at the 5% level.
Finally, the alternative measures yield higher standard errors than the baseline. This occurs because they generate mini-experiments with fewer observations. The baseline technique is a good measure of pass-through because it is unbiased and precise.

I further test the baseline by splitting its results into three separate periods. The first includes the mini-experiments that start from January 1, 2004 to September 30, 2006, the second from October 1, 2006 to July 31, 2009, and the third from August 1, 2009 to June 30, 2012. The magnitudes fluctuate significantly over the years but there is no systematic pattern across countries. The variance is generally highest in the 2004-6 period and lowest in the 2006-9. Except for Australia, this reflects the lower sample size in the first period and higher in the second.

In this section I compared the baseline method for dividing mini-experiments to two others. Additionally I split the baseline results into three periods lasting two years and ten months. I found the baseline technique to be an unbiased and precise measure of my current results, and saw no pattern in the results over time. Thus the baseline technique is a good measure of pass-through for the full span of my data set, and I will use it for the rest of the paper.

4.2 Sale Attributes

Now that I’ve investigated pass-through timing, I take a snapshot with the baseline technique in order to explore other pass-through phenomena. In this section I focus on how three attributes of a sale impact the pass-through of an item. These attributes are the uniqueness of an item, the trade volume of the seller, and the price of the item.

Economic theory predicts that pass-through is higher for more unique items. The intuition is that the more unique the item, the more control the seller has over its price, because
there are less readily available substitutes. If the exchange rate changes, the seller faces relatively low competition in the home country so can change the price by a relatively large amount. In the following analysis I repeat the baseline query but split the results into two categories: mainstream and unique. The first is meant to represent mainstream items a consumer purchases from a retail outlet, and the latter used or handcrafted items someone buys from a boutique store or another person. I divide the groups by eBay’s 33 meta categories, and place 17 in mainstream and 16 in unique. Some divisions are easy to make, for example I place consumer electronics and clothing in mainstream and antiques and collectibles in unique. Others are more difficult, and I search listings on eBay to define its category. I run separate regressions for mini-experiments in which the seller sold an item in the mainstream group, and in the unique group. Table 4 presents the results as well as provides a full list of the categories within each group.

In all cases but Japan, the pass-through in unique items is higher than in mainstream with statistical significance. I cannot explain why Japan’s pass-through behaves differently than in the other countries, and treat it as an outlier. For every country but Japan, U.S. import pass-through is at least four times higher for unique items than mainstream. For Canada and Germany, pass-through for mainstream items is not greater than zero with statistical significance, so the net U.S. import-pass through from these countries is due solely to their unique items. The estimates for Germany are the most divergent, with pass-through of 0.05 for mainstream items and nearly 0.4 for unique. In total, the more unique items in my data display higher pass-through, with the exception of those in Japan.

The percent of total chart also offers interesting information. Items sold from Australia, Canada, and the United Kingdom are about 75% mainstream and 25% unique, while in Germany and Japan are about 55% mainstream and 45% unique. This sheds some light on the relatively
high pass-through for Germany into the United States overall: because Germany has a higher ratio of unique to mainstream items, and the pass-through for unique items is higher, its pass-through should be higher all else equal. The differing unique to mainstream items ratio is not the only reason for Germany’s relatively high pass-through, however, because within each group Germany’s pass-through coefficient is still higher than those of the other countries, except for mainstream items in Japan. In fact the relative pass-through magnitudes within both groups reflect the baseline results, with Germany’s greatest, followed by Australia and the United Kingdom’s, followed by Canada. So the type of item only partially explains differences in U.S. import pass-through between different exporting countries. Splitting the data into different groups leads to interesting insights about my data, which likely carry over into pass-through in general.

   After dividing the data by category, I do so by seller volume. I group the mini-experiments into those where the seller has been a top seller and those where she has not. Being a top seller depends on monthly quantity and estimate of items sold, so has varied over time. According to eBay’s website, it currently requires selling at least 100 items for a total of at least $1000 annually. Splitting the data by whether the seller ever became a top seller between 2004 and 2012 is not perfect. Ideally, I would use whether the seller was a top seller at the time of each sale. However, the closest data eBay provides is the top seller start date, so I divide the groups by whether the seller has a start date or not.

   Economic theory suggests that a higher-volume seller should exhibit higher pass-through. The main reasons are experience, because the seller understands how much she can alter the prices, and the magnitude of the potential gains and losses. Because the seller is dealing with a greater total volume of sales, the total profits and losses from a fluctuation exchange rate is
greater, so she has more incentive to pass the change in the exchange rate through the item’s price. The results appear in Table 5.

The percentages are balanced across countries, with about 60% of sales coming from top sellers and 40% from non-top sellers. Pass-through for top sellers is higher than for non-top sellers with statistical significance in Australia, Germany, and the United Kingdom, and not statistically different in Canada and Japan. In all countries, the size of the difference is smaller than that between mainstream and unique items. For example in the United Kingdom, the pass-through for mainstream items is 0.05 and unique items 0.22, for a difference of 0.17, whereas the pass-through for items sold by non-top sellers is 0.04 and top sellers 0.12, for a difference of 0.08. Thus the data suggest selling a higher volume of items raises pass-through, but to a lesser degree than selling more unique items. Because its effect on pass-through is small and its prevalence is relatively even across countries, being a top seller does not help explain differences in U.S import pass-through between different exporting countries. The important take-away is that the trend in the data matches economic theory of higher pass-through for higher-volume sellers.

For the last split, I divide sales into three price categories, low, mid, and high. Low-priced items cost less than $20, mid between $20 and $99.99, and high at least $100. I actually divide items based on the minimum price within a mini-experiment, so placed mini-experiments with a minimum price less than $20 in the low-priced category, and so on. Here, economic theory suggests higher price items should garner higher pass-through. The reason is the same as the second one for top sellers: the more expensive the item, the greater the magnitude that profits or losses from sales will fluctuate due to changes in the exchange rate, so the greater the pass-through. The results appear in Table 6.
Many individual countries display a pattern. For example, pass-through increases with increasing price in the United Kingdom, with an estimate of 0.084 for low, 0.089 for mid, and 0.131 for high. But the opposite occurs in Germany: pass-through is 0.409 for low, 0.074 for mid, and 0.031 for high. Combined, the data are erratic and the magnitude of an item’s price has no discernible effect on pass-through. This result could arise for several reasons. For example, perhaps $100 items are not perceived as expensive to sellers, because even if the exchange rate changes by 10% for a $100 item, the maximum expected change in revenue from higher pass-through is $10, and the actual change is likely much lower. I could examine even more expensive items, but the evidence would be scant as the percent of total chart shows that on average only about 10% of the items sold for $100 or more. Or following behavioral economics, people might actually think in percentage rather than absolute terms for individual items, so are not more sensitive to the exchange rate at higher prices. Whatever the case, it appears that within the parameters of eBay’s marketplace, price doesn’t have an effect on pass-through.

Finally, the discrepancies like Japan’s opposite trend for unique and mainstream items compared to the other countries, or the price effect’s divergence from economic theory, could be due to confounding factors I just analyzed. For example, perhaps high-priced items are typically less unique, so even if they do yield a higher pass-through, the lower pass-through due to being mainstream may cancel out the effect. To account for such possibilities I consider cross-divisions between multiple groupings, for example splitting countries into four categories: top seller-unique, top seller-mainstream, not top seller-unique, and not top seller-mainstream. This line of analysis does not change any results or offer new insights, however, and the standard errors ballooned, so I do not present the data.
In this section, I cut the baseline into two or three slices based on different sales attributes. I found that sales of more unique items and from higher-volume sellers yielded higher pass-through than their counterparts, in conformity with economic theory. While theory predicts higher-priced items should yield higher pass-through, I found no such effect. Throughout the paper I have explored U.S. import pass-through. Though I have only brushed the surface of interesting pass-through phenomena to uncover with sales into the United States, I want to explore differences between pass-through involving other countries and expand my analysis to a broader context.

4.3 Import, Export, and Country-Pair Pass-Through with Other Countries

This part of the paper is ambitious. In it I expand my analysis to a variety of OECD countries. I explore the relationship between import and export pass-through and look for patterns in pass-through estimates for individual country pairs. My evidence is scant but important because it adds to a new line of inquiry in the literature.

First, there is a data problem. While the U.S. eBay site is popular, those in other countries are much less frequented. To expand the data set, I consider all OECD countries that have eBay sites. This is important because beside in Canada, eBay only allows users to post listings in the home currency of each site. To study pass-through into, for example, Poland, I look at sales in New Zlotys, which only occur on the Polish site. The OECD countries that have eBay sites are Australia, Austria, Canada, France, Germany, Italy, Ireland, the Netherlands, Poland, Switzerland, the United Kingdom, and the United States. Japan, interestingly, does not have a site that users can sell from. My second step was to measure pass-through between these countries using the baseline measure. Many of the estimates have large standard errors or few
observations, so I focus only on import pass-through for Australia, the United Kingdom, and the United States, and export pass-through for Australia, Canada, the United Kingdom, and the United States. The data for other countries are sparse and sporadic, so contain little meaning.

Table 7 presents the results. For reference, consider the row labeled “US.” Its numbers for Australia, Canada, Japan, Germany, and the United Kingdom are the baseline estimates. Thus I am measuring import pass-through for the column countries. Conversely, I am measuring export pass-through into the row countries. Most of the related literature has focused on import pass-through. The estimates they report match those on the right margin of Table 7. Recent studies like Berman, Martin, and Meyer (2012), Amiti, Itskhoki, and Konings (2012), Choudhri and Hakura (2012) have examined export pass-through, and the estimates they report match those on the bottom margin of the table. As far as I know, no one has reported results that fit into a grid like mine, which reflects country-pair pass-through. For example, the box for the row labeled “France” and column “Australia” indicates pass-through from Australia into France, and makes up Australia’s contribution to France’s import pass-through and France’s contribution to Australia’s export pass-through. I can generate these estimates because my data is at the individual transaction level rather than country level. Throughout the paper I have in fact been analyzing a new type of estimate, specifically country-pair pass-through into the United States from Australia, Canada, Germany, Japan, and the United Kingdom. What does the expanded data set reveal?

Starting at import pass-through, I estimate it to be 0.17 for Australia, 0.02 for the United Kingdom, and 0.11 for the United States. Again, these estimates come from the baseline measure of pass-through so the trends are more meaningful than the numbers themselves. The trend then, is that import pass-through from my data is highest in Australia, followed by the
United States and then the United Kingdom. This compares to Campa and Goldberg’s short-run pass-through estimates of 0.55 for Australia, 0.39 for the United Kingdom, and 0.26 for the United States as well as Choudhri and Hakura’s estimates of 0.63 for Australia, 0.37 for the United Kingdom, and 0.38 for the United States. Considering that other papers estimate a U.S. import pass-through of 0.2 to 0.25, on net the literature finds Australia’s import pass-through highest, followed by the United Kingdom’s and then the United States’. Thus my results are not perfectly in line with those in the literature.

For export pass-through, I estimate Australia’s to be the lowest, at -0.01, followed by the United Kingdom’s at 0.14 and the United States’ at 0.19. This compares to Choudhri and Hakura’s estimates of 0.46 for Australia, 0.25 for the United Kingdom, and 0.17 for the United States. Here our trends are completely different, but the literature estimates are less established. Interestingly, the trend in my export pass-through estimates is opposite the trend in the literature’s import pass-through estimates. This suggests the possibility that there is an inverse relationship between a country’s import and export pass-through. Data from only three countries does not produce enough information to test it, but the prospect is intriguing.

This idea is rooted in Goldberg and Knetter’s (1996) argument: because the dollar is a universal currency, many foreign firms’ costs are denoted in dollars. So changes in the exchange rate with the dollar affect their costs relatively little and do not lead to a large price change. Equivalently from the perspective of the combined Amiti, Itskhoki, and Konings (2012) and Choudhri and Hakura (2012) model I mention in the literature review, foreign firms are more likely to follow LCP when selling to the United States. I claim that Goldberg and Knetter’s argument hold in the reverse direction: if the home country’s currency is influential, home firms are also more likely to price in it when selling abroad, so are more likely to follow PCP. Then
home and foreign firms’ decision to follow PCP is inversely related. Since import pass-through is directly related with the share of foreign PCP firms and export pass-through directly related with the share of home PCP firms, a country’s import and export pass-through are inversely related.

Consider Australia. Of the countries I examine it has the highest import pass-through and lowest export pass-through, essentially at zero. One possible explanation is that because Australia’s economy is relatively focused on minerals and mining, its currency has relatively little world influence. But a country does not need global influence to affect pass-through, it can work locally as well within country-pair pass-through. For example, local influence likely affects pass-through between the United Kingdom and Ireland. The estimate for Ireland’s export pass-through into the United Kingdom is low, actually negative, while the estimate for the United Kingdom’s export pass-through into Ireland high, at nearly 0.6. This reflects the pound’s strong influence on Ireland.

The pattern of pass-through between the United States and Canada as well as United Kingdom and Ireland matches that between Australia and the world. Thus country-pair pass-through is a useful to check to test phenomena at the aggregate level. But such data also allow for more detailed comparisons. Taking Australia again, its export pass-through estimate seems to fall into two groupings. One is around 0.085 for the United Kingdom and the United States and one around 0 for the cluster of countries using the Euro, with Canada’s too difficult to discern. Then perhaps the pass-through from one country to a group countries is similar to each other. Canada’s export pass-through provides further supporting evidence. Estimates cluster around 0 for its pass-through to Australia, the United Kingdom, and the United States, and 0.2 for its pass-through to the countries that use the Euro. Again, it imparts a similar pass-through
on countries that are similar to each other. One caveat is that country-pair pass-through may be less relevant than currency-pair pass-through. In this case, the clustering of countries that use the Euro might occur because they represent the same currency in a currency-pair pass-through. Nevertheless this does not explain the clustering around Australia, Canada, the United Kingdom and the United States.

In this section I estimated pass-through between a variety of OECD countries. I posited that import and export pass-through are inversely related, that the greater a currency’s influence the lower its country’s import pass-through and higher its export pass-through, and that a country has similar pass-through with a group of similar countries. I explored these ideas with my evidence and introduced the concept of country-pair pass-through to dive deeper into the data. However, I did not perform any statistical tests so cannot comment on my hypotheses’ veracity.

5 Conclusion

In this paper I explored exchange rate pass-through, a topic historically addressed with aggregate variables, using micro data. This approach allowed me to examine the literature’s questions about the micro causes of pass-through in a new way. Specifically, I broke down the literature’s finest time division of pass-through, quarterly pass-through, into smaller intervals to view monthly, weekly, and daily trends. I investigated how three micro phenomena mentioned in the literature affect pass-through. Lastly, I explored pass-through on a larger scale by estimating import and export pass-through for a variety OECD countries and drawing insights from these estimates.

I have only touched on a few of the theories data from eBay and similar platforms could address. Others are whether an environment with greater exchange rate volatility leads to greater
pass-through, whether pass-through occurs only after changes in the exchange rate exceed a certain threshold, and how the demand for an item changes when the price of a substitute item changes. These ideas lead to the broader concept of pricing decisions that underlies pass-through. When and how often do producers change prices? Do they do so regularly, at the beginning of each week, month, or year? Or do they mainly change prices after a shock? This is just a taste of questions related to my paper that future research could address. Further, research outside online markets would benefit my findings, especially those in section 4.3.

Using big data in research has both advantages and disadvantages. One advantage, running as the theme of my paper, is that it allows exploration of topics at a finer level of detail than in the past, which can lead to new insights. Additionally, it is flexible, and is easy to divide to test different theories, as I did with sale attributes. This feature of big data is also dangerous, however, because small changes in the method of division can lead to large changes in the results. In this paper I try to justify my results as much as possible, for example comparing the baseline division to two alternative divisions. But small changes in how I determined the groups in Section 4.2 changed the numbers noticeably, and my method for pruning Table 7 was somewhat arbitrary. I used my best judgment, and chose the groups to stay true to their meaning, and only cut results when they offered no information. Researchers must be careful not to massage big data to fit into their desired results. Finally, as seen Section 4.3, big data can actually be quite limiting. It is restricted only to advanced economies, and within those only to data that the government or companies collect for their own purposes. While it exposes details, it is less successful at showing the big picture. Researchers should keep in mind big data’s advantages and disadvantages as they consider using it in the future.
References


Figure 1: Seller experiment divided into mini-experiments

My data makes use of seller experiments, or sets of sales where the seller, leaf category, and auction title and subtitle are identical. Above is an example experiment consisting of 10 sales from January 8th to June 16th. I divide each experiment into mini-experiments lasting at most two months. I would divide the above experiment into a mini-experiment consisting of four observations from January 8th to March 7th, a mini-experiment consisting of four observations from March 8th to May 7th, and a mini-experiment consisting of two observations from May 8th to July 7th.
For this figure I calculate U.S. import pass-through from Australia, Canada, Germany, Japan, and the United Kingdom. To do so I choose all mini-experiments on the United States eBay site where the transaction currency is dollars, the seller is from the relevant foreign country, and the buyer is from the United States. I calculate the lagged monthly exchange rates for each mini-experiment and regress the total item prices (the sum of their price and shipping fee) on each lagged rate separately. Consider the monthly lag 2 regression for a mini-experiment lasting between January 8th and March 7th. For each observation between January 8th and February 7th, the lagged exchange rate is the average exchange rate between November 8th to December 7th, while for each observation between February 8th and March 7th, the lagged exchange rate is the average exchange rate from December 8th to January 7th. Finally, I graph the estimates from the monthly lag 0, 1, 2, 3, and 4 regressions along with their 95% confidence intervals.
Figure 2(b): Pass-through weekly lags

This figure is similar to 2(a) except I run separate regressions for each weekly lag rather than monthly lag. Each mini-experiment is then split into nine weeks rather than two months. I graph the estimates and confidence intervals from the weekly lag 0-8 regressions. U.S. import pass-through peaks on daily lag 4 from Australia, 16 from Canada, 0 from Germany, 8 from Japan, and 8 from the United Kingdom.
Figure 2(c): Pass-through daily lags

This figure is similar to 2(a) and 2(b) except I run regressions for each daily lag. Each mini-experiment is split into 59-62 days, corresponding to its length. I graph the estimates and confidence intervals from the daily lag 0-28 regressions.
The pass-through measurement I use for the rest of the paper is the estimate from the daily lag 0 regression. In this figure I split the baseline for each country into three time periods: mini-experiments starting on January 1, 2004 to starting on September 30, 2006, on October 1, 2006 to on July 31, 2009, and on August 1, 2006 to on June 30, 2012. The periods approximately divide the 8.5 years of data into three segments of two years and ten months, although the divisions are not exact because some mini-experiments overlap either the first and second or second and third segments. The chart reveals the number of observations for each period within each country.

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>Germany</th>
<th>Japan</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan. 2004 – Sep. 2006</td>
<td>170,000</td>
<td>1,500,000</td>
<td>70,000</td>
<td>50,000</td>
<td>170,000</td>
</tr>
<tr>
<td>Oct. 2006 – July 2009</td>
<td>140,000</td>
<td>1,800,000</td>
<td>70,000</td>
<td>160,000</td>
<td>530,000</td>
</tr>
<tr>
<td>Aug. 2009 – June. 2012</td>
<td>150,000</td>
<td>1,500,000</td>
<td>90,000</td>
<td>140,000</td>
<td>510,000</td>
</tr>
</tbody>
</table>
Table 1: Summary statistics

<table>
<thead>
<tr>
<th>Country</th>
<th>Observations</th>
<th>Mini-Experiments</th>
<th>Average Days per Mini-Experiment</th>
<th>Median Days per Mini-Experiment</th>
<th>Average Observations per Mini-Experiment</th>
<th>Median Observations per Mini-Experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>460,000</td>
<td>60,000</td>
<td>18</td>
<td>10</td>
<td>7.5</td>
<td>3</td>
</tr>
<tr>
<td>Canada</td>
<td>4,9000,000</td>
<td>790,000</td>
<td>20</td>
<td>15</td>
<td>6.2</td>
<td>3</td>
</tr>
<tr>
<td>Germany</td>
<td>240,000</td>
<td>50,000</td>
<td>19</td>
<td>11</td>
<td>5.0</td>
<td>3</td>
</tr>
<tr>
<td>Japan</td>
<td>360,000</td>
<td>80,000</td>
<td>18</td>
<td>11</td>
<td>4.4</td>
<td>3</td>
</tr>
<tr>
<td>UK</td>
<td>1,200,000</td>
<td>180,000</td>
<td>16</td>
<td>7</td>
<td>6.9</td>
<td>3</td>
</tr>
</tbody>
</table>

This table contains summary statistics for the data on U.S. import pass-through by exporting country. The data are collected from fixed-price sales with flat-rate shipping on eBay between January 1, 2004 and June 30, 2012. Figure 1 details how I constructed mini-experiments.

Table 2: Short-run pass-through broken down by months

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>Germany</th>
<th>Japan</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Lag 0</td>
<td>0.094***</td>
<td>0.014</td>
<td>0.175***</td>
<td>0.0499</td>
<td>-0.0254</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.011)</td>
<td>(0.061)</td>
<td>(0.031)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Monthly Lag 1</td>
<td>0.053</td>
<td>0.015</td>
<td>0.121**</td>
<td>0.0399</td>
<td>0.0791***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.011)</td>
<td>(0.061)</td>
<td>(0.031)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Monthly Lag 2</td>
<td>0.024</td>
<td>-0.009</td>
<td>-0.005</td>
<td>0.1261***</td>
<td>0.1375***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.010)</td>
<td>(0.057)</td>
<td>(0.030)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Sum of Monthly Lags</td>
<td>0.172***</td>
<td>0.020</td>
<td>0.291***</td>
<td>0.216***</td>
<td>0.191***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.015)</td>
<td>(0.091)</td>
<td>(0.043)</td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

This table presents U.S. import pass-through estimates by exporting country. Within each country I regress an item’s total price (the sum of its price and shipping fee) on monthly lags of the average exchange rate in a single regression. The sums of the coefficients on the monthly lags are then an approximation for the total pass-through within one quarter. Figure 2(a) details how I calculated the lagged monthly exchange rate. For all the tables, a number followed by “*” indicates it is statistically different than zero at the 10% level of significance, “**” at the 5% level, and “***” at the 1% level.
Table 3(a): Baseline pass-through

<table>
<thead>
<tr>
<th></th>
<th>Day-of Pass-Through</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.083*** (0.022)</td>
</tr>
<tr>
<td>Canada</td>
<td>0.017*** (0.007)</td>
</tr>
<tr>
<td>Germany</td>
<td>0.198*** (0.038)</td>
</tr>
<tr>
<td>Japan</td>
<td>0.063*** (0.019)</td>
</tr>
<tr>
<td>UK</td>
<td>0.095*** (0.012)</td>
</tr>
</tbody>
</table>

This table presents my baseline snapshot of pass-through, which is the daily lag 0 coefficient presented in Figure 2(c).

Table 3(b): Baseline with test for robustness

<table>
<thead>
<tr>
<th></th>
<th>1-Month Partition</th>
<th>2-Month Partition (Baseline)</th>
<th>8-Calendar Week Partition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.067** (0.031)</td>
<td>0.083*** (0.022)</td>
<td>0.103*** (0.032)</td>
</tr>
<tr>
<td>Canada</td>
<td>0.019** (0.010)</td>
<td>0.017*** (0.007)</td>
<td>0.029*** (0.009)</td>
</tr>
<tr>
<td>Germany</td>
<td>0.251*** (0.062)</td>
<td>0.198*** (0.038)</td>
<td>0.253*** (0.045)</td>
</tr>
<tr>
<td>Japan</td>
<td>0.073*** (0.029)</td>
<td>0.063*** (0.019)</td>
<td>0.048* (0.025)</td>
</tr>
<tr>
<td>UK</td>
<td>0.112*** (0.018)</td>
<td>0.095*** (0.012)</td>
<td>0.074*** (0.016)</td>
</tr>
</tbody>
</table>

In this table I re-present my baseline pass-through coefficients, along with coefficients that arise from two alternative methods to divide experiments into mini-experiments. The first divides experiments by one-month intervals rather than two. The second cuts mini-experiments with similar lengths as my baseline but with different start dates. In the baseline the first mini-experiment starts on the first day of the experiment, the second mini-experiment on the first day of the experiment’s third month, and so on. In the alternative method, I divide the 8.5-year interval in which I collected data into approximately 55 eight-week periods, and only start mini-experiments on the first day of one of these periods.
Table 4: Pass-through differentiated by category

<table>
<thead>
<tr>
<th></th>
<th>Mainstream</th>
<th>Unique</th>
<th>Significantly Higher (Lower)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.045*** (0.012)</td>
<td>0.184*** (0.078)</td>
<td>X</td>
</tr>
<tr>
<td>Canada</td>
<td>-0.018** (0.008)</td>
<td>0.091*** (0.014)</td>
<td>X</td>
</tr>
<tr>
<td>Germany</td>
<td>0.053 (0.034)</td>
<td>0.376*** (0.078)</td>
<td>X</td>
</tr>
<tr>
<td>Japan</td>
<td>0.100*** (0.026)</td>
<td>0.018 (0.028)</td>
<td>(X)</td>
</tr>
<tr>
<td>UK</td>
<td>0.051*** (0.012)</td>
<td>0.220*** (0.031)</td>
<td>X</td>
</tr>
</tbody>
</table>

Percent of Total

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>Germany</th>
<th>Japan</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mainstream</td>
<td>76%</td>
<td>73%</td>
<td>58%</td>
<td>53%</td>
<td>75%</td>
</tr>
<tr>
<td>Unique</td>
<td>24%</td>
<td>27%</td>
<td>42%</td>
<td>47%</td>
<td>25%</td>
</tr>
</tbody>
</table>

In this table I split each country’s data into two groups, “mainstream” and “unique,” and calculated their daily lag 0 pass-through, as in the baseline. The first group is meant to represent mainstream items a consumer purchases from a retail outlet, and the latter used or handcrafted items someone buys from a boutique store or another person. I divided the groups by the 33 high-level categories eBay defines for its items, which it calls meta categories. Some divisions were easy to make; for others I had to search listings on eBay. Mainstream contains 17 meta categories: Baby; Books; Business & Industrial; Cameras & Photo; Clothing, Shoes & Accessories; Cell, Phones & Accessories; Computers/Tablets & Networking; Consumer Electronics; DVDs & Movies; Health & Beauty; Home & Garden; Jewelry & Watches; Pet Supplies; Sporting Items; Tickets; Travel; and Video Games & Consoles. Unique contains 16: Antiques; Art; Coins & Paper Money; Collectibles; Crafts; Dolls & Bears; Entertainment Memorabilia; Everything Else; Gift Cards & Coupons; Music; Musical Instruments & Gear; Pottery & Glass; Sports Mem, Cards & Fan Shop; Specialty Services; Stamps; and Toys & Hobbies. I had the most difficulty categorizing Books and Musical Instruments & Gear, but items sold in the former seemed more institutional while in the latter more eclectic. In the top chart’s rightmost column I mark whether, within each country, the pass-through coefficient for at least one group is statistically different than the other at a 95% confidence level. Finally, the bottom chart presents the percentage of observations that fall into each group by country.
Table 5: Pass-through differentiated by sale volume

<table>
<thead>
<tr>
<th></th>
<th>Top Seller - No</th>
<th>Top Seller - Yes</th>
<th>Significantly Higher (Lower)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>-0.010 (0.024)</td>
<td>0.117*** (0.028)</td>
<td>X</td>
</tr>
<tr>
<td>Canada</td>
<td>0.026** (0.011)</td>
<td>0.015* (0.008)</td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>0.149*** (0.044)</td>
<td>0.247*** (0.062)</td>
<td>X</td>
</tr>
<tr>
<td>Japan</td>
<td>0.051 (0.033)</td>
<td>0.071*** (0.023)</td>
<td></td>
</tr>
<tr>
<td>UK</td>
<td>0.039** (0.019)</td>
<td>0.121*** (0.015)</td>
<td>X</td>
</tr>
</tbody>
</table>

Percent of Total

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>Germany</th>
<th>Japan</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Seller - No</td>
<td>28%</td>
<td>32%</td>
<td>49%</td>
<td>37%</td>
<td>41%</td>
</tr>
<tr>
<td>Top Seller - Yes</td>
<td>72%</td>
<td>68%</td>
<td>51%</td>
<td>63%</td>
<td>59%</td>
</tr>
</tbody>
</table>

I follow the same method in this table as in Table 4 except I divide data in each country by whether the seller has ever been a top seller. More specifically, eBay records the date a user becomes a top seller, so if a mini-experiment was run by a person with a top seller start date I placed it in the “top seller – yes” group, and if by a person without a top seller start date in the “top seller – no” group. Being a top seller depends on monthly quantity and estimate of items sold, so has varied over time. According to eBay’s website it currently requires selling at least 100 items for a total of at least $1000 annually. Again, in the top chart’s rightmost column I mark whether, within each country, the pass-through coefficient for at least one group is statistically different than the other at a 95% confidence level. The bottom chart presents the percentage of observations that fall into each group by country.
Table 6: Pass-through differentiated by item price

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Mid</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>0.069 (0.042)</td>
<td>0.097*** (0.010)</td>
<td>0.099*** (0.022)</td>
</tr>
<tr>
<td>Canada</td>
<td>0.024** (0.010)</td>
<td>0.002 (0.006)</td>
<td>0.015* (0.009)</td>
</tr>
<tr>
<td>Germany</td>
<td>0.409*** (0.083)</td>
<td>0.074*** (0.025)</td>
<td>0.031 (0.037)</td>
</tr>
<tr>
<td>Japan</td>
<td>0.088** (0.044)</td>
<td>0.028 (0.018)</td>
<td>0.113*** (0.026)</td>
</tr>
<tr>
<td>UK</td>
<td>0.084*** (0.017)</td>
<td>0.089*** (0.011)</td>
<td>0.131*** (0.023)</td>
</tr>
</tbody>
</table>

Percent of Total

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>Germany</th>
<th>Japan</th>
<th>UK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>52%</td>
<td>64%</td>
<td>46%</td>
<td>38%</td>
<td>65%</td>
</tr>
<tr>
<td>Mid</td>
<td>42%</td>
<td>29%</td>
<td>41%</td>
<td>48%</td>
<td>30%</td>
</tr>
<tr>
<td>High</td>
<td>6%</td>
<td>7%</td>
<td>12%</td>
<td>14%</td>
<td>4%</td>
</tr>
</tbody>
</table>

I follow the same method in this table as in Tables 4 and 5 except I divide data in each country by the price of items sold. More specifically, I considered the minimum total price (the sum of the item price and shipping fee) of items in each mini-experiment. If this price was less than $20 I label the mini-experiment “low price,” at least $20 but less than $100 “mid price,” and at least $100 “high price.” Once again, the bottom chart presents the percentage of observations that fall into each group by country.
Table 7: Pass-through expanded to more countries

<table>
<thead>
<tr>
<th></th>
<th>Australia</th>
<th>Canada</th>
<th>UK</th>
<th>US</th>
<th>Austria</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>Ireland</th>
<th>Japan</th>
<th>Netherlands</th>
<th>Poland</th>
<th>Spain</th>
<th>Swiss</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>—</td>
<td>-0.009 (0.020)</td>
<td>0.186 *** (0.008)</td>
<td>0.116 *** (0.007)</td>
<td>0.340 *** (0.114)</td>
<td>0.255 *** (0.067)</td>
<td>-0.037 (0.060)</td>
<td>0.085 (0.089)</td>
<td>0.352 *** (0.131)</td>
<td>0.409 *** (0.040)</td>
<td>0.217 * (0.131)</td>
<td>-0.100 (0.64)</td>
<td>0.580 *** (0.187)</td>
<td>0.057 (0.065)</td>
<td>0.18</td>
</tr>
<tr>
<td>UK</td>
<td>0.087 *** (0.014)</td>
<td>-0.019 (0.014)</td>
<td>—</td>
<td>0.055 *** (0.006)</td>
<td>-0.056 (0.112)</td>
<td>0.130 *** (0.040)</td>
<td>0.089 *** (0.012)</td>
<td>-0.234 *** (0.054)</td>
<td>-0.183 *** (0.028)</td>
<td>0.070 ** (0.046)</td>
<td>0.103 *** (0.032)</td>
<td>0.016 (0.015)</td>
<td>0.006 (0.043)</td>
<td>0.220 * (0.127)</td>
<td>0.02</td>
</tr>
<tr>
<td>US</td>
<td>0.083 *** (0.022)</td>
<td>0.017 *** (0.007)</td>
<td>0.095 *** (0.012)</td>
<td>—</td>
<td>0.207 ** (0.086)</td>
<td>0.209 ** (0.089)</td>
<td>0.198 *** (0.038)</td>
<td>-0.076 (0.064)</td>
<td>0.208 *** (0.073)</td>
<td>0.063 *** (0.019)</td>
<td>0.012 (0.056)</td>
<td>-0.018 (0.038)</td>
<td>0.092 (0.081)</td>
<td>0.180 (0.131)</td>
<td>0.11</td>
</tr>
<tr>
<td>Canada</td>
<td>-1.011 (0.729)</td>
<td>—</td>
<td>0.206 (0.118)</td>
<td>0.023 (0.043)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>France</td>
<td>-0.069 ** (0.029)</td>
<td>0.160 ** (0.020)</td>
<td>0.069 ** (0.012)</td>
<td>0.109 *** (0.009)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>-0.061 (0.052)</td>
<td>0.216 ** (0.028)</td>
<td>0.155 *** (0.018)</td>
<td>0.165 *** (0.012)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Italy</td>
<td>-0.126 (0.120)</td>
<td>0.185 ** (0.037)</td>
<td>0.087 (0.052)</td>
<td>0.438 ** (0.054)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Ireland</td>
<td>0.283 (0.450)</td>
<td>0.350 (0.358)</td>
<td>0.587 *** (0.180)</td>
<td>0.596 *** (0.232)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Poland</td>
<td>N/A</td>
<td>N/A</td>
<td>0.143 (0.255)</td>
<td>0.138 (0.156)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Spain</td>
<td>0.005 (0.097)</td>
<td>0.402 (0.065)</td>
<td>0.089 (0.050)</td>
<td>0.315 *** (0.046)</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>-0.01</td>
<td>0.15</td>
<td>0.14</td>
<td>0.19</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table presents daily lag 0 pass-through between various OECD countries. The row countries are the importers and the column countries the exporters. Note that the sales occur on the row countries’ sites. To get oriented, consider the squares corresponding to the United States row and column countries of Australia, Canada, Germany, Japan, and the United Kingdom. These are sales to the United States on the US eBay site from the baseline countries, and in fact the numbers are those of the baseline. I included all the OECD countries that have a website on which users can sell items in both the rows and columns. These countries are Australia, Austria, Canada, France, Germany, Italy, Ireland, the Netherlands, Poland, Switzerland, the United Kingdom, and the United States. I choose to keep just the complete rows for Australia, the United Kingdom, and the United States, and columns for Australia, Canada, the United Kingdom, and the United States, because estimates for the other countries had large standard errors or few observations. The initial table was not as large as it might seem because pass-through between any two countries that both use the Euro does not exist. Finally, on the margins of the table I included the average, excluding the highest and lowest estimate, of pass-through for each row and column.