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ESSAYS ON AGRICULTURAL MARKET AND POLICIES: IMPORTED SHRIMP, ORGANIC COFFEE, AND CIGARETTES IN THE UNITED STATES

Xiaojin Wang
University of Kentucky, xiaojin.wang2010@uky.edu
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Dr. Michael Reed, Major Professor

Dr. Carl Dillon, Director of Graduate Studies

ESSAYS ON AGRICULTURAL MARKET AND POLICIES: IMPORTED SHRIMP, ORGANIC COFFEE, AND CIGARETTES IN THE UNITED STATES

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in Agricultural Economics
in the College of Agriculture, Food and Environment
at the University of Kentucky

By

Xiaojin Wang

Director: Dr. Michael Reed, Professor of Agricultural Economics

Lexington, Kentucky

2016

ABSTRACT OF DISSERTATION

ESSAYS ON AGRICULTURAL MARKET AND POLICIES:
IMPORTED SHRIMP, ORGANIC COFFEE, AND CIGARETTES
IN THE UNITED STATES

This dissertation focuses on topics in areas of agricultural and food policy, international trade, agricultural markets and marketing. The dissertation is structured as three papers. The first paper, Chapter 1, evaluates the impact of agricultural trade policies. Imported shrimp, which comprises nearly ninety percent of all United States shrimp consumption, have become the subject of antidumping and countervailing duty investigations in the past decade. I estimate the import demand for shrimp in the United States from 1999-2014, using the Barten's synthetic model. I test the hypothesis of possible structural breaks in the import demand introduced by various trade policies: antidumping/countervailing duty investigations and impositions, and import refusals due to safety and environmental issues. Results show that these import-restricting policies have significant effects on the import shrimp demand, indicating that the omission of them would lead to biased estimates.

Chapter 2, the second paper, examines how the burden of state cigarette tax is divided between producers/retailers and consumers, by using the Nielsen store-level scanner data on cigarette prices from convenience stores over the period 2011–2012. Cigarette taxes were found more than fully passed through to retail prices on average, suggesting consumers pay excess burden and market power exists in the cigarette industry. Utilizing information on the attributes of cigarette products, we demonstrated that tax incidence varied by brand and package size: pass-through rates for premium brands and carton-packaged cigarettes are higher than those for discount brands and cigarettes in packs, respectively, indicating possibilities of different demand elasticities across product tiers.

Chapter 3, the third paper, focuses on identifying the demographic characteristics of households buying organic coffee, by examining the factors that influence the probability that a consumer will buy organic coffee, and which factors affect the amount organic coffee purchased. Using nationally representative household level data from 55,470 households over the period of 2011 to 2013 (Nielsen Homescan), and a censored demand model, we find that economic and demographic factors play a crucial role in the household choice of purchasing organic coffee. Furthermore, households are less sensitive to own-price changes in the case of organic coffee versus conventional coffee.

KEYWORDS: Aquaculture Trade, Temporary Trade Barriers, Consumer Demand, Tax Incidence, Organic Food Marketing, Scanner Data

Xiaojin Wang
Student name

June 15, 2016
Date

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By

Xiaojin Wang

Dr. Michael Reed
Director of Dissertation

Dr. Carl Dillon
Director of Graduate Studies

June 15, 2016
Date

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Introduction

This dissertation focuses on topics in areas of agricultural and food policy, international trade, agricultural markets and marketing. One overarching goal of this dissertation is to understand the economic effects of various agricultural policy instruments, both domestically and internationally. In general, the importance of policies such as investment in education, health and sanitary facilities, and transportation infrastructure- which have a broad impact on agricultural sector productivity, has been an uncontroversial subject among economists, policy-makers, and development institutions. However, there is a set of policies that affects particular agricultural commodities or techniques of production, for which little consensus has emerged on appropriate levels of use. These commodity-specific policies include taxes, subsidies, international trade restrictions, and quantitative controls on particular outputs and inputs and policies that affect the macroprices (interest rates, wage rates, and exchange rates).

Another goal is conduct consumer demand analysis for a specific product, particularly taking product differentiation into consideration, either by origin of country or by method of production. Consumer demand for food is an important element in the formulation of various agricultural and food policies. Estimates of consumer demand quantify the effects of prices and total expenditures on the demand for food, which in turn, informs policymakers and researchers about how consumers make food purchasing decisions and helps policymakers design effective nutrition policy. In addition, knowledge of consumers' demand can help producers make important decisions, such as whether to adjust production practices, adopt new technologies, or change marketing and pricing strategies.

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Chapter 1. The Impact of Antidumping/Countervailing Duties on Demand for Imported Shrimp in the United States

1.1 Introduction

In recent years, imported shrimp has frequently been the subject of antidumping investigations (imports sold at less than fair value, LTFV) and countervailing duty investigations (subsidized imports) in the United States. On December 31, 2003, Ad Hoc Shrimp Trade Action Committee, Washington, DC — an ad hoc committee of vessel owners and shrimp processors — filed anti-dumping petitions with the Department of Commerce (DOC) against shrimp importers from six countries: Brazil, China, Ecuador, India, Thailand, and Vietnam. The Southern Shrimp Alliance (SSA) complained that they were the victims of "dumping" — that they were being driven out of business by foreign shrimp producers who were selling their shrimp at LTFV in the U.S. market.

In January 2005, after one year of investigations, the U.S. International Trade Commission (USITC, Commission) found that the increasing quantity of subject imports forces the share of U.S. apparent consumption of domestic warmwater shrimp to decline from 15.2 percent in 2001 to 11.9 percent in 2003. The subject imports had significant price-depressing effects: when comparing prices of imported and domestic shrimp, the subject imports undersold the domestically processed product in 58.6 percent of all such comparisons. These declines in prices led to decreases in operating revenues for fishermen and processors, poor financial performance, and declining employment. The number of production and related workers dropped from 2,180 in 2001 to 1,616 in 2003. Over 65 percent of domestic processors had operating profits in 2001, over half the producers had operating losses in 2002 and 2003 (USITC, 2005, p.29-44). Therefore, the USITC determined that an industry in the United States was materially injured[1] by frozen warmwater shrimp imports, resulting in trade-weighted antidumping duties of 17.22 percent on shrimp imports from the six countries found to be sold in the United States at LTFV (USITC, 2005; SSA, 2005) (Table 1).

Table 1. U.S. Antidumping and Countervailing Duty Investigations on Imported Shrimp, 1999-2014

AD/CVD	Country	Initiation	Prelim	Final	Duty Order	Min Margin (%)	Max Margin (%)	5 Year Sunset Reviews
AD	Brazil	27-Jan-04	4-Aug-04	23-Dec-04	1-Feb-05	4.97	67.8	Continued
AD	Ecuador	27-Jan-04	4-Aug-04	23-Dec-04	1-Feb-05	2.48	4.42	Revoked**
AD	India	27-Jan-04	4-Aug-04	23-Dec-04	1-Feb-05	4.94	15.36	Continued
AD	Thailand	27-Jan-04	4-Aug-04	23-Dec-04	1-Feb-05	5.29	6.82	Continued
AD	China (PRC)	27-Jan-04	16-Jul-04	8-Dec-04	1-Feb-05	27.89	112.81	Continued
AD	Vietnam	27-Jan-04	16-Jul-04	8-Dec-04	1-Feb-05	4.3	25.76	Continued
CVD	China (PRC)	25-Jan-13	4-Jun-13	19-Aug-13	ITC Neg Final			
CVD	Ecuador	25-Jan-13	4-Jun-13	19-Aug-13	ITC Neg Final			
CVD	India	25-Jan-13	4-Jun-13	19-Aug-13	ITC Neg Final			
CVD	Indonesia	25-Jan-13	4-Jun-13	19-Aug-13	ITC Terminated			
CVD	Malaysia	25-Jan-13	4-Jun-13	19-Aug-13	ITC Neg Final			
CVD	Thailand	25-Jan-13	4-Jun-13	19-Aug-13	ITC Terminated			
CVD	Vietnam	25-Jan-13	4-Jun-13	19-Aug-13	ITC Neg Final			

Source. −United States Department of Commerce. International Trade Administration (ITC). Enforcement and Compliance. Antidumping and Countervailing Case Information.
*Antidumping duty order on frozen warmwater shrimp from Ecuador was revoked on August 15, 2007 as a result of World Trade Organization ("WTO") panel findings. (Federal Register /Vol. 72, No. 163 /Thursday, August 23, 2007.)

On December 28, 2012, the Coalition of Gulf Shrimp Industries, Biloxi, MS, the same petitioner in the prior antidumping investigations, launched a petition, which alleged material injury by subsidized imports from China, Ecuador, India, Indonesia,

[1] The statute defines "material injury" as "harm which is not inconsequential, immaterial, or unimportant." In assessing whether the domestic industry is materially injured by reason of subject imports, the Commission considers all relevant economic factors that bear on the state of the industry in the United States (but only in the context of U.S. production operations). These factors include output, sales, inventories, capacity utilization, market share, employment, wages, productivity, profits, cash flow, return on investment, ability to raise capital, and research and development (19 U.S. Code § 1677(7)).

Malaysia, Thailand, and Vietnam. The petition requested the Commission and the DOC to impose duties on imports from these countries. On August 19, 2013, the DOC published its final determinations that certain frozen warmwater shrimp from China, Ecuador, India, Malaysia, and Vietnam received government subsidy rates[2] ranging from 18.1 %, 10.1 % to 13.5 %, 10.5 % to 11.1 %, 10.8 % to 54.5% and 1.1 % to 7.8 %, respectively, and negative determinations in the countervailing duty investigations of imports from Indonesia and Thailand (Table 1). However, the USITC later determined on October 21, 2013, that the domestic industry was neither materially injured or threatened with material injury, nor materially retarded by reason of imports from China, Ecuador, India, Malaysia, and Vietnam of frozen warmwater shrimp (USITC, 2013).

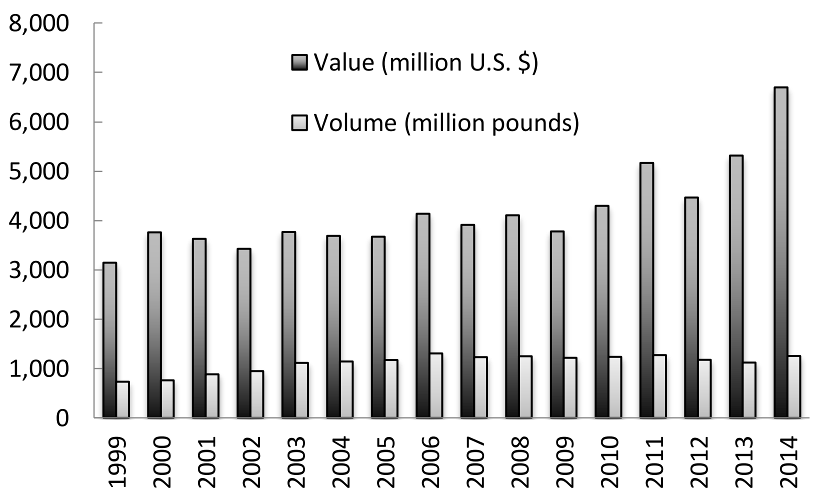

Figure 1. U.S. Shrimp Imports Volume and Value, 1999-2014
(Data source: Aquaculture Data, ERS, USDA.)

Undoubtedly, the increasing price-competitive imports have brought shrimp to attention for investigations. U.S. shrimp imports, valued at $6.7 billion in 2014, increased nearly 113% from 1999, with an average annual growth rate of 3.3% (Figure 1). Shrimp

[2] The countervailable subsidy/ actionable subsidy is a subsidy described in Article 3 or 6.1 of the Agreement on Subsidies and Countervailing Measures, WTO, which includes a direct transfer of funds from the government (e.g. grants, loans, and equity infusion), tax incentives, export financing, etc.

imports accounted for 27 % of the value of total edible fishery products imports. Seven major suppliers have accounted for most of these imports. These exporting countries include China, Ecuador, India, Indonesia, Mexico, Thailand, and Vietnam. In 2014, imports from these seven countries accounted for 84 per cent of the total U.S. shrimp imports by volume. Thailand is the biggest source, accounting for about 29% of the imports in 2014 (Table 2). As for type of preparation, the majority of imported shrimp comes as frozen shrimp. During the period 1999 – 2014, frozen shrimp accounted for 76.3% of the total imports by volume. Other forms of preparation include fresh (whether shell-on or peeled), canned, and breaded (Economic Research Service, 2014).

Table 2. U.S. Shrimp Imports 1999-2014, Volume by Selected Sources

Countries	1999-2014 (Million Pounds)	Share to total (%)
Thailand	5,185.99	29
Ecuador	1,919	11
China (Mainland)	1,539.82	9
Indonesia	1,870.8	10
Mexico	1,500.71	8
India	1,040.07	6
Vietnam	1,487.36	8
Malaysia	512.88	3
ROW	2,762.44	16
Total	17,819.08	100

Source. − Aquaculture Data, ERS, USDA.

Increases in U.S. shrimp imports have been driven by steady increases in United States per capita shrimp consumption. Shrimp has been the most consumed seafood in the U.S. since 2001, followed by canned tuna and salmon. In 1999, per capita shrimp consumption was 3.0 pounds, while U.S. per capita shrimp consumption was 4.2 pounds in 2011. U.S. shrimp consumers rely heavily on imports, which provided 93% of the total supply in 2011 (National Marine Fisheries Services, 2012).

In contrast, the domestic production of shrimp has been decreasing. The average of U.S. commercial landings of shrimp was 282 million pounds for the years 2007-2011, which fell from 318 million pounds for the years 1999-2003. Estimated shrimp production from aquaculture and breaded shrimp production have fluctuated but both have declining trends from 1999 to 2012. Shrimp from aquaculture was 4.6 million pounds ($13.7 million in value) in 1999; it fell down by 24% to 3.5 million pounds ($6.1 million in value) in 2011. The production of breaded shrimp in 2012 was 79.7 million pounds valued at $194 million, while in 1999 production was 119.1 million pounds valued at $352 million.

As one of the primary seafood commodities traded in the US seafood market, shrimp have constantly been the subject of trade remedy laws investigations. Surprisingly, little work has been conducted to assess the degree to which import demand changes as relative prices by source of imports. There is only one study to our knowledge that empirically investigates the shrimp import demand in the US. Jones, et al. (2008) estimate the U.S. demand for domestic and imported shrimp differentiated by exporting country from January 1995 to December 2005 using a Netherlands Central Bureau Statistic (CBS) demand system model. They test the monthly seasonality and stability of demand from each country and predicted that despite the countervailing duties imposed by the United States, shrimp demand from these countries would remain fairly stable. They assume that the import demands for shrimp are not affected by trade policies, even though antidumping duties are imposed during their study period.

There is a literature on the trade effects of the temporary trade barrier (TTB) policies/ trade remedy laws (antidumping, countervailing duties and safeguards), but it concentrates on the manufacturing industry (Blonigen, 2003a; Blonigen, 2003b; Bown and Crowley, 2007; Vandenbussche and Zanardi 2010; Pierce, 2011). One interesting phenomenon, which is found in some literature on the trade effects of antidumping duties is that the mere initiation of an unfair trade investigation reduces imports from the targeted country even when no final AD duties are levied, which is referred to the 'investigation effect' or 'harassment effect' (Prusa, 1992; Staiger and Wolak, 1994; Prusa, 2001).

There are a few studies that focus on the TTB policies for the agricultural sector. Carter and Gunning-Trant (2010) did an empirical study U.S. agricultural antidumping and countervailing duty cases from 1980 to 2005. They find that when the ruling is affirmative and AD or CVD duties are imposed, trade destruction affects U.S. agricultural imports from named countries for at least three years after the investigation year. In contrast to previous literature's findings for manufactures, they find no evidence of an investigation effect when the ruling is negative in their study of antidumping duties and no significant trade diversion in the U.S. agriculture sector. For disaggregate commodity studies, Asche (2001) investigates the case of US imposition of antidumping duties against Norwegian Salmon in 1991 and finds significant trade destructive and price effects of the antidumping duty. Malhotra, Rus, and Kassam (2008) and Keithly and Poudel (2008) are two descriptive analyses on antidumping legislation on U.S. imports of fresh tomatoes and shrimp. Notably, the latter find significant investigation and trade diversion effects, which contradicts Carter and Gunning-Trant (2010)'s finding and makes their principal assumption that the estimated parameters are identical across panels questionable. Also Keithly and Poudel (2008) point out the trade effect of antidumping duties on subject products and non-subject products. Carter and Mohapatra (2013) measure the responsiveness of U.S. domestic frozen concentrated orange juice (FCOJ) prices to imports from Brazil, in light of the imposition of antidumping duties on orange juice from Brazil in 2006. They model the role of inventories and find that there is only a very weak FCOJ domestic price response to imports from Brazil.

We explicitly model trade policies in a system-wide demand analysis approach and investigate the impact of antidumping/countervailing duties on the U.S. demand for imported shrimp, using monthly data differentiated by country of origin during the January 1999 through August 2014 time period. Specific objectives of this paper are (1) to estimate econometrically the demand for imported shrimp in the U.S. by country of origin, (2) to measure the impact of antidumping/countervailing duties on import demand and to obtain demand elasticities from the empirically estimated import demand parameters, (3) to conclude and discuss potential policy implications from the results.

1.2 Empirical methods

We assume that shrimp is differentiated by exporting source where Thai, Ecuadorian, Chinese shrimp, etc., are treated as individual products that make up the product group. Source differentiation implies that shrimp from one country is an imperfect substitute for shrimp from another country. To limit the analysis to shrimp, we assume a multistage budgeting process where total expenditures are first allocated across product groups and then group expenditures are allocated across the goods within each product group. In this context, total shrimp demand is determined in the first stage, and conditional on total shrimp expenditures, the demand for shrimp from each source is determined in the second stage (Seale et al. 1992). Preferences are assumed to be blockwise dependent (block independence) or weakly separable at the product group level, which implies that the utility interaction between shrimp and non-shrimp products is either zero (strong separability) or independent of the country of origin (weak separability) (Theil and Clements, 1987). Given the focus on imports, it also assumed that domestically produced and imported shrimp are weakly separable. The separability assumption is plausible because domestic shrimp is often considered superior to imports due to the high quality (wild caught). However, limited data did not allow for domestic shrimp to be included in the model.

Four popular demand systems are commonly used in the empirical analysis of consumer behavior to analyze agricultural import demand: Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), the Rotterdam (Theil, 1965), National Bureau of Research (NBR) (Neves, 1987), and Central Bureau of Statistics (CBS) (Keller and Van Driel, 1985) models. All of these models are based on consumer theory and derived from utility maximization. In addition, they are all constructed to satisfy the adding-up, homogeneity, and symmetry theoretical restrictions. In spite of the similarities, however, there is little guidance on how to choose a particular functional form from among the set of alternatives.

Barten (1993) nests differential versions of the four demand systems into a synthetic model by exploiting the similarities among the models. He parameterizes, rather than assumes, the impacts of expenditure shares on marginal expenditure shares and Slutsky substitution terms. Due to its nesting of the four functional forms, Barten's synthetic model and its several variants have been widely used for demand estimation of agricultural products (Brown, Lee, and Seale, 1995; Eales, Durham and Wessells, 1997;

Maynard and Veeramani, 2003; Okrent and Alston, 2012). Another attractive feature of the model is the flexibility to add more variables into the system in order to explain the variation in demand, such as advertising and other demand shifters.

Barten's synthetic model takes the following form:

$$w_{it}dlnq_{it} = c_i + (\alpha_i + \delta_1 w_{it})dlnQ_t + \sum_{j=1}^{n}\left(b_{ij} - \delta_2 w_{it}\left(\delta_{ij} - w_{jt}\right)\right)dlnp_{jt} + \beta_i X_{it} + \xi_{it}, \quad i = 1, \dots, n, \; t = 1, \dots, T. \tag{1}$$

where subscripts *I, j* represent different goods, *n* denotes the number of goods; *t* denotes the time period and *T* denotes the sample size;

q_i and p_j are the price and quantity for good *I* and *j* respectively;

w_{it} is the expenditure share of the *i*th good in time period *t* ($w_{it}= p_{it}q_{it}/\sum_{i=1}^{n} p_{it}q_{it}$);

$dlnQ_t$ is a Divisia volume index, that is $dlnQ_t = \sum_{i=1}^{n} w_{it}dlnq_{it}$;

c_i is the constant term to represent changes in consumer preferences or technologies;

α_i and b_{ij} are expenditure and price coefficients to be estimated (assumed constant); δ_1 and δ_2 are nesting parameters; δ_{ij} denotes the Kronecker delta, which is 1 when *i*=*j*, 0 otherwise; X_{it} is a vector of other control variables or demand shifters;

ξ_i is the random error term.

Restricting the values of the nesting parameters (δ_1 and δ_2) yields the following demand systems:

Rotterdam: $\delta_1 = 0$ and $\delta_2 = 0$;

FDLAIDS: $\delta_1 = 1$ and $\delta_2 = 1$;

CBS: $\delta_1 = 1$ and $\delta_2 = 0$;

NBR: $\delta_1 = 0$ and $\delta_2 = 1$.

By testing the nesting parameters, we could find out whether any of the systems nested within the Barten's synthetic model are consistent with the data, given the maintained hypothesis that one of the differential forms is appropriate.

Elasticities are calculated from estimates as follows (typically at the sample means):

expenditure elasticity

$$\eta_i = (\alpha_i + \delta_1 \bar{w}_i)/\bar{w}_i$$

compensated (Hicksian) price elasticity

$$\eta_{ij} = \left(b_{ij} - \delta_2 \bar{w}_i (\delta_{ij} - \bar{w}_j)\right)/\bar{w}_i$$

uncompensated (Marshallian) price elasticity

$$\eta_{ij}^* = \eta_{ij} + \bar{w}_j \eta_i$$

Restrictions from consumer demand theory can be invoked a prior or tested: adding-up $(\sum_{i=1}^{n} b_{ij} = 0, \sum_{i=1}^{n} a_i = 1 - \delta_1)$, homogeneity $(\sum_{j=1}^{n} b_{ij} = 0)$, and Slutsky symmetry $(b_{ij} = b_{ji})$. Adding-up (i.e. the expenditure shares sum across *n* goods equal 1) is automatically satisfied by construction and implies that the resulting demand system is singular. Homogeneity implies that the sum of the price coefficients is 0 within a given demand equation; and symmetry means that the compensated (Hicksian) substitution matrix should be symmetric, e.g. the appropriate cross-price parameters between equations are equal.

Barten's synthetic model is in essence a system of differential demand equations in which all variables are presented in terms of infinitesimal changes. For application to discrete data, the infinitesimal changes in Equation (1) are approximated by their discrete definite differences. As monthly data are used in this study, the twelfth differencing is applied to correct for seasonality of each variable (Seale, Marchant, and Basso, 2003): $dlnp_t$ is replaced with the change in the logarithm of q_t from period t -12 to t, e.g., $dlnq_t \approx \Delta lnq_t = ln(q_{it}) - ln(q_{it-12})$; $dlnQ_t \approx \sum_{i=1}^{n} w_{it} \Delta lnq_{it}$, $dlnp_t \approx \Delta lnp_t = ln(p_{it}) - ln(p_{it-12})$, $\forall\, i = 1 \dots n$. As a convention, expenditure shares wit are all replaced by their arithmetic average of the expenditure share in t-12 and t, f_{it}=(wi, t+wi, t-12)/2 in both estimations and the calculation of elasticities.

1.3 Variable construction and data

Monthly import expenditures and quantities by country from January 1999 to August 2014 are obtained from the Foreign Agricultural Trade Statistics (U.S. Department of Agriculture). Import values are on a cost-insurance-freight basis. The eight major exporting countries for shrimp to the U.S. are China, Ecuador, India, Indonesia, Malaysia, Mexico, Thailand, and Vietnam. The ROW (rest of the world) is an aggregation of the exporting countries not specified. Using expenditures and quantities, unit values are calculated as proxies for import prices (dollar per pound). Imported shrimp is an aggregation for 31 products of 10-digit HS codes (or 6 products of 6-digit HS codes[3]) (under the 2014 Harmonized Tariff Schedule of the United States (HTS)) including all types of preparation.

A summary of the descriptive statistics is presented in Table 3. During the data period, Thailand had the largest average share (29.8%), accounting for almost one third

[3] According to the Harmonized Tariff Schedule of the United States (2014), shrimp products are under 6-digit HS codes: 0306.16, 0306.17, 0306.26, 0306.27; 1605.21 and 1605.29.

of total U.S. shrimp imports. The ROW came in second with a 14.9% share, while China and Malaysia had the smallest shares (6% and 2.3%, respectively). Shrimp from Vietnam and Mexico was the most expensive, on average, with prices at \$5.37 and \$5.11/lbs., respectively. The mean price of shrimp from China was the lowest of all imported products (\$2.78/lbs.).

Table 3. Descriptive Statistics on U.S. Imports of Shrimp by Country: January 1999 – August 2014

	China	Ecuador	India	Indonesia	Malaysia	Mexico	Thailand	Vietnam	ROW
Import price ($ per lb)									
Mean	2.78	3.26	4.32	4.14	3.70	5.11	3.98	5.37	3.41
SD	0.57	0.72	0.67	0.83	0.87	1.17	0.90	0.81	0.56
Min	1.59	2.27	2.45	2.43	1.89	2.98	2.65	3.86	2.48
Max	4.65	5.21	6.47	6.63	6.59	9.06	6.44	8.04	4.87
Import quantity (1,000 lbs)									
Mean	8,064	9,897	7,419	9,507	2,643	5,367	27,253	7,614	14,481
SD	5,289	4,418	4,957	5,112	2,451	5,601	11,014	4,055	5,136
Min	745	2,326	1,414	1,792	32	102	7,321	367	5,623
Max	25,417	22,719	25,113	23,171	11,852	25,249	54,978	17,774	28,827
Import share (%)									
Mean	0.060	0.095	0.089	0.109	0.023	0.070	0.298	0.107	0.149
SD	0.032	0.048	0.049	0.055	0.018	0.060	0.078	0.039	0.067
Min	0.006	0.022	0.019	0.021	0.000	0.001	0.100	0.014	0.056
Max	0.171	0.291	0.241	0.264	0.066	0.260	0.466	0.189	0.354

We tested the monthly series of expenditure shares and logged values of prices and quantities for stationarity. Unit roots tests include the augmented Dickey-Fuller (ADF)(1979), Phillips-Perron (PP) (1988), and Dickey-Fuller generalized least squares (DFGLS) (Elliott, Rothenberg and Stock 1996). They test the null hypothesis of a unit root process against the alternative hypothesis of stationarity. The DFGLS test has substantially improved power over the other two tests when an unknown mean or trend is present (Elliot, Rothenberg, and Stock, 1996). An alternative to the DFGLS test is the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) test, which tests the null of trend stationarity against the alternative of a unit root. The KPSS test is often used in conjunction with those tests to detect "long memory" or fractional integration; a noninteger value of the integration parameter implies that the series is neither I (0) nor I (1) (Lee and Schmidt, 1996 and Baum, 2001). With the DFGLS test (Table 4), we failed to reject the null hypothesis of a unit root for all the monthly logged import quantities, prices, and expenditure shares series. Using the KPSS test, we could not reject the null hypothesis of trend stationarity in favor of a unit root process for all the series except for logged prices for Vietnam, and expenditure shares of Indonesia, Mexico and the ROW. Detection of unit roots in these data suggests that a differencing approach to estimation is necessary.

Table 4. Tests for Unit Roots in Monthly Shrimp Import Quantities, Prices, and Expenditure Shares

	Quantities			Prices			Expenditure Shares		
	No. of Lags	Test Statistic	5% Critical Value	No. of Lags	Test Statistic	5% Critical Value	No. of Lags	Test Statistic	5% Critical Value
Dickey-Fuller Generalized Least Squares (DFGLS) H_0: I(1)									
China	10	-0.400	-2.845	12	-1.707	-2.814	12	-1.123	-2.814
Ecuador	12	-1.411	-2.814	13	-2.131	-2.798	9	-0.432	-2.860
India	13	-0.990	-2.798	10	-1.391	-2.845	13	-0.860	-2.798
Indonesia	12	-1.555	-2.814	3	-1.507	-2.936	12	-2.404	-2.814
Malaysia	8	-1.545	-2.873	11	-2.113	-2.835	10	-1.685	-2.848
Mexico	12	-2.102	-2.814	12	-2.040	-2.814	12	-1.518	-2.814
Thailand	12	-2.087	-2.814	11	-1.512	-2.830	12	-1.378	-2.814
Vietnam	9	-0.550	-2.860	13	-3.313	-2.798	7	-1.223	-2.888
ROW	10	-0.354	-2.845	13	-2.255	-2.798	12	-1.884	-2.814
Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) H_0: I(0)									
China	10	0.32	0.146	12	0.231	0.146	12	0.22	0.146
Ecuador	12	0.185	0.146	13	0.269	0.146	9	0.193	0.146
India	13	0.173	0.146	2	0.162	0.146	13	0.17	0.146
Indonesia	12	0.223	0.146	3	0.821	0.146	12	0.127	0.146
Malaysia	8	0.355	0.146	11	0.229	0.146	10	0.278	0.146
Mexico	12	.0796	0.146	1	0.172	0.146	12	0.0974	0.146
Thailand	10	0.152	0.146	11	0.333	0.146	12	0.201	0.146
Vietnam	9	0.257	0.146	13	0.13	0.146	7	0.281	0.146
ROW	10	0.358	0.146	13	0.216	0.146	12	0.139	0.146

Note. − The unit root tests were applied to the levels of expenditure shares and the logarithmic transformations of the price and quantity. For the DFGLS test, lag length was determined by the Ng-Perron sequential t-test procedure. Critical values for the DFGLS test and the KPSS test reported in this table can be found in Elliot, Rothenberg, and Stock (1996) and Kwiatkowski, et al. (1992) respectively.

In order to capture the investigation effect of the AD/CVD investigations that occurred during the study period, we include time dummy variables ($ADIE_t$), which denote investigation periods (=1 for the investigation period, i.e., the month of investigation initiation to the month of final ruling). Antidumping duties were imposed for imports from Brazil, China, Ecuador, India, Thailand and Vietnam on February 1, 2005. The trade-weighted average dumping margins for the named countries are incorporated into the model[4] to measure the impact of antidumping duties on demand (United States International Trade Commission, 1995). These variables ($\Delta\tau_{it}$) are the changes of assigned dumping margins (in levels) for products exported to the U.S. from the named countries. Information of preliminary, final, and Sunset (five-year reviews) antidumping and countervailing duties are from the United States International Trade Commission, and the International Trade Administration, United States Department of Commerce. Rates of AD are obtained from various issues of the Federal Register. Prior to the months of final determination, AD duty rates are set to zero. The duties in our sample range from a minimum of 2.48% against imports of shrimp from Ecuador to a maximum 112.81% against China.

As the investigation period for each country differs, we use two CVD investigation dummies ($\mathrm{CVDIE_t}$). For named countries Indonesia and Thailand, the

[4] Antidumping duty rates are calculated as monthly weighted-average dumping margin percentages for each exporter. The weight is the ratio of dumped import quantities to the total value of U.S. sales during the period of investigation. The weighted-average margins for these individual firms are then weight-averaged to calculate an “All Others” rate to be applied to imports from firms that were not investigated (International Trade Administration, 2009). This rate can be regarded as the average tariff for each named country. AD duties are reviewed on an annual basis and are often revised. Sunset reviews of AD orders are conducted five years after they become effective.

investigation period is from Jan-Aug 2013. For named countries China, Ecuador, India, Malaysia, Vietnam and non-named countries, the investigation period is from Jan-Oct 2013 (Table 4).

By including both investigation dummies and antidumping duty rates, we are able to track the effects of the antidumping ruling in all its phases, from the initiation of the investigation, determination of antidumping duty rates, and to the periods of antidumping imposition.

In addition, we have two import restriction variables ($IMRE_i$) for China and Mexico, regarding safety and environmental concerns. One for China is the import refusal due to drug residuals in shrimp of some exporting companies from July to Oct 2007 (FDA, 2007). In March 2010, the U.S. withdrew the Mexican shrimp importation certification under the Sea Turtle Protection Law. The import ban was removed on October 15, 2010, when Mexico's Turtle Excluder Device (TED) program certification was reinstated (CBP, 2010).

1.3.1 Test of endogeneity

Since we only estimate the demand side of imported shrimp, it is a common practice to test price endogeniety to determine whether to use instruments from the supply side. The Wu-Hausman endogeniety test, as described in Johnson and DiNardo (1997, P. 342), was employed in this study to jointly test for endogeniety of import price variables. Instruments include price lags, input prices and supply shocks. One major input for shrimp production is feed (mainly fishmeal). Thus we use monthly nominal fishmeal prices from the Global Economic Monitor (GEM) Commodities database, World

Databank (2014) as an instrument. The supply shocks take the form of dummy variables indicating epidemics and natural disasters (=1, for Thailand from Aug 2011 to Dec 2012, accounting for the flood and the outbreaks of Early Mortality Syndrome (EMS); =1 for Ecuador from May 1999 to Dec 2000, White spot syndrome (WSS); =1 for China from Sept 2009 to Jul 2011, WSS and EMS; =1 for Vietnam EMS outbreaks from Jan 2011 to Dec 2012, =0 for all other time periods) (FAO, 2013). First, each import price was regressed on the aforementioned instruments, and the residuals from the price equations were then included as explanatory variables in the original demand models. Exogeneity is implied by the coefficients on these residuals being statistically zero. Test results indicate that the estimates on these residuals were not significantly different from zero. Thus, price exogeneity could not be rejected. The demand system can be consistently estimated via seemingly unrelated regression (SUR) without resorting to an IV estimator such as 3SLS.

So the final estimation equation is a Rotterdam model:

$$f_{it}\Delta lnq_{it} = c_{it} + \alpha_i \Delta lnQ_t + \sum_{j=1}^{n} b_{ij}\Delta lnp_{jt} + \beta_0 ADIE_t + \beta_1 \Delta\tau_{it} + \beta_2 CVDIE_t + \beta_3 IMRE_i + \xi_{it}$$

(2)

1.4 Estimation results and discussion

Barten’s synthetic model is used for model selection and estimated by iterated seemingly unrelated regression (SUR) (Stata version 13), which uses the asymptotically efficient, iterative feasible generalized least-squares (FGLS) algorithm described in

Greene (2012, 292–304). In order to deal with the singularity problem, the equation of the ROW is dropped from estimation. FGLS yields maximum-likelihood estimates of the demand parameters to ensure invariance with respect to the choice of which equations are deleted (Barten, 1969)[5].

First, we test the functional form by using Wald and the likelihood ratio tests (Table 5). For the Wald test, the joint null hypothesis $\delta_1 = \delta_2 = 0$ cannot be rejected at the 5% level of significance. (The significance level of the hypothesis test is 53%, we cannot reject it at any significance level below 53%.) For the likelihood ratio test, the unrestricted synthetic model rejects all of the models except for the Rotterdam model at the 5% level of significance (the p-value on the likelihood ratio test statistics is 0.21). Also by Akaike's and Bayesian information criteria, the Rotterdam model has the smallest values for both, indicating a better-fitting model. Therefore, the Rotterdam model is selected to estimate the demand system.

Table 5. Wald Tests and Log-Likelihood Ratio Tests for Nested Models of Barten's Synthetic Model

Wald Tests and Log-Likelihood Ratio Tests for Nested Models of Barten's Synthetic Model						
	Wald test $\chi^2(2)$	p-value	Likelihood Ratio Test	p-value	AIC	BIC
Rotterdam ($\delta_1 = \delta_2 = 0$)	1.26	0.53	2089.25	0.21	-4094.50	-3966.68
FDLAIDS ($\delta_1 = \delta_2 = 1$)	1783.55	0.00	2068.45	0.00	-4052.89	-3925.07
CBS ($\delta_1 = 1$, $\delta_2 = 0$)	1881.74	0.00	2025.93	0.00	-3967.85	-3840.03
NBR ($\delta_1 = 0$, $\delta_2 = 1$)	78.73	0.00	2049.23	0.00	-4014.45	-3886.63

Continued

[5] We checked that our estimates were indeed invariant to the equation eliminated by arbitrarily omitting different equations, and comparing parameter estimates, standard errors.

Table 5. Continued

Likelihood Ratio Test Results for Theoretical Constraints for the Rotterdam model			
Model Restrictions	Log-likelihood value	LR Statistic	P-value
Unrestricted	3976.35	21.93	0.003(7)*
Homogeneity	3965.38	44.30	0.002(21)
Symmetry	3954.20	75.82	0.000(28)
Homogeneity and Symmetry	3938.44	21.93	0.003(7)

Note. – * The numbers of restrictions are in parentheses.

We then tested whether the data supported the restrictions of homogeneity and symmetry from demand theory. If those theoretical constraints are not rejected, we can impose them to save some degrees of freedom and gain efficiency (Capps Jr, et al. 2003). Both models are estimated in four ways: (1) without homogeneity or symmetry (unrestricted), (2) with homogeneity imposed, (3) with symmetry imposed, and (4) with homogeneity and symmetry jointly imposed (restricted models). Log-likelihood ratio (LR) tests are employed in pairwise comparison for each restricted model against the unrestricted model. Log-likelihood values and the chi-square (LR) test statistics and p-values are given in Table 5. Homogeneity and symmetry (both singly and jointly imposed) were overwhelmingly rejected at any reasonable significance level[6] and are not imposed.

After fitting the model using SUR, we conduct a Breusch-Pagan test of independence based on the correlation matrix. Test statistics reject the null hypothesis that there are no correlations among the disturbances. It suggests that there is likely to be

[6] The rejection of homogeneity and symmetry is common in past consumer demand studies (e.g. Deaton and Muellbauer, 1980; Bryant and Davis, 2008; Muhammad and Jones, 2011). This may be due to inappropriate asymptotic standard tests that are biased towards rejecting the homogeneity and symmetry conditions. The likelihood ratio test statistics is asymptotically distributed as chi-square. Using finite sample may get test statistics with lower values (Syriopoulos and Thea Sinclair, 1993; Keuzenkamp, and Barten, 1995; Chambers and Nowman, 1997).

some gain in efficiency by using SUR rather than fitting the model separately by OLS.

1.4.1 Estimation results

Estimation results for imported shrimp by source are presented in Table 6. We find significantly negative AD investigation effects for China, India, and Vietnam (named countries) and positive investigation effects for the Indonesia and Malaysia (non-named country), which is consistent with the findings from previous studies (Staiger and Wolak, 1994; Prusa, 2001) [7]. This phenomenon indicates that in order to deal with the uncertainties regarding the AD rulings, U.S. buyers of imported shrimp responded in the investigation phase (Jan–Dec 2004), even before the antidumping duties were officially imposed. Because establishing sound and reliable ties with new suppliers requires time and planning, importers seek new suppliers from countries not targeted by the tariff before any official rulings are made. Investigation effects are not statistically significant for Ecuador and Thailand (named countries) and Mexico (non-named).

To understand the magnitude of the effect, we use results from the Rotterdam model (Table 6) and follow the formula in Greene (2012, P150) to calculate the percentage change in the dependent variable associated with AD investigation dummy variables. The quantities demanded for imported shrimp from China, India and Vietnam decreased by 4.30%, 2.76% and 5.73%, respectively, during the investigation period,

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[7] Staiger and Wolak examined the trade impacts of U.S. antidum
ping law and the determinants of suit-filing activity from 1980 to 1985. They found that during the investigation period a petitioning firm benefits from roughly one-half of the decline in imports that would have occurred if final AD duties had been imposed from the initial date of filing. Prusa also analyzed antidumping effects by the United States from 1987 to 1997. He found that imports fall dramatically during the investigation period, regardless of the case's ultimate outcome. Specifically, the value of imports from named countries falls by 50-70 per cent over the first three years of protection.

while the demand for Indonesia and Malaysia shrimp increased by 6.08% and 4.92%, respectively. The AD investigation does not have a statistically significant effect on shrimp imports from Thailand.

Table 6. Parameter Estimates of Demand for Imported Shrimp by Source in the U.S.

	Demand For Imports From							
	China	Ecuador	India	Indonesia	Malaysia	Mexico	Thailand	Vietnam
Prices of Imports From								
China	-0.050**	0.019	0.000	-0.054**	-0.002	0.025	0.081**	0.023
	(0.020)	(0.020)	(0.021)	(0.021)	(0.013)	(0.020)	(0.040)	(0.024)
Ecuador	0.028	-0.077***	0.051*	0.052**	-0.027	-0.105***	0.062	-0.009
	(0.025)	(0.025)	(0.026)	(0.026)	(0.017)	(0.026)	(0.049)	(0.030)
India	0.057***	0.009	-0.058***	-0.005	-0.028**	-0.022	-0.048	0.036
	(0.022)	(0.020)	(0.022)	(0.022)	(0.014)	(0.021)	(0.042)	(0.027)
Indonesia	-0.176***	0.031	-0.029	-0.026	0.063***	0.041	-0.032	0.059
	(0.034)	(0.035)	(0.036)	(0.036)	(0.022)	(0.035)	(0.067)	(0.042)
Malaysia	-0.011	-0.035***	0.029**	-0.010	0.002	0.019*	0.044**	0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.007)	(0.011)	(0.022)	(0.014)
Mexico	-0.009	0.013	-0.000	0.024**	0.008	-0.034***	-0.048**	0.056***
	(0.012)	(0.011)	(0.012)	(0.012)	(0.008)	(0.012)	(0.023)	(0.014)
Thailand	0.054	0.044	0.028	0.099***	0.001	0.030	-0.169**	-0.064
	(0.036)	(0.033)	(0.037)	(0.035)	(0.022)	(0.036)	(0.067)	(0.042)
Vietnam	0.080***	-0.022	-0.014	-0.048**	-0.033**	-0.010	0.050	-0.028
	(0.022)	(0.022)	(0.023)	(0.023)	(0.014)	(0.022)	(0.044)	(0.027)
ROW	0.003	0.022	-0.009	0.038	0.018	0.021	0.039	-0.051
	(0.028)	(0.027)	(0.030)	(0.030)	(0.018)	(0.029)	(0.055)	(0.035)
Divisia index	0.118***	0.038**	0.121***	0.048***	0.016	0.054***	0.384***	0.171***
	(0.016)	(0.015)	(0.017)	(0.017)	(0.010)	(0.016)	(0.031)	(0.019)
	0.039	-0.094***	-0.008	0.008	-0.107***	-0.006	-0.085*	
Exchange rate	(0.084)	(0.023)	(0.024)	(0.015)	(0.028)	(0.022)	(0.046)	
AD Investigation	-0.044***	0.007	-0.028***	0.059***	0.048***	0.002	-0.031*	-0.059***
Effects	(0.009)	(0.009)	(0.010)	(0.010)	(0.006)	(0.009)	(0.018)	(0.011)
Antidumping	-0.026***	0.120	-0.014	NA	NA	NA	1.149***	-0.043
Duties	(0.008)	(0.149)	(0.090)				(0.254)	(0.040)
CVD	0.004	-0.018*	0.064***	-0.022**	-0.035***	-0.000	-0.018	0.021*
investigation	(0.010)	(0.009)	(0.010)	(0.011)	(0.006)	(0.010)	(0.019)	(0.011)
Import alert or	-0.032***	NA	NA	NA	NA	-0.036***	NA	NA
refusal	(0.011)					(0.008)		
Intercepts	0.008**	0.005**	0.007**	0.006**	0.000	-0.003	-0.015***	0.009***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Observations	176	176	176	176	176	176	176	176
R^2	0.576	0.655	0.442	0.352	0.478	0.385	0.661	0.577

Note. −Standard errors in parentheses. ***, **, and * denote the significance levels of 1%, 5% and 10%.

Data from the report of Fisheries of the United States 2004 (National Marine Fisheries Service, NMFS) and trade statistics on U.S. shrimp imports, Economic Research Service (ERS) also can demonstrate this investigation effect. In 2003, shrimp imports from Brazil, China, Ecuador, India, Thailand, and Vietnam totaled more than 822 million pounds, accounting for 74 % of total shrimp imports. In 2004, the year the Department of Commerce investigated the anti-dumping petition; imports from the six countries targeted by the anti-dumping petition fell 12 % to 712 million pounds, amounting to 62 % of total shrimp imports. Brazilian exports of shrimp were seriously affected by the antidumping duties. During the investigation year of 2004, imports from Brazil plummeted from 48 million pounds in 2003 to 20 million pounds, finally falling to zero imports in 2007.

Yet total U.S. shrimp imports rose to 1.1 billion pounds in 2004, 28.9 million pounds more than the quantity imported in 2003, an increase of almost 3%. Shrimp imports from several non-targeted countries increased dramatically: imports from Malaysia increased by 880 %, from Indonesia by 117 %, and from Bangladesh (not included in the analysis) by 113 %. Overall, U.S. shrimp imports from the countries not targeted by the anti-dumping petition rose from 290 million pounds in 2003 to 429 million pounds in 2004, an increase of 48 %.

Countervailing duty investigation has different trade flow influences from AD investigation. It does have significant impact on newly named countries (i.e., Indonesia and Malaysia), with their demands decreased by 2.18% and 3.44%, respectively. CVD investigation does not affect all other countries, except India, albeit contrary to expectations. The India shrimp import is expected to decline but actually increased by 6.61%. This interesting result shows that imports from named country, which are already subject to ADD, does not slow down due to the CVD investigation. That is because the probability of double remedies is quite low given previous WTO cases (Durling and Prusa, 2012).

Coefficients on U.S. imposition of antidumping measures against imported shrimp are only statistically significant for China and Thailand, though their directions differed. As expected, antidumping duties have a trade destruction effect for China. On the other hand, the trade creation effect on another named-country, Thailand, is not anticipated. With respect to the size of the estimates, imposition of a 1% antidumping duty is associated with a 0.03% decrease in quantities demanded for China shrimp and a 1.15% increase in demand for shrimp from Thailand. The non-significance of antidumping duties for other named countries may be due to the fact that antidumping duties only cover certain frozen warmwater shrimp, accounting for about 30-40% of total shrimp imports (the scope of this study) by volume. Antidumping duties do not seem to affect total shrimp imports from these countries, namely, Ecuador, India and Vietnam.

This phenomenon reflects the way exporters respond to the anti-dumping duties. The Department of Commerce imposed the anti-dumping duties against shrimp imports from Brazil, China, Ecuador, India, Thailand, and Vietnam in January 2005, and total shrimp imports from the six named countries actually increased rather than decreased. In 2005, shrimp imports from the six countries increased to 744 million pounds, up 4.5 % from the 2004 total of 712 million pounds. Imports from Thailand increased by 21% from 292.5 million pounds in 2004 to 355.2 million pounds in 2005. In 2006, imports from the six jumped 14.5 % to 851 million pounds.

One possible reason is that in order to avoid ADD, exporters try to export more non-subject products. Shrimp have many species and are in many different forms of preparation. The anti-dumping duties do not cover all shrimp species, nor do they cover all forms of processed shrimp products. In particular, value-added shrimp products, such as breaded shrimp and prepared shrimp meals, are exempt from the tariff. NMFS data show that, while shrimp producers in Brazil, India, and Vietnam found other markets for their shrimp (primarily Europe and Japan), Ecuador and especially China and Thailand shifted their production to value-added products that are exempt from the tariff. U.S. imports of breaded shrimp increased 169 % from 36.5 million pounds to more than 98 million pounds in 2005, and then rose another 11% in 2006. U.S. imports of prepared shrimp meals increased moderately in 2005, and then jumped 40% from 184 million pounds in 2005 to 257 million pounds in 2006. China and Thailand now account for 93 % of U.S. imports of breaded shrimp and 75 % of U.S. imports of prepared shrimp meals.

After analyzing the investigation effect and trade effects of antidumping duties, we can conclude that U.S. shrimp buyers have rendered the anti-dumping tariff ineffective as a means of protection due to switching to new exempt suppliers of frozen shrimp and foreign producers.

Coefficients on import alert/refusals all have negative signs in agreement with a priori expectations. Imports from China and Mexico due to the trade restricting policies slowed down by 3.15% and 3.54%, respectively. The magnitude of the impact for Mexico is a little bit larger than that for China. The reason for this might be that importation certification withdrawal has broader influence as it is nationwide, while the import refusal is usually on a firm level.

1.4.2 Demand elasticities

Expenditure and compensated price elasticities for imports of shrimp into U.S. are presented in Table 7. All expenditure elasticities are positive and all own-price elasticities are negative except for Ecuador and Malaysia. China, India, Thailand and Vietnam have high expenditure elasticities (1.89, 1.41, 1.28 and 1.59 respectively), while Indonesia and Mexico have low expenditure elasticities (0.45 and 0.78, respectively). These indicate that as the overall expenditure on shrimp increases by 1%, imports from China will increase as twice as much; imports from India, Thailand and Vietnam would increase by approximately 1.50%, while imports from Indonesia and Mexico will increase less than proportionately. These expenditure elasticities show that the market for imported shrimp tends to be concentrated on major exporting countries.

Table 7. Expenditure and Compensated Price Elasticities of Demand for Imported Shrimp by Source in the U.S.

w.r.t.	Elasticities of Demand For Imports From							
Prices of Imports From	China	Ecuador	India	Indonesia	Malaysia	Mexico	Thailand	Vietnam
China	-0.919**	0.18	-0.083	-0.532**	-0.12	0.307	0.19	0.639**
	(0.324)	(0.220)	(0.249)	(0.201)	(0.534)	(0.288)	(0.135)	(0.209)
Ecuador	0.274	-0.875**	0.458	0.438	-1.168	-1.587***	0.088	-0.354
	(0.404)	(0.274)	(0.301)	(0.242)	(0.681)	(0.372)	(0.162)	(0.203)
India	0.759*	0.066	-0.795**	-0.081	-1.194*	-0.39	-0.269	-0.263
	(0.361)	(0.230)	(0.267)	(0.211)	(0.582)	(0.317)	(0.144)	(0.215)
Indonesia	-3.037***	0.291	-0.485	-0.29	2.545**	0.501	-0.244	-0.621**
	(0.550)	(0.374)	(0.421)	(0.328)	(0.903)	(0.498)	(0.221)	(0.215)
Malaysia	-0.228	-0.388**	0.302*	-0.102	0.072	0.258	0.115	-0.346**
	(0.191)	(0.136)	(0.140)	(0.107)	(0.302)	(0.161)	(0.074)	(0.131)
Mexico	-0.276	0.109	-0.098	0.194	0.269	-0.537**	-0.248**	-0.206
	(0.187)	(0.122)	(0.141)	(0.114)	(0.315)	(0.172)	(0.076)	(0.204)
Thailand	0.295	0.358	-0.1	0.779*	-0.162	0.193	-0.945***	-0.015
	(0.567)	(0.356)	(0.415)	(0.319)	(0.884)	(0.504)	(0.218)	(0.410)
Vietnam	1.075**	-0.289	-0.309	-0.496*	-1.435*	-0.231	0.028	-0.435
	(0.362)	(0.238)	(0.268)	(0.214)	(0.583)	(0.315)	(0.145)	(0.248)
Expenditure	1.891***	0.415*	1.406***	0.448**	0.651	0.779***	1.276***	1.588***
	(0.257)	(0.168)	(0.193)	(0.155)	(0.427)	(0.232)	(0.103)	(0.179)

Note. − Standard errors are calculated by the delta method (Feiveson, 1999) and in parentheses. ***, **, and * denote the significance levels of 1%, 5% and 10%.

The compensated price elasticities represent the substitution effect of price changes. The own-price elasticities for all countries are inelastic, except for Indonesia, Malaysia and Vietnam, which are not statistically significant. The elasticity magnitudes are similar to those from Jones, et al. (2008), which are smaller in absolute value. Thailand has the most price-elastic demand (-0.945) among them, followed by China with an own-price elasticity of -0.919, indicating shrimp imports from Thailand and China are relatively sensitive to own price changes compared to other countries. Own-price elasticities of demand for these two countries were close to unity. It implies that the percentage changes in quantities demanded for Thailand or China shrimp are equal to those in prices, so a change in price by either country will not affect the total import expenditure for shrimp from that country. Ecuador, India and Mexico shrimp are less responsive to changes in prices (with own-price elasticities -0.88, -0.80, and -0.54, respectively). Demand for Mexico shrimp is the most price-inelastic (-0.54) among the statistically significant own-price elasticities. Specifically, in response to a 1% increase in price, the demand for the Mexico shrimp would decrease by only 0.54%. It is possible for these three countries to gain revenue by raising the prices, as demands for their shrimp are price-inelastic. This also implies that an increase in these countries' shrimp prices would result in a less than proportionate decrease in the quantity of shrimp demanded from them by the United States.

Cross-price elasticities of demand for imported shrimp in United States indicate various relationships between shrimp imports from the exporting sources. For instance, the China/Indonesia cross-price elasticity is -3.04, indicating a complimentary relationship, while the China/Vietnam cross-price elasticity is 1.08, reflecting a substitutional relationship. As for the magnitude of responsiveness, Mexico/Vietnam has a cross-price elasticity of -1.59. When price of Vietnamese shrimp increase by 1%, imports from Mexico would decrease by 1.59%. Most of the cross-price elasticities are either insignificant or have small magnitudes (less than unity), showing that shrimp from these countries do not have a strong substitutional or complementary relationship, possibly due to the fact that highly aggregated data are used in this study. Thus it is not surprising that complementary relationships do exist between different subspecies and types of preparation of shrimp. For instance, in 2012, more than half (55%) of the total breaded frozen shrimp was provided by China; more than one third (33%) of the cold-water peeled frozen shrimp imports are from Thailand; imports from Thailand, Indonesia, India, Vietnam and Ecuador accounted for 81% of the total shrimp warm-water peeled frozen (NMFS, 2013).

1.5 Summary and conclusions

This paper aims to estimate the import demand for shrimp in the United States using monthly data from Jan 1999 to Aug 2014. Imported shrimp are from eight different sources: China, India, Indonesia, Malaysia, Mexico, Thailand, Vietnam, and rest of the world (ROW). Using Barten's synthetic model selection procedure, the Rotterdam model is chosen to estimate demand system. Even though aggregated data are used, we still found statistical evidence of trade destruction and creation effects arising from AD/CVD investigations, contrary to the findings from Carter and Gunning-Trant (2010). These effects differ by country and whether the country is already subject to trade remedy measures.

Significant investigation effect and insignificant trade effects of antidumping duties are found from the estimation results. We observe responses the following reactions to the antidumping ruling: U.S. shrimp importers switching to new suppliers of frozen shrimp during the investigation period; and foreign producers subject to the tariff are switching production to shrimp products exempt from the tariff after the imposition of antidumping duties. These actions have rendered the anti-dumping duties ineffective in deterring imports from named countries. Thus AD duties fail as a good means of protecting U.S. domestic shrimpers. On the other hand, some domestic industries may pursue the process-filing strategy and therefore initiate antidumping procedures for the investigation effects alone. Further studies are needed to empirically examine how trade remedy measures affect the industry of the subject product in named countries, would producers in named country switch to non-subject production to avoid duties?

In addition to trade remedy measures, we also find significant impact of import refusals due to safety and environmental issues. Failure to include those trade policy variables in demand analysis would lead to biased estimates.

Chapter 2. Cigarette Tax Pass-Through by Product Characteristics: Evidence from Nielsen Retail Scanner Data

2.1 Introduction

Smoking is the leading cause of preventable death and a significant contributor to health care costs in the United States, responsible for more than 480,000 deaths and costs of approximately $300 billion per year (Centers for Disease Control and Prevention 2015a). To protect the public health and reduce the burden of illness and death caused by tobacco use, federal, state, and local governments have taken significant steps to regulate tobacco sales, marketing, and use. Such efforts include, for example, the 1998 Master Settlement Agreement (MSA), which restricts the advertising, marketing and promotion of tobacco products and requires that participating manufacturers make annual payments to the settling states in perpetuity for recovery of their tobacco-related health care costs[8]; an increase in federal tax rate for cigarettes from $0.39 to $1.01 per pack since April 2009[9] (Alcohol and Tobacco Tax and Trade Bureau 2012); passage of the Family Smoking Prevention and Tobacco Control Act on June 22, 2009, which gives the Food and Drug Administration (FDA) the authority to regulate the manufacture, distribution, and marketing of tobacco products and ban cigarettes with characterizing flavors such as fruit and candy (with a special exception for menthol cigarettes); enforcement of the Prevent All Cigarette Trafficking Act on June 29, 2010, which aims to fight crime and increase

[8] All payments are based primarily on the number of cigarettes sold. States are about to receive $250 billion over the first twenty-five years of the agreement, including payments to the four states (Mississippi, Florida, Texas and Minnesota) that settled previously. For analysis of the effects of the MSA payment see articles: Sloan, Trogdon, and Mathews (2005); Trogdon and Sloan (2006); Ciliberto and Kuminoff (2010); and Lillard and Sfekas (2013).

[9] Via the Children's Health Insurance Program Reauthorization Act of 2009.

government revenues by ensuring the collection of federal, state and local tobacco taxes on cigarettes and smokeless tobacco sold via the Internet or other mail-order sales; and frequent tax rate increases by state and local governments (since 2000, 47 states, the District of Columbia, and several U.S. territories have implemented or passed more than 115 cigarette tax rate increases) (Orzechowski and Walker 2014), etc.

Among all these policies, increases in cigarette prices through increased taxes have been regarded as the single most effective means of reducing consumption and lowering the smoking rate. Numerous economic studies have documented that cigarette tax or price increases reduce both adult and youth smoking. It is estimated that every 10 percent increase in the real price of cigarettes reduces overall cigarette consumption by approximately 3 to 5 percent and youth cigarette demand by about 7 percent (Chaloupka and Warner 2000; Jha and Chaloupka 2000; Ross and Chaloupka 2003; Chaloupka, Straif, and Leon 2010; CDC 2012; Nikaj and Chaloupka 2013; Callison, and Kaestner 2014). Taxes make up a substantial portion of the retail cigarette price. Federal and state excise taxes on average accounted for 44.3 percent of the retail price of cigarettes in 2012. In addition, cigarette sales are subject to local excise taxes in some counties and cities. In 2011 and 2012, more than 590 counties and cities in 7 states (Alabama, Alaska, Illinois, Missouri, New York, Ohio and Virginia) levied local tobacco taxes. Average local excise taxes were $0.030 and $0.031 per pack, respectively, in 2011 and 2012 (Orzechowski and Walkeron 2012; 2014). The extent to which taxes are passed through to retail prices, however, depends on the sellers' pricing strategies: specifically whether they overshift or undershift the tax increases. Overshifted taxes put more burdens on smokers who continue to smoke after the tax increase but are also more effective in reducing tobacco use compared with undershifted taxes. Thus, understanding the magnitude of tax incidence is important for tobacco control policy.

The recent studies on cigarette tax incidence can be categorized into two strands based on the types of research questions posed. The first strand typically uses survey data and focuses on tax pass-through and smoker heterogeneities. For example, smokers can be classified as heavy smokers, and light and intermittent smokers (LITS), or those who use price-minimizing strategies versus those who do not. DeCicca, Kenkel, and Liu (2013) and Pesko, Licht and Kruger (2013) used self-reported prices from the 2003 and 2006-2007 Current Population Survey Tobacco Use Supplements (TUS-CPS) and both found pass-through rates of about one. Their results also provided evidence that consumers avoided the tax by using price minimization strategies, such as purchasing cigarettes by the carton, in a nearby lower tax jurisdiction, or online. Goldin and Homonoff (2013) used data obtained from the Tax Burden on Tobacco 2008 report and found that excise tax was fully passed on to consumers with a pass-through rate of 1.126. They also investigated the link between the salience of a tax and the distribution of its burden across consumers by focusing on the heterogeneity in consumer attentiveness to posted (excise tax) and registers taxes (sales tax rate). Using data on cigarette consumption between 1984 and 2000, they found that both high- and low-income consumers responded to changes in the cigarette excise tax, but that only low-income consumers responded to changes in the sales tax rate (added at the register) on cigarettes. Xu, Malarcher, and Kruger (2014) employed data from the 2009–10 National Adult Tobacco Survey (NATS) and found that the magnitude of cigarette tax effect on retail price depends on smokers' price-minimizing strategies such as carton purchase, coupon use, purchase from Indian reservations and purchase of generic brands. Excise tax was undershifted to some smokers who used price-minimizing strategies with a pass-through rate ranging from 30 percent to 83 percent, while excise tax was overshifted to smokers of premium brands who purchased by pack outside Indian reservations with pass-through rates from 1.07 to 1.10.

The second strand of research explores the relationships between cigarette taxes incidence and retail prices differentiated by product characteristics. They mainly use micro-level price data from retail stores. Sullivan and Dutkowsky (2012) used tax data from 443 municipalities and market-level cigarette price data covering from 1990 to 2004. Their results demonstrated overshifting of federal, state, and local excise taxes, and they did not find any significant difference in the magnitude of tax incidence between premium and generic cigarette brands. Harding, Leibtag, and Lovenheim (2012) used the Nielsen Homescan panel data from January 1, 2006, through December 31, 2007, and found that cigarette taxes were less than fully passed through (86–90% pass-through rate) to consumer prices on average, suggesting that consumers and producers split the burden of these taxes. Espinosa and Evans (2012) found that retail prices increased dollar-for-dollar with excise tax changes by using 2001–2006 monthly retail scanner data for supermarkets in 29 states. Their estimation results demonstrated that smokers paid the entire tax burden of higher excise taxes with an almost complete pass through (99% pass-through rate). While there was limited evidence of tax-induced brand substitution toward name brands from generic brands, they found some evidence for a sizable substitution away from carton to pack sales, suggesting that tax hikes encourage within-brand changes in purchase but little between-brand substitution. Chiou and Muehlegger (2014) studied how consumers adapted to cigarette tax increases in the short- and long-term by using store-level scanner data for 85 supermarkets in the Chicago metropolitan area from 1989 to 1996. They considered four cigarette classes (branded vs. discount, pack vs. carton) and found that tax incidence varied across each class of cigarette: Pass-through rates for premium packs and cartons were lower than discount packs and cartons, indicating possible substitution toward high-tier cigarettes. Brock, et al. (2015) investigated the impact of a cigarette excise tax hike by the state of Minnesota in 2013. They used data on retail prices of four specific cigarette products in 61 convenience stores in Minnesota, North Dakota, South Dakota and Wisconsin between May 2013 and January 2014. They found that the market overshifted the cigarette tax increase to consumers in Minnesota.

We use Nielsen store-level scanner data on cigarette prices from convenience stores over the period 2011–2012 to measure the incidence of cigarette excise taxes. Our study contributes to the literature in the following ways. We use store-level sales data for 1,865 convenience stores in 560 counties from the 48 contiguous states, utilizing 20 million observations at the Universal Product Code (UPC)-store-week level. Because the data provide detailed product descriptions for each good at the UPC level, we are able to control for price variations using observed product characteristics and also examine how tax incidence interacts with product heterogeneity. Existing studies using scanner data typically have access to data that is either limited to a specific region or from chain supermarkets and drug stores, which account for a minority of cigarette sales (Espinosa and Evans 2012; Chiou and Muehlegger 2014). We use convenience store retail sales data because a majority of sales of cigarette products occur in convenience stores.

Nielsen's convenience store sample represents all convenience store types and includes chain stores, non-chain and independent convenience stores, and convenience stores found in gas stations. Per Nielsen and IRI, convenience stores have accounted for the majority of retail cigarettes sales (86.9% compared with 6.7% and 6.4% in grocery and drug stores, respectively, in 2014). Study by Harding, Leibtag, and Lovenheim (2012) is the most comparable one to ours to date. They use Nielsen Homescan data whose credibility is often questioned since the data are self-recorded and the recording process is time-consuming. Recent studies by Einav, Leibtag, and Nevo (2008 and 2010) find price is the most poorly recorded variable in the Homescan data. They find that recording discrepancies between Homescan and retailer prices are evident and potentially impact results. Such differences are mainly due to standard recording errors and Nielsen price imputation. Thus using Homescan price data may lead to biased estimation results. Utilizing information on cigarette products attributes, we examine whether tax incidence varies by product characteristics, especially by brand and package size.

The rest of the paper proceeds as follows. Section II presents the empirical methodology for cigarette excise tax incidence. Section III describes the data and variable construction. Section IV discusses the estimation procedure and empirical results, and Section V concludes with a discussion and summary of our findings.

2.2 Theoretical model

We first consider the tax incidence[10] using the partial equilibrium model of competitive

[10] Here we only consider the incidence of excise tax, sales tax (ad valorem) is not discussed.

markets, which is the main thrust of the literature in studying the effects of taxes (Kotlikoff and Summers, 1987; Marion and Muehlegger, 2011; Weyl, & Fabinger, 2013). One important assumption is that the excise tax on cigarette manufactures does not shift backwards to laborers in the form of lower wages, and it only forward to consumers in the form of higher price. For partial equilibrium analysis to be appropriate, it is necessary that the product in question have a market that is small relative to the entire economy. We then extend our analysis of tax incidence to imperfect competition with monopolistic and oligopolistic firms (Fullerton and Metcalf, 2002; Sullivan and Dutkowsky, 2012; Weyl and Fabinger, 2013)

Perfect competitive market

The analysis is depicted in Figure 1.1. In the absence of taxation, equilibrium is attained where supply equals demand and the equation,

$$Q_D\ (P_D) = Q_S\ (P_S) \qquad \text{(A 1.1)}$$

The imposition of the cigarette excise tax (per-unit t), which is paid by suppliers, introduces a "wedge" between the price consumers pay (P_D) and what suppliers receive (P_S). Under perfect competition, both consumers and producers take prices as given and choose quantities as to maximize their utility and profit, respectively.

The new equilibrium will satisfy the condition that,

$$Q_D\ (P_D + t) = Q_S\ (P_S) \qquad \text{(A 1.2)}$$

Taking total differentiation of the market equilibrium conditions yields equations expressed in terms of infinitesimal (infinitely small) changes.

$$dQ_D = dQ_S \text{ or } D_P dP_D = S_P\, dP_S \qquad \text{(A 1.3)}$$

where D_P and S_P are the price derivatives of the demand and supply functions, respectively, i.e. $D_P = \partial Q_D/\partial P_D$ and $S_P = \partial Q_S/\partial P_S$.

As $P_D - P_S = t$ or $dP_D - dP_S = dt$, substitute into (1.3) to solve for the effect of the tax on P_D:

$D_P dP_D = S_P (dP_D - dt)$

$$\frac{dP_D}{dt} = \frac{S_P}{S_P - D_P} \qquad \text{(A 1.4)}$$

By multiplying $\frac{P_S}{Q_S}$, the standard representation of incidence is obtained:

$$\frac{dP_D}{dt} = \frac{S_P}{S_P - D_P} = \frac{\frac{\partial Q_S}{\partial P_S}}{\frac{\partial Q_S}{\partial P_S} - \frac{\partial Q_D}{\partial P_D}} = \frac{\frac{\partial Q_S}{\partial P_S} \cdot \frac{P_S}{Q_S}}{\left(\frac{\partial Q_S}{\partial P_S} - \frac{\partial Q_D}{\partial P_D}\right) \cdot \frac{P_S}{Q_S}} = \frac{e_S}{e_S - e_D} = \frac{1}{1 - \frac{e_D}{e_S}} \qquad \text{(A 1.5)}$$

where e_S and e_D represent the price elasticities of supply and demand, both at old equilibrium points before tax imposition. Because $e_S \geq 0$and $e_D \leq 0$, we can easily get $\frac{dP_D}{dt} \geq 0$, that is, the firm passes on at least some of the tax to the final price of the good. The principle illustrated in Equation shows that the pass-through rate is determined by the relative elasticity of supply and demand.

The extent to which consumers or producers pay the tax depends on the price elasticities of demand and supply. If $e_D = 0$ (demand is perfectly inelastic) or $e_D = -\infty$(supply is perfectly elastici), then $\frac{dP_D}{dt} = 1$ and the per-unit tax is completely paid by consumers. Conversely, if $e_D = -\infty$ (demand is perfectly elastic) or $e_S = 0$(supply is perfectly inelastic), then $\frac{dP_D}{dt} = 0$, then the entire excise tax will be borne by suppliers. more generally, taxes are borne by those who can not easily adjust. The greater consumers' abilities to substitute other commodities for the taxed commodity, the greater their ability to shift taxes.

Monopoly

Given an excise tax increase, a monopoly's profit can be written as:

$$\pi_m = [\, P_m - t]\, \mathrm{Q}_m - c\mathrm{Q}_m$$

$$= \; P_m\, \mathrm{Q}_m - (c + t)\mathrm{Q}_m \qquad \text{(A 2.1)}$$

As excise tax is a unit tax, it can be treated as an increase in marginal cost. To maximize profits, a monopoly choses output level at which marginal revenue is equal to marginal cost: MR=MC< P_m, where MC= $c + t$.

i.e. the first order condition for monopoly, given by:

$$P_m + \frac{dP_m}{d\mathrm{Q}_m}\mathrm{Q}_m = c + t \qquad \text{(A 2.2)}$$

This condition implies that the gap between a price of a firm's output and its marginal cost is inversely related to the price elasticity of the demand curve faced by the firm, i.e. $\frac{P_m - (c+t)}{P_m} = -\frac{1}{e_D}$.

Differentiating Equation (A 2.2) with respect to t:

$$\frac{dP_m}{d\mathrm{Q}_m}\frac{d\mathrm{Q}_m}{d\mathrm{t}} + \frac{dP_m}{d^2\mathrm{Q}_m}\frac{d\mathrm{Q}_m}{d\mathrm{t}}\mathrm{Q}_m + \frac{dP_m}{d\mathrm{Q}_m}\frac{d\mathrm{Q}_m}{d\mathrm{t}} = \frac{d\mathrm{c}}{d\mathrm{Q}_m}\frac{d\mathrm{Q}_m}{d\mathrm{t}} + 1 \qquad \text{(A 2.3)}$$

Make some arrangement, we get :

$$\frac{\mathrm{dP}_m}{\mathrm{dt}} = \frac{1}{1 + \frac{dP_m}{d\mathrm{Q}_m}\mathrm{Q}_m + \left(1 - \frac{\frac{d\mathrm{c}}{d^2\mathrm{Q}_m}}{\frac{dP_m}{d\mathrm{Q}_m}}\right)} \qquad \text{(A 2.4)}$$

The above expression for pass-through may be further simplified:

$$\frac{\mathrm{dP}_m}{\mathrm{dt}} = \frac{1}{1 + \eta + k} \qquad \text{(A 2.5)}$$

where $\eta = \frac{dP_m}{d\mathrm{Q}_m}\mathrm{Q}_m$ is the elasticity of the slope of the inverse demand function and

$k = 1 - \frac{\frac{dc}{d^2 Q_m}}{\frac{dP_m}{dQ_m}}$, measures the relative slopes of the demand and marginal cost curves.

A monopolist can shift more than 100% of an excise tax (t) when $1/\ 1 + \eta + k$ >1, or $-1 < \eta + k < 0$. With linear costs, overshifting occurs when $-2 < \eta < -1$. Overshifting cannot occur in the simple case of linear demand and linear costs ($\eta = 0$ and $k = 1$). If demand is of the constant elasticity type, and costs are linear, then overshifting will always occur in the monopoly model.

Similarly, we could extend the monopoly model to a the Cournot–Nash oligopoly model in which identical firms compete by choosing levels of output conditional on their expectations of their competitors' output levels. To simplify matters, we will assume there are fixed N firms in the market, which are identical and that the equilibrium is symmetric.

$$\frac{dP_m}{dt} = \frac{N}{N+\eta+k} \qquad \text{(A 2.6)}$$

Now, the degree of forward shifting of the unit tax on output depends on the elasticity of the slope of the inverse demand function (η), the number of firms (N), and the relative slopes of the marginal cost and inverse demand functions (k). Overshifting occurs when the producer price rises by more than the excise tax[11].

2.3 Empirical model

Following the literature, the pass-through equation is identified through a

[11] See more models on oligopoly with differentiated products in Fullerton and Metcalf (2002).

reduced-form regression of prices on excise taxes. The suggested reduced form is a market equilibrium price equation, which represents the outcome of the interplay of supply and demand in a cigarette market. Apart from taxes, other exogenous determinants of demand and cost conditions are included as right-hand-side variables. One advantage of the reduced form is that it contains all the variables in the model but does not need to specify the underlying structural relationships.

Specifically, we estimate cigarette tax incidence by assuming that the cigarette price is a function of the relevant state excise tax, product attributes, county economic, social and demographic controls, and county and time fixed effects:

$$(1) \quad P_{uijt} = \beta_1 \tau_{jt} + \boldsymbol{\beta_2}(Brand + Carton + Strength + Style + Type)_u + \boldsymbol{\beta_3 X_{jt}} + \theta_j + \delta_t + \varepsilon_{uijt}$$

where P_{uijt} is the monthly average tax inclusive cigarette price per pack paid for UPC *u* in store *i* located in county *j* at time *t*, $\beta's$ are coefficients to be estimated where bold denotes vector, tax inclusive price includes federal, state and local excise taxes. τ_{jt} is the state excise tax on cigarette per pack in county *j*. The coefficient of interest, β_1, represents the pass-through rate of excise tax, which measures how much of the tax is passed on to consumers in the form of higher prices. We include a set of attribute variables for each product at the UPC level *u*: type, style, strength, brand, and carton (see the data section for an explanation of these categories). $\boldsymbol{X_{it}}$ is a vector of county-level demand shifters which include demographic and economic variables (percentage of male, black, Asian, Hispanic populations; per capita income; unemployment rate; and percentages of high school graduates and college graduates, respectively).

We include county fixed effects (θ_j) to account for unobservable time-invariant price differences across counties. We also include time effects (δ_t) (calendar month and year), capturing time trends in smoking demand as well as yearly shocks to national cigarette consumption, such as national antismoking campaigns, smoking bans, and seasonal or monthly patterns in cigarette demand. They can also account for the annually adjusted escrow taxes (from the Master Settlement Agreement Payment), which are imposed as a unit tax and uniformly across states[12]. The ε_{uijt} term is independently and identically distributed error term with zero mean and variance σ^2. Although our unit of observation is at the store-month level, most of the independent variables vary at the county level; within a county, there is little independent variation between stores. For estimates of Equation (1), we therefore cluster our standard errors at the county level to account for correlated error terms by county over time.

In addition to the basic model specified in Equation (1), we also test for heterogeneous effects based on store locations. First, following Chiou and Muehlegger (2014), we include the inverse-distance weighted tax differential to the neighboring state divided by the distance to the state as a proxy for the incentive to cross border. We also add a dummy variable that indicates whether the store is located in a higher-tax state compared to its closest neighboring state as well as its interaction with the home state excise tax. The model becomes:

$$(2)\quad P_{uijt} = \beta_1 \tau_{jt} + \boldsymbol{\beta_2}(Brand + Carton + Strength + Style + Type)_u +$$

[12] Lillard and Sfekas (2013) conduct several simple analyses of cigarette tax incidence and find pass-through rates are different for specifications with and without the escrow tax. The results of the model with year fixed effects are the same regardless of whether the escrow tax is included or excluded (the tax is uniform across all states and therefore can be taken care of by the fixed effects). Thus, failing to (include escrow tax) add time fixed effects to the model will lead to biased point estimates of the tax coefficient.

$\boldsymbol{\beta_3 X_{jt}} + \beta_4(\tau_{jt} - \tau_{nt})/d_{jn} + \beta_5 HT_{jt} + \beta_6 HT_{jt} * \tau_{jt} + \theta_j + \delta_t + \varepsilon_{uijt}$

where *n* denotes the closest county in the closest state to county j, τ_{nt} is the excise tax for the state where county *n* is located, $(\tau_{jt} - \tau_{nt})$ is the tax difference between the two states, d_{jn} is the distance between the centroids of counties j and *n*, HT_{jt} is a dummy variable that takes on the value of one if $\tau_{jt} - \tau_{nt} > 0$, and all other variables are as previously defined. For stores located in a higher tax state, closest state has a lower tax $(\tau_{jt} - \tau_{nt} > 0)$, there exists a cross-state avoidance opportunity, which should be discounted by the distance representing potential transportation costs (fuel costs, travel time, toll prices, etc.). The larger the ratio $(\tau_{jt} - \tau_{nt})/d_{jn}$ is and the higher the incentive for cross-border shopping is, the lower the willingness to pay for cigarettes in the home state (assuming retail prices reflect consumer's willingness to pay for a product). But, if a store is located in a state that has a lower tax than its closest neighbor $(\tau_{jt} - \tau_{nt} < 0)$, retail prices should be higher with the availabilities of tax avoidance opportunities for consumers in neighboring states. Thus, we expect a negative sign for β_4. Equation (2) allows the price (and the tax pass-through) to depend on the inverse distance weighted tax difference between the home and closest state. The effect of the tax difference on the incidence of state cigarette taxes becomes smaller as the distance increases.

Second, previous studies found a significant association between one state's tax system and its neighboring states' tax systems (Egger, Pfaffermayr, and Winner 2005; Agrawal 2013, 2014, and 2015), which raises the possibility that state tax rates could be endogenously determined. In line with the spatial tax competition models, a general specification for a spatial econometric model can be written as:

(3) $$\tau_{jt} = \rho \sum_{n=1}^{N} w_{jn}\, \tau_{nt} + \zeta_s + \delta_t + u_{jt}$$

where w_{jn} is the (j, n)th element of a contiguity spatial-weighting matrix W associated to the endogenous spatial lag. In a contiguity matrix, contiguous units (also known as neighbors) are assigned weights of 1, and noncontiguous units are assigned weights of 0.

Using geospatial data from 2010 Census TIGER/Line Shapefiles, which contain boundary and polygon information of each state in a coordinate dataset to identify its neighbors, we construct a row-normalized contiguity weight matrix by the Stata command spmat. With row-normalized contiguity weights, each neighbor is given equal weight. As an example, consider the state of Illinois, which has six neighbors. The weights given to Indiana, Kentucky, Wisconsin, Missouri, Iowa, and Michigan would be 1/6 each; all other states are given zero weight (Drukker, et al. 2013)[13].

The $\sum_{n=1}^{N} w_{jn}\,\tau_{nt}$ term is the spatial lag of τ_{jt}. The ρ term is the unknown spatial autoregressive parameter to be estimated. State fixed effects (ζ_s) and time (year/month) dummies (δ_t) are also included. u_{jt} is the error term. We fit Equations (1) and (3) by using the three-stage least squares (3SLS) estimator, which is an instrumental variable (IV) technique for a system of simultaneous equations.

2.4 Variable construction and data

In this section, we discuss the construction of variables for estimation as well as the sources of our data. Table 8 summarizes variable descriptions and summary statistics.

[13] The normalized matrix $W = (w_{jn})$ is computed from the underlying matrix $\widetilde{W} = (\widetilde{w}_{jn})$, where the elements are assumed to be nonnegative; In a row-normalized matrix, each element in row j is divided by the sum of row j 's elements: the (j, n)th element of W becomes $w_{jn} = \widetilde{w}_{jn}/r_j$, where r_j is the sum of the jth row of $\widetilde{W}$. After row normalization, each row of W will sum to 1.

Table 8. Summary Statistics

Variable description	Mean	Std. Dev.	Min	Max
Excise tax inclusive price of cigarette (per 20-pack)	$5.752	1.467	$2.359	$20
State excise tax rate on cigarette	$1.549	1.049	$0.170	$4.350
Product attributes				
Type (=0 regular, =1 menthol, menthol variants (menthol gold, menthol blue, etc.) and other flavors (bold taste fresh, etc.))	0.373	0.483	0	1
Style (=0 filtered, =1 non-filtered)	0.028	0.164	0	1
StrengthL (=1 light, =0 all others)	0.320	0.466	0	1
StrengthU (=1 ultra light, =0 all others)	0.104	0.306	0	1
SrengthR (=1 regular, =0 all others)	0.576	0.494	0	1
Carton (=1 carton, =0 single pack)	0.189	0.391	0	1
Premium (=1 premium brand, =0 discount brand)	0.749	0.436	0	1
Economic variables				
Per capita personal income, annual ($1,000)	42.755	9.963	21.403	121.459
Monthly unemployment rate	7.706	2.349	0.800	22.600
Demographic variables				
Percentage of male population	0.493	0.012	0.466	0.603
Percentage of female population	0.507	0.012	0.399	0.534
Percentage of white population	0.858	0.113	0.191	0.987
Percentage of black population	0.082	0.102	0.001	0.734
Percentage of American Indian and Alaska Native population	0.013	0.035	0.000	0.768
Percentage of Asian population	0.026	0.027	0.001	0.186
Percentage of Hispanic	0.112	0.133	0.004	0.955
Percentage of Non-Hispanic	0.888	0.133	0.045	0.996
Percentage of population in age group <15 years old	0.193	0.027	0.067	0.308
Percentage of population in age group 15-24 years	0.140	0.032	0.050	0.334
Percentage of population in age group 25-44 years	0.252	0.030	0.135	0.369
Percentage of population in age group 45–64 years	0.272	0.029	0.146	0.401
Percentage of population in age group 65 years and older	0.143	0.041	0.059	0.492
Percent of adults with less than a high school diploma	0.125	0.053	0.031	0.382
Percent of adults with a high school diploma only	0.303	0.062	0.124	0.515
Percent of adults completing some college or associate's degree, bachelor's degree or higher	0.571	0.089	0.265	0.815

Price and Product Characteristics Data

We use the Nielsen ScanTrack retail scanner data from January 1, 2011, through December 31, 2012, which cover a total of about 20 million weekly transactions made in 1,865 convenience stores throughout the 48 contiguous states (Alaska, Hawaii, and the District of Columbia not included). Each transaction is identified using a unique UPC, a 12-digit barcode scanned by the retailer at the point of purchase. The data were obtained through the James M. Kilts Center for Marketing at Chicago Booth. We aggregate the data to monthly by location (store) and product (UPC). This aggregation leads to more than 6 million observations. Price of each observation is a monthly average price for a product with a particular UPC sold in a particular store. As almost all of the tax changes during our period of analysis occurred from the first day of a month (see below), monthly aggregates mean all months contain data either from before or after tax changes (there is one exception: Illinois increased its tax at the end of June 2012, so we assume the tax change started from July 1st).

One of the major advantages of our data is that we observe the UPC code of each product purchased. Each UPC represents a unique cigarette product with some characteristics, such as flavor type (regular, menthol and menthol variants), style (filtered or non-filtered), strength (regular, light, or ultra light), brand (premium or discount), and package (carton or pack). This categorization allows us to construct product attribute variables and explicitly incorporate them into the model rather than simply using the UPC fixed effects. In addition, we use the brand information in Nielsen data to group brands into premium and discount cigarettes following the industry brand categorization used in Cornelius, et al. (2013). By definition, a premium (or name-brand) product (such as Marlboro, Newport, and Camel) is perceived to have a higher value than one that is merely marketed as a discount (or generic/economy) brand product (such as Basic, Doral, Tahoe, Malibu, and USA Gold) (see the Appendix for detailed brand classifications). As for the package, we restricted our attention to cigarettes sold either as part of twenty-cigarette packs or as cartons (i.e., ten packs of twenty cigarettes per pack), eliminating promotional packages containing only two, three, or five packs. Multipacks usually have special price promotion offers, such as manufacturers' "buy one get one free" promotions for two packs. These restrictions eliminated fewer than 2 percent of cigarette sales in our sample. In our final dataset, 81.1 percent of the cigarettes are sold in pack versus 18.9 percent sold in cartons. Considering both package and brand, premium packs account for the majority of the cigarettes (60.6%), followed by discount packs (20.5%). Premium and discount brands sold in carton constitute the rest at 13.8 percent and 5.1 percent, respectively. Premium pack cigarettes sell for slightly higher with an average price at $6.13, 64 cents more than the discount pack at $5.49. This price difference becomes more pronounced for cigarettes sold in cartons: the average premium carton is sold at $100.19, 15.6 percent more expensive than discount carton cigarettes (at $ 86.66) (see Table 9).

Table 9. Average Consumer Price and Percentage by Characteristics of Cigarette Tiers

Brand	Premium		Discount	
Average price	$5.92		$5.26	
Share (%)	74.42		25.58	
Package	Pack		Carton (10 packs)	
Average price	$5.97		$4.83 (per pack)	
Share (%)	81.11		18.89	
Brand and package	Premium Packs	Premium Cartons	Discount Packs	Discount Cartons
Average price	$6.13	$5.01 (per pack)	$5.49	$4.33 (per pack)
Share (%)	60.64	13.77	20.47	5.12
Type	Regular		Menthol, menthol variants and other flavors	
Average price	$5.68		$5.87	
Share (%)	62.75		37.25	
Style	Filtered		Non-filtered	
Average price	$5.73		$6.58	
Share (%)	97.22		2.78	
Strength	Regular		Light	Ultra Light
Average price	$5.65		$5.83	$6.06
Share (%)	57.55		32	10.45

Tax Data

The federal excise tax for cigarette has been $1.007 per pack of twenty cigarettes, effective April 1, 2009 (Alcohol and Tobacco Tax and Trade Bureau 2012). State excise tax data and information about general sales tax application to cigarettes were obtained from the Tax Burden on Tobacco 2014 report published by Orzechowski and Walkeron, Tax Foundation (2014), and state revenue departments. The mean state excise tax rate was $1.55 per pack (Table 8). Considerable variation exists in cigarette excise tax rates across states. For the years 2011 and 2012, New York State had the highest state cigarette excise tax in the United States at $4.35 per pack, while Missouri had the lowest at $0.17 per pack. During the period from 2011 to 2012, four states increased the excise tax on cigarettes: Connecticut increased excise tax by $0.40 from $3.00 to $3.40 effective July 1st, 2011; Vermont increased by $0.38 to $2.62 effective July 1st, 2011; Illinois increased its tax by $1.00 to $1.98 effective June 24, 2012; Rhode Island increased it tax by $0.04 to $3.50 effective July 1st, 2012. New Hampshire is the only state that decreased the tax (by $0.10 from $1.78 effective July 1st, 2011). This reduction was the first time a state decreased its cigarette excise tax since 2004 (CDC, 2012).

Social, Economic, and Demographic Data

We matched the Nielsen data with economic, demographic and geographic data for each county. The monthly unemployment rate by county was from Local Area Unemployment database, U.S. Bureau of Labor Statistics. Annual county population estimates by age, sex, race, and Hispanic origin data was from County Characteristics Resident Population Estimates, U.S. Census Bureau, Population Division, released June 2014. Annual per capita personal income was from the Local Area Personal Income and Employment dataset, Bureau of Economic Analysis. Education data is a 5-year average of 2009-2013 from the Census Bureau's American Community Survey, available in County-level Data Sets, ERS, USDA.

Geographic Data

Coordinates information of the centroid of the census tract for each county, was retrieved from the National Counties Gazetteer File, 2014 Census Gazetteer Files, U.S. Census Bureau. We calculated the crow-flies distance (or the "Great Circle" distance in miles) from the centroid of the county where a store is located to the closest county that is in another state. The average distance is 82 miles.

2.5 Empirical results

Table 10 presents our estimates of equations (1), (2) and (3) using both OLS and 3SLS estimators. Columns (1) - (6) are results of OLS estimates while column (7) shows results for 3SLS estimates. Each column of the table contains estimates from a separate regression that adds time and county fixed effects, product attributes, social, economic and demographic controls sequentially across columns in order to examine the sensitivity of our estimates to the inclusion of different sets of controls.

Table 10. Estimates of the Effect of Cigarette Excise Taxes on Consumer Prices

Independent variables	**Dependent variable: Tax inclusive cigarette price per pack**						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State excise tax	1.116***	1.113***	1.096***	1.065***	1.051***	1.194***	1.051***
	(0.025)	(0.025)	(0.045)	(0.043)	(0.020)	(0.037)	(0.000)
Higher-tax state						0.220***	
						(0.063)	
Higher-tax state* State excise tax						-0.177***	
						(0.046)	
Tax difference (inverse distance weighted)						-1.835	
						(1.152)	
Style				0.628***	0.610***	0.610***	0.609***
				(0.014)	(0.014)	(0.014)	(0.002)
Type				0.058***	0.048***	0.049***	0.048***
				(0.006)	(0.007)	(0.007)	(0.001)
Strength light				0.304***	0.307***	0.306***	0.307***
				(0.004)	(0.004)	(0.004)	(0.001)
Strength ultra light				0.448***	0.465***	0.464***	0.465***
				(0.008)	(0.008)	(0.008)	(0.001)
Carton				-0.415***	-0.498***	-0.487***	-0.498***
				(0.043)	(0.040)	(0.040)	(0.001)

Continued

Table 10. Continued

Independent variables	Dependent variable: Tax inclusive cigarette price per pack						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Premium brand				0.791***	0.772***	0.776***	0.772***
				(0.019)	(0.017)	(0.018)	(0.001)
Unemployment rate					-0.041***	-0.048***	-0.041***
					(0.008)	(0.007)	(0.000)
Per capita income ($1,000)					0.006***	0.002	0.006***
					(0.002)	(0.002)	(0.000)
High school grads					-0.207	-0.327	-0.209***
					(0.993)	(0.602)	(0.015)
College degree and higher					0.215	0.307	0.214***
					(0.713)	(0.376)	(0.010)
Male population					-3.598***	-1.518	-3.594***
					(1.380)	(1.238)	(0.027)
Black					-0.767***	-0.628***	-0.767***
					(0.202)	(0.146)	(0.004)
AIAN					0.780**	0.698*	0.779***
					(0.377)	(0.370)	(0.009)
Asian					0.045	0.123	0.045***
					(0.894)	(0.702)	(0.016)
Hispanic					-0.303	-0.476**	-0.304***
					(0.267)	(0.209)	(0.004)
Age 15-24					0.566	-0.275	0.559***
					(1.094)	(0.969)	(0.019)
Age 25-44					0.940	0.654	0.938***
					(1.696)	(1.498)	(0.029)
Age 45-64					-0.551	-1.802	-0.561***
					(1.122)	(1.097)	(0.022)
Age 65 +					0.825	0.819	0.824***
					(1.045)	(0.904)	(0.018)
Constant	4.023***	3.993***	4.016***	3.374***	5.065***	0.610***	5.069***
	(0.044)	(0.039)	(0.068)	(0.067)	(1.146)	(0.014)	(0.022)
Month fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	No	No	Yes	Yes	No	No	No
Product attributes	No	No	No	Yes	Yes	Yes	Yes
Economic, social and demographic controls	No	No	No	No	Yes	Yes	Yes
R-squared	0.637	0.643	0.706	0.786	0.745	0.751	

Notes: Robust standard errors clustered at the county level are in parentheses.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.
Observations for Columns (1)-(3) are 6,596,906; while sample sizes reduce to 6,587,905 for Columns (4)-(7), due to the fact that there're 9,001 observations that have missing product

Columns (1) - (5) contain the results of estimates of Equation (1). In column (1), we only included state excise tax as a regressor. We found overshifting of taxes to consumer prices: A one-cent increase in taxes is associated with a 1.12-cent increase in price (per pack). In column (2), we added time fixed effects, which absorbed some of the tax variations and slightly reduced the estimated pass-through rate. Column (3) shows the results of incidence when both county and time fixed effects were included, which is a model widely used in previous comparable studies. The pass-through rate is 1.10 in this case. Including monthly and county effects reduced the pass-through, likely because factors such as seasonal production cost changes, seasonal retailer pricing and discounting practices, and differences in local cigarette excise taxes were largely accounted for. Most counties and cities do not have their own cigarette tax rates because state law prohibits them, but there are major exceptions. More than 600 local jurisdictions nationwide have their own cigarette tax rates or fees, notably New York City ($1.50 per pack) and Chicago-Cook County ($2.68 per pack) (Campaign for Tobacco-Free Kids, 2015). Escrow tax, which is per-pack payment and uniform nationwide, is subject to annual adjustment. Data on local taxes and escrow taxes were not available to us.

When product attributes were added, the pass-through rate was further reduced to 1.07 (column 4). Product attributes explain the differences in prices, which can vary substantially across products with different brands, styles, packages, etc. Coefficients on product attribute variables have the expected signs and are all statistically significant at the 1 percent level. The coefficient on the dummy variable for premium brands is positive, and the largest effect among product attributes in the model. On average on a per-pack price basis, (all other attributes equal), prices for premium brands cigarettes are 79 cents higher than discount brand cigarettes. Similarly, unfiltered cigarettes sell for 63 cents more than filtered cigarettes; in terms of strength, prices for ultra light and light cigarettes are 45 and 30 cents higher than prices for regular ones, respectively; consumers pay 60 cents more for menthol or other flavored cigarettes than regular cigarettes; cigarettes sold in cartons are 42 cents cheaper per pack than those sold as single packs.

Column (5) replaced the county fixed effects with county-level economic, social and demographic variables[14]. Controlling for county demographic and economic characteristics further decreased the pass-through rate to 1.05. Our results show that cigarette prices are lower in counties with higher percentages of male and black populations. These consumer groups are reported to have higher rates of smoking. Counties with a higher unemployment rate also have lower cigarette prices. Interestingly, counties that have higher percentages of American Indian have higher cigarette prices, likely because American Indian/Alaska Natives (AI/ANs) have a higher prevalence of smoking than most other racial/ethnic groups in the United States (CDC 2015b).

Column (6) expands the specification in column (5) by incorporating inverse distance-weighted tax differential from neighboring states' excise tax. At the mean of distance, which is 82 miles, the average tax differential effect is -0.02 (=-1.84/82), though not statistically significant. For stores located in the higher-tax state ($\tau_{jt} - \tau_{nt} > 0$), the pass-through rate is 1.02 (1.194-0.177), while for stores located in the lower-tax state $\left(\tau_{jt} - \tau_{nt} < 0\right)$, the pass-through rate is 1.19.[15] This result is consistent with previous studies (Hanson and Sullivan 2009; Harding, Leibtag and Lovenheim 2012; Chiou and Muehlegger 2014), which found pass-through rates declined for stores closer to the border with a lower-priced jurisdiction. As the cost of travel to low-tax county decreases,

[14] County education variables are five-year average, which are time-invariant during our study period. Thus they serve the same purpose of the county fixed effects. To avoid the multicollinearity issue, in column (5) we only keep the county education variables.

[15] In a similar approach, we classified counties into three categories: counties not on state borders, counties on the state borders with the lowest state tax compared to its neighbors, all other counties on state borders to see tax incidence varies across stores in different locations. The tax pass-through rates for these three categories are 1.14, 1.05, and 1.00, respectively. Results are presented in Appendix Table A1.

demand will become more tax elastic as it becomes easier for consumers to avoid high taxes. This might also suggest manufacturers'/retailers' spatial pricing strategies to reduce the price variability among different tax jurisdictions (Shang, et al. 2013).

Column (7) shows the results of equations (1) and (3) using the 3SLS estimator as a robustness check. The tax incidence rate is 1.05, which is identical to the result from column (5). For the tax competition equation (3), the estimate of the impact of neighboring counties' tax rates on one state's cigarette excise tax is a quantitatively small but statistically significant 0.06, which is similar to previous studies (Agrawal 2014). This means that a one-dollar increase in neighbor's state tax rate implies a 6-cent increase in the own state tax rate. Therefore, taking into consideration that state taxes are positively correlated will make the tax pass-through rate even bigger (i.e., less room for tax avoidance by shopping in neighbor states).

Overall, our estimates are very robust across specifications and we found a more than complete pass-through rate, which is similar to other recent estimates using disaggregated data (Keeler, et al. 1996; Hanson and Sullivan 2009; Sullivan and Dutkowsky 2012; Goldin and Homonoff 2013; Xu, Malarcher, and Kruger 2014; Brock, et al. 2015). This overshifting of excise tax suggests an inelastic demand for cigarettes, which is consistent with cigarette demand studies (Chaloupka et al. 2002; Zheng et al. 2014). It also suggests the existence of market power and strategic behavior among firms from the supply side, which is supported by the facts that U.S. cigarette manufacturing is heavily concentrated[16], the tax incidence theory (Fullerton and Metcalf, 2002), and

[16] Top three manufacturers—Philip Morris USA, R.J. Reynolds, and Lorillard—represented 84% of cigarettes sold in 2009. The fourth- and fifth-largest manufacturers (Commonwealth Brands and Liggett and Myers) together comprise approximately 7 percent of the market. Hundreds of small firms together account for the remaining 10 percent (GAO, 2011). According to concentration ratios data from the 2007

findings by previous empirical studies on cigarette market structure (Adhikari 2004; Raper, Love, and Shumway 2007; Sephton 2008). Nonetheless, our estimate is higher than the most comparable recent studies that use scanner data. Harding, Leibtag, and Lovenheim (2012) examined nationally representative consumer panel data of cigarette purchases from a broad set of retailers ranging from 2006 to 2007 and found excise taxes were undershifted to consumer prices; Espinosa and Evans (2012) reported evidence of a full pass-through rate by using scanner data from 29 states over the period of 2001-2006; and Chiou and Muehlegger (2014) found an 80 percent pass-through rate for cigarettes sold in the Chicago area from 1989 to 1996. The use of different data, focus periods, and estimation techniques likely explain the variability of tax incidence estimates, in addition to other possible factors such as structural changes in the industry and continued decline of the smoking rate in the United States.

Overshifting also implies that the cigarette excise tax may induce a substitution of quality for quantity. The basic theory outlining the impact of excise taxes for multi-attribute was first proposed by Barzel (1976), who argued that an increase in a per-unit tax could introduce a shift to higher quality products (thus more expensive products). This is because the price of higher-quality goods will increase by a smaller percentage than will the price of lower-quality goods. Barzel's theory had supporting empirical evidence from Sobel and Garrett (1997), who directly tested the hypothesis by using market share data and found that a 3-cent excise tax leads to a 1-percentage-point increase in market share of premium cigarettes. We therefore investigate whether tax

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Economic Census of the United States, the top four cigarette manufacturing companies accounted for 97.8% of total value of shipments ($34.7 billion) for the 20 largest companies. Due to its high level of concentration, the cigarette manufacturing industry is often used as an example of a less than perfectly competitive industry.

pass-through rate is different for premium cigarettes versus discount cigarettes. Furthermore, we also examine whether tax incidence differs by package (carton vs. pack). The intuition behind this is that heavy smokers rely more on carton cigarettes, which may lead to a high pass-through rate for carton cigarettes.

Table 11. Cigarette Excise Tax Incidence by Brand and Package

	Dependent variable: Tax inclusive cigarette price per pack			
Independent variables	(1)	(2)	(3)	(4)
State excise tax (tax)	1.035***	1.000***	0.982***	0.982***
	(0.021)	(0.015)	(0.016)	(0.015)
Carton*tax	0.126***		0.129***	
	(0.034)		(0.033)	
Premium*tax		0.069***	0.071***	
		(0.014)	(0.001)	
Premium*Carton*tax				0.231***
				(0.031)
Discount *Carton*tax				0.072**
				(0.032)
Premium* Pack*tax				0.071***
				(0.014)
Premium*Carton				0.056***
				(0.015)
Style	0.611***	0.607***	0.609***	0.612***
	(0.014)	(0.014)	(0.014)	(0.014)
Type	0.049***	0.049***	0.049***	0.051***
	(0.007)	(0.007)	(0.007)	(0.007)
Strength light	0.306***	0.305***	0.305***	0.304***
	(0.004)	(0.004)	(0.004)	(0.004)
Strength ultra light	0.466***	0.463***	0.464***	0.464***
	(0.008)	(0.007)	(0.008)	(0.008)
Carton	-0.647***	-0.497***	-0.650***	-0.698***
	(0.069)	(0.040)	(0.068)	(0.067)
Premium brand	0.773***	0.663***	0.660***	0.629***
	(0.017)	(0.014)	(0.001)	(0.017)
Unemployment rate	-0.041***	-0.041***	-0.041***	-0.041***
	(0.008)	(0.000)	(0.000)	(0.008)
Per capita income ($1,000)	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.000)	(0.000)	(0.002)
High school grads	-0.344	-0.217	-0.358	-0.364
	(0.983)	(0.996)	(0.986)	(0.989)
College degree and higher	0.108	0.212	0.103	0.099
	(0.706)	(0.715)	(0.708)	(0.710)

Continued

Table 11. Continued

Independent variables	Dependent variable: Tax inclusive cigarette price per pack (1)	(2)	(3)	(4)
Male population	-3.584***	-3.599***	-3.585***	-3.587***
	(1.365)	(1.381)	(1.366)	(1.367)
Black	-0.768***	-0.768***	-0.768***	-0.770***
	(0.199)	(0.202)	(0.200)	(0.200)
AIAN	0.731**	0.777**	0.728*	0.724*
	(0.372)	(0.376)	(0.372)	(0.371)
Asian	0.008	0.062	0.025	0.015
	(0.892)	(0.893)	(0.891)	(0.893)
Hispanic	-0.350	-0.303	-0.350	-0.353
	(0.264)	(0.268)	(0.265)	(0.265)
Age 15-24	0.578	0.579	0.592	0.599
	(1.086)	(1.095)	(1.087)	(1.088)
Age 25-44	0.924	0.961	0.946	0.955
	(1.690)	(1.700)	(1.694)	(1.697)
Age 45-64	-0.495	-0.512	-0.453	-0.445
	(1.114)	(1.124)	(1.116)	(1.117)
Age 65 +	0.759	0.830	0.762	0.770
	(1.044)	(1.047)	(1.046)	(1.048)
Constant	5.184***	5.136***	5.260***	5.283***
	(1.137)	(1.153)	(1.144)	(1.146)
Observations	------------------------6,587,905----------------------------			
R-squared	0.745	0.745	0.746	0.746

Notes: Robust standard errors clustered at the county level are in parentheses.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.
All regressions include county fixed effects, purchase month fixed effects, product attribute variables as well as the full set of economic, social, demographic controls shown in Table 10.

Table 11 presents the separately estimated tax pass-through for each class of cigarette, considering four cigarette classes (premium vs. discount, pack vs. carton) by adding interaction terms that are the products of state excise tax with attribute dummies. Results in Table 11 should be compared with the general pass-through rate of 1.05 in column (5) of Table 10. In column (1) of Table 11, we only included an interaction term between carton sales and tax and found that the amount of tax pass-through for cigarettes sold in carton is 13 cents more than those sold by pack, given a $1 tax increase. In column (2), we included only an interaction term for premium brand cigarettes. Consumers bear 7 cents more pass-through for the premium brands than the discount brands, suggesting that the consumption of discount brands (likely by low-income consumer) is slightly more price sensitive compared to premium brands. The difference between tax pass-through rates of cartons and packs is larger than the difference between premium and discount brands. In column (3), both interaction terms were included. An additional $1 tax is associated with 98 cents price increase for a pack of discount brand cigarette. Compared with that base, discount carton, premium pack, and premium carton pass-through are 13 cents, 7 cents and 20 cents higher, respectively. In column (4), we incorporated three-way interaction terms, which allowed tax incidence to vary across combinations of different package and brand types. Based on the estimates, tax pass-through rates for all other categories are all statistically significant at the 5 percent level or better and larger than that of the baseline category discount pack. The tax pass-through rates rank is: premium carton (1.21), discount carton (1.05), premium pack (1.05), and discount pack (0.98)[17]. In addition, we also used Wald tests to perform pairwise comparisons among the non-baseline categories. Results show that the pass-through rate for discount carton is smaller than that of premium carton, and the rate of premium pack is smaller than that of premium carton, with the differences both being significant at the 1% significance level.

A higher tax pass-through rate for premium brands compared with discount brands may suggest that consumers are more loyal to premium brands and hence are less sensitive to the price changes of premium brands. A possible reason for the finding of higher tax pass-through rate for cartons compared with packs is that carton buyers tend to be more addicted smokers. Our findings indicate possibilities of different demand

[17] We also partition our sample and fit separate regressions for each product group and get slightly different results because the separate analysis assumes different variances. Nonetheless, the pass-through rate ranking remains the same: premium carton (1.21), discount carton (1.08), premium pack (1.04), and discount pack (1.02). Results are presented in Appendix Table A2.

elasticities across product tiers and are broadly consistent with the fact that high taxation and MSA enforcement have reduced the pricing advantages of discount brands.

Our results are similar to estimates from Espinosa and Evans (2012) in that they also found a slightly higher pass-through rate for name-brand (1.04) than generic cigarettes (1.01), and a higher pass-through rate for cigarettes sold in cartons (1.03) versus single packs (0.96). Nonetheless, they further found that given a tax hike, the market shares of discount brand cigarette increased, while the carton market share decreased, contrary to Barzel's theory. On the other hand, Chiou and Muehlegger (2014) found suggestive evidence that tax rates reduced consumption of low-price cigarettes relative to consumption of high-price cigarettes in the long run. However, they estimated a reverse direction of "flight to quality" in the short run: the quantity of low-price cigarettes rises immediately following a tax change. They also found that premium pack and carton cigarettes have lower tax pass-through rates than discount pack and carton cigarettes. As mentioned before, the large differences in datasets (especially as their estimates were based only on the Chicago Metropolitan Statistical Area, where there are large tax avoidance opportunities, while our coverage is much broader) might contribute to these discrepancies.

2.6 Conclusions

We empirically investigated the cigarette excise tax pass-through by using Nielsen ScanTrack data for sales in convenience stores from January 2011 to December 2012. Our store-level data allow us to observe product attributes at the UPC level, which helps to explain variations between price tiers and improves the estimates of tax impact. We linked the market data with county economic, social and demographic information, which were used as controls. We found that cigarette taxes were more than fully passed through to consumer prices, suggesting smokers bear excess burdens of excise taxes. On average, a $1 cigarette tax increase over shifted to consumer prices: They pay the entire amount of the tax as well as a premium of between 5 and 19 cents per pack of cigarettes.

We also found that tax incidence differed by class of cigarette. Pass-through rates for premium brands and cartons of packaged cigarettes are higher than those for discount brands and cigarettes in packs, respectively, indicating possibilities of different demand elasticities across product tiers. Because premium brands command a higher brand loyalty and carton buyers tend to be heavy smokers, consumers of premium brands and carton-packaged cigarettes bear a higher tax burden. Such results might lead to important policy implications. For example, cigarette manufacturers might respond differently to a tax increase by package of cigarette, i.e., they undershift tax into prices for packs, while overshift tax into prices of cartons. Carton buyers, who are typically heavy smokers less likely to quit smoking, are expected to bear more economic burdens.

As more studies begin to focus on tax incidence under imperfect competition, and supply chains and optimal taxation (Kopczuk, et al. 2013; Weyl and Fabinger 2013; Peitz, and Reisinger 2014), future research of cigarette tax incidence might explore the market structure of the cigarette industry and develop models for analysis of tax incidence in a market with geographically differentiated taxes and different levels of competition at each segment of the vertical supply chain.

Chapter 3. Who's Buying Organic Coffee? Demographic Characteristics of Consumers in the United States

3.1 Introduction

Consumer demand for organic products in the United States has grown by double-digits every year over the past two decades — and organic sales increased from $3.6 billion in 1997 to over $39 billion in 2014 according to Organic Trade Association (OTA, 2015). Coffee is the largest category by far of the organic imports, valued at $333 million in 2014 (OTA, 2015), making the United States the single largest importer of organic coffee in the world. The United States is a nation of coffee drinkers with only one state—Hawaii—able to grow coffee, so most organic coffee is imported and certified under a foreign organic equivalency standard.

As a household **staple** in the U.S., coffee is consumed across all incomes, ages, genders and states. With increasing availability of sustainable coffees, such as certified fair trade, organic, shade grown, bird-friendly and carbon neutral, more consumers are interested in using their purchasing power to express their support of a broad range of social and environmental issues. Knowledge of price sensitivity and demographic profiling with respect to consumption of organic and conventional coffee is important for manufacturers, retailers, advertisers, nutritionists, and other stakeholders from a competitive intelligence and strategic decision-making perspective.

Several studies have been performed on the U.S. demand for coffee. Most of them estimated the demand for regular coffee either as a sole good, or as part of the larger category of non-alcoholic beverages. Yen et al. (2004) estimated the demand for coffee and tea using data from the National Food Stamp Program Survey, which included prices, incomes, and demographic information to estimate household beverage consumption in a translog demand system. Estimated own-price elasticities for coffee/tea were -0.470 (compensated) and -0.890 (uncompensated), respectively. The expenditure elasticity was 1.130. Pofahl et al. (2005) estimated a demand system for non-alcoholic beverages in which coffee was one category by using three types of Almost Ideal Demand System (AIDS) models (linear approximated AIDS, non-linear AIDS and quadratic AIDS (QUAIDS)) and Nielsen Homescan Panel data over the period 1998 to 2001. They found that coffee was price elastic, with the four-year average compensated own-price elasticity at -1.137; the average expenditure elasticity for coffee was 0.678. Zheng and Kaiser (2008) investigated impacts from cross-commodity advertising on nonalcoholic beverage demands in the US from 1974 to 2005. They also employed the AIDS model and estimated jointly for five categories of nonalcoholic beverages: fluid milk, juice, soft drinks, bottled water, and coffee and tea. The estimated own-price elasticities for coffee and tea together were: uncompensated (-0.462) and compensated (-0.083)-the lowest among all beverages; the expenditure elasticity was 3.144. While coffee and tea were price inelastic goods, they also found that coffee/tea had the highest own-advertising elasticity (0.138), suggesting that advertising was the most successful in enhancing coffee/tea demand. Dharmasena and Capp Jr. (2009) estimated the demand for at-home nonalcoholic beverage consumption in the United States using Nielsen Homescan panel data over the period January 1998 through December 2003 and the AIDS model. As a single category, coffee had estimated own-price elasticities of -0.464 for compensated and -0.517 for uncompensated. The expenditure elasticity was 0.628. Alviola et al. (2010)

also did a study of U.S. demand for at-home nonalcoholic beverages using the 1999 Nielsen Homescan Panel. Both AIDS and QUAIDS models were used, results had expenditure elasticities of 0.974 and 0.838 for coffee, respectively. The compensated own price elasticities were elastic for both AIDS (-1.527) and QUAIDS (-1.487) models.

Another strand of coffee demand research took product differentiation into account and relied on the stated preferences approach. Basu and Hicks (2008) investigated label performance and consumer willingness to pay for fair trade coffee in the United States and Germany. They found that in both countries respondents who chose generic coffee tended to ignore the organic feature of the coffee, while they show strong willingness to pay for Fair Trade coffee. Strzok and Huffman (2012) did experiments in the Ames, Iowa area, asking participants' WTP for organic and conventional coffee, maple syrup and olive oil. They found that participants were willing to pay 46 cents (per ounce) more for an organic than conventional coffee. Individuals with more education and higher income were willing to pay more for organic relative to conventional products. Hainmueller, Hiscox, and Sequeira (2014) conducted field experiments in a U.S. grocery store chain and found that consumers were willing to pay higher premiums for coffee with eco-labels. They also found that consumers exhibited differential levels of price sensitivity for different types of Fair Trade labeled coffee. Consumers buying the lower-priced coffee blend (CB) were price sensitive, while consumers buying the higher priced French Roast (FR) Regular coffee were much less price sensitive.

Following a few studies which analyzed U.S. consumer behavior of organic vegetables, fresh fruit and vegetables, poultry meat and milk by identifying household economic and socio-demographic factors (Dettmann and Dimitri 2009; Kasteridis and

Yen, 2012; Smith, Huang, and Lin, 2009; Van Loo, et al., 2010; Alviola and Capps, 2010), our study aims to examine the driving factors determining U.S. household demand for organic coffee, particularly own-price effects and income effects, as well as the effects of socio-demographic characteristics of households. We use Nielsen Homescan data, which provide detailed product characteristics information as well as a vast array of household socio-demographic data. A typical problem for demand estimation studies that use household-level microdata and mainly measure the effects of demographic variables, is that for a given good, many households have no consumption, implying a censored dependent variable. Techniques that do not take this censored dependent variable into account will yield biased results. Heckman's two-step technique is utilized to combat this problem. A household's binary decision of whether or not to buy organic (or non-organic) coffee is followed by the continuous choice of how much to buy. The results are then presented and compared with those obtained using an uncensored technique.

To our knowledge, no previous studies have investigated the sociodemographic characteristics of households buying organic coffee by using scanner data. Our study aims to fill this gap. The rest of the paper proceeds as follows. Section II presents the empirical methodology. Section III describes the data and variable construction. Section IV discusses the estimation procedure and empirical results, and Section V concludes with a discussion and summary of our findings.

3.2 Methodology

A household's decision to buy certified organic coffee or conventional coffee is assumed to occur in a two-stage decision process. A consumer first chooses whether to purchase organic (conventional) coffee and then decides the quantity. This two-stage decision is estimated using the Heckman's selection model, also known as the type-II Tobit model (Amemiya, 1985, pp. 385– 387), or the Heckit method. Although it was originally intended to solve the selection bias problem in missing data contexts, it has been widely used to model the appearance of a large cluster of zeros. It views the outcome of a discrete choice as a reflection of an underlying regression and provides consistent estimates to correct for the bias that occurs if the sample selection is based on unobservables (Heckman, 1979). Although here we don't have a missing data problem, we use it as a corner solution in response to a data censoring problem[18]. It explicitly allows correlation between the participation and amount decisions (after conditioning on covariates). The first stage decision (whether to buy or not to buy organic coffee) can be modeled as a dichotomous choice problem indicated by a binary indicator variable, which is a function of the latent variables and is estimated as a probit model by maximum likelihood. The second stage (how much to buy) is estimated with ordinary least squares (OLS).

In the first stage, the selection mechanism can be expressed as a probit equation (participation/selection equation):

$$\text{Prob}\,(Qorganic_{it} > 0) = \text{Prob}(Qorganic_{it} > 0 \mid \Upsilon, \boldsymbol{W}_{it}, u_{it})$$

$$= \boldsymbol{\Phi}\,(\gamma_0 + \gamma_2\, Income_{it} + \gamma_3\, Household\ size_{it} + \gamma_4\, Employment_{it}$$

[18] Wooldridge (2010, p667) recommends the use of the term 'corner solution model' instead of 'censored regression model (tobit)'. Although the econometric models for corner solution responses and censored data have similar statistical structures, the underlying assumptions are different. For the former model, we are able to observe the entire possible range of the response variable. Data censoring arises because of a survey sampling scheme or institutional constraints. Censored regression model aims to investigate an underlying response variable that are not fully observed because it is censored above or below certain values.

$$+ \gamma_5\, Education_{it} + \gamma_6\, Age_{it} + \gamma_7\, Children_{it} + \gamma_8\, Race_i$$

$$+ \gamma_9\, Hispanic_i + \gamma_{10} Household\ head_{it} + u_{it}) \qquad u_{it} \sim N[0,1]$$

where $Qorganic_{it}$ denotes the quantity of organic coffee household i purchases in year t. Probability is 1 if household i consumes any organic coffee in year t ($Qorganic_{it} > 0$) and 0 otherwise. Φ is the cumulative distribution function for a standard normal distribution. $\boldsymbol{W}_{it}$ is a vector of variables that are related to the decision to purchase organic coffee. In line with the literature, household socioeconomic characteristics are included; γs are vectors of parameters to be estimated; u_{it} is the error term.

From these estimates, the nonselection hazard—what Heckman (1979) referred to as the the inverse Mills ratio (IMR), λ_{it}—for each observation in the selected sample is computed as

$$\hat{\lambda}_{it} = \frac{\phi(W_{it}'\hat{\Upsilon})}{\boldsymbol{\Phi}(W_{it}'\hat{\Upsilon})}$$

where ϕ is the probability density function of a standard normal distribution.

In the second stage, we estimate the equation of primary interest: i.e., the demand for organic coffee as

$$Qorganic_{it} = \boldsymbol{X}_{it}'\boldsymbol{\beta} + \varepsilon_{it} \qquad\qquad \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$$

$\boldsymbol{X}_{it}$ constitutes the vector of explanatory variables related to the amount of organic coffee purchased. $\boldsymbol{\beta}$s are vectors of parameters to be estimated; ε_{it} is the error term; ε_{it} and u_{it} are assumed to have a bivariate normal distribution with zero means and correlation ρ: $\mathrm{corr}(u_{it}, \varepsilon_{it}) = \rho$ and $(u_{it}, \varepsilon_{it}) \sim N_2\, [(0, 0), (1, \sigma_\varepsilon^2, \rho\sigma_\varepsilon)]$. The IMR is added as an additional "control" variable to incorporate the censoring latent variables and correct possible selection bias. Hence, using the moments of the incidentally truncated bivariate normal distribution theorem (Johnson and Kotz, 1974; see also Greene, 2012, p. 873), the second-stage regression model (outcome/intensity equation) can be written as:

$$\begin{aligned} Qorganicit \mid Qorganicit>0 &= E[Qorganicit \mid Qorganicit>0] + vit \\ &= E[Qorganicit \mid uit>-W_{it}'\Upsilon] + vit \\ &= X_{it}'\beta + E[\varepsilon it \mid uit>-W_{it}'\Upsilon] + vit \\ &= X_{it}'\beta + \rho\sigma\varepsilon\hat{\lambda}_{it} + vit = X_{it}'\beta + \beta_\lambda\hat{\lambda}_{it} + vit \quad v_{it} \sim N(0, \sigma_v^2) \end{aligned}$$

Or

$$\begin{aligned} lnQorganic_{it} \mid Qorganic_{it}>0 = \beta_0 &+ \beta_1 lnPorganic_{it} + \beta_2 lnPNon\_organic_{it} \\ &+ \beta_3 Income_{it} + \beta_4\ Household\ size_{it} + \beta_5\ Employment_{it} \\ &+ \beta_6\ Education_{it} + \beta_7\ Age_{it} + \beta_8\ Children_{it} \\ &+ \beta_9\ Race_i + \beta_{10}\ Hispanic_i + \beta_{11} Household\ head_{it} \\ &+ \beta_\lambda \lambda_{it} + v_{it} \end{aligned}$$

We use a logarithmical transformation to ameliorate potential nonnormality and heteroscedasticity of the error term; thus the coefficient on price is the price elasticity[19].

The problem of sample selection bias can be regarded as a misspecification problem arising through the omission of a regressor variable, the nonlinear selectivity correction term λ_{it}. There are only two cases where bias will not be a problem: First, if the coefficient on the IMR (λ_{it}) is not statistically significant from zero; second, if ρ =0.

The sample selection model can also be estimated by maximum likelihood, which

[19] Wooldridge (2010, P697-703) named this type of model the exponential type II Tobit (ET2T) model.

estimates all the parameters in both equations simultaneously and provides full-information maximum likelihood (FIML) estimates that are viewed more efficient than the two-step estimates (Heckit). Because it uses the likelihood function rather than the method of moments and the estimation of ρ is subject to the constraint $-1 < \rho < 1$, while the moment-based estimator of ρ is not bounded by zero and one. The two-step estimator estimates the single coefficient on λ and the structural parameters σ and ρ are deduced by the method of moments while the maximum likelihood estimator computes estimates of these parameters directly (Greene, 2012, P878). In addition, the two-part model (2PM), which runs a separate probit or logit for sample inclusion followed by a regression, has also been widely used as an alternative method. It assumes that conditional on a set of observed covariates, the mechanisms determining Pr and Y are independent (Manning, Duan, and Rogers 1987). Dow and Norton (2003) proposed an adapted empirical mean square error test to choose between Heckit and the 2PM (i.e. the Toro-Vizcarrondo and Wallace empirical mean square error test of the difference in the marginal effects of interest).

There are a few issues which need to be addressed when using the Heckman selection model: exclusion restriction, marginal effects, and collinearity (Puhani, 2000; Vance,2014). The exclusion restriction requires that X should be a strict subset of W, so the selection equation has at least one more identifying variable than in the outcome equation. The reason for this is that while the IMR is a nonlinear function of W, it is often well approximated by a linear function. If no variables that are in X are excluded from W, there is no exclusion restriction. Thus $\hat{\lambda}_{it}$ can be highly correlated with the elements of X, causing inflated standard errors and parameter instability (including the t -test on the IMR term) (Moffitt, 1999). In order to correctly and sufficiently identify the model, one needs to assume that there is at least one element of W that appears in P() that does not appear in E[y|y>0]. The incorporation of theoretically supported exclusion restrictions in the first stage of the Heckit ameliorates these problems by reducing multicollinearity among the predictors and the IMR in the outcome equation. In their absence, however, the consequences for the model estimates can be profound. Nonetheless, such exclusion assumptions are often unavailable or hard to defend. Shrestha & Feiock (2011) and Karreth & Tir (2013) provide a theoretical justification that elaborates why these variables are hypothesized to uniquely determine the selection process but not the outcome variable.

For the probit model, we have categorical explanatory variables (coded as dummy or indicator variables). Marginal effects are the partial effects of each explanatory variable on the probability that the observed dependent variable $Y_i > 0$. The appropriate marginal effect for a binary independent variable, say, d, would be:

$$\text{Marginal effect} = \text{Prob}[Y = 1 \mid \bar{W}_{\text{it}}, d = 1] - \text{Prob}[Y = 1 \mid \bar{W}_{\text{it}}, d = 0]$$

$$= \boldsymbol{\Phi}\left(\bar{W}'_{it|x_{itk}=n}\hat{\Upsilon}\right) - \boldsymbol{\Phi}\left(\bar{W}'_{it|x_{itk}=base}\hat{\Upsilon}\right)$$

where $\bar{W}_{\text{it}}$, denotes the means of all the other variables in the model.

If a variable appears only in the outcome equation, the coefficient on it can be interpreted as the marginal effect of a one unit change in that variable on Y|Y is observed---which is a conditional mean. Price variables only appear in the demand equation. The coefficient is the marginal effect:

$$\frac{\partial E[lnQorganic_{it} \mid Qorganic_{it} > 0]}{\partial lnPorganic_{it}} = \beta_1$$

which is the own-price elasticity of demand;

$$\frac{\partial E[lnQorganic_{it} \mid Qorganic_{it} > 0]}{\partial lnPNon\_organic_{it}} = \beta_2$$

is the cross-price elasticity of demand.

Sigelman & Zeng (1999) demonstrate that the marginal effects of the variables that appear in both the selection and outcome equations are generally not given by the coefficient estimates, themselves, but rather must be calculated by differentiating the outcome equation. A change in an explanatory variable that is common to both stages of the decision process has two effects: (1) it affects the likelihood of whether the commodity will be consumed; and (2) if the commodity is consumed, it affects the expenditure on that commodity(Akay and Tsakas, 2008, Hoffmann and Kassouf, 2005, Saha, et al., 1997, Vance, 2009, Yen, 2005; Yen and Rosinski, 2008). W and X have some common variables. The marginal effect of the regressors on y_i in the observed sample consists of two components. There is the direct effect on the mean of y_i, which is β. In addition, for a particular independent variable, if it appears in the probability that is positive, then it will influence y_i through its presence in λ_i. The full effect of changes in a regressor that appears in both X_i and W_i on y is derived by differentiating the conditional mean of the demand equations (2).

For a given continuous variable, x_{itk} denotes the *k*th regressor common to both $\boldsymbol{W}_{it}$ and $\boldsymbol{X}_{it.}$

$$\frac{\partial E[lnQorganic_{it} \mid Qorganic_{it} > 0]}{\partial x_{itk}} = \beta_k + \beta_\lambda \frac{\partial \lambda_{it}}{\partial x_{itk}} = \beta_k - \beta_\lambda \gamma_k (\lambda_{it}^2 + \lambda_{it} W_{it}' \hat{\Upsilon})$$

Because 0<$\lambda_{it}^2 + \lambda_{it} W_{it}' \hat{\Upsilon}$ <1, the additional term serves to reduce the marginal effect. So for every element of X, the marginal effect is less than the corresponding coefficient. It is quite possible that the magnitude, sign, and statistical significance of the effect might all be different from those of the estimate of β_k.

For our model, the majority of the explanatory variables are categorical variables; their marginal effects are calculated as the discrete first difference from the base category. The discrete difference is not equal to the derivative for the logistic regression, probit, etc. The discrete difference calculation is generally viewed as better for factor variables than the derivative calculation because the discrete difference is what would actually be observed.

The partial effect for level n of categorical variable x_{itk}, is discrete first difference from the base category:

$$\frac{\Delta \mathrm{E}[\mathrm{lnQorganic_{it}} \mid \mathrm{lnQorganic_{it}} > 0, \mathrm{x_{itk}}]}{\Delta \mathrm{x_{itk}}}$$

$$= \mathrm{E}[\mathrm{lnQ_{it}} \mid \mathrm{Q_{it}} > 0, \mathrm{x_{itk}} = \mathrm{n}] - \mathrm{E}[\mathrm{lnQ_{it}} \mid \mathrm{Q_{it}} > 0, \mathrm{x_{itk}} = \mathrm{base}]$$

$$= \beta_k + \beta_\lambda \Delta\gamma_k = \beta_k + \beta_\lambda\left(\gamma_{k|x_{itk}=n} - \gamma_{k|x_{itk}=base}\right)$$

$$= \beta_k + \beta_\lambda \left[\frac{\phi\left(\overline{W}'_{it|x_{itk}=n}\hat{\Upsilon}\right)}{\Phi\left(\overline{W}'_{it|x_{itk}=n}\hat{\Upsilon}\right)} - \frac{\phi\left(\overline{W}'_{it|x_{itk}=base}\hat{\Upsilon}\right)}{\Phi\left(\overline{W}'_{it|x_{itk}=base}\hat{\Upsilon}\right)}\right]$$

Since $lnQorganic_{it}$ is the natural logarithm of organic coffee demand, the conditional marginal effect equation shown above corresponds to a relative change in quantities.

If ME is the estimated value of the conditional marginal effect, the estimated percentage change in organic coffee quantity (level) purchased associated with the change in x_{itk} is [exp(ME) – 1]100%.

Conventional coffee demand can be modeled in a similar way. We tried several functional forms such as linear, quadratic and linear-log to find that Linear-Log model (we used logged price variables in the model) outperforms other functional forms as far as the model fit, significance of variables and loss matrices, such as AIC and Schwarz criteria, are concerned.

3.3 Data and variable construction

We extract ground and whole bean coffee product[20] data from the 2011-2013 Nielsen Homescan panel dataset, which covers nearly 0.7 million monthly transactions made by 55,470 households located in 264 counties from the 48 continental states plus the District of Columbia. The households in the Nielsen data set constitute a stratified random sample, selected on both demographic and geographic targets, aiming to construct a nationally representative panel of consumer purchases. With no intentional clustering, the stratification ensures that the sample matches the demographic profile of consumers according to the U.S. Census (the census tract level).

[20] Instant coffee, coffee beverage, and coffee substitutes (coffee partners and alternatives) are excluded since ground and whole bean coffee products have the largest degree of product variety, with number of UPCs accounting for almost 80% of the total.

Once enrolled, households are provided with a scanner and are required to scan all items following a purchase. The barcode is scanned and the Universal Product Code (UPC) is recorded for each product. Households are further instructed to enter the price and quantity for that particular purchase. If the purchase is made in Nielsen cooperating retailers, the price prompt is bypassed and filled by Nielsen with the average weighted price for the item that week in that particular store. Compared to Nielsen Retail Scanner data, the Homescan data have more retail channel types. In our dataset, consumers purchase coffee products via 62 different retail channels, with the majority of purchases made in grocery stores, followed by discount stores[21] and warehouse clubs.

For each household, Nielsen records a wealth of socioeconomic characteristics as well as the main place of residence and store locations for their shopping trips. The demographic information (education level, age, and racial/ethnic composition) is provided for both the female and the male heads of households. In this study, we implicitly assume that females make the majority of coffee purchases: if a female was present in the household, her demographic information was used; otherwise the male's demographic information was used. We followed this rule for age, education and employment. Age of the household head includes four groups: those less than 35, 35–49 years, 50-64 years, and 65 older. Education of household head has four categories: less than high school education, high school graduate, or some college, college graduate or higher. In addition, we also construct dummy variables, which indicate households only with female or male heads.

[21] Nielsen codes all mass merchandisers, including Kmart, Target, and Wal-Mart in the "Discount Store" channel.

Income, presence of children, race, and ethnicity are reported for the entire household. Race consists of five categories, representing Caucasian, Asian, African American, and other, while ethnicity indicates whether the household is of Hispanic origin. Nielsen classifies household income into 16 grouped categories, ranging from a low of under $5,000 a year to a high of over $100,000 per year, which we reclassified into four categories: low, lower middle, upper middle, and upper incomes. Low incomes included all households with incomes $24,999 and below, lower middle incomes were households between $25,000 and $49,999, upper middle incomes fell into the range of $50,000 to $69,999, and upper incomes were households with incomes $70,000 and greater a year. In order to capture whether the presence of children in households influences a household's decision to purchase organic coffee, households are assigned to one of two groups: those with at least one child under the age of 18, and households without children under 18 (including those with no children).

Table 12 presents summary statistics of the model's variables. In our final dataset, there were 540 different brands and 6,714 ground and whole bean coffee products at the UPC level. Used as the first stage discrete dependent variable, an organic household is defined as a household that makes at least one purchase of a relevant organic coffee product during the year. In our sample, 5,360 households were organic coffee buyers, while 109,272 households were conventional coffee buyers. Quantity data are standardized in terms of ounces; unit values (dollars per ounce, after coupon values) are used as proxies for prices. The average price for organic coffee was 14 cents higher than that for conventional coffee per ounce. The majority of households in our sample were

Caucasian, income ranges of either \$25,000-49,999 or ≥\$70,000, had two household members and no children under 18.

Table 12. Descriptive Statistics of Analysis Variables (2011-2013)

Variable	Observations	Mean	Std.	Min	Max
Conventional coffee					
Quantity (oz)	109,272	176.89	191.06	1	3909.8
Price (\$/oz)	109,272	0.35	0.16	0	3.29
Expenditure	109,272	54.42	61.09	0	2006.7
Organic coffee					
Quantity (oz)	5,360	41.71	65.34	1.25	1120
Price (\$/oz)	5,360	0.49	0.23	0	1.68
Expenditure	5,360	17.69	28.79	0	393.16
Household Income					
≤\$24,999	114,632	0.158	0.365	0	1
\$25,000~49,999	114,632	0.309	0.462	0	1
\$50,000~69,999	114,632	0.188	0.390	0	1
≥\$70,000	114,632	0.345	0.475	0	1
Household Size					
1	114,632	0.208	0.406	0	1
2	114,632	0.468	0.499	0	1
3	114,632	0.146	0.353	0	1
4	114,632	0.111	0.314	0	1
5	114,632	0.043	0.203	0	1
6+	114,632	0.024	0.153	0	1
Age and presence of children					
No children under 18	114,632	0.800	0.400	0	1
Children under 18	114,632	0.200	0.400	0	1
Female household head Age					
<35	114,632	0.045	0.207	0	1
35-49	114,632	0.218	0.413	0	1
50-64	114,632	0.424	0.494	0	1
65+	114,632	0.230	0.421	0	1
Female household head employment (per week)					
Under 30 hours	114,632	0.121	0.326	0	1
30-34	114,632	0.046	0.210	0	1
35+	114,632	0.321	0.467	0	1
Not employed	114,632	0.429	0.495	0	1
Female head education					
Less than HS	114,632	0.024	0.154	0	1
HS graduate	114,632	0.242	0.428	0	1
Some college	114,632	0.292	0.455	0	1
BA +	114,632	0.359	0.480	0	1
Male household Head Age					
<35	114,632	0.030	0.169	0	1
35-49	114,632	0.176	0.381	0	1
50-64	114,632	0.352	0.478	0	1
65+	114,632	0.222	0.416	0	1
Male household head employment					
Under 30 hours	114,632	0.049	0.215	0	1
30-34	114,632	0.025	0.156	0	1
35+	114,632	0.420	0.494	0	1
Not employed	114,632	0.286	0.452	0	1

Continued

Table 12. Continued

Variable	Observations	Mean	Std.	Min	Max
Male head education					
Less than HS	114,632	0.041	0.198	0	1
HS graduate	114,632	0.201	0.401	0	1
Some college	114,632	0.23	0.421	0	1
BA +	114,632	0.307	0.461	0	1
Female household head only	114,632	0.221	0.415	0	1
Male household head only	114,632	0.082	0.275	0	1
Race					
White	114,632	0.87	0.336	0	1
Black	114,632	0.067	0.251	0	1
Asian	114,632	0.022	0.147	0	1
Other	114,632	0.04	0.197	0	1
Hispanic Origin					
Yes	114,632	0.053	0.224	0	1
No	114,632	0.947	0.224	0	1

A problem arising due to zero consumption is that of missing prices. In order to estimate cross price elasticities, prices must be available for all items for all households. However, for households not consuming a particular item, there will be no data on the price of that item. Usually the missing prices are imputed by performing a regression with the data on the price of the item from those households who did consume it. These regressions specify the price as a function of regional dummies, seasonal dummies, and income. These regressions are then used to estimate the missing prices for those households which did not consume that particular item. The properties of estimates using data obtained in this manner were discussed by Dagenais (1973) and Gourieroux and Monfort (1981). Kyureghian, Capps, and Nayga (2011) perform a comprehensive analysis of different imputation methods on missing prices using Nielsen data, and conclude that the method of regression and/or conditional mean method is the best and leads to unbiased estimates in the majority of cases.

The procedure of using information provided by other customer's purchases for missing prices is actually superior to ignoring that information and treating the missing prices as missing at random. So instead of imputation, we calculated the annual average prices for both organic and non-organic coffee sold in stores located in a specific area sharing the first three-digit zip codes, which describe the sectional center facility (SCF) or "sec center." An SCF is a central mail processing facility with those three digits. The SCF sorts mail to all post offices with those first three digits in their ZIP codes. We then match these prices to each household by using the store zip code information in which they made the purchase.

3.4 Empirical results

For comparison, we estimated the parameters of the sample selection model by maximum likelihood. Maximum likelihood, Heckman two-step, and two-part estimates of the organic and non-organic demand equations are shown in Table 13 and Table 14, respectively. Maximum likelihood estimates are FIML estimates, which are consistent and efficient, we focus on the results throughout. Probit model coefficients are almost identical among the three estimators. Coefficients on prices are similar across different estimators, while there are some differences for coefficients on demographic variables. The likelihood-ratio test reported for the MLE output is an equivalent test of $\rho = 0$ and is computationally the comparison of the joint likelihood of an independent probit model for the selection equation and a regression model on the observed demand data against the Heckman model likelihood. Chi-squared test statistics, which are statistically significant at the 1% level, justify the Heckman selection equation with these data for both the organic and non-organic demand.

Table 13. Estimated Selection Corrected Organic Coffee Demand Equation

	Maximum Likelihood		***Two-Step***		***Two-Part***	
Variables	Probit	Demand	Probit	Demand	Probit	Demand
	Prob(Q>0)	ln(Quantity)	Prob(Q>0)	ln(Quantity)	Prob(Q>0)	ln(Quantity)
ln(Price OG)		-0.617***		-0.611***		-0.611***
		(0.051)		(0.049)		(0.042)
ln(Price Non OG)		-0.655***		-0.732***		-0.731***
		(0.107)		(0.240)		(0.112)
Household income						
$25,000-$49,999	0.065***	0.029	0.064***	0.220	0.064***	-0.057
	(0.022)	(0.053)	(0.022)	(1.559)	(0.022)	(0.043)
$50,000-$69,999	0.116***	0.107*	0.114***	0.449	0.113***	-0.041
	(0.025)	(0.060)	(0.025)	(2.759)	(0.025)	(0.048)
≥$70,000	0.152***	0.199***	0.147***	0.651	0.146***	0.021
	(0.024)	(0.059)	(0.024)	(3.539)	(0.024)	(0.047)
Household size						
2	-0.043	-0.099	-0.041	-0.229	-0.041	-0.053
	(0.026)	(0.065)	(0.026)	(0.997)	(0.026)	(0.053)
3	-0.094***	-0.205**	-0.095***	-0.468	-0.095***	-0.062
	(0.032)	(0.080)	(0.032)	(2.290)	(0.032)	(0.066)
4	-0.094**	-0.173*	-0.091**	-0.443	-0.092**	-0.053
	(0.037)	(0.092)	(0.037)	(2.205)	(0.037)	(0.076)
5	-0.106**	-0.178	-0.104**	-0.484	-0.105**	-0.041
	(0.046)	(0.113)	(0.046)	(2.504)	(0.046)	(0.095)
6+	-0.068	-0.180	-0.064	-0.384	-0.065	-0.109
	(0.054)	(0.128)	(0.054)	(1.572)	(0.054)	(0.104)
Age and presence of children						
Children under 18	-0.007	0.039	-0.008	0.025	-0.009	0.057
	(0.025)	(0.062)	(0.026)	(0.236)	(0.025)	(0.052)
Female head age						
<35	0.300***	0.240	0.298***	1.100	0.299***	-0.181
	(0.067)	(0.162)	(0.069)	(7.203)	(0.068)	(0.123)
35-49	0.255***	0.263*	0.255***	0.994	0.257***	-0.104
	(0.063)	(0.150)	(0.064)	(6.173)	(0.064)	(0.114)
50-64	0.213***	0.187	0.208***	0.815	0.210***	-0.086
	(0.062)	(0.147)	(0.063)	(5.069)	(0.062)	(0.112)
65+	0.118*	0.059	0.115*	0.410	0.116*	-0.088
	(0.062)	(0.147)	(0.063)	(2.820)	(0.062)	(0.112)
Female head employment						
Under 30 hours	0.076***	0.046	0.076***	0.259	0.076***	-0.066*
	(0.021)	(0.048)	(0.021)	(1.829)	(0.021)	(0.039)
30-34 hours	0.041	0.059	0.038	0.185	0.037	0.020
	(0.031)	(0.074)	(0.031)	(0.943)	(0.031)	(0.063)
35+ hours	0.006	-0.012	0.004	0.013	0.003	-0.002
	(0.017)	(0.041)	(0.017)	(0.130)	(0.017)	(0.033)
Female head education						
Less than HS	-0.327***	-0.590***	-0.329***	-1.514	-0.329***	-0.091
	(0.052)	(0.129)	(0.053)	(7.994)	(0.053)	(0.106)

Continued

Table 13. Continued

Variables	Maximum Likelihood Probit Prob(Q>0)	Maximum Likelihood Demand ln(Quantity)	Two-Step Probit Prob(Q>0)	Two-Step Demand ln(Quantity)	Two-Part Probit Prob(Q>0)	Two-Part Demand ln(Quantity)
HS graduate	-0.254***	-0.467***	-0.256***	-1.180	-0.256***	-0.078**
	(0.019)	(0.048)	(0.019)	(6.187)	(0.019)	(0.039)
Some college	-0.104***	-0.150***	-0.105***	-0.435	-0.104***	0.012
	(0.016)	(0.039)	(0.016)	(2.513)	(0.016)	(0.032)
Female head only	0.041*	-0.041	0.038	0.085	0.038	-0.078
	(0.024)	(0.060)	(0.024)	(0.929)	(0.024)	(0.049)
Race and ethnicity						
Black	-0.252***	-0.480***	-0.251***	-1.199	-0.252***	-0.115**
	(0.030)	(0.071)	(0.030)	(6.089)	(0.030)	(0.059)
Asian	0.048	0.043	0.049	0.186	0.051	-0.020
	(0.040)	(0.095)	(0.040)	(1.180)	(0.040)	(0.075)
Other	0.006	0.052	-0.003	0.097	-0.003	0.111
	(0.036)	(0.098)	(0.035)	(0.216)	(0.035)	(0.082)
Non-Hispanic	-0.017	0.051	-0.020	0.012	-0.023	0.100
	(0.031)	(0.076)	(0.031)	(0.521)	(0.031)	(0.063)
Male head only (=1) ×Male head age						
<35	0.341**	0.288	0.326**	1.305	0.326**	-0.096
	(0.137)	(0.406)	(0.135)	(7.906)	(0.135)	(0.318)
35-49	0.346***	0.312*	0.344***	1.305	0.344***	-0.174
	(0.077)	(0.175)	(0.076)	(8.316)	(0.077)	(0.136)
50-64	0.214***	0.266*	0.203***	0.919	0.203***	0.040
	(0.065)	(0.156)	(0.065)	(4.949)	(0.065)	(0.122)
Male head employment						
Under 30 hours	-0.211**	-0.281	-0.210**	-0.879	-0.210**	0.030
	(0.098)	(0.220)	(0.099)	(5.136)	(0.099)	(0.181)
30-34 hours	0.064	-0.122	0.059	0.070	0.059	-0.179
	(0.119)	(0.302)	(0.120)	(1.563)	(0.119)	(0.238)
35+ hours	-0.026	-0.078	-0.025	-0.152	-0.024	-0.045
	(0.058)	(0.146)	(0.057)	(0.684)	(0.058)	(0.120)
Male head education						
Less than HS	-0.498**	-1.046	-0.525**	-2.287	-0.525**	-0.013
	(0.229)	(0.770)	(0.232)	(12.846)	(0.226)	(0.779)
HS graduate	-0.422***	-0.936***	-0.419***	-2.149	-0.419***	-0.324*
	(0.081)	(0.217)	(0.081)	(10.258)	(0.081)	(0.165)
Some college	-0.076	-0.183	-0.076	-0.400	-0.076	-0.078
	(0.051)	(0.124)	(0.051)	(1.834)	(0.051)	(0.097)
Rho(ρ)		0.930				
		(0.008)				
Sigma(σ)		1.817				
		(0.045)				
Lambda (λ)		1.690		4.967		
		(0.054)		(27.874)		
Constant	-1.825***	-1.669***	-1.814***	-9.075	-1.811***	1.910***
	(0.065)	(0.223)	(0.067)	(61.642)	(0.066)	(0.169)
Observations	114,624	114,624	114,624	114,624	114,632	5,352
R-squared						0.131

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 14. Estimated Selection Corrected Non-Organic Coffee Demand Equation

Variables	***Maximum Likelihood*** Probit Prob(Q>0)	Demand ln(Quantity)	***Two-Step*** Probit Prob(Q>0)	Demand ln(Quantity)	***Two-Part*** Probit Prob(Q>0)	Demand ln(Quantity)
ln(Price Non OG)		-0.737***		-0.798***		-0.871***
		(0.017)		(0.011)		(0.020)
ln(Price OG)		0.027***		0.031***		0.159***
		(0.009)		(0.012)		(0.010)
Household income						
$25,000-$49,999	-0.035*	0.024*	-0.055**	0.030	-0.064***	0.008
	(0.019)	(0.013)	(0.023)	(0.022)	(0.022)	(0.012)
$50,000-$69,999	-0.042*	0.039***	-0.094***	0.050	-0.113***	0.015
	(0.021)	(0.015)	(0.026)	(0.031)	(0.025)	(0.014)
≥$70,000	-0.033	0.038***	-0.112***	0.054	-0.146***	0.018
	(0.021)	(0.015)	(0.025)	(0.035)	(0.024)	(0.014)
Household size						
2	0.043*	0.217***	0.042	0.210***	0.041	0.208***
	(0.024)	(0.016)	(0.027)	(0.024)	(0.026)	(0.015)
3	0.086***	0.201***	0.098***	0.189***	0.095***	0.207***
	(0.028)	(0.020)	(0.033)	(0.037)	(0.032)	(0.018)
4	0.092***	0.224***	0.093**	0.212***	0.092**	0.226***
	(0.033)	(0.023)	(0.038)	(0.039)	(0.037)	(0.021)
5	0.136***	0.229***	0.102**	0.212***	0.105**	0.230***
	(0.042)	(0.029)	(0.047)	(0.046)	(0.046)	(0.027)
6+	0.051	0.277***	0.057	0.265***	0.065	0.253***
	(0.046)	(0.034)	(0.056)	(0.046)	(0.054)	(0.032)
Age and presence of children						
Children under 18	-0.008	-0.124***	0.007	-0.123***	0.009	-0.108***
	(0.023)	(0.016)	(0.027)	(0.021)	(0.025)	(0.015)
Female head age						
<35	-0.191***	-0.307***	-0.333***	-0.280***	-0.299***	-0.385***
	(0.057)	(0.040)	(0.071)	(0.104)	(0.068)	(0.036)
35-49	-0.167***	-0.074**	-0.284***	-0.052	-0.257***	-0.149***
	(0.052)	(0.036)	(0.066)	(0.088)	(0.064)	(0.033)
50-64	-0.175***	0.100***	-0.233***	0.118	-0.210***	0.032
	(0.051)	(0.035)	(0.065)	(0.075)	(0.062)	(0.032)
65+	-0.160***	0.091***	-0.127*	0.106*	-0.116*	0.061*
	(0.051)	(0.035)	(0.065)	(0.056)	(0.062)	(0.032)
Female head employment						
Under 30 hours	-0.045**	-0.021	-0.076***	-0.015	-0.076***	-0.050***
	(0.018)	(0.014)	(0.021)	(0.028)	(0.021)	(0.012)
30-34 hours	-0.000	-0.061***	-0.037	-0.058**	-0.037	-0.070***
	(0.028)	(0.020)	(0.032)	(0.028)	(0.031)	(0.018)
35+ hours	0.021	-0.046***	-0.008	-0.046***	-0.003	-0.048***
	(0.015)	(0.011)	(0.018)	(0.014)	(0.017)	(0.010)

Continued

Table 14. Continued

Variables	*Maximum Likelihood* Probit Prob(Q>0)	Demand ln(Quantity)	*Two-Step* Probit Prob(Q>0)	Demand ln(Quantity)	*Two-Part* Probit Prob(Q>0)	Demand ln(Quantity)
Female head education						
Less than HS	0.142***	0.060**	0.328***	0.033	0.329***	0.145***
	(0.040)	(0.026)	(0.054)	(0.089)	(0.053)	(0.024)
HS graduate	0.140***	0.036***	0.252***	0.014	0.256***	0.107***
	(0.016)	(0.011)	(0.020)	(0.070)	(0.019)	(0.011)
Some college	0.035**	0.039***	0.107***	0.030	0.104***	0.075***
	(0.014)	(0.010)	(0.016)	(0.035)	(0.016)	(0.010)
Female head only	0.066***	-0.222***	-0.023	-0.222***	-0.038	-0.223***
	(0.022)	(0.015)	(0.025)	(0.020)	(0.024)	(0.014)
Race and ethnicity						
Black	0.269***	-0.465***	0.275***	-0.487***	0.252***	-0.369***
	(0.027)	(0.016)	(0.030)	(0.071)	(0.030)	(0.015)
Asian	-0.018	-0.208***	-0.014	-0.202***	-0.051	-0.197***
	(0.037)	(0.026)	(0.041)	(0.035)	(0.040)	(0.023)
Other	0.079**	-0.075***	0.014	-0.080***	0.003	-0.059***
	(0.032)	(0.022)	(0.036)	(0.029)	(0.035)	(0.021)
Non-Hispanic	0.032	0.076***	-0.001	0.074***	0.023	0.080***
	(0.027)	(0.019)	(0.031)	(0.025)	(0.031)	(0.018)
Male head only (=1) ×						
Male head age						
<35	-0.154	-0.266***	-0.336**	-0.239*	-0.326**	-0.336***
	(0.120)	(0.086)	(0.139)	(0.141)	(0.135)	(0.077)
35-49	-0.175***	-0.004	-0.359***	0.022	-0.344***	-0.122***
	(0.066)	(0.045)	(0.078)	(0.110)	(0.077)	(0.041)
50-64	-0.142***	0.130***	-0.206***	0.145**	-0.203***	0.073**
	(0.053)	(0.034)	(0.066)	(0.066)	(0.065)	(0.031)
Male head employment						
Under 30 hours	0.232***	-0.108**	0.206**	-0.125	0.210**	-0.051
	(0.082)	(0.051)	(0.102)	(0.082)	(0.099)	(0.048)
30-34 hours	-0.119	0.089	-0.073	0.102	-0.059	0.061
	(0.094)	(0.073)	(0.124)	(0.102)	(0.119)	(0.066)
35+ hours	0.036	-0.078**	0.021	-0.080*	0.024	-0.072**
	(0.048)	(0.034)	(0.059)	(0.045)	(0.058)	(0.031)
Male head education						
Less than HS	0.250	-0.109	0.508**	-0.143	0.525**	0.008
	(0.174)	(0.091)	(0.240)	(0.162)	(0.226)	(0.089)
HS graduate	0.226***	-0.089**	0.418***	-0.120	0.419***	0.006
	(0.063)	(0.038)	(0.083)	(0.106)	(0.081)	(0.036)
Some college	0.028	0.038	0.084	0.030	0.076	0.060**
	(0.044)	(0.031)	(0.052)	(0.047)	(0.051)	(0.028)

Continued

Table 14. Continued

Variables	*Maximum Likelihood*		*Two-Step*		*Two-Part*	
	Probit Prob(Q>0)	Demand ln(Quantity)	Probit Prob(Q>0)	Demand ln(Quantity)	Probit Prob(Q>0)	Demand ln(Quantity)
Rho(ρ)		-0.948		-1.000		
		(0.002)				
Sigma(σ)		1.233		1.590		
		(0.003)				
Lambda (λ)		-1.169		-1.591		
		(0.005)		(1.381)		
Constant	1.558^{***}	3.738^{***}	1.747^{***}	3.715^{***}	1.811^{***}	3.536^{***}
	(0.055)	(0.043)	(0.068)	(0.142)	(0.066)	(0.042)
Observations	96,155	96,155	96,155	96,155	114,632	96,155
R-squared						0.1517

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Own price elasticities for organic and non-organic coffee are -0.617 and -0.737, respectively. They are both less than 1, indicating coffee in general has an inelastic demand. Compared to non-organic coffee, organic coffee consumers are less sensitive to price changes. This is consistent with findings from Hainmueller, Hiscox, and Sequeira (2014), while at odds with Alviola and Capps (2010), who found the demand for organic milk was elastic, but the demand for conventional milk was inelastic. The cross-price elasticity is negative, indicating that they regard non-organic coffee as a complementary good. For non-organic consumers, organic coffee is a substitute, positive cross-price elasticity. This interesting result show that with respect to non-organic coffee, organic coffee may be perceived either as a substitute or a complement.

Table 15. Marginal Effects

Variables	Organic coffee Probit Prob(Q>0)	Organic coffee Demand ln(Quantity)	Non-Organic coffee Probit Prob(Q>0)	Non-Organic coffee Demand ln(Quantity)
ln(Price OG)		-0.617***		0.027***
		(0.051)		(0.009)
ln(Price Non OG)		-0.655***		-0.737***
		(0.107)		(0.017)
Household income				
$25,000-$49,999	0.006***	-0.527***	-0.004*	0.033**
	(0.002)	(0.100)	(0.002)	(0.014)
$50,000-$69,999	0.011***	-0.713***	-0.005**	0.060***
	(0.002)	(0.059)	(0.003)	(0.017)
≥$70,000	0.015***	-0.736***	-0.004	0.061***
	(0.002)	(0.056)	(0.002)	(0.017)
Household size				
2	-0.005	-0.034	0.005*	0.257***
	(0.003)	(0.050)	(0.003)	(0.018)
3	-0.010***	-0.063	0.011***	0.252***
	(0.003)	(0.059)	(0.004)	(0.022)
4	-0.010**	-0.034	0.011***	0.283***
	(0.004)	(0.070)	(0.004)	(0.026)
5	-0.011**	-0.021	0.016***	0.304***
	(0.005)	(0.086)	(0.005)	(0.034)
6+	-0.007	-0.076	0.006	0.338***
	(0.005)	(0.093)	(0.006)	(0.040)
Age and presence of children				
Children under 18	-0.001	0.050	-0.001	-0.119***
	(0.003)	(0.051)	(0.003)	(0.013)
Female head age				
<35	0.029***	-0.183	-0.021***	-0.300***
	(0.006)	(0.098)	(0.006)	(0.025)
35-49	0.023***	-0.108	-0.018***	-0.109***
	(0.005)	(0.098)	(0.005)	(0.029)
50-64	0.019***	-0.120	-0.019***	0.057*
	(0.005)	(0.095)	(0.005)	(0.033)
65+	0.010**	-0.110	-0.017***	0.053
	(0.005)	(0.096)	(0.005)	(0.033)
Female head employment				
Under 30 hours	0.008***	-0.064*	-0.006**	-0.033***
	(0.002)	(0.034)	(0.002)	(0.011)
30-34 hours	0.004	-0.002	-0.000	-0.059***
	(0.003)	(0.055)	(0.003)	(0.017)
35+ hours	0.001	-0.021	0.003	-0.039***
	(0.002)	(0.031)	(0.002)	(0.009)

Continued

Table 15. Continued

Variables	Organic coffee Probit Prob(Q>0)	Organic coffee Demand ln(Quantity)	Non-Organic coffee Probit Prob(Q>0)	Non-Organic coffee Demand ln(Quantity)
Female head education				
Less than HS	-0.029***	-0.100	0.017***	0.103***
	(0.004)	(0.089)	(0.004)	(0.025)
HS graduate	-0.024***	-0.087***	0.017***	0.075***
	(0.002)	(0.033)	(0.002)	(0.011)
Some college	-0.011***	0.002	0.004**	0.050***
	(0.002)	(0.030)	(0.002)	(0.010)
Female head only	0.004*	-0.096**	0.008***	-0.185***
	(0.003)	(0.044)	(0.003)	(0.011)
Race and ethnicity				
Black	-0.021***	-0.099**	0.028***	-0.331***
	(0.002)	(0.047)	(0.002)	(0.010)
Asian	0.005	-0.028	-0.002	-0.192***
	(0.004)	(0.070)	(0.005)	(0.019)
Other	0.001	0.044	0.009***	-0.053***
	(0.004)	(0.087)	(0.004)	(0.019)
Non-Hispanic	-0.002	0.026	0.004	0.009
	(0.003)	(0.047)	(0.003)	(0.008)
Male head only (=1) × Male head age				
<35	0.003**	-0.188	-0.002	-0.268***
	(0.001)	(0.299)	(0.001)	(0.056)
35-49	0.003***	-0.175	-0.002***	-0.055
	(0.001)	(0.107)	(0.001)	(0.038)
50-64	0.002***	-0.046	-0.001***	0.092***
	(0.001)	(0.111)	(0.001)	(0.033)
Male head employment				
Under 30 hours	-0.002**	0.033	0.002***	-0.051
	(0.001)	(0.167)	(0.001)	(0.044)
30-34 hours	0.001	-0.195	-0.001	0.056
	(0.001)	(0.202)	(0.001)	(0.065)
35+ hours	-0.0002	-0.039	0.000	-0.066**
	(0.000)	(0.113)	(0.000)	(0.028)
Male head education				
Less than HS	-0.004**	-0.257	0.003	-0.049
	(0.002)	(0.503)	(0.002)	(0.080)
HS graduate	-0.003***	-0.262**	0.002***	-0.034
	(0.001)	(0.131)	(0.001)	(0.033)
Some college	-0.001	-0.068	0.000	0.047*
	(0.000)	0.091	(0.000)	(0.028)
Observations	5,352		96,147	

[*]Marginal effects are all calculated at the means of covariates by using –predictnl- in Stata, in which standard errors are computed using the delta method.

Marginal effects for the probit models are calculated and presented in Table 15.

The first stage probit model results indicate: compared to households with annual income below \$25,000, households with higher income were more likely to purchase organic coffee. The probability increases with income. For instance, the probability of buying organic coffee for household with income in the range of \$25,000-\$49,999 is 0.6% higher, while that for income higher than \$70,000 is 1.5% higher (holding education level constant). As the number of household members increases, it less likely that households would purchase organic coffee. Hence, relative to single-member households, households with more members are less likely to consume organic coffee. Looking at the marginal effects, we found that for household size equal to or greater than three members, the probability of purchasing organic coffee decrease by around 1%. Presence and age of children did not seem to have any impact on households' decisions to buy organic coffee. Households with female heads who were younger than 35 years old and worked less than 30 hours per week had higher possibilities of buying organic coffee. African Americans were less likely to purchase organic coffee when compared with Caucasians. Asian and other race had an insignificant effect on the likelihood of purchasing organic coffee. Probabilities in purchasing organic coffee for Hispanic origin households with only female head were not significantly different from non-Hispanic, households with only male head. The level of education of the household head played an important role in the purchase of organic coffee. From Table 4, lower levels of education decreased a consumer's likelihood of purchasing organic coffee. For those households with female head on educational levels corresponding to Bachelor's degree or higher, the likelihood of buying organic coffee increased by 3% relative to household female heads with less than a high school education or high school graduate.

The second stage demand estimation results show the magnitudes of factors affecting the amount purchased, once the decision to purchase organic coffee and conventional coffee was made. Household income produced predictable results in the first stage of the decision (whether to buy organic), but in the second stage of the decision (how much to buy), households from all income tiers actually purchased significantly less organic coffee than those in the lowest tier, all else constant. In terms of household size, there is no significant relationship between household size and the quantity purchased for organic coffee. As for race, African Americans were not likely to try organic coffee, and those who did were likely to spend much less on organic coffee than Whites, while Asians and other races did not differ significantly from Whites in terms of quantities purchased for organic coffee. Compared with female heads that held Bachelor's degree or higher, all other education levels had a negative impact on the organic coffee purchase. Households with female heads who are high school graduate buy 8.7% less organic coffee. Household with male head ages who are high school graduate buy 26.2% less organic coffee. Coefficients on all other variables were statistically insignificant.

3.5 Conclusions

Both industry and academic studies have investigated the demographic profile of the organic consumer and, to date, these studies have yielded conflicting results. This article adds to the body of literature by analyzing purchase and demographic data in an effort to develop a demographic profile of the organic coffee consumers. The results support the findings of some studies and contradict others, which justifies the need for this study as consumer demographic profiles might differ significantly by product. For instance, like many other studies, education and income were significant factors, while race, Hispanic origin, age and presence of children play different roles in making decisions to buy organic products. In addition, our results show the importance of market segmentation when analyzing price elasticities.

As organic markets continue to grow, the findings of this analysis will enhance marketing efforts of organic coffee in targeting the primary consumer of organic coffee, particularly high-income households who have at least bachelor's degrees, and households headed by individuals age under 49. Also, owing to our findings concerning own-price elasticities, retailers could raise both prices of organic and conventional coffee to increase sales revenue, as demand for both products would only fall proportionally, holding all other factors constant.

3.6 Limitations of the study

Like many models for censoring and truncation, the Heckman's selection model (regardless of the estimator used) rest upon parametric distribution of the unobservable error terms in the model (bivariate normality assumption), which has been regarded as a potential drawback(Greene, 2012; Puhani, 2000). Sam and Zheng (2010) further argued that maximum likelihood and two-step estimators of censored demand systems yield biased and inconsistent parameter estimates when the assumed joint distribution of disturbances is incorrect. They propose a semiparametric estimator that retains the computational advantage of the two-step approach but is immune to distributional misspecification (does not assume a normally distributed error in the first-stage equation) and accommodates a certain form of heteroskedasticity. The key difference between the proposed estimator and the two-step estimator is that the parameters of the binary censoring equations are estimated using a distribution-free single-index model.

The number of households purchasing only organic coffee was 507, the number of households purchasing both organic coffee and conventional coffee was 3,842, and the number of households purchasing only conventional coffee was 55,334. Work is underway in estimating a polytomous choice model dealing with the aforementioned three choices.

As with most research endeavors, data limitations were encountered. The largest constraint is that our data do not account for consumer preferences that underlie a consumer's decision to purchase organic products. Expanding the model to include variables that capture nondemographic factors leading to a consumer's choice to purchase organic coffee would likely strengthen the results. One way to gather this hard-to-find information would be to ask households in the Nielsen panel questions that capture their preferences about health and environmental issues. Including such information would make it possible to fine-tune the analysis of the organic consumer's demographic profile.

Appendix

A.1 Derivations of Barten's Synthetic Model

Barten's synthetic model (Barten, 1993) nests four popular demand systems: the Rotterdam (R), the FDLAIDS (F), the NBR (N), and the CBS (C) models, which can be rewritten so they all have the same right-hand-side terms:

(A.1.0) $y_R = \quad w_i d \ln q_i \quad = \theta_i \, d \ln Q + \sum_{j=1}^{N} \pi_{ij} d \ln p_j,$

(A.1.1) $y_F = \quad d\, w_i \quad = \beta_i \, d \ln Q + \sum_{j=1}^{N} \gamma_{ij} d \ln p_j,$

(A.1.2) $y_C = \quad w_i (d \ln q_i - d \ln Q) \quad = \beta_i \, d \ln Q + \sum_{j=1}^{N} \pi_{ij} d \ln p_j,$

(A.1.3) $y_N = \quad d\, w_i + w_i d \ln q_i \quad = \theta_i \, d \ln Q + \sum_{j=1}^{N} \gamma_{ij} d \ln p_j,$

where w_i is the budget share for good i, q_i is quantity, p_i is price, and $d \ln Q$ is the Divisia volume index: $d \ln Q = \sum_{j=1}^{N} w_i d \ln q_i$.

The four differential demand systems have the same set of RHS variables. However, the four models have different left-hand side (LHS) variables: LHS in the Rotterdam model corresponds to the quantity component of the change in the budget share; it is simply the change in the budget share of commodity i in the FDLAIDS model; the dependent variable in the CBS model is the expenditure share weighted deviation of the log change in q_i form the average log change in the quantities Q of all n goods, i.e., the weighted change in the volume share q_i/Q of the ith commodity; NBR's LHS corresponds to the (budget share) weighted change in real expenditure on commodity i.

The four systems also share similarity and discrepancies in assumptions concerning the constancy of certain parameters. The Rotterdam and NBR models have the same coefficient on the expenditure term (i.e., $\theta_i = \frac{\partial q_{it} p_{it}}{\partial \sum_{j=1}^{N} q_{jt} p_{jt}}$), which is the (constant) marginal budget share. FDLAIDS and CBS models share the same marginal budget share (i.e., $\beta_i = \theta_i - w_i$), which varies with the expenditure share. The Slutsky terms (i.e., π_{ij}) are considered to be constants in the Rotterdam and CBS models and < 0 imposed by negativity of the substitution effect. Negativity of the substitution effect does not necessarily impose negativity of price coefficients $(\mathrm{i.e.}, \gamma_{\mathbf{ij}})$, as in the NBR and FDLAIDS models (Neves, 1994).

Using the matrix expressions, we can combine the four models into the one general form:

(A.1.4) $\alpha_R \boldsymbol{y}_R + \alpha_F \boldsymbol{y}_F + \alpha_C \boldsymbol{y}_C + \alpha_N \boldsymbol{y}_N = X\Omega$

where $\mathbf{y}_i$, $i = R, C, N, F$ is a $t \times 1$ vector of transformed basic endogenous variables; $\mathbf{X}$ is a $t \times k$ matrix of exogenous price and expenditure variables; and $\Omega = \alpha_R\omega_R + \alpha_C\omega_C + \alpha_F\omega_F + \alpha_N\omega_N$ and ω_i, $i=R, C, N, F$ compose a $k \times 1$ vector of coefficients. Without loss of generality, Barten set the sum of the α's to one and solved for α_R.

(A.1.5) $\alpha_R = 1 - \alpha_F - \alpha_C - \alpha_N$.

Substituting α_R into **(A.1.4)** and solving for $\mathbf{y}_R$ yields

(A.1.6) $y_R = \alpha_C(y_R - y_C) + \alpha_F(y_R - y_F) + \alpha_N(y_R - y_N) + X\Omega$.

Unconstrained estimation of the αs is not possible since α_R is a linear combination of α_F, α_C, and $\boldsymbol{\alpha}_N$. However, **(A.1. 6)** can be rewritten using the fact that

(A.1.7) $y_R - y_C + y_F - y_N = 0$,

or (A.1.8) $(y_R - y_C) - (y_R - y_F) + (y_R - y_N) = 0$.

Solving (A.1.8) for $\mathbf{y}_R - \mathbf{y}_F$ yields

(A.1.9) $(\mathbf{y}_R - \mathbf{y}_F) = (\mathbf{y}_R - \mathbf{y}_C) + (\mathbf{y}_R - \mathbf{y}_N)$,

and substituting this into **(A.1.6)** gives

(A.1.10) $\mathbf{y}_R = X\Omega + \alpha_C(\mathbf{y}_R - \mathbf{y}_C) + \alpha_F(\mathbf{y}_R - \mathbf{y}_F) + \alpha_N(\mathbf{y}_R - \mathbf{y}_N)$,

$= X\Omega + (\alpha_C + \alpha_F)(\mathbf{y}_R - \mathbf{y}_C) + (\alpha_N + \alpha_F)(\mathbf{y}_R - \mathbf{y}_N)$

$= X\Omega + \delta_1(\mathbf{y}_R - \mathbf{y}_C) + \delta_2(\mathbf{y}_R - \mathbf{y}_N)$

The nesting coefficient $\delta_1 = \alpha_C + \alpha_F$ measures the difference between the marginal budget shares of the Rotterdam model and the marginal budget shares of the CBS and FDLAIDS models. The nesting coefficient $\delta_2 = \alpha_N + \alpha_F$ measures the difference between the price coefficients of the Rotterdam model and price coefficients of the FDLAIDS and NBR models.

Substituting (A.1.0) - (A.1.3) into (A.1.10) yields

(A.1.11) $\boldsymbol{w_i\, d\ln q_i = X\Omega + \delta_1\, d\ln Q + \delta_2 (w_i\, d\ln q_i - d\,w_i - w_i\, d\ln Q)}$,

Using the total differential of the budget share

(A.1.12) $dw_i = w_i d\ln q_i + w_i d\ln p_i - w_i d\ln M$,

and the logarithmic differential of the budget equation for rearranging,

(A.1.13) $\boldsymbol{dlnM = dlnP + dlnQ} = \sum_{j=1}^{N} w_i d\ln p_i + \sum_{j=1}^{N} w_i d\ln q_i$.

Barten's synthetic model takes the form:

$$(A.1.14)\quad w_i dlnq_i = \alpha_0 + (\alpha_i + \delta_1 w_i) dlnQ + \sum_{j=1}^{n} \left(b_{ij} - \delta_2 w_i(\delta_{ij} - w_j)\right) dlnp_j$$

where δ_1 and δ_2 are nesting parameters, $\alpha_i = \delta_1\beta_i + (1 - \delta 1)\theta_i$ and $b_{ij} = \delta_2\gamma_{ij} + (1 - \delta_2)\pi_{ij}$ are expenditure and price coefficients to be estimated, δ_{ik} is the Kronecker delta, w_i is a $t \times 1$ vector of expenditure shares for good i, p_i is a $t \times 1$ vector of prices of good k, and $dlnQ$ is a $t \times 1$ vector of Divisia volume indexes.

The following list shows the values for $\boldsymbol{\delta_1}$ and $\boldsymbol{\delta_2}$ that allow Barten's synthetic model to collapse into the various nested models:

Rotterdam $\delta_1 = 0$ and $\delta_2 = 0$; FDLAIDS $\delta_1 = 1$ and $\delta_2 = 1$;

CBS $\delta_1 = 1$ and $\delta_2 = 0$; NBR $\delta_1 = 0$ and $\delta_2 = 1$.

A.2 State Cigarette Excise Tax Rates (Dollars Per 20-Pack), 2011 and 2012[a]

	2011		2012	
State	**Tax Rate**	**Rank**	**Tax Rate**	**Rank**
Alabama	$0.425	46	$0.425	46
Alaska	$2.00	10	$2.00	10
Arizona	$2.00	10	$2.00	10
Arkansas	$1.15	27	$1.15	27
California	$0.87	31	$0.87	31
Colorado	$0.84	32	$0.84	32
Connecticut	$3.00	4	$3.40	3
Delaware	$1.60	19	$1.60	19
Florida	$1.339	24	$1.339	24
Georgia	$0.37	47	$0.37	47
Hawaii	$3.00	4	$3.20	4
Idaho	$0.57	40	$0.57	40
Illinois	$0.98	30	$0.98	30
Indiana	$0.995	29	$0.995	29
Iowa	$1.36	23	$1.36	23
Kansas	$0.79	34	$0.79	34
Kentucky	$0.60	38	$0.60	38
Louisiana	$0.36	48	$0.36	48
Maine	$2.00	10	$2.00	10
Maryland	$2.00	10	$2.00	10
Massachusetts	$2.51	8	$2.51	9
Michigan	$2.00	10	$2.00	10
Minnesota[b]	$0.48	43	$0.48	43
Mississippi	$0.68	35	$0.68	35
Missouri	$0.17	50	$0.17	50
Montana	$1.70	16	$1.70	15
Nebraska	$0.64	36	$0.64	36
Nevada	$0.80	33	$0.80	33
New Hampshire	$1.78	15	$1.68	17
New Jersey	$2.70	6	$2.70	6
New Mexico	$1.66	18	$1.66	18
New York	$4.35	1	$4.35	1
North Carolina	$0.45	44	$0.45	44
North Dakota	$0.44	45	$0.44	45
Ohio	$1.25	25	$1.25	25
Oklahoma	$1.03	28	$1.03	28
Oregon	$1.18	26	$1.18	26
Pennsylvania	$1.60	19	$1.60	19
Rhode Island	$3.46	2	$3.46	2

South Dakota	$0.57	40	$0.57	40
South Dakota	$1.53	21	$1.53	21
Tennessee	$0.62	37	$0.62	37
Texas	$1.41	22	$1.41	22
Utah	$1.70	16	$1.70	15
Vermont	$2.24	9	$2.62	7
Virginia	$0.30	49	$0.30	49
Washington	$3.025	3	$3.025	5
West Virginia	$0.55	42	$0.55	42
Wisconsin	$2.52	7	$2.52	8
Wyoming	$0.60	38	$0.60	38
District of Columbia	$2.50	(9)	$2.86	(6)

Note: [a]. The federal excise tax of $1.0066 per pack and local taxes are not included.
All the state rates are as of January 1, 2012 and 2012, respectively. New tax rates usually become effective in the beginning of the state fiscal years (i.e. July 1st, except for Alabama, Michigan, New York and Texas).
[b]. In addition to cigarette excise taxes, Minnesota imposes a $0.75 (per pack) Health Impact Fee, which rescinds in June 30, 2013.
Source: Tax Foundation; Orzechowski & Walker, Tax Burden on Tobacco; state revenue departments.

TABLE A1
Cigarette Tax Incidence by County Location

Independent Variables	Dependent variable: Tax inclusive cigarette price per pack			
	Two-way Interaction effects	County I: on state borders, the lowest tax	County II: all other counties on state borders	County III: counties not on state borders
State excise tax (tax)	0.999***	1.185***	0.975***	1.024***
	(0.023)	(0.051)	(0.023)	(0.026)
County I*tax	0.142***			
	(0.048)			
County III*tax	0.047			
	(0.037)			
County I	-0.209***			
	(0.080)			
County III	-0.145**			
	(0.070)			
Style	0.609***	0.643***	0.637***	0.585***
	(0.014)	(0.032)	(0.025)	(0.020)
Type	0.049***	0.037***	0.016*	0.068***
	(0.007)	(0.009)	(0.007)	(0.010)
Strength light	0.307***	0.286***	0.320***	0.308***
	(0.004)	(0.011)	(0.007)	(0.006)
Strength ultra light	0.465***	0.428***	0.481***	0.471***
	(0.008)	(0.014)	(0.013)	(0.012)
Carton	-0.493***	-0.421***	-0.361***	-0.541***
	(0.040)	(0.040)	(0.041)	(0.062)
Premium brand	0.773***	0.804***	0.803***	0.756***
	(0.017)	(0.045)	(0.038)	(0.022)
Unemployment rate	-0.043***	-0.050**	-0.077***	-0.034**
	(0.008)	(0.016)	(0.013)	(0.011)
Per capita income ($1,000)	0.005**	0.002	-0.011	0.011**
	(0.002)	(0.003)	(0.007)	(0.004)
High school grads	-0.185	-3.456*	0.528	1.640*
	(0.817)	(1.352)	(1.107)	(0.750)
College degree and higher	0.348	-1.401	0.943	1.430**
	(0.532)	(0.802)	(0.780)	(0.478)
Male population	-2.980**	-3.359	-6.923**	-0.663
	(1.215)	(2.842)	(2.259)	(1.445)
Black	-0.716***	-0.731*	-0.738**	-0.525***
	(0.161)	(0.290)	(0.246)	(0.155)
AIAN	0.739*	0.015	0.78	1.841***
	(0.391)	(0.327)	(0.587)	(0.464)
Asian	0.027	-1.709	7.465*	-0.352
	(0.826)	(2.091)	(3.712)	(0.816)
Hispanic	-0.312	-0.231	0.301	-0.267
	(0.239)	(0.446)	(0.464)	(0.262)
Age 15-24	0.383	-1.093	2.583	-0.193

	(1.083)	(2.002)	(1.704)	(1.522)
Age 25-44	0.834	7.66	4.151	-1.792
	(1.631)	(4.310)	(2.303)	(2.042)
Age 45-64	-0.847	-1.903	4.842**	-2.313
	(1.119)	(2.395)	(1.612)	(1.671)
Age 65 +	0.937	5.579*	2.193	-0.656
	(1.103)	(2.678)	(1.810)	(1.365)
Constant	4.994***	5.264*	4.255*	3.558**
	(1.053)	(2.201)	(1.678)	(1.177)
Observations	6,587,905	1,489,564	1,464,370	3,633,971
R-squared	0.746	0.768	0.762	0.697

Notes: Robust standard errors clustered at the county level are in parentheses.
*** Significant at 1%, ** Significant at 5%, * Significant at 10%.
All regressions include county fixed effects, purchase month fixed effects, product attribute variables as well as the full set of economic, social, demographic controls shown in Table 3.

TABLE A2
Separate Regression Results For Cigarette Tax Incidence By Product Group

Independent Variables	Dependent variable: Tax inclusive cigarette price per pack			
	(1) Premium carton	(2) Premium pack	(3) Discount pack	(4) Discount carton
State excise tax (tax)	1.213***	1.043***	1.022***	1.084***
	(0.019)	(0.023)	(0.018)	(0.013)
Style	1.187***	0.721***	-0.309***	-0.199***
	(0.019)	(0.021)	(0.022)	(0.047)
Type	0.224***	0.058***	-0.081***	0.010
	(0.008)	(0.006)	(0.009)	(0.007)
Strength light	0.277***	0.410***	0.103***	0.065***
	(0.008)	(0.008)	(0.009)	(0.010)
Strength ultra light	0.300***	0.620***	0.198***	0.015
	(0.011)	(0.009)	(0.012)	(0.013)
Unemployment rate	-0.002	-0.049***	-0.057***	-0.003
	(0.004)	(0.010)	(0.008)	(0.005)
Per capita income ($1,000)	0.004***	0.008***	0.004*	0.003***
	(0.001)	(0.003)	(0.002)	(0.001)
High school grads	-0.249	-0.448	0.585	0.491
	(0.502)	(1.383)	(0.917)	(0.457)
College degree and higher	-0.040	0.191	0.594	0.055
	(0.307)	(1.012)	(0.651)	(0.275)
Male population	-0.179	-5.438***	-2.384*	1.721**
	(0.851)	(1.802)	(1.427)	(0.826)
Black	0.113	-1.171***	-0.991***	0.120
	(0.110)	(0.280)	(0.189)	(0.106)
AIAN	0.226*	0.938*	0.764*	0.301**
	(0.116)	(0.479)	(0.395)	(0.144)
Asian	0.410	-0.364	-0.481	0.177
	(0.434)	(1.097)	(0.927)	(0.465)
Hispanic	0.164	-0.360	-0.500*	0.072
	(0.129)	(0.347)	(0.264)	(0.121)
Age 15-24	0.883	1.290	-0.765	-0.954
	(0.741)	(1.365)	(1.134)	(0.687)
Age 25-44	-0.743	2.744	-0.794	-3.368***
	(1.061)	(2.189)	(1.730)	(1.043)
Age 45-64	2.619***	-0.457	-3.429***	0.111
	(0.573)	(1.399)	(1.268)	(0.644)
Age 65 +	-0.430	1.951	-0.197	-2.955***
	(0.706)	(1.358)	(1.011)	(0.694)
Constant	2.681***	6.105***	6.120***	3.028***
	(0.533)	(1.537)	(1.140)	(0.549)
Observations	908,417	4,000,462	1,341,922	337,104
R-squared	0.808	0.716	0.689	0.766

Notes: Robust standard errors clustered at the county level are in parentheses.

*** Significant at 1%, ** Significant at 5%, * Significant at 10%.

All regressions include county fixed effects, purchase month fixed effects, product attribute variables as well as the full set of economic, social, demographic controls shown in Table 3.

TABLE A3
Categorization of Cigarette Brands as either Premium or Discount

Brand Description	Category	Manufacturer
1839	Discount	U.S. Flue-Cured Tobacco Growers
1st Class	Discount	U.S. Flue-Cured Tobacco Growers
305's	Discount	Dosal Tobacco Corporation
305's Silver	Discount	Dosal Tobacco Corporation
Basic	Discount	Philip Morris USA
Benson & Hedges	Premium	Philip Morris USA
Cambridge	Discount	Philip Morris USA
Camel	Premium	RJ Reynolds
Camel Crush	Premium	RJ Reynolds
Camel Exotic Blends	Premium	RJ Reynolds
Camel Ninety Nines	Premium	RJ Reynolds
Camel No. 9	Premium	RJ Reynolds
Camel Signature	Premium	RJ Reynolds
Camel Turkish Gold	Premium	RJ Reynolds
Camel Turkish Jade	Premium	RJ Reynolds
Camel Turkish Royal	Premium	RJ Reynolds
Camel Turkish Silver	Premium	RJ Reynolds
Camel Wides	Premium	RJ Reynolds
Capri	Premium	RJ Reynolds
Carlton's	Premium	RJ Reynolds
Checkers	Discount	King Maker Marketing
Chesterfield	Premium	Philip Morris USA
Ctl Br	Discount	
Decade	Discount	Cheyenne International, LLC
Doral	Discount	RJ Reynolds
Eclipse	Discount	RJ Reynolds
Eve	Discount	Ligget Group
Fortuna	Discount	Commonwealth Brands
Gold Coast	Discount	King Maker Marketing
GPC	Discount	RJ Reynolds
Grand Prix	Discount	Ligget Group
Kamel	Discount	RJ Reynolds
Kent	Premium	Lorillard Tobacco Company
Kent Golden Lights	Premium	Lorillard Tobacco Company
Kent III	Premium	Lorillard Tobacco Company
Kool	Premium	RJ Reynolds
Kool Flow	Premium	RJ Reynolds
Kool Groove	Premium	RJ Reynolds
Kool Xl	Premium	RJ Reynolds
L & M	Premium	Philip Morris USA

L & M Turkish Night	Premium	Philip Morris USA
Liggett Select	Discount	Ligget Group
Lucky Strike	Premium	RJ Reynolds
Major Brand	Discount	
Marlboro	Premium	Philip Morris USA
Marlboro Blend No. 27	Premium	Philip Morris USA
Marlboro Blend No. 54	Premium	Philip Morris USA
Marlboro Eighty-Threes	Premium	Philip Morris USA
Marlboro NXT	Premium	Philip Morris USA
Marlboro Skyline	Premium	Philip Morris USA
Marlboro Special Blend	Premium	Philip Morris USA
Maverick	Discount	Lorillard Tobacco Company
Maverick Silver	Discount	Lorillard Tobacco Company
Merit	Premium	Philip Morris USA
Merit Ultima	Premium	Philip Morris USA
Misty	Discount	RJ Reynolds
Monarch	Discount	RJ Reynolds
More	Premium	RJ Reynolds
More White Lights	Premium	RJ Reynolds
Natural American Spirit	Premium	Santa Fe Natural Tobacco Co
Newport	Premium	Lorillard Tobacco Company
Newport Ice	Premium	Lorillard Tobacco Company
Newport M Blend	Premium	Lorillard Tobacco Company
Now	Premium	RJ Reynolds
Old Gold	Discount	Lorillard Tobacco Company
Pall Mall	Discount	RJ Reynolds
Pall Mall Red	Discount	RJ Reynolds
Parliament	Premium	Philip Morris USA
Pyramid	Discount	Ligget Group
Raleigh	Discount	RJ Reynolds
Rave	Discount	Commonwealth Brands
Salem	Premium	RJ Reynolds
Salem Green Label	Premium	RJ Reynolds
Saratoga	Premium	Philip Morris USA
Sonoma	Discount	Commonwealth Brands
Tahoe	Discount	S&M Brands, Inc.
Tareyton	Premium	RJ Reynolds
Tourney	Discount	Ligget Group
True	Premium	Lorillard Tobacco Company
Tuscany	Discount	Commonwealth Brands
USA	Discount	Vector Tobacco, Inc
USA Gold	Discount	Vector Tobacco, Inc
Vantage	Premium	RJ Reynolds

Viceroy	Discount	RJ Reynolds
Virginia Slims	Premium	Philip Morris USA
Virginia Slims Luxury	Premium	Philip Morris USA
Virginia Slims Superslims	Premium	Philip Morris USA
Wave	Discount	Japan Tobacco International
Wides	Discount	
WildHorse	Discount	U.S. Flue-Cured Tobacco Growers
Winston	Premium	RJ Reynolds
Winston S2	Premium	RJ Reynolds
Winston Select	Premium	RJ Reynolds

Source: Brand categorization is from the supplementary file of the paper: Cornelius, Monica E., et al. (2013). Trends in the use of premium and discount cigarette brands: findings from the ITC US Surveys (2002–2011). *Tobacco control*, tobaccocontrol-2013.
Manufacturer information is from Tobacco Product Manufacturers Directory, Department of Revenue, Massachusetts.
Alphabetic Listing of Cigarette Brands, Nebreska Department of Revenue.

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Vita

Xiaojin Wang
Place of birth: Wenxi, Shanxi, China

EDUCATION

- M.Sc., International Trade 2010
  Sichuan University, Chengdu, China
- B.Sc., International Trade 2007
  Sichuan University, Chengdu, China

AREAS OF INTEREST

- International Trade; Agricultural and Food Policy
- Agricultural Markets and Marketing
- Applied Econometrics; Public Economics

MANUSCRIPTS UNDER REVIEW

- Wang, X., & Reed, M. The Impact of Antidumping/Countervailing Duties on Demand for Imported Shrimp in the United States. *Marine Resource Economics*. Revise and Resubmit.
- Wang, X., Zheng, Y., Reed, M., & Zhen, C. Cigarette Tax Pass-Through by Product Characteristics: Evidence from Nielsen Retail Scanner Data. *Economic Inquiry*. Under Review. Available at SSRN: http://ssrn.com/abstract=2686274.

WORKING PAPERS

- Trade Destruction and Deflection Effects arising from Antidumping/Countervailing Duties on Agricultural Commodities (joint with Michael Reed)
- Who's Buying Organic Coffee? Demographic Characteristics of U.S. Consumers (joint with Michael Reed, Yuqing Zheng)
- The Value of Credence Attributes: A Hedonic Analysis of Shrimp Retail Prices in the United States (joint with Michael Reed, Yuqing Zheng)
- Is Fair Trade Fair for Consumers? A Hedonic Analysis of U.S. Retail Fair Trade Coffee Prices

CONFERENCE PRESENTATIONS (SELECTED)

- Wang, X., Zheng, Y., Reed, M. (2016). The Value of Country-of-Origin and Wild-Caught Labels: A Hedonic Analysis of Shrimp Retail Prices in the United States. *Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2016 Annual Meeting, San Antonio, Texas, February, 6-9 2016.*
- Wang, X., Zheng, Y., Reed, M., & Zhen, C. (2015). Spatial Analysis of Cigarette Tax Pass-Through: Evidence from Nielsen ScanTrack Data. *Selected Paper prepared for presentation at the 2015 Annual Meeting, San Francisco, CA, July 26-28*. Agricultural and Applied Economics Association.
- Wang, X., & Reed, M. (2015). Trade Deflection arising from US Antidumping Duties on Imported Shrimp. In *2015 Annual Meeting, January 31-February 3, 2015, Atlanta, Georgia (No. 196978)*. Southern Agricultural Economics Association.

- Wang, X., & Reed, M. (2014). Estimation of US Demand for Imported Shrimp by Country: A Two-stage Differential Production Approach. In *Selected Paper, SAEA 2014 Annual Meeting. February 1-4, 2014, Dallas, TX*.
- Wang, X., & Reed, M. (2013). Estimation of Import Demand for Fishery Products in the US Using the Source-Differentiated AIDS Model. In *2013 Annual Meeting, August 4-6, 2013, Washington, DC (No. 150207)*. Agricultural and Applied Economics Association.

TEACHING EXPERIENCES

Department of Agricultural Economics, *University of Kentucky*, KY

- Teaching Assistant
- Guest Lecturer

OTHER EXPERIENCES

- Academic Journal Reviewer, *Canadian Journal of Agricultural Economics*, 2015
- Research Assistant, International Programs for Agriculture, *College of Agriculture, University of Kentucky,* Aug 2014-Present
- Abstract Reviewer, Demand and Price Analysis section for the *2015 AAEA & WAEA Joint Annual Meeting* in San Francisco, CA 2015

AWARDS & SCHOLARSHIPS

- Research Assistantship, Department of Agricultural Economics, *University of Kentucky*, 2014-present
- Graduate Student Travel Funding, *University of Kentucky* Graduate School, 2012-2016
- Tuition Scholarship, *University of Kentucky* Graduate School, 2010-2014
- National Scholarship Fund, *China Scholarship Council*, 2010-2014

COMPUTER SKILLS

- Statistical and mathematical software: experienced user of SAS, Stata, and R; familiar with GAMS and SPSS
- Programming languages: proficient in SQL, MS Excel (VBA)
- Geospatial analysis software: familiar with ArcGIS and GeoDa
- Microsoft Office Suite, Keynote, EndNote, Tableau, LaTex

LANGUAGE

English (Fluent); Mandarin Chinese (Native); Japanese (Basic)

PROFESSIONAL AFFILIATIONS

- American Agricultural Economics Association
- Southern Agricultural Economics Association