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EXCHANGE RATE PASS-THROUGH TO
U.S. IMPORT PRICES: EVIDENCE FROM
THE WINE MARKET

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WORKING PAPER No. 23

EXCHANGE RATE PASS-THROUGH TO U.S. IMPORT PRICES:
EVIDENCE FROM THE WINE MARKET

by

Patricia A. Robinson

A thesis submitted in partial fulfillment of the requirements
for graduation with Honors in Economics–Mathematics.

Whitman College
2009

Certificate of Approval

This is to certify that the accompanying thesis by Patricia A. Robinson
has been accepted in partial fulfillment of the requirements
for graduation with Honors in Economics–Mathematics.

Karl Storchmann, Ph.D.

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May 11, 2009

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Abstract

This paper investigates exchange rate pass-through in the United States market for imported wine. Exchange rate pass-through (ERPT) is defined as the percent change in the price of an imported good due to a one percent change in the exchange rate. The goal of the analysis is to determine the extent and timing of exchange rate pass-through for various countries, wine types, and price brackets in the U.S. wine market.

In the spirit of Wheeler (2004), we first employ a static, fixed effects model to quantify ERPT for each country. Though some of the results of this model are consistent with economic theory, the time-series nature of the data gives reason to doubt the soundness of this static specification. We expect that pass-through will affect prices across a number of time periods, requiring the implementation of a true dynamic model. Thus, we introduce a distributed Koyck lag model and a generalized method of moments estimator to obtain more robust results.

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Until recent years wine was with us, we were the centre, the unavoidable reference point. Today, the barbarians are at our gates: Australia, New Zealand, the USA, Chile, Argentina, South Africa.

— French Ministry of Agriculture, 2001

1 Introduction

Every country that opens its economy to the rest of the world must decide whether it will adopt a fixed or flexible exchange rate regime. The collapse of the Bretton Woods system of fixed exchange rates in 1971 changed the state of the international economy. Countries switched to flexible exchange rates, and academic interest in open macroeconomic theory escalated. The widespread adoption of floating exchange rates represented a hope that international markets would settle at their natural equilibria. However, nominal exchange rates have remained highly volatile. Furthermore, exchange rate fluctuations do not always move in accordance with the state of the economy: a change in the exchange rate is not always matched by a proportional change in prices. This phenomenon is known as incomplete exchange rate pass-through.

Exchange rate pass-through (ERPT) refers to the degree to which prices of traded goods reflect changes in the exchange rate between the trading countries (Menon 1995).¹ Exchange rate pass-through has been a topic of academic interest since the 1970s. However, no published study uses disaggregate data from the wine industry to analyze exchange rate pass-through. This paper seeks to fill that gap and provide a useful analysis of ERPT for the increasingly global wine industry. In particular, how much are exchange rate shocks reflected in import prices? Who bears the burden of this kind of shock? We use econometric analysis to determine the degree of pass-through to imported wine prices in the United States. The results provide insight into the structure of the wine market. This information contributes to the body of ERPT literature, and it may also serve as a valuable resource for producers of both foreign and domestic wine.

Section 2 gives an overview of the literature on exchange rate pass-through. The purpose of this section is two-fold: first, it provides reference to a number of previous studies that form the backbone of the empirical work in this paper; second, it presents some current and complex issues in exchange rate pass-through research. Section 3 gives a brief overview of the fundamental economic theory related to exchange rate pass-through. In Section 4, we develop and present results of the empirical model, beginning with a description of the data, specification, and methodology, and ending with

¹Hereafter the terms exchange rate pass-through (ERPT) and pass-through are used interchangeably.

the results and their implications. Section 5 concludes with a summary of the findings and offers suggestions for future study of ERPT in the wine industry.

2 Presentation of Related Literature

Existing literature on the relationship between goods prices and exchange rates deals primarily with three levels of theory: the law of one price and purchasing power parity², incomplete pass-through, and pricing-to-market. The law of one price lays the theoretical foundation for complete exchange rate pass-through. In a comprehensive study of commodity price data across seven centuries, Rogoff, Froot and Kim (1995) find that the law of one price is not supported by empirical data, neither historically nor today. In spite of free trade and lower transportation costs, prices in the goods market continue to deviate from the law of one price. Goldberg and Knetter (1997) note the consistent rejection of the law of one price with empirical evidence.

In accordance with the rejection of the law of one price, empirical research shows that exchange rate pass-through is incomplete across most industries. Economists have developed a variety of models to determine ERPT values and explain the degree of pass-through. For example, Feenstra, Gagnon, and Knetter (1996) use a Bertrand differentiated products model to show that

²The law of one price states that identical goods must be sold for the same real price regardless of location or currency. The extension of the law of one price to the concept of purchasing power parity and the implications of these ideas are further discussed in Section 3.

international automobile firms with large market shares tend to have high pass-through values. Lee and Tcha (2005) report similar findings for the sheep meat industry, in which a large market share leads to more complete pass-through. Their analysis uses a double-log specification with instrumental variables to examine the pass-through elasticity of sheep meat exports from Australia and New Zealand. In another study of the automobile market, Banik and Biswas (2007) employ cointegration techniques and find that low price competition leads to high pass-through values. Brissimis and Kosma (2007) extend a simple law of one price regression to a Cournot model in order to analyze the market power of Japanese firms in U.S. markets. Hellerstein (2008) uses data from the beer market to conduct a welfare analysis of ERPT. Her results suggests that foreign manufacturers generally bear more of the burden of a change in the exchange rate than do domestic consumers, manufacturers, or retailers.

Trends in exchange rate pass-through are visible across many models and industries. Menon (1995) provides an excellent survey of both the theoretical and empirical literature on exchange rate pass-through up to the mid-1990s. Although economists continue to develop new models and debate the exact mechanisms of ERPT today, there exists a wide body of evidence for incomplete pass-through of exchange rate shocks to prices in the goods market. Further research, especially at the disaggregated product level (Menon 1995), will help solidify theories about the sources and welfare implications of incomplete exchange rate pass-through.

Much of the ERPT literature focuses on a situation called *pricing-to-market* to explain the cause of incomplete pass-through. Paul Krugman coined the term pricing-to-market in the mid-1980s, describing it as “the phenomenon of foreign firms maintaining or even increasing their export prices to the US when the dollar rises” (Krugman 1986). Pricing-to-market may be a cause of incomplete pass-through in some cases, but not in all. In particular, pricing-to-market cannot exist under the assumption of perfect competition because foreign firms do not have the power to set their export prices. In fact, Krugman (1986) makes a point of using the wine market as a counter example of pricing-to-market. An appreciation of the U.S. dollar would make French wine cheaper in the United States and therefore encourage U.S. citizens to buy more French wine. Krugman (1986) argues that “if the US market is a significant share of French demand, this will drive up the price of wine in francs” and as a result, French wine prices will not fall as much as the dollar appreciates. This outcome is considered a case of incomplete exchange rate pass-through, but it is not caused by pricing-to-market, in which producers adjust export prices following an exchange rate movement. Rather, market share plays a key role in determining the degree of exchange rate pass-through.³

A recent and controversial topic in the ERPT literature is the change in pass-through values over time. Marazzi and Sheets (2007) present evidence of

³For his seminal work on pricing-to-market theory, see Krugman (1986). For examples of empirical applications of pricing-to-market, see Knetter (1989), Gron and Swenson (1996), Gaulier, Lahrèche-Révil, and Mèjean (2008), and Goldberg and Hellerstein (2008).

a significant decline in exchange rate pass-through to U.S. import prices since the 1970s. They find a decline in ERPT estimates from values above 0.5 in the 1970s and 1980s to values as low as 0.2 in the 21st century. They attribute this in part to global changes such as the rise of competition from China; they also suggest that U.S. imports now include fewer material-intensive goods, which could contribute to such a decline. Campa and Goldberg (2005) do not find robust evidence of declining ERPT to U.S. import prices, but they do present evidence of a slight decline in ERPT to aggregate import prices in other OECD countries due to changing import baskets. In a study of imported French wines, Wheeler (2004) finds ERPT coefficients of 0.73 and 0.50 for the ten-year periods beginning in 1970 and 1993, respectively, which also suggests a decline in exchange rate pass-through. The growing body of literature that addresses changes in ERPT over time demonstrates that the pass-through phenomenon continues to be a dynamic topic of research.

As the body of ERPT literature grows in new directions, this study contributes in important ways. First, this paper seeks to extend the work done by Wheeler (2004) in estimating ERPT values for wine prices. We contribute a new set of data and more detailed estimations of variations across countries, wine types, and price brackets. Second, the wine industry continues to grow both domestically and abroad. The global wine market presents a fascinating playground upon which to analyze pricing patterns and market structure. Finally, Menon (1995) notes that only a few studies use disaggregated product-level data. He explains the problems associated with price proxies

and aggregate data that are apparent in previous studies, and suggests that future research focus on disaggregate data. The difficulty in obtaining this kind of data is undoubtedly the reason that so few studies employ it. The availability of U.S. wine prices under certain state liquor laws makes the wine market a particularly unique avenue for studying ERPT, as described further in Section 4.2.

3 Application of Economic Theory

3.1 The law of one price and purchasing power parity

The law of one price states that identical goods must be sold for the same real price regardless of location or currency, assuming perfectly competitive markets and the absence of transportation costs or barriers to trade. The law of one price implies that the dollar price of a French Bordeaux is the same in the United States as it is in France. This is represented mathematically by the equation

$$p_{\$} = E_{\$/\epsilon} \times p_{\epsilon}, \quad (1)$$

where subscripts denote currencies, p is real price, and E is the real foreign exchange rate. Equation (1) states that the U.S. price of a good in dollars ($p_{\$}$) must be the same as the French price of that good (p_{ϵ}) if euros are converted into dollars. In fact, the law of one price says that any homogenous good must have the same dollar price wherever it is sold. The theoretical validity

of the law of one price is made clear by the assumptions of identical goods and zero transportation costs because traded goods will be subject to arbitrage and prices will equilibrate.

A related concept is purchasing power parity, which states that the exchange rate between two countries' currencies equals the ratio of the countries' price levels. Thus, purchasing power parity predicts

$$E_{\$/\epsilon} = \frac{P_{\$}}{P_{\epsilon}}, \quad (2)$$

where $P_{\$}$ is the price of a basket of goods and services in the United States and P_{ϵ} is the price level of the same basket in France. Rearranging this equation yields

$$P_{\$} = E_{\$/\epsilon} \times P_{\epsilon}, \quad (3)$$

which looks similar to the law of one price, as stated in equation (1). The law of one price refers to individual commodities, whereas purchasing power parity extends this idea to the aggregate. In fact, if the law of one price holds for every good, then purchasing power parity necessarily holds. But to be precise, purchasing power parity says that countries' price levels are equal when converted to the same currency. In other words, a currency has the same purchasing power in the domestic market as it does in any foreign market (Krugman 2006).

The statement in equation (2) is known as *absolute* purchasing power parity. Like the law of one price, it assumes that there are no transportation

costs, trade barriers, or other sources of friction in the market. Because these assumptions are unrealistic, absolute purchasing power parity is unlikely to exist in practice. Instead, economists often consider a related proposition known as relative purchasing power parity, which relates *changes* in prices to *changes* in the exchange rate. Relative purchasing power parity states that the percentage change in the exchange rate between two countries' currencies over any time period is equal to the difference between the percentage changes in the countries' price levels over the same time period (Krugman 2006). This proposition provides a bridge between the law of one price, absolute purchasing power parity, and the concept of exchange rate pass-through.

3.2 Definition of exchange rate pass-through

Exchange rate pass-through is defined as the percentage change in domestic price due to a percentage change in the nominal exchange rate.

$$\text{ERPT} = \frac{\% \Delta P_{\$}}{\% \Delta E_{\$/\text{€}}} \quad (4)$$

If ERPT equals one, pass-through is said to be complete. If ERPT is less than one, pass-through is said to be incomplete. In order to discuss varying degrees of exchange rate pass-through, it is useful to begin with the conditions under which we would expect complete exchange rate pass-through—that is, the conditions that would ensure that any change in the exchange rate is matched by an equivalent change in the price of traded goods.

The law of one price and absolute purchasing power parity lay the theoretical foundation for the relationship between prices and the exchange rate, but relative purchasing power parity allows us to consider a more realistic model. Assuming small changes in prices and the exchange rate, we approximate equation (3) using a natural logarithm transformation. This approximation yields the equation for relative purchasing power parity:

$$\% \Delta P_{\$} = \% \Delta E_{\$/\text{€}} + \% \Delta P_{\text{€}}. \quad (5)$$

Equation 5 states that the percentage change in the domestic price level over any time period equals the sum of the percentage change in the exchange rate between two currencies and the percentage change in the foreign price level over the same time period. For example, if French prices are held constant, then a real depreciation of the dollar against the euro leads to an increase in U.S. prices for French imports of the same percentage by which the exchange rate rises. This relationship describes complete exchange rate pass-through because $ERPT = 1$ when $\% \Delta P_{\$} = \% \Delta E_{\$/\text{€}}$.

Relative purchasing power parity predicts complete exchange rate pass-through. However, as noted in Section 2, there is strong empirical evidence that exchange rate shocks are not always passed through completely to import prices. Consider again the example of the United States importing French wine. When the dollar appreciates against the euro, French wine becomes cheaper in the United States, so Americans will buy more French wine.

As Krugman (1986) notes, this will drive up the French price in euros if the United States is a significant source of demand. Thus, the domestic price of imported wine will not fall as much as the dollar appreciates. This simple example suggests that the degree of pass-through is likely to depend on a number of factors, including the type of good and the market structure of the trading countries. The empirical analysis that follows attempts to measure the degree and timing of this pass-through for various wines imported into the United States.

4 Empirical Model

This section presents a model of exchange rate pass-through from a number of different angles. Section 4.1 begins with a historical overview of the international wine market, providing a backdrop against which to analyze the empirical results. Section 4.2 describes the sources and structure of the data set. Section 4.3 provides the theoretical groundwork for the empirical model. Section 4.4 presents a static model of exchange rate pass-through, and Section 4.5 introduces a more realistic dynamic approach to measuring exchange rate pass-through for our panel-data model.

4.1 The Wine Market

Civilizations have grown grapes to make wine for more than six thousand years. By the fourth century AD, systematic wine grape cultivation had

been well-established in the Old World. Explorers took grape vines to the Americas as early as the sixteenth century. Although wine-making began as a small, family-centered business, countries all over the world now recognize the potential to make a profit in this expanding, global industry.

The amount of growth in the wine industry is quantified in the *Global Wine Statistical Compendium*, in which Anderson and Norman (2003) present a comprehensive set of comparative international wine statistics. Historically, most wine was produced to satisfy domestic demand, with only 10 percent by volume of global wine production being exported. However, the wine trade has expanded in the last fifty years, with total exports growing to 15 percent of global wine production by 1990 and approximately 25 percent in 2001 (Anderson 2004). The modern international wine market began to flourish with the recent, competitive emergence of New World countries like Australia, South Africa, and the United States. During the past twenty years, these countries have gained significant market power, and their role in the industry has become increasingly prominent.

Table 1 summarizes wine production and consumption by volume for a number of important wine-producing countries. Between 1996 and 2003, New World countries including Australia, Chile and South Africa gained a larger share of global wine production. During that time, Old World countries such as France and Italy not only lost significant shares of global production, but also experienced a reduction in production volume.

The large-scale wine industry in the United States began in the Napa

Table 1: Wine production and consumption by country

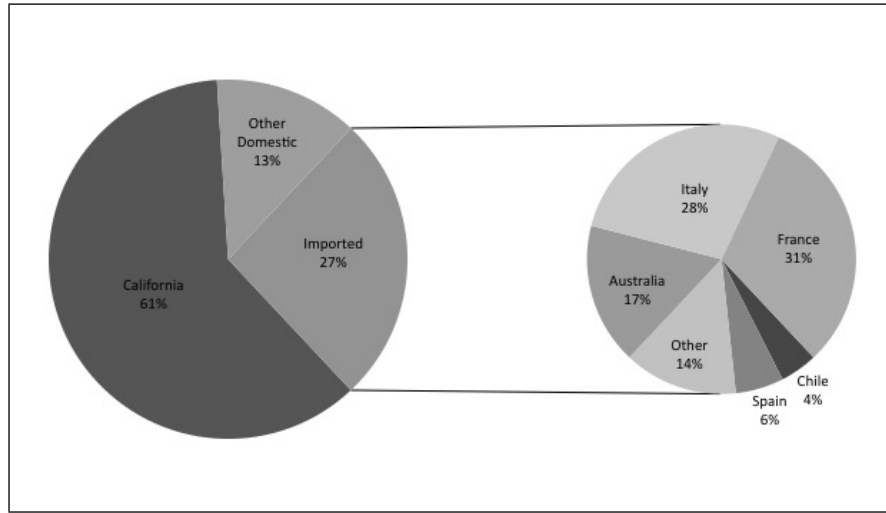
	Production				Consumption		
	1996–2000 [†]		2003		2003		
	Volume	% of total	Volume	% of total	Volume	% of total	per capita
France	56,271	20.8	46,360	17.3	33,340	14.2	54.77
Italy	54,386	20.1	44,086	16.5	29,343	12.5	50.48
Spain	34,162	12.6	41,843	15.6	13,798	5.9	34.16
United States	21,381	7.9	24,156	9.0	24,363	10.3	8.16
Argentina	13,456	5.0	13,225	4.9	12,338	5.2	30.91
Australia	7,380	2.7	10,194	3.8	4,196	1.8	20.71
South Africa	7,837	2.9	8,853	3.3	3,487	1.5	7.89
Germany	9,989	3.7	8,191	3.1	20,150	8.6	24.45
Portugal	6,828	2.5	7,340	2.7	5,290	2.2	49.88
Chile	5,066	1.9	6,682	2.5	2,552	1.1	15.82
Greece	3,832	1.4	3,799	1.4	2,450	1.0	22.92
New Zealand	568	0.2	550	0.2	660	0.3	16.19
World Total	270,826	100	267,441	100	235,458	100	—

Volume is in thousands of hectoliters, and consumption per capita is expressed in liters.

[†] Average values obtained from the years 1996–2000.

Source: *World Statistics* (2007).

Valley of California but has expanded to states across the nation. In recently-developed wine clusters—groups of wineries and firms in related industries such as tourism—the production focus is on premium wines. Some Washington state wineries such as Cayuse Vineyards have received ratings as high as ninety-nine (out of one hundred) from wine critic Robert Parker and do not sell a single bottle of wine for less than \$50. Although the production of premium wines has brought attention to the quality of U.S. wines, it does not



Source: Hodgen 2008.

Figure 1: Origins of wine consumed in the United States, 2007

satisfy the domestic demand for wine, which has been growing significantly faster than domestic supply since at least the early 1990s (Anderson 2004).

In 2007, U.S. wine consumption totaled approximately 24 million hectoliters, more than a quarter of which was imported. Historically, three-quarters of U.S. imports originated in Old World countries, but recently, that share has fallen in the face of competition from New World producers. As illustrated by Figure 1, only 31 percent of U.S. imports by volume came from France in 2007. An additional 28 percent came from Italy and 6 percent from Spain, yielding an approximate total of 65 percent of U.S. imports from Old World countries. The remaining 35 percent came primarily from New World countries, with 17 percent from Australia, 4 percent from Chile, and approximately 2 percent from Argentina and 1 percent from South Africa. A share of 2 percent may seem small, but the United States is the largest

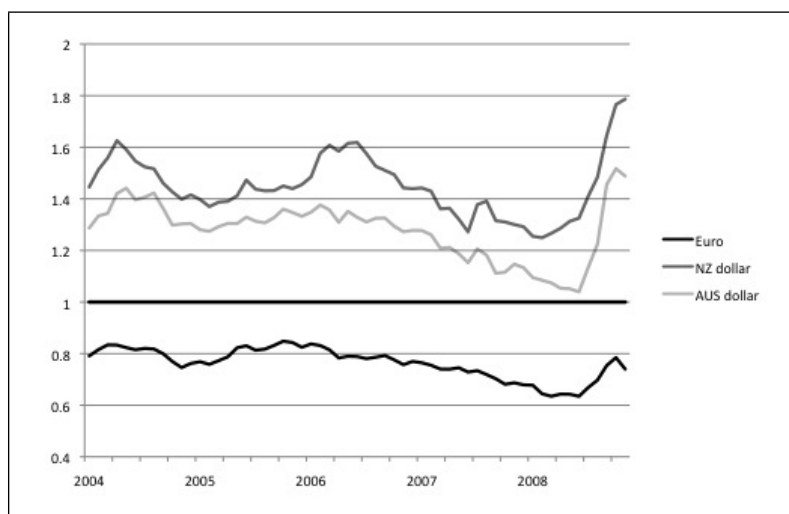
importer of Argentine wine (Anderson 2004). In fact, the United States is arguably one of the largest sources of export demand for many Old and New World countries. As such, it provides a diverse and important market in which to study exchange rate pass-through.

4.2 Data Description

4.2.1 Data sources

The availability of appropriate data also makes the U.S. wine market a suitable market for a study of ERPT. The wine market in the United States is subject to numerous regulations. Following national Prohibition, the 21st Amendment to the Constitution provided states with broad powers and authority to regulate the sale and distribution of alcohol within their borders (in addition to Federal requirements). Each state created its own system of alcoholic beverage control. There are two general classifications: control states and license states. Control states, 18 in number, are the sole wholesalers of distilled spirits. Some control states also act as retailers to various degrees. The remaining 32 license states do not participate in the sale of alcoholic beverages but rather regulate sales by issuing licenses to industry members that do business within their states.

Control states that are engaged in the retail sale of alcohol regularly publish price lists for wine, beer and spirits. The wine data used in this study are from the Utah Department of Alcoholic Beverage Control (DABC).



All exchange rates expressed as foreign currency per US dollar.

Figure 2: Exchange rate history

Each month the Utah DABC publishes a full price list of more than two thousand items sold in the state of Utah. Because Utah, like all control states, stipulates fixed markups on the wholesale price, we can infer the wholesale price from the published retail price.⁴ This wholesale price, which matches the price at the winery, is the best measure of price by which to analyze exchange rate pass-through.

The other critical component of the data set is exchange rate information. Historical records of exchange rates are available from various online sources.

⁴A change in the Utah state legislature in 2007 complicates this slightly. Through June 2007, the “landed case cost” of each wine was marked up by 64.5% plus a 13% wine tax and an “averaged sales tax”. Beginning in July 2007, the markup increased to 86% and did not include any sales tax, which is now added at the place of retail and not included in the prices published after June 2007 (David M. Willis, e-mail message to the author, February 5, 2009). Inadequate sales tax information impeded our ability to accurately account for this in a simple price adjustment, so we use a structural dummy variable to capture this effect.

The exchange rate data used in this study are from the Federal Reserve Statistical Release (Federal Reserve Bank). The reported exchange rate for country i in month m is an average based on the daily noon rates for each day in month m . All exchange rates are expressed as foreign currency per US dollar. The exchange rate histories from 2002 through 2008 of the euro, the New Zealand dollar, and the Australian dollar relative to the US dollar are shown in Figure 2. The darkened line at $y = 1$ represents the US dollar.

4.2.2 Variable description and construction

The Utah DABC Price Books (2008) contains 184,899 observations with the following identifiers: date, product category, cs code, size, case pack, product name, see also, status, cost per ounce, old retail price, new retail price, and comments. The date refers to the month for which the listed retail prices apply and is determined from the name of the file (e.g., 2005_01.pdf refers to the price list for January 2005). The product category is a three-letter code that refers to the wine type and country of origin, such as “Sparkling Wine – Italian”. The cs code is a six-digit code that is associated with a generic product name, but not a specific vintage (year of grape harvest). A single producer may export a product with different vintages and use the same cs code; however, different products from a single producer have different cs codes. Size refers to the capacity of the container in milliliters. Case pack is the number of containers in a case of the product (e.g., a standard 750 mL bottle of wine has a case pack of twelve). The product name is the most

Table 2: Variables

Variable	Description
<i>cscode</i>	Product code that is unique to each wine, not including vintage
<i>winecode</i>	Product code that is unique to each wine, including vintage
<i>year</i>	Year of published retail price
<i>month</i>	Month of published retail price
<i>time</i>	Time of published retail price, 1–47 by consecutive months
<i>exchangerate</i>	Foreign currency of <i>country</i> per U.S. dollar during <i>month</i> of <i>year</i>
<i>price</i>	Nominal price in dollars
<i>country</i>	Country of origin
<i>type</i>	Sparkling, white, blush, rose, or red
<i>vintage</i>	Year of grape harvest
<i>size</i>	Bottle size in milliliters

specific identifier of the listed product. It usually includes the winery name, wine varietal (type of grape), and vintage. The column labelled “see also” may include a second product category under which the wine is listed. The status is a single-character code denoting one of the following seven possible characteristics: general distribution, discontinued general item, special order, regular limited item, limited discontinued, limited allocated product, or unavailable limited item. Cost per ounce is calculated by the Utah DABC and is the current retail price divided by the number of fluid ounces in the container. The old retail price, if listed, is the retail price from the previous month. The new retail price is simply the current retail price for the month. Comments include notes of price increases and decreases.

The final set of variables summarized in Table 2 is generated from the

original DABC identifiers described above. Each observation in the data set is defined by these eleven variables: *cscode*, *winecode*, *month*, *year*, *time*, *exchangerate*, *price*, *country*, *type*, *vintage*, and *size*.⁵ The values of *cscode* and *size* correspond to the original cs code and the bottle size listed in the Utah DABC Price Books (2008). The variable *winecode* is a numeric six- or ten-digit code generated by appending the four-digit vintage (found in the product name) to the cs code. If the wine has no vintage, then *winecode* has the same six-digit value as *cscode* for that observation. We created this variable in order to track each vintage of a particular wine, for quality is often dependent on the year of grape harvest. In fact, the variable *vintage* serves as a proxy for a number of variables including climate, cost, and quality—none of which are explicit in the data set. The variables *month* and *year* simply refer to the date of the price list publication—from January 2005 through November 2008.⁶ It is important to note that *year* is not the same as *vintage*. In fact, the difference between *year* and *vintage* gives the age of the wine—another potentially relevant characteristic. To generate the variable *time*, we simply assign an integer value to each month in succession. Thus, the values of *time* range from 1 to 47.⁷ The variable *exchangerate* contains the foreign exchange rate, as defined in Section 4.2.1, given the values of *country* and

⁵All variable names used in statistical analysis are set in italics throughout the text.

⁶The price list for November 2008 is not included in the Utah DABC Price Books CD (2008), but was downloaded from the Utah DABC website during the month of October 2008. Price information for the month of March 2006 is missing.

⁷Although the values of *time* range from 1 to 47, the variable never takes on the value 15 because there are no observations for the month of March 2006.

time. The variable *price* is the current retail price. Finally, *country* and *type* are categorical variables for the country of origin and wine type, which are determined from the DABC product codes.

4.2.3 Data set structure and summary statistics

There are three conditions that require paring down the data set for the purposes of this analysis. First, the DABC may list wines under multiple categories. For example, a particular French Merlot by Barton & Guestier appears under the category Red Varietal/Merlot and under the category French Red/Varietal in the January 2005 price list. The variables *type* and *country* retain all the information from these categorizations, so we remove one of the duplicate observations without losing any data. Second, some wines are not listed under any specific country category and are therefore not usable in a study of exchange rate pass-through.⁸ Finally, the bottle size is not necessarily proportional to price; for example, a 1500 mL bottle of wine does not always cost exactly twice as much as a standard 750 mL bottle of the same wine. Thus, we choose only those observations for which bottle size is 750 mL. This condition alone still preserves approximately 80 percent of the original data set. After making these changes to the data set, about 68,000 working observations remain. Table 3 lists summary statistics for all the variables after making these adjustments to the data.

⁸Theoretically, one could determine by hand the countries of origin for such observations given the unique product name.

Table 3: Descriptive statistics for all variables

Variable	<i>N</i>	Mean	Median	Mode	St. dev.	Min	Max
<i>cscode</i>	67945	—	—	—	—	—	—
<i>winecode</i>	67945	—	—	—	—	—	—
<i>year</i>	67945	2006.6	2007	2008	1.127	2005	2008
<i>month</i>	67945	6.5	6	11	3.393	1	12
<i>time</i>	67945	25.9	27	47	13.776	1	47
<i>exchangerate</i>	63875	1.060	0.785	—	1.110	0.635	10.111
<i>price</i>	67945	43.94	19.95	—	59.003	0.30	976.89
<i>country</i>	67945	—	—	France	—	0	12
<i>type</i>	67945	—	—	Red	—	1	5
<i>vintage</i>	56278	2002.8	2003	2005	2.326	1990	2008
<i>size</i>	67945	750	750	750	0.000	750	750

A panel model contains both cross-sectional and time-series dimensions.⁹ The data is organized in a panel defined by the variables *time* and *winecode*. The variable *time* defines the time-series dimension of the panel, and the variable *winecode* identifies each unique wine that makes up one of the n cases in the cross-sectional dimension of the panel. As noted above, observations without vintages are still identified by their *winecode*, which takes the same value as the original cs code (held by the variable *cscode*) in such cases. The final data set contains 67,945 observations that span 47 months and 9,646 wines, with gaps.

In anticipation of determining exchange rate pass-through coefficients for each country, we include a table of summary statistics organized by country.

⁹For a visual representation of the panel, see Figure 3 on page 29.

Table 4: Selected descriptive statistics by country

Country	Label [†]	Frequency	%	Mean price
France	1	22,979	33.8	80.35
Italy	2	12,107	17.8	31.50
Australia	12	10,298	15.2	27.07
Spain	3	6,605	9.7	25.90
Domestic	0	3,336	4.9	17.89
New Zealand	11	2,725	4.0	18.30
Germany	4	2,581	3.8	22.77
Chile	9	2,122	3.1	18.87
Argentina	10	1,948	2.9	20.12
South Africa	8	1,912	2.8	17.06
Austria	5	561	0.8	27.07
Greece	7	525	0.8	14.44
Portugal	6	246	0.4	20.28
Total	—	67,945	100	36.99

[†] Assigned arbitrarily for statistical analysis.

Table 4 breaks down the distribution of observations among countries and gives the mean price in dollars of a 750 mL bottle of wine for each country. It is interesting to note that most countries with lower mean prices (less than \$21) are part of the New World—South Africa, New Zealand, Chile, Argentina, and Portugal. France has a mean price of \$80.35, which is more than twice that of Italy, the country with the second-highest mean price of \$31.50.

Finally, Table 5 gives correlation coefficients between important variables. A value of one implies perfect correlation, whereas a value of zero implies no

Table 5: Correlation matrix for key variables

	<i>price</i>	<i>exchangerate</i>	<i>time</i>	<i>vintage</i>	<i>country</i>
<i>price</i>	1.000				
<i>exchangerate</i>	-0.0989	1.000			
<i>time</i>	0.0034	-0.0214	1.000		
<i>vintage</i>	-0.336	0.0910	0.464	1.000	
<i>country</i>	-0.192	0.344	0.0293	0.258	1.000

correlation. For example, the high correlation coefficient between *vintage* and *time* suggests that there is a strong relationship between the age of the wine and the time at which it is sold. We expect *country* and *exchangerate* to be correlated. The negative sign on the correlation coefficient between *vintage* and *price* indicates that older wines tend to have higher prices. Stata's calculation of correlation for categorical variables, such as *country*, is not clearly specified.

4.3 Empirical Framework

The primary question in an analysis of exchange rate pass-through is

Does a change in the value of a foreign country's currency affect the prices charged for imported wines in the United States?

To answer this question, we consider models in which the price of each imported wine is a function of the value of the currency of the country of origin.

$$\text{Price of imported wine} = f(\text{Value of foreign currency})$$

The general regression model given by Goldberg and Knetter (1997) for an ERPT study has the form

$$p_t = \alpha + \delta X_t + \gamma E_t + \psi Z_t + \varepsilon_t, \quad (6)$$

where t refers to the time period, X is a measure of cost, E is the exchange rate, Z denotes other control variables, and ε is an error term. The law of one price and purchasing power parity predict that $\alpha = 0$, $\delta = 1$, and $\gamma = 1$. In other words, if $\gamma = 1$ then exchange rate pass-through is complete, and if $\gamma < 1$ then pass-through is incomplete (Brissimis and Kosma 2007).

Although we do not have data on the cost of production, we assume that cost per acre is independent of climate and depends only on crop yield, which is captured by dummy variables for the vintage, or year of grape harvest (Ashenfelter and Storchmann 2009). We first consider a static fixed-effects specification for each country given by the general form

$$p_{it} = \alpha_i + \gamma E_{it} + \psi Z_{it} + \delta X_i + \varepsilon_{it}, \quad (7)$$

where i refers to the wine, t refers to the month of sale, p is the wine price, E is the exchange rate, Z denotes time-dependent control variables, X denotes independent variables that capture fixed effects, and ε is the error term. The coefficient γ gives the degree of exchange rate pass-through.

In order to truly measure exchange rate pass-through, the model should specify a change in price as a function of a change in the exchange rate. Consider two forms of equation (7), the first in time period t and the second in time period $(t-1)$. For simplicity, we assume E_t is the only time-dependent regressor and α_i captures fixed effects for wine i , so Z_{it} and X_i do not appear in the following equations.

$$p_{it} = \alpha_i + \gamma E_{it} + \varepsilon_{it} \quad (7a)$$

$$p_{i(t-1)} = \alpha_i + \gamma E_{i(t-1)} + \varepsilon_{i(t-1)} \quad (7b)$$

Taking the difference between equation (7a) and equation (7b) yields

$$p_{it} - p_{i(t-1)} = \gamma[E_{it} - E_{i(t-1)}] + v_{it}, \quad (8)$$

which defines a change in price as a function of a change in the exchange rate. Equation (8) has neither a constant term nor the fixed effects denoted previously by α_i because this method isolates the external variables. Note that the term v_{it} now denotes the standard error term.

It is possible that an exchange rate shock is not passed through to import prices immediately. Two, three, or more months may pass before prices reflect exchange rate movement. To account for this possibility, we modify equation (8) to include a simple lag on E_{it} :

$$p_{it} - p_{i(t-1)} = \gamma[E_{i(t-k)} - E_{i((t-k)-1)}] + v_{it} . \quad (9)$$

The variable k can take on values from zero—indicating simultaneous pass-through—to twenty-four—a two-year lag in pass-through. Equation (9) is the best specification for measuring exchange rate pass-through. However, there are a number of ways to estimate the coefficient γ in such an equation, and each has its own tradeoffs. We consider two estimation methods in detail in Sections 4.4 and 4.5.

4.4 Static Panel

One way to determine the ERPT coefficient γ is to estimate a double-log functional form using ordinary least squares (OLS). This method involves estimating the logarithm of *price* using the logarithm of *exchangerate* as a regressor. The double-log specification implies that γ is a constant exchange rate elasticity that measures the percentage change in price due to a percentage change in the exchange rate.

In the spirit of Wheeler (2004), we first estimate the logged dependent

variable *price* for each country using the static model described the equation

$$price = \beta_0 + \beta_1(exchangerate) + \beta_2(time) + \varepsilon_t, \quad (10)$$

where *price* and *exchangerate* are logged, β_0 is a constant term and β_1 is the exchange rate pass-through coefficient in the short-run. The coefficient β_2 captures how prices change over time. Estimating an equation that does not include *time* as a regressor would cause severe omitted variable bias because the nominal variable *price* certainly changes over time.¹⁰

4.4.1 Static panel results for all countries

We must recall the economic theory behind exchange rate pass-through before interpreting the estimation results. In the case of complete pass-through, a currency depreciation should increase the prices of imported goods by the same amount as the depreciation. As noted in Section 4.2, all exchange rates are expressed as foreign currency per U.S. dollar, so a depreciation of the dollar lowers the exchange rate. Thus, we expect a fall in *exchangerate* to correspond to a rise in *price*—in other words, the ERPT coefficient should be negative. Furthermore, previous research provides strong evidence that pass-through is rarely complete, so we expect the absolute value of the coefficient to be less than one.

¹⁰In addition, nominal variables are particularly vulnerable to nonstationarity, which could cause spurious correlation and inflate the *t*-scores. Including the variable *time* in the regression removes the time trend but does not guarantee stationary time-series variables (Studenmund 2006).

The results of estimating equation (10) for each country are summarized in Table 9 (see page 46). The ERPT coefficients vary significantly among countries. Only four of the ten estimates yield negative ERPT coefficients, and only three of those—France, Spain, and Germany—are statistically significant. The erroneous signs in the other estimates suggest a misspecification or other failure in the model. The variable *time* has a statistically significant negative coefficient in all but one of the estimates. This implies that nominal prices for wines from almost all countries have fallen over time. The overall-fit, as measured by the adjusted R^2 , is very high for all but one of the countries; however, the estimates that yield incorrect signs on ERPT coefficients are still troubling.

One potential drawback of using a fixed-effects panel model is that it requires a certain amount of within-group variation to produce meaningful results. This is not a problem as long as the relevant variables take on a number of different values within each group and across time. Consider the schematic illustration of our panel-data shown in Figure 3. The diagram is a conceptual representation of how the data for any single country is organized in a panel. One can imagine that each cell also includes relevant characteristics of each observation in addition to *price* and *exchangerate*. A strong panel would exhibit a large degree of variation in each characteristic (e.g., *price*) within each column. The exchange rate certainly varies across time, as illustrated in Figure 2. However, *price* does not always exhibit a high degree of fluctuation. Most wines in our dataset are not sold in every

	$winecode_1$	\dots	$winecode_n$
$time_1$	$price_{11}$ $exchangerate_{11}$	\dots	$price_{n1}$ $exchangerate_{n1}$
\vdots	\vdots	\ddots	\vdots
$time_t$	$price_{1t}$ $exchangerate_{1t}$	\dots	$price_{nt}$ $exchangerate_{nt}$

Figure 3: Schematic diagram of panel-data

month, or their prices do not necessarily change each month. A panel with missing values is called an unbalanced panel. By inspection of the data, we find missing values or prices with very little variation for countries with few observations, such as Austria, Portugal and Greece. This may explain why the model does not yield strong results for these countries.

In comparison, France has the largest number of observations and categories as well as the highest ratio of observations to categories. This indicates that French wines have the longest time-series—a boon for panel-data analysis. The results from the estimate of French wine prices are also the most consistent with economic theory. The statistically significant ERPT coefficient is negative and of absolute value less than one. Although 21 percent is lower than expected, it is still a reasonable degree of pass-through. The coefficient on *time* is negative, which suggests that nominal prices for imported French wines have fallen over time. The adjusted R^2 is high, and the number of observations and categories are both large. Given this strong evidence of a

robust panel, we turn our attention to finding deeper estimates of exchange rate pass-through for those wines imported from France.

4.4.2 A second look at France

A wine's import price may be largely determined by factors other than the exchange rate. The specification for the estimates in Table 9 includes *time* and *winecode* dummies as additional regressors, but it is also worth considering *vintage*, *month*, *year*, *type*, and *cscode* more closely as explanatory variables.

The variable *vintage*—year of grape harvest—is a proxy for a number of other variables that affect price, including climate, cost, and quality. Thus, *vintage* should be included explicitly in the regression. Similarly, the month and year during which the wine is being sold could have a bearing on the price. For instance, the variable *month* may capture seasonal pricing patterns. Another variable inherent to the data set is *type*, which is a categorical variable that may take on one of five values—sparkling, white, blush, rosé, or red—and can be included in the regression by generating a dummy variable for each value. Another characteristic that is not explicit in the data set but still has significant relevance is the producer of the wine. After all, the producer sets his wholesale price—assuming, quite realistically, that the market is not perfectly competitive. The variable *cscode* identifies the producer in some cases, though not exclusively. Different products from a single producer have different cs codes. In the case where a single producer sells only one

Table 6: Static panel estimate for France with additional dummies

dependent variable — <i>price</i>		
Predictor	Coefficient	Robust t-statistic
<i>exchangerate</i>	−0.617 ***	−8.27
<i>time</i>	−0.00314 ***	−6.83
<i>d_legislature</i>	−0.136 ***	−12.44
constant	3.767 ***	142.11
other dummies	<i>year, month, type</i>	
<i>N</i> : 22979		*** Sig. at $p < 0.01$
adjusted R^2 : 0.8780		** Sig. at $p < 0.05$
<i>winecode</i> categories: 1499		* Sig. at $p < 0.10$

product, then the cs code for that product will identify the producer.

Most of these additional predictors can be added to the model with sets of dummy variables. The regression should include dummies that have both explanatory power and theoretical validity. Including dummy variables for the relevant factors described above yields the results summarized in Table 6. This model differs from the previously estimated model because it includes dummies for *year*, *month* and *type*, as well as a structural break denoted by *d_legislature*, which captures the change in Utah state legislature beginning in July 2007 (see footnote 4).

As expected, the coefficient on *exchangerate* is negative. The coefficient on *time* is also negative, which is consistent with the previous estimate. In addition, the absolute value of the ERPT coefficient has increased to

0.617—or a 62 percent pass-through. The previous model yielded a much lower ERPT coefficient of 0.211 (see Table 9, column 1). The added dummy variable *d_legislature*, which has a value of one for all time periods after June 2007, has a negative coefficient. This is consistent with the fact that since July 2007, sales tax has not been included in the Utah DABC prices as it was previously. The estimate in Table 6 also includes dummies with statistically significant coefficients for the variable *month*. In addition, the estimation technique generates dummies for each value of *winecode* through the **absorb**(*winecode*) option (see Appendix A). The inclusion of additional dummies is founded on more realistic assumptions and produces a higher pass-through coefficient, which is consistent with economic theory.

4.4.3 A closer look at France

We can use the improved model to explore exchange rate pass-through in the market for French wine imports from different angles. For instance, it would be interesting to examine how ERPT varies across price brackets and among wine types. We use the same specification, but run it on only certain segments of the dataset, such as all French wines with *price* greater than sixty dollars. The results of these regressions are summarized in Table 10 (see page 47).

We include column (1) for reference—it matches the France column from Table 9. Column (2) is the second estimation of all French wine prices and matches the results presented in Table 6. The results reported in column

(3) use *cscode* instead of *wincode* as the categorical identifier. The estimation uses the option **absorb**(*cscode*), which generates a dummy for each value of *cscode*, and also includes a dummy variable for each value of *vintage* (1990–2008). We include column (3) as a comparison to column (2) because the option **absorb**(*wincode*) does not allow for the inclusion of *vintage* dummies, though it does generate the cross-section according to unique wines. In contrast, **absorb**(*cscode*) generates the cross-section according to the generic product code but does allow for *vintage* dummies. Because *cscode* does not exactly identify the producer of the wine, this is a tradeoff. However, estimations (2) and (3) yield very similar results, suggesting that the model is robust to this change in specification. For consistency we report the remaining static results using *wincode* as the categorical identifier.

Columns (4) through (9) estimate the same specification as column (2) but restrict the observations to the conditions given at the top of each column. For example, column (6) only uses data for red wines, and column (7) uses only those observations with prices less than or equal to thirty dollars. Restricting the data set reduces the sample size and the number of categories, potentially reducing the explanatory power of the fixed-effects model. Nevertheless, the ERPT coefficients are all negative and most of the estimates are statistically significant. Interestingly, the results in columns (4), (5), and (6) suggest that pass-through is highest for sparkling wines and lowest for white wines. One explanation for this is that France may have greater market power in producing sparkling wines like Champagne and red

Table 7: Summary of best available ERPT coefficient estimates from static fixed-effects panel-data models for selected countries

Country	1970–1980 [†]	1993–2003 [†]	2005–2008 [‡]
France	0.729	0.503	0.617
Spain	—	—	0.069
Germany	—	—	0.185
Australia	—	0.258	(0.100)
South Africa	—	0.080	(0.033)
Chile	—	0.276	—

[†] Source: Wheeler (2004).

[‡] See Tables 9 and 10.

wines such as Bordeaux, and this market power allows French producers to pass-through exchange rate shocks more completely to these wines. Though the results from columns (7), (8) and (9) do not offer definitive explanations of exchange rate pass-through across price brackets, the pass-through coefficient for wines with prices greater than 60 dollars is significantly lower than the average pass-through coefficient for French wines. It is also interesting to note that the price of high-end wines is positively correlated with time, indicating that price of these wines rises over time. This is in contrast with the general trend of falling prices exhibited elsewhere in the results.

4.4.4 Conclusion

Wheeler (2004) analyzes exchange rate pass-through in the wine market using a similar static approach. He looks at wine price data from two ten-year time periods beginning in 1970 and 1993 for France, Australia, Chile, and

South Africa. He includes a simple lag on the exchange rate to determine the timing of pass-through. However, in all cases but one, pass-through is strongest at one month after the price is published and in most cases the results are not significantly different from the un-lagged specification. His relevant ERPT coefficient estimates are displayed in the second and third columns of Table 7. All coefficients with expected signs are expressed in absolute value; coefficients with unexpected signs are enclosed in parentheses. Wheeler (2004) expresses exchange rates as U.S. dollars per foreign currency, and thus expects positive coefficients. He finds ERPT coefficients of 0.258 for Australia and 0.729 and 0.503 for France. For comparison, our best un-lagged estimate of pass-through to French wine prices is a reasonable 0.617.

Although we did not conduct an extensive analysis of each country, the specification that includes additional dummies does not improve estimates of ERPT for other countries. Thus, the static model does not provide conclusive estimates of exchange rate pass-through for all of the countries in the data set. Though nearly all of the coefficients are statistically significant, and each estimation has a high adjusted R^2 value, using ordinary least squares is a naïve approach to estimating the dynamic panel specification given by equation (9). In Section 4.5, we address the shortcomings of the static model by introducing a Koyck lag model and a sophisticated statistical estimation method.

4.5 Dynamic Panel

The static model assumes that pass-through is simultaneous. However, this assumption is unrealistic. There are a number of reasons that we do not expect a change in the exchange rate to have an instantaneous impact on import prices. First, prices are only published once per month, usually before exchange rate information for the entire month is available. Second, there are frictions in the market that impede immediate pass-through of pricing shocks. Finally, we do not necessarily expect an exchange rate fluctuation to only affect prices in one time period. Future wine prices are affected by current exchange rate changes and current wine prices are determined by past exchange rate changes. In other words, prices are sticky—the impact of an exchange rate change increases over time such that the long-run effect on prices is larger than the short-run effect. A simple lag on the exogenous variable *exchangerate*, like that employed by Wheeler (2004), is not sufficient to capture this total effect. Instead, we introduce a distributed, geometric Koyck lag model to quantify the duration of the exchange rate impact and the slope of its decline.

4.5.1 Introduction to dynamic models

The simplest way to account for an expected time-delay in a time-series model is to lag the independent variable. This is called a simple lag and has the general form

$$Y_t = \alpha_0 + \beta_0 X_{t-1} + \varepsilon_t. \quad (11)$$

However, the independent variable X is often expected to have an impact across multiple time periods. In this case, the model would include terms for multiple lags of the independent variable. This is called a distributed lag and has the form

$$Y_t = \alpha_0 + \beta_0 X_{t-1} + \beta_1 X_{t-2} + \beta_2 X_{t-3} + \dots + \varepsilon_t. \quad (12)$$

If the impact of X falls over time, then the absolute values of the coefficients β_n should fall as n increases. In practice, a distributed lag model often exhibits severe multicollinearity among the lagged values of X , which may lead to biased estimates of the coefficients. Using multiple lags also reduces the degrees of freedom. One way to overcome these problems is to simplify a distributed lag model to a dynamic model.

A dynamic model adds only the lagged dependent variable as a regressor, as in the following equation:

$$Y_t = \alpha_0 + \lambda Y_{t-1} + \beta_0 X_t + \varepsilon_t. \quad (13)$$

It can be shown with a simple, iterative substitution that this dynamic model may be used to represent a distributed lag model. Furthermore, the coefficients on the lagged X 's of the distributed lag model will decline smoothly due to the geometric nature of the series of lagged X 's, as long as $0 < \lambda < 1$. This is known as a Koyck lag model.

The benefits of using a dynamic model include more degrees of freedom

and the avoidance of multicollinearity problems associated with a distributed lag. However, a dynamic model is prone to serial correlation that causes bias in the estimated coefficients and the standard errors. Three ways to correct for this are to improve the specification, to use instrumental variables, or to employ a modified generalized least-squares method of estimation (Studenmund 2006). We use instrumental variables with the system generalized method of moments (GMM) estimator, as described in the following sections.

4.5.2 Dynamic model specification

The distributed, geometric Koyck lag model that we use is given by the equation

$$\ln p_{it} = \alpha + \lambda \ln p_{i(t-1)} + \gamma \ln E_{it} + \varepsilon_{it}, \quad (14)$$

where the subscripts t and i refer to *time* and to the cross-section identifier, p is the wine price, E is the exchange rate in foreign currency per US dollar, and ε is the error term. In this dynamic specification, the lagged dependent variable appears on the right-hand side of the equation as a regressor. This is a key difference between equation (14) and our static estimation of equation (9), which attempts to capture a change in price over time with a logarithmic specification alone. Furthermore, in equation (14), the coefficient γ is the short-run elasticity and the long-run elasticity is defined as $\frac{\gamma}{1-\lambda}$, which will be greater than γ as long as $0 < \lambda < 1$.

There are at least two problems with estimating this Koyck lag model.

First, as mentioned in Section 4.5.1, OLS estimates will suffer from severe serial correlation due to the inclusion of the lagged dependent variable. Second, as first shown by Nickell (1981), estimating a dynamic panel model with fixed effects will yield biased coefficient estimates because the fixed effects are correlated with the lagged dependent variable (Storchmann 2008). This coefficient bias is particularly severe for a panel with a short time series and a large cross section, as noted in much of the literature that discusses dynamic panel-data models.

Researchers in the field of econometrics have proposed a number of possible remedies for these problems. Anderson and Hsiao (1981) suggest using a first-difference transformation, which eliminates both the constant term and fixed effects. After making this transformation, the differenced lagged dependent variable will still be correlated with the differenced error term, so an instrumental variable—such as the second lag of the dependent variable—is necessary. Arellano and Bond (1991) argue that the Anderson-Hsiao method does not produce an efficient estimate because it does not take into account all orthogonality conditions. They propose a generalized method of moments (GMM) procedure, which specifies the model as a system of equations and allows instruments to differ across time periods. A further extension of the Arellano-Bond estimator, called the system GMM estimator, may include lagged differences as instruments (Storchmann 2008).

4.5.3 Estimation methodology

David Roodman wrote the program **xtabond2**, introduced in 2003, in order to implement system GMM in Stata. Roodman (2006) thoroughly describes the design and implementation of the **xtabond2** estimator, the details of which are beyond the scope of this paper. However, it is important to note the reasons that we use this estimator for a dynamic panel analysis of our data. The Anderson-Hsiao and Arellano-Bond estimators were designed for dynamic panel-data models, especially in the case of few time periods and a large cross-section (small T , large N). An appropriate model should also have a linear functional relationship, a dynamic dependent variable, independent variables that are not strictly exogenous, and fixed individual effects (Roodman 2006). Our dynamic panel-data model satisfies all of these criteria, which makes it suitable for the **xtabond2** estimator.

4.5.4 Results

We estimate the dynamic model of French wine prices given by equation (14) with one-step system GMM, using explanatory variables as instruments and cluster-robust standard errors.¹¹ Table 11 on page 48 presents the results of this estimation for different conditions. Column (1) is an estimation of all French wine prices using *winecode* as the group variable and price lags of one and deeper as instruments. The estimation in column (2) is the same as that in column (1) except *cscode* is the group variable. Columns (3) through

¹¹Further explanation of these **xtabond2** options is included in Appendix A.

(8) estimate the same specification as columns (1) and (2) but restrict the observations to the conditions given at the top of each column. For example, column (5) only uses data for red wines, and column (6) only uses observations with prices less than or equal to thirty dollars.

The dynamic model for all French wine prices is robust to the group variable and the number of instruments.¹² As shown in columns (1) and (2) of Table 11, the coefficients are stable to the change from *winecode* to *cscode* as the group variable, which defines the cross-section and thus the fixed effects. The notable difference between these two estimations is the value of the Hansen test of overidentifying restrictions. Roodman (2006) warns that the Hansen test is prone to weakness, especially when the number of instrumental variables is large. The test has a p -value of 0.000 when *winecode* is the group variable, but the p -value jumps to 0.891 if *cscode* is the group variable. The stability of the coefficients suggests that the results are robust, so we do not rely solely on the Hansen test. The coefficient estimates also vary only slightly when the lag limits are restricted and the number of instruments are reduced—another good measure of robustness, as noted by Roodman (2006). The *exchangerate* coefficients in these two estimates are lower in absolute value than the *exchangerate* coefficients from the static model. In addition, across all the dynamic estimates in Table 11, the *time* coefficient is positive, whereas in the static model it is negative for nearly all estimates.

¹²This is illustrated in detail by Table 12 on page 49, which shows regression results for three different lag limits first using *winecode* as the group variable, then using *cscode* as the group variable.

Table 8: Summary of ERPT coefficient estimates for French wines

Condition	Static	Short-run	Long-run
all	0.617	0.482	0.731
<i>type</i> = sparkling	0.816	0.894	0.961 ⁺
<i>type</i> = white	0.351	0.740	1.510
<i>type</i> = red	0.698	0.115 ⁺	0.182 ⁺
<i>price</i> ≤ 30	0.009 ⁺	0.293	0.439
30 ≤ <i>price</i> ≤ 60	0.003 ⁺	0.252	0.430
<i>price</i> ≥ 60	0.390	0.218 ⁺	0.245 ⁺

⁺ Not significant at a level of 10 percent.

Short-run coefficients are dynamic estimates of γ .

Long-run coefficients are the values of $\frac{\gamma}{1-\lambda}$.

The *type*- and *price*-restricted estimates of the dynamic model yield less significant results than the analysis of these conditions in the static model. Although sparkling wines still have the largest ERPT coefficient, white wines have a much higher ERPT coefficient than in the static model, and the ERPT coefficient is not statistically significant for red wines. The ERPT coefficients across price brackets decrease as *price* increases, though the coefficient for the condition *price* ≥ 60 is not statistically significant. The Arellano-Bond and Hansen tests also exhibit some weaknesses for estimates (3) through (8).

4.5.5 Conclusion

To conclude our discussion of the dynamic model, we compare these results with the static model results obtained in Section 4.4. Table 8 summarizes

the ERPT coefficients determined by each model. The first column gives the values of the ERPT coefficient γ from the static model estimation. The second column gives the values of the coefficient γ from the dynamic model estimation. These are short-run estimates of exchange rate pass-through. The last column gives the values of the expression $\frac{\gamma}{1-\lambda}$, where γ and λ refer to coefficients from the dynamic model. These are long-run estimates of exchange rate pass-through.

There are no strong trends within wine types or price brackets and across both models. However, as expected, the dynamic Koyck lag model yields long-run ERPT values greater than the short-run counterparts. In other words, exchange rate pass-through tends to become more complete over time. This is consistent with the expectation that frictions in the market cause prices to be sticky in the short-run. Although the static model estimate of pass-through for all French wine prices falls conveniently in between the short- and long-run estimates, the power of the dynamic model lies in its ability to illustrate this movement of prices over time.

5 Conclusion

The relationship between the exchange rate and prices of traded goods is a widespread topic of research in economics. However, most papers focus on aggregate-level price data, and no published study has considered exchange rate pass-through to imported wine prices. We choose to analyze exchange rate pass-through in the U.S. market for imported wines because the wine industry is expanding rapidly in many countries around the world, and the United States plays an increasingly dominant role in this global industry as both a producer and consumer of wine. Furthermore, the availability of appropriate data made this a particularly accessible market to study.

This paper uses a large set of price data from the Utah Department of Alcoholic Beverage Control to provide new evidence of exchange rate pass-through in the wine market. We construct two panel models—static and dynamic—and estimate ERPT coefficients for wines from various exporting countries. The results from the static panel model indicate a pass-through value of about 62 percent for French wines imported into the United States. The dynamic panel model yields pass-through values of 48 percent in the short-run and 73 percent in the long-run for French wines. A deeper analysis indicates that sparkling French wines have a higher pass-through value than red or white French wines, but the results of estimates for other wine types and price brackets are not consistent across both models.

This paper extends the idea of exchange rate pass-through to the wine

market and uses sophisticated statistical methods to estimate a dynamic panel model of wine prices. It also reveals more information about exchange rate pass-through by considering different product types and price brackets. Although the data set used here includes wines from twelve countries, there is not enough variation within each country to yield significant results. The results of this study would be even more meaningful if they were compared to ERPT estimates for wines imported to the United States from countries other than France. In order to explain trends of globalization in the wine industry, an ERPT analysis could work toward producing robust results for a variety of wine-producing countries from the Old and New World. We hypothesize that market share plays a role in a producer's pricing patterns, but future research could focus on solidifying the factors that determine the degree of exchange rate pass-through.

Table 9: Static panel estimates of wine prices by country

Predictors	dependent variable — <i>price</i>											
	France 1	Italy 2	Spain 3	Germany 4	Austria 5	Portugal 6	Greece 7	South Africa 8	New Zealand 11	Australia 12		
<i>exchangerate</i>	-0.211 *** (-3.62)	0.0786 ** (2.00)	-0.0689 * (-1.67)	-0.185 ** (-2.36)	0.332 *** (3.04)	0.0804 (1.64)	0.232 *** (4.06)	0.0326 (0.62)	-0.00684 (-0.15)	0.100 *** (4.47)		
<i>time</i>	-0.00464 *** (-11.08)	-0.00326 *** (-9.54)	-0.00589 *** (-14.29)	-0.106 *** (-13.55)	-0.00802 *** (-6.62)	-0.000655 (-1.49)	0.00286 *** (5.65)	-0.00746 *** (-11.37)	-0.00627 *** (-11.13)	-0.00517 *** (-19.26)		
constant	3.830 *** (286.92)	3.208 *** (319.65)	3.0587 *** (284.38)	3.214 *** (189.57)	3.474 *** (113.67)	2.934 *** (249.74)	2.613 *** (228.20)	2.810 *** (28.55)	2.982 *** (123.84)	2.99 *** (318.01)		
<i>N</i>	22979	12107	6605	2581	561	246	525	1912	2725	10298		
adjusted <i>R</i> ²	0.876	0.9328	0.948	0.930	0.936	0.996	0.966	0.956	0.011	0.967		
categories [†]	1499	1032	553	192	42	24	36	169	231	744		

Robust t-stats are in parentheses.

The variables *price* and *exchangerate* are logged.

[†] Number of unique values of the panel variable *winecode*, which defines the cross-section.

Chile and Argentina (countries 9 and 10) are omitted due to the absence of exchange rate data.

*** Significant at $p < 0.01$.

** Significant at $p < 0.05$.

* Significant at $p < 0.10$.

Table 10: Static panel estimates of French wine prices

Predictors	dependent variable — <i>price</i>								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>exchangerate</i>	all	all	all	<i>type=sparkling</i>	<i>type=white</i>	<i>type=red</i>	<i>price</i> ≤ 30	30 ≤ <i>price</i> ≤ 60	<i>price</i> ≥ 60
<i>time</i>	-0.211 *** (-3.62)	-0.617 *** (-8.27)	-0.626 *** (-7.62)	-0.816 *** (-3.86)	-0.351 *** (-3.38)	-0.698 *** (-6.54)	-0.00886 (-0.19)	-0.00346 (-0.24)	-0.390 *** (-6.46)
<i>d_red</i>	-0.00464 *** (-11.08)	-0.00314 *** (-6.83)	-0.00411 *** (-7.93)	-0.00125 (-1.03)	-0.00899 *** (-12.23)	-0.00225 *** (-3.55)	-0.00464 *** (-11.87)	0.000982 *** (7.35)	0.00138 *** (3.8)
<i>d_legislature</i>	—	-0.104 *** (-3.00)	-0.115 *** (-3.26)	—	—	—	—	0.0135 *** (4.27)	—
constant	3.83 *** (286.92)	-0.136 *** (-12.44)	-0.139 *** (-11.31)	-0.129 *** (-5.26)	-0.148 *** (-8.05)	-0.133 *** (-8.50)	-0.0680 (0.00856)	-0.0483 *** (-18.82)	-0.0801 *** (-9.97)
other dummies	—	3.767 *** (142.11)	3.545 *** (49.67)	3.958 *** (84.05)	3.610 *** (127.99)	3.764 *** (136.62)	2.803 (203.52)	3.779 *** (874.23)	4.774 *** (330.16)
<i>N</i>	—	—	<i>vintage</i>	—	—	—	—	—	—
adjusted <i>R</i> ²	—	<i>month</i>	<i>month</i>	<i>month</i>	<i>month</i>	<i>month</i>	<i>month</i>	<i>month</i>	<i>month</i>
absorb	22979	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>
categories [†]	0.875	22979	22979	2795	7105	13079	8416	6355	8208
	<i>winecode</i>	0.878	0.861	0.835	0.896	0.87	0.903	0.948	0.9284
	1499	<i>winecode</i>	<i>cscode</i>	<i>winecode</i>	<i>winecode</i>	<i>winecode</i>	<i>winecode</i>	<i>winecode</i>	<i>winecode</i>
	—	1499	1041	129	518	853	776	489	543

Robust t-stats are in parentheses.
 The variables *price* and *exchangerate* are logged.
[†] Number of unique values of the panel variable (*winecode* or *cscode*), which defines the cross-section.
 *** Significant at $p < 0.01$.
 ** Significant at $p < 0.05$.
 * Significant at $p < 0.10$.

Table 11: Dynamic panel estimates of French wine prices I

Predictors	dependent variable — <i>price</i>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>L.price</i>	0.320 *** (8.23)	0.345 *** (9.17)	0.070 (1.39)	0.510 *** (5.97)	0.368 *** (7.92)	0.332 *** (3.60)	0.414 *** (5.54)	-0.111 *** (-3.80)
<i>exchangerate</i>	-0.497 *** (-4.62)	-0.482 *** (-4.75)	-0.894 ** (-2.40)	-0.740 *** (-4.89)	-0.115 (-0.97)	-0.293 ** (-2.28)	-0.252 *** (-2.78)	-0.218 (-1.31)
<i>time</i>	0.0168 *** (9.05)	0.0161 *** (9.55)	-0.0128 ** (-2.36)	0.0135 *** (4.60)	0.0124 *** (7.21)	0.00489 ** (2.46)	0.0009 (0.88)	0.00539 ** (2.30)
<i>d.legislature</i>	-0.122 *** (-4.81)	-0.117 *** (-5.61)	—	-0.130 *** (-3.50)	—	-0.321 (-13.4)	-0.0287 *** (-2.26)	-0.0872 *** (-2.89)
constant	0.940 *** (7.78)	1.767 *** (15.72)	4.499 *** (7.44)	0.740 *** (3.45)	1.800 *** (15.98)	2.198 *** (9.70)	1.986 *** (6.67)	5.802 *** (27.67)
<i>N</i>	18510	18860	1132	6312	11416	6670	5010	7180
group variable	<i>winecode</i>	<i>cscode</i>	<i>cscode</i>	<i>cscode</i>	<i>cscode</i>	<i>cscode</i>	<i>cscode</i>	<i>cscode</i>
number of groups	1355	1011	43	334	635	508	377	408
lag limits (# #) †	(1 .)	(1 .)	(1 2)	(1 8)	(1 10)	(1 10)	(1 9)	(1 9)
number of instruments	993	1000	121	356	420	424	386	393
Wald test for overall fit χ^2	8104.07	5626.34	343.71	3133.71	3233.97	750.86	2486.08	479.42
Arellano-Bond test for AR(2)	2.91 (0.004)	3.01 (0.003)	-0.95 (0.342)	2.61 (0.009)	2.23 (0.026)	3.95 (0.000)	1.51 (0.130)	1.93 (0.054)
Hansen test of overid. restrictions	1197.62 (0.000)	920.06 (0.891)	33.76 (1.000)	315.79 (0.779)	535.14 (0.000)	413.32 (0.300)	9.3×10^7 (0.000)	374.88 (0.391)

The system GMM is estimated one-step and robust z-statistics are in parentheses.

The variables *price* and *exchangerate* are logged.

† This row gives the system GMM lag limits on *L.price*, where (.) denotes the longest possible lag.

Regressions (1) through (8) include dummies for *vintage* and *year*. (1), (2), (6), (7) and (8) also include dummies for *type*.

*** Significant at $p < 0.01$.

** Significant at $p < 0.05$.

* Significant at $p < 0.10$.

Table 12: Dynamic panel estimates of French wine prices II

		dependent variable — <i>price</i>					
Predictors		(1)	(2)	(3)	(4)	(5)	(6)
		<i>winecode</i> lag(1 1)	<i>winecode</i> lag(1 6)	<i>winecode</i> lag(1 .)	<i>cscode</i> lag(1 1)	<i>cscode</i> lag(1 6)	<i>cscode</i> † lag(1 .) ‡
<i>L.price</i>		0.244 *** (6.16)	0.311 *** (8.08)	0.320 *** (8.23)	0.231 *** (6.10)	0.331 *** (8.85)	0.345 *** (9.17)
<i>exchangerate</i>		-0.474 *** (-4.17)	-0.523 *** (-4.76)	-0.497 *** (-4.62)	-0.466 *** (-4.25)	-0.528 *** (-4.92)	-0.482 *** (-4.75)
<i>time</i>		0.0188 *** (8.88)	0.0168 *** (9.13)	0.0168 (9.05)	0.0188 *** (9.36)	0.0162 *** (9.65)	0.0161 *** (9.55)
<i>d_legislature</i>		-0.132 *** (-4.86)	-0.125 *** (-4.88)	-0.122 *** (-4.81)	-0.134 *** (-5.82)	-0.122 *** (-5.71)	-0.117 *** (-5.61)
constant		1.063 *** (8.50)	0.955 *** (7.88)	0.940 *** (7.78)	1.899 *** (18.74)	1.791 *** (16.60)	1.767 *** (15.72)
other dummies		<i>vintage</i>	<i>vintage</i>	<i>vintage</i>	<i>vintage</i>	<i>vintage</i>	<i>vintage</i>
		<i>type</i>	<i>type</i>	<i>type</i>	<i>type</i>	<i>type</i>	<i>type</i>
		<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>	<i>year</i>
<i>N</i>		18510	18510	18510	18860	18860	18860
number of groups		1355	1355	1355	1011	1011	1011
number of instruments		108	294	993	109	295	1000
Wald test for overall fit χ^2		6636.48 (0.000)	7886.88 (0.000)	8104.07 (0.000)	6837.35 (0.000)	4688.17 (0.000)	5626.34 (0.000)
Arellano-Bond test for AR(2)		2.91 (0.004)	2.89 (0.004)	2.91 (0.004)	2.77 (0.006)	2.97 (0.003)	3.01 (0.003)
Hansen test of overid. restrictions		363.53 (0.000)	984.95 (0.000)	1197.62 (0.000)	3643.66 (0.000)	755.37 (0.000)	920.06 (0.891)

Robust z-statistics are in parentheses.

The system GMM is estimated one-step.

The variables *price* and *exchangerate* are logged.

† This is the panel variable, which defines the cross-section groups.

‡ This row gives the system GMM lag limits on *L.price*, where (.) denotes infinity.

*** Significant at $p < 0.01$.

** Significant at $p < 0.05$.

* Significant at $p < 0.10$.

A Using Stata

Much of my work on this project involved learning how to implement econometric techniques in the command-driven statistical package Stata. This section of the appendix is included as a technical supplement to the methodology sections of the text. Its two-fold purpose is to illustrate what I have learned about estimating panel-data and to help other beginning Stata users with this type of estimation.

Estimating a static panel in Stata

Stata provides a few ways to estimate a static panel-data model, including the commands **xi: reg**, **xtreg**, and **areg**. Each of these commands accounts for fixed effects by effectively generating dummy variables for each group. We use **areg** for all of the static estimates because of its simple syntax, but each command will produce the same coefficients if it is executed with the appropriate parameters.

Stata's **areg** command is designed to fit a linear regression with a large number of dummy variables, as in our fixed-effects panel-data model. To estimate equation (10), we use the command

```
areg price exchangerate time if country==#, absorb (winecode) robust ,
```

where # corresponds to a country code and can take on any integer value from 1 (France) through 12 (Australia). In addition to taking a dependent variable (*price*) and explanatory independent variables (*exchangerate*, *time*)

as arguments, **areg** requires the option **absorb()**, which defines the group category. For almost all of the static regressions, we choose *winecode* as the group identifier because this specifies the cross-section according to each unique wine, including vintage. The option **absorb(*winecode*)** generates a dummy variable for each value of *winecode*. Stata suppresses the dummy coefficients in its output, but does include the overall-fit effect of the dummy variables in its R^2 calculation.¹³ The **robust** option uses the robust (or sandwich) estimator of variance to produce heteroskedasticity-corrected standard errors. The default confidence level for confidence intervals is 95 percent.

Estimating a dynamic panel with **xtabond2**

The **xtabond2** syntax is complex and includes many optional parameters. For a complete description of the design and implementation of **xtabond2**, see Roodman (2006). A simplified version of the syntax that includes options relevant to the present ERPT model is given by the following line of code:

```
xtabond2 depvar varlist, gmm(varlist, laglimits(# #)) iv(varlist) robust .
```

The first occurrence of *varlist* is a list of all the explanatory variables. Each of these variables should appear a second time after the comma, in either the **gmm()** or the **iv()** option, as part of the instrument matrix. Strictly exogenous regressors, including *exchangerate* and all dummy variables, should be included as iv-style instruments in the **iv()** option. The option **gmm()**

¹³This is in contrast with the R^2 calculation of **xtreg**—another reason that we choose to use **areg**.

should contain endogenous variables as well as predetermined but not strictly exogenous variables. In our model, the only variable included in `gmm()` is the lagged dependent variable, *L.price*.

The default lag range for gmm-style instruments is lag one and deeper. The option `laglimits(# #)` overrides this default, which is represented by (1 .). We change the lag range for three reasons. First, fewer lags produce faster estimation for preliminary testing. Second, the number of instruments increases greatly with the depth of the lag range. The design of the estimator is such that we do not want the number of instruments to exceed the number of groups. Finally, Roodman (2006) notes the importance of testing the robustness of the results by restricting the number of instruments. This is easily done by constricting the lag limits.

By default, the command executes one-step system GMM. The **robust** option causes Stata to output standard errors that are robust to heteroskedasticity and autocorrelation within individuals (Roodman 2006).¹⁴ The default confidence level is 95 percent.

¹⁴The **robust** option produces Windmeijer-corrected standard errors in two-step estimation.

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