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Impacts of Social Interaction on Consumer Behavior

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ABSTRACT

This dissertation explores the impacts of social interactions on consumer behavior.

We first examine whether a consumer's willingness to pay is higher for quiet handbags than for loud handbags. We use the transaction data for the sales of pre-owned Louis Vuitton handbags from two websites (i.e., eBay and Tradesy). We find that the amount consumers are willing to pay for quiet handbags is around $150 and $135 higher than for loud handbags on eBay.com and Tradesy, respectively. This result provides empirical evidence that consumers with high social capital are willing to pay more for quiet luxury goods. We also find that that the premium of a consumer's willingness to pay for quiet luxury goods decreases as the condition of the goods deteriorates. The decrease in the price premium by each condition is around $7. The premium of a consumer's willingness to pay for quiet luxury goods using the BuyItNow option is around $48 greater than that of the auction option.

We then use a more general dataset, the Consumer Expenditure Survey (CEX) from the Bureau of Labor Statistics (BLS), to estimate the magnitude of peer effect using a two-part model with instrument variables to overcome the endogeneity and censored data issues. We find that a $1.00 increase in peers' average consumption leads to a $0.60 increase on average in the individual's consumption for outerwear and footwear. The coefficients are positive, which means that the conformism effect dominates. We also find that peers' consumption has no significant influence on underwear consumption.

Next, we examine the process of consumption-related decision making within households. When family members make consumption decisions, they think about not only themselves, but also other family members. We find that when a wife's relative salary compared to her husband's salary increases, womenswear consumption will increase while menswear consumption will decrease. We estimate the Pareto weight to be negatively correlated with the ratio of the wife's salary to the husband's salary. When the wife's salary increases, the ratio will increase, and the weight of the husband's utility will decrease.

Chapter 1: Is Quiet Better Than Loud? Status Signaling in Online Luxury Markets

1.1 Introduction

Luxury goods have a long history. Tracing back to hundreds of years ago, people use hand silverware, hand-painted china, and expensive table linens at meals when less expensive substitutes are available. This phenomenon was coined by Veblen (1899): conspicuous consumption; that is, the use of money or other resources to display a higher social status. The luxury goods, also called "Veblen goods", are different from the typical goods in terms of demand patterns. The demand for the "Veblen goods" increases as the price increases, instead of decreases according to the law of demand, because higher price confers greater status.

Luxury goods is a fast-growing market. According to an industry report,[1] the core market for personal luxury goods reached a fresh record high of €262 billion in 2017, the compound annual growth rate is around 6 percent from 1996 to 2017. Typical personal luxury goods include handbags (e.g., Coach, Louis Vuitton, etc.), Designer clothing and footwear (e.g., Gucci, Dior, etc.), luxury jewelry and watches (e.g., Cartier, Tiffany & Co., etc.), and premium cosmetics and fragrances (e.g., Chanel, Lancôme, etc.).

A unique feature about luxury goods is their explicit effort in branding. Because luxury goods are to signal a consumer's high social status, the conventional wisdom is that the luxury goods need to be "loud" in communicating the status through their brand. The apparent logos on

[1] 16th edition of Bain & Company's annual global luxury study

handbags or on clothes make others aware they are luxury and expensive. At least, this is a tradition for hundreds of years' experience. In the recent years, there has been a debate on whether brand logos should be shown on the product (e.g., Kapferer 2010; Krabtree 2016; Cavender et al 2014; Ghosh 2013; Han 2008; Duran 2017). The pro-logo side argues that consumers buy obvious logo product to show their status because it was more apparent to be seen, whereas the no-logo side argues that consumers choose no-logo goods because of the snobbism effect; that is, they do not want to be imitated by others (e.g., Kapferer 2010; Duran 2017). According to a NPD report,[2] one third of luxury handbags purchased in the U.S. in the year ending June 2016 did not have any visible branding and customers stated that it was important to them that the logo on their handbags should be subtle.

The debate in the industry challenges the Veblen's conspicuous consumption theory that luxury goods are to signal a social status so that their demands increases in prices. If a luxury handbag does not have a visible logo, it counters to the functionality of a Veblen good. In other words, Veblen's conspicuous consumption theory suggests that the luxury goods with obvious logos (i.e., loud handbag) should have higher prices than the luxury goods without logos (i.e., quiet handbag). The reality seems to suggest otherwise that the luxury goods without logos should have higher prices than the luxury goods with logos. Therefore, given the debate and the mixed messages, an empirical examination of the Veblen's conspicuous consumption theory is warranted and has potential to make important theoretical contributions.

[2] The Importance of Visible Logos on Handbags is Diminishing, Reports NPD https://www.npd.com/wps/portal/npd/us/news/press-releases/2016/the-importance-of-visible-logos-on-handbags-is-diminishing/

An extensive body of literature has examined the pricing for luxury goods (e.g., Kapferer and Laurent 2016; Yeoman and Beattie 2006; Amaldoss and Jain 2005; Truong and el. 2011; Sahalia, Parker and Yogo 2004). On the pricing between loud and quiet luxury goods in particular, however, few papers have looked at the different pricing between loud and quiet luxury goods. Among the very few, Han et al (2010) compare the price of loud handbags and quiet handbags (as well as Mercedes emblem), and find that, on average, luxury brands Gucci and LV charge more for quiet handbags than for the loud products. On average, an increase in brand prominence of 1.0 on the seven-point scale equates to a $122.26 decrease in price for Gucci and a $26.27 decrease for LV handbags.

Han et al. (2010) approach the issue from the supply-side perspective in that they collect and compare the list price of all handbags from the brands. There are two potential issues. First, their study does not consider sales as they do not have sales data. The brand firm may price quiet handbags higher than loud handbags but the quiet handbags may not sell as much as the loud handbags. Second, they have to rely on expert judges to evaluate the quietness and the loudness of handbags, which can be subjective. We approach this issue from the consumer's perspective and use a well-controlled setting and larger dataset. In particular, we identified two similar handbags of the same LV brand, same size and same price, one with the LV logo (i.e., loud handbags) and the other one without the LV logo (i.e., quiet handbags). We collected sales data for the selected handbags from two popular online markets that sell pre-owned products (i.e., eBay.com and Tradesy), and developed econometric models to test the differences in the sales price. The idea of using sales data for the pre-owned products in online markets is that the prices are a reasonable proxy for the consumer's willingness to pay.[3] Furthermore, we expand the study to examine the different pricing between products based on the conditions of the handbags and between auction and buy-it-now options.

Our key findings are that: (1) The consumer's willingness to pay is higher for the quiet handbags than for the loud handbags, everything else being equal. The price of quiet handbags is about $150 higher than that of loud handbags. (2) The price premium of quiet handbags decreases as a handbag's condition worsens. The decrease in the price premium by each condition is around $7. And, (3) The price premium of quiet handbags is higher for price sensitive consumers. The premium of consumer's willingness to pay for quiet luxury goods using BuyItNow option is around $48 greater than that of auction option.

Our paper makes important contributions to the interface of information systems and marketing. First, the theory in conspicuous consumption is inconsistent from anecdotes in the market on whether loud or quiet luxury goods can command higher price premium. Although a few papers made attempts to examine this phenomenon, they used either analytical modeling or a very limited dataset. We are able to collect a larger dataset and systematically examine the issue, and our findings provide evidence that supports the subtle signal conspicuous consumption theory. Second, most studies have analyzed the behavior of wealthy consumers using new products. We extend their research settings to the pre-owned luxury goods market so that we can

[3] Because in the context of a second-price sealed-bid auction, Vickrey (1961) proved that truth-telling is a dominant strategy.

study the less wealthy consumers whose purchase behavior may differ based on the conditions of the luxury goods. Therefore, our research fills a gap in the literature by focusing on consumers who are less wealthy and yet buy luxury goods from the pre-owned luxury goods market.

The rest of the paper is structured as follows. Section 2 discusses the theory and develops the hypotheses. Section 3 describes our research setting, data, variables, and econometric models. Section 4 presents the analysis and results. Section 5 concludes our analysis and discusses limitations and potential future research.

1.2 Theory and Hypothesis

1.2.1 Literature Review

Conspicuous Consumption —signal status

Based on Veblen's conspicuous consumption theory, several theoretical papers in economics have developed models of conspicuous consumption. Duesenberry (1949) propose that the conspicuous consumption depends not only on their own spending but also depends on the spending of others in their groups. Hirsch (1976) include status variables in their utility functions and find that an individual's satisfaction that is derived from goods and services depends not only on their own consumption, but also on the consumption of others. Frank (1985) define the term "positional goods" whose value depends relatively on how they compare with the goods owned by others and show the patterns of how conspicuous consumption externalities may cause inefficiencies. Ireland (1994) develops a signaling model of conspicuous consumption as a signal of wealth. Bagwell and Bernheim (1996) develop a model where status depends upon the perception of consumers' wealth among social contacts and consumers have private information about the value of their assets and attempt to signal their wealth by consuming a conspicuous good, and explain why people desire to signal wealth (i.e., the Veblen effect, defined as a willingness to pay a higher price for a functionally equivalent good will be arise).

In marketing, some researchers study the conspicuous consumption from consumer's behavior perspective. For example, Wernerfelt (1990) shows that, although price is related to status, price alone does not determine the desirability of a status brand. Both price and brand choice are signals to other consumers about that consumer's status and consumers' decisions are also affected by their desire for status. Chao (1996) investigates brand-buying patterns among four cosmetics products and finds that more "status" accompanies the purchase of more socially visible products; that is, consumers are willing to pay more for expensive goods whose logos are evident to others. O'cass and McEwen (2004) analyze a survey data from individuals between 18 and 25 years old and find that the status consumption and conspicuous consumption are distinct constructs and the characteristic of an individual determines their consumer behavior, for example, young status-conscious consumers are more likely to be affected by interpersonal influence. Using a sample of 302 middle age consumers (40-60) in the context of automobile buying behavior, Shukla (2008) find psychological and brand antecedents are of crucial importance among middle-aged consumers in influencing their conspicuous consumption. Chaudhuri et al. (2011) develop and validate a measure of individual differences in conspicuous consumption orientation and conclude that conspicuous consumption can be regarded as an inmate trait level that motivates consumers to engage in visible forms of consumption to exhibit their uniqueness, as expressed through product selection and usage.

Inconspicuous consumption—loud vs. quiet goods

Eckhardt et al. (2014) summarize the studies of inconspicuous consumption via a wide-ranging synthesis of the literature. They redefine the luxury construct and re-evaluate the signaling quality of brands. Han et al. (2010) divide consumers into four groups based on their wealth and desire to signal status. Each group has a different preference for conspicuously or inconspicuously branded luxury goods. These researchers also classify luxury goods as being one of two types: “loud” (a lot of obvious logos) or “quiet” (no obvious logos). Wealthy consumers with little need to signal status prefer quiet luxury goods that only a few people can recognize while wealthy consumers who want to signal status use loud luxury goods. In addition, those who want to pretend or appear to be wealthy but cannot afford luxury goods will buy counterfeits. In Han et al. (2010) four-group model, only wealthy people buy quiet handbags. Berger and Ward (2010) hypothesize that consumers with more cultural capital in a particular domain prefer subtle signals, which provide differentiation from the mainstream. They identify cultural capital as a dimension in addition to both wealth and a consumer’s need to signal status, which is a measure of their knowledge of those handbags. Consumers with more cultural capital believe that subtle signals are effective among people with the requisite knowledge to decode their meaning.

Carbajal et al. (2015) propose a theoretical model using a signaling game and assume that social capital will influence consumer's utility. At the perfect Bayesian equilibrium with endogenous price, they show that poorly connected consumers choose loud status goods while wealthy well-connected consumers choose subtle status goods in order to be distinguished from poorly connected consumers. Furthermore, the wealthy, well-connected consumers would like to pay more for the subtle goods as compared with loud goods. Carbajal et al. (2015) conclude that consumption of subtle status goods is therefore not only a signal of wealth but also a signal of social capital.

All of these studies find that subtle goods have higher prices than loud goods, although their explanations are different. Han et al. (2010) conclude that consumers carry quiet handbags because they have a low desire to signal status, whereas Berger and Ward (2010) find that people use subtle signals not because of their low desire to signal status but because of their high cultural capital. The data in their studies are also somewhat limited. Our study is different from these studies by providing more detailed empirical evidence using a well-selected setting with a relatively large dataset.

1.2.2 Hypotheses

As discussed above, Han et al. (2010) differentiate consumers by two dimensions: wealth and desire to signal, which results in four groups of consumers. Carbajal et al. (2015) and Berger and Ward (2010) add another dimension of social capital and argue consumers with high social capital (i.e., well-connected consumers) choose quiet goods to separate them from poorly-connected consumers who choose loud goods ("nouveau riche"). Essentially, Carbajal et al. (2015), Berger and Ward (2010) and Han et al. (2010) are consistent in that consumers with high social capital have low desire to signal to pubic. In the case that consumers are sufficiently wealthy to afford the luxury goods, their preference is separated by their social capital or desire to signal. For consumers with low social capital, they tend to buy loud luxury goods to show off their status. They tend not to buy quiet luxury goods because their low social capital makes the quiet goods ineffective in signaling their status. For consumers with high social capital, they do not want to be considered as "nouveau riche"; hence, they prefer to purchase quiet luxury goods so that only their peers with high social capital can recognize their status. As a result, they are willing to pay more for quiet luxury goods. As discussed in Carbajal et al.'s (2015), after considering social capital, sellers can charge a higher price for a quiet luxury good relative to the price of a loud luxury good and there exists a separate equilibrium in which only high social capital type chooses the quiet good. Therefore, we posit that the customers with high social capital are willing to pay more for the quiet luxury goods than the customers with low social capital. We propose the following hypothesis:

H1. *Consumer's willingness to pay for quiet luxury goods is higher than that for loud luxury goods.*

For the consumers who are not sufficiently wealthy to afford luxury goods but have low social capital or high desire to signal status, they tend to use loud counterfeits to emulate the wealthy group of consumers they desire to be recognized with (Han et al. 2010). Alternatively, they may buy pre-owned handbags of lower conditions that are sold for cheaper prices. Similarly, for the consumers who are not sufficiently wealthy to afford luxury goods but have high social capital, they also would like to pay more to buy quiet luxury goods rather than loud luxury goods in order to distinguish themselves from the less connected peers and imitate the wealthy and well-connected consumers. This group of consumers, however, is of smaller number since most customers who buy pre-owned luxury goods in poor conditions are more willing to imitate the consumers using loud signal. While the willingness to pay for the pre-owned luxury goods decreases with the lowering conditions in general, it is expected to be more robust for the loud luxury goods than for the quiet luxury goods. That is, the willingness to pay for the loud luxury goods drops less than the quiet luxury goods when the condition of the goods becomes worse. Hence, we propose the following hypothesis:

H2. *The premium of the consumer's willingness to pay for the quiet luxury goods is decreasing when the conditions of the luxury goods are lower*.

There are many online websites selling the pre-owned luxury goods. eBay.com is one of the major online auction and shopping websites where people can buy pre-owned luxury goods. eBay.com provides an online auction platform for consumers to bid. Buyers can bid for an item within a limited time and the highest bidder will be awarded the purchase of the item. In addition to the auctions, eBay.com also offers a "Buy It Now" (BuyItNow) option; that is, a buyer can purchase an item right away at the set price without having to wait for the duration of the sales listing to expire. The theoretical implications for the BuyItNow option are that the consumers who use BuyItNow are different from those who use the auctions. In general, the time-sensitive buyers will choose the BuyItNow option (Mathews 2006). Since when auction participants make no distinction as to when a transaction occurs, the seller can optimally choose a BuyItNow price so high that the auction participants never exercise the option, resulting in auctions have lower sales price than BuyItNow (Mattews and Katzman 2006). Therefore, between the consumers who use BuyItNow with those who use auctions, those who use BuyItNow are more affluent and have higher social capital, thereby, more likely to buy quiet luxury goods. Hence, we propose the following hypothesis:

H3. *The premium of consumer's willingness to pay for quiet luxury goods with BuyItNow option is greater than that with auction option.*

1.3 Empirical Context and Data

1.3.1 Louis Vuitton Speedy Handbags

In order to test our hypotheses, the ideal setting would be to find two products that are identical except for the logo appearance (i.e., loud vs. quiet). We conducted an extensive search among luxury handbags and found two products from the LV product lines that are potentially met with the criteria. They are the LV Monogram Speedy 30 handbag (Monogram handbag) and the LV Damier Ebene Speedy 30 handbag (DE handbag). The Monogram handbag is a loud handbag as it has the LV logo prominently displayed on the handbag, whereas the DE handbag is a quiet handbag that has no obvious logos. These two handbags, as shown in Table 1.1, are of the same size, the same material and the same retail price.

In addition, we chose the LV brand to study because it is one of the world's leading international fashion powerhouses. The LV logo is well recognized by consumers as a signal for luxury goods and status. It appears on most of its products, ranging from luxury trunks and leather goods to ready-to-wear shoes, watches, jewelry, accessories, sunglasses and books. The company's classic "Speedy" handbag product line, from which we chose our products, was launched in 1930 and has been LV's iconic products.

1.3.2 Data

We collected data from the eBay.com. eBay.com is an online auction and shopping website where consumers and businesses buy and sell a broad variety of goods and services. Sellers on eBay.com. can choose to auction their products or offer them for sale at a fixed price. If the auction option is selected, sellers list their products with a minimum required price and buyers can then bid within a limited time period. The highest bidder wins the auction. In addition to the auctions, eBay.com also offers "Buy It Now" (BuyItNow) option, that is, buyers can purchase a product right away at a set price. We collected both auctions and BuyItNow data from eBay.com America, where buyers reside in the U.S. and sellers can be located anywhere. Data from eBay.com have been widely used in prior studies (e.g., Resnick et al. 2006; Bajari and Hortacsu 2003; Roth and Ockenfels 2002).

We collected transaction data on all Monogram and DE handbags sold on eBay.com from February 25, 2016 to October 9, 2016. During the data collection period, 3,578 handbags in total were sold, among which 3,205 were Monogram handbags and 373 were DE handbags, and 1,871 handbags were sold through auctions and 1,707 were sold through BuyItNow option. The transaction data includes transaction price, product information, product description, product pictures, shipping information, and seller's reputation and experience.

Because the samples are pre-owned handbags, their prices vary by the handbag conditions. While some sellers construct their own standards to describe condition levels, the standards vary among the sellers. Therefore, we develop a system to evaluate the conditions based on each handbag's descriptions and pictures. The system is presented in Table 1.2. We evaluate each handbag by examining their descriptions and pictures and rate it from 1 (finest) to 7 (poorest) as shown in Table 1.2. Similar evaluation systems have been used in the description in eBay.com when sellers are selling good.[4]

Table 1.3 presents the distribution of products and their prices by conditions. It can be seen from the table that the handbags with poor condition ratings have lower prices, for example, the first column shows that the price of auction loud handbags drop from $740.3 to $98.62 when the condition change from very good (condition =1) to very bad (condition =7). We can also see that a greater number of loud handbags are sold in the group with low condition ratings level

[4] https://www.eBay.com.com/itm/Auth-LOUIS-VUITTON-SPEEDY-40-Hand-Bag-Doctor-Purse-Monogram-M41522-Brown/232944040583?epid=1841597860&hash=item363c8bfa87

(i.e., levels 4, 5 and 6), whereas quiet handbags are sold at a high condition rating levels (i.e., levels 1, 2 and 3).

1.4 Analysis and Results

1.4.1 Econometric Model

In section 1.2.2, we proposed three hypotheses. H1 examines the effect of quiet handbags (*DE*) on consumer's willingness to pay (*Price*), H2 examines whether the effect of quiet handbags on price is decreasing when condition *(Condition)* is worsening, and H3 examines whether the effect of quiet handbags on price is greater for BuyItNow option *(BuyItNow)* than auction option. Hence, the dependent variable is *Price,* which is the transaction price for the handbags. To test the H1, the independent variable is a dummy variable with 1 indicating the transaction is for a quiet handbag (*DE)*. H1 is supported if the coefficient of *DE* is positive. To test H2, we add an interaction term between DE and conditions (*DE*Condition)*, a widely-used method to test differing effects (Aiken et al. 1991). H2 is supported if the coefficient of *DE*Condition* is negative. To test H3, we add an interaction term between the interaction term of DE and BuyItNow (*DE*BuyItNow*) where BuyItNow is a dummy variable equaling 1 when a handbag is sold using the BuyItNow option, and 0 when it was sold using auction option.

We also include a number of control variables for the heterogeneity among sellers. In particular, we include:

(1) Sellers reputation (*Reputation*). We collected information of each seller's reputation and experience, which also influences price. eBay.com reports two different measures of a seller's performance, a feedback score which is also called star rating and a positive rating percentage. We allocated feedback scores of one for each positive rating, zero for each neutral rating and negative one for each negative rating. This means that the more positive ratings a seller receives, the higher their score. The percentage of positive ratings shown on the website is calculated based on the total number of positive feedback ratings for transactions that took place during the last 12 months. It is from when we collected the data (we collected data from February 2016 to October 2016), excluding any repeat feedback ratings from the same purchasers within the same calendar week, divided by the sum of positive and negative feedback ratings[5].

(2) Number of evaluations the seller gets (*Experience*). This number called star rating shows on eBay.com right next to the next to sellers' username. It shows how many buyers have left feedback for a seller. The more buyers who have rated their experience positively with a seller, the more assured you can be of getting great service.

(3) Whether it is free shipping or not (*Freeshipping*). We also collected information on the shipping fees of each handbag sold, which includes free shipping, a fixed shipping fee and fees that vary by shipping distance and time. To simplify this shipping fee data, we

[5] The description of seller ratings is on eBay.com website. https://www.eBay.com.com/help/buying/resolving-issues-sellers/seller-ratings?id=4023

constructed a binary variable, *Free Shipping*, which equals one for free shipping and zero otherwise.

(4) Whether the seller is in US or not (*USlocation*). eBay.com sellers are located inside and outside of the United States. Therefore, we constructed a binary *US Location* variable to reflect the varying shipping costs. If a seller located in the United States purchased a handbag, then the *US Location* equals one and zero otherwise.

Hence, the baseline model for testing H1 is as follows. To test H2 and H3, we will add two interaction terms *DE*Condition* and *DE*BuyItNow* to the model.

$$Price = \beta_0 + \beta_1 * DE + \beta_2 * BuyItNow + \beta_3 * Condition + \beta_4 * Free\ shipping + \beta_5 * US\ location + \beta_6 * Reputation + \beta_7 * Experience + \beta_8 * DE * Condition + \beta_9 * DE * BuyItNow + \mathcal{E}$$

Table 1.4 presents the summary statistics and correlation matrix of the variables. To check potential multicollinearity, we computed the variance inflation factor (VIF) scores for all independent variables in our models. The VIF scores for all independent and control variables are between 1.00 and 1.90, lower than the commonly accepted cutoff of 10 (Kennedy 2003), indicating that multicollinearity is not a concern.

1.4.2 Estimation Results

To demonstrate the robustness of our results, we estimate two variants of our model. We first estimate a baseline model (Model 1) where only main effect of *DE* variable is entered into the equation (i.e., no interaction terms), and then estimate the full model by adding the interaction. We use Ordinary Least Squares (OLS) to estimate the model.

Table 1.5 presents the estimation results. For both models, the estimates for *DE* variable are consistent in terms of sign and significance, demonstrating the robustness of our results. For model 1, the coefficient of *DE* is positive and significant (α=149.6, $p < 0.001$), indicating that consumers have higher willingness to pay for quiet bags. Hence, H1 is supported. The estimate suggests that the quiet handbags are $149.6 or 60% (the average price of all loud bags is $247.4) more expensive than loud bags on average.

For Model 2 that adds the interaction terms from Model 1, the coefficient of *DE* is positive and significant (α=189.0, $p < 0.001$), consistent with model 1 estimation, but the coefficient of *DE*Condition* is negative and significant (α = -7.34, $p <0.01$). Since the coefficient for the interaction term is at the opposite sign of the linear term, the results indicate that the price difference between the quiet and loud handbags is decreasing when the conditions of the handbags worsen. This suggests that when the handbag condition worsens by one level, the price premium of DE handbags will decrease by $7.34. Hence, H2 is supported. To further explore this result, we split the data into two subsets, auctions and BuyItNow, and estimated the model using the subsets of data separately. The results are shown in columns III and IV of Table 1.5. The coefficient of *DE*Condition* is negative and significant in the auction subset (α = -9.64, $p < 0.01$), but insignificant in the BuyItNow subset. The results suggest that the finding that price premium of DE handbags is smaller when the condition is worse is only the case for the auctions but not for the BuyItNow.

The coefficient of *DE*BuyItNow* is positive and significant (α = 47.73, $p < 0.001$). This is at the same sign to *DE*, indicating that the price premium of DE handbags is greater for handbags sold through BuyItNow than those through auctions. The result lends support to H3 that the premium of consumer's willingness to pay for quiet luxury goods of BuyItNow is greater than that of Auction. This result suggests that the price premium of DE handbags sold using BuyItNow option is $47.73 higher than those using auctions. Hence, H3 is supported. We also note that the coefficient of BuyItNow variable is positive. This is consistent with our assumption that the handbags on BuyItNow have higher price and consumers who buy these handbags tend to care less about price.

We also use the subset of our data for loud handbags and quiet handbags to perform the regressions separately for robustness checks. The results are consistent and are shown in Columns V and VI of Table 1.5. Some control variables are significant with expected signs. The coefficients of Condition are negative and significant, suggesting that as condition of the handbags is getting worse, the price decreases significantly. The coefficients of *Freeshipping* and *USlocation* are all positive and significant suggesting that if the seller provides free shipping, the price will be higher than non-free shipping handbags. And if the handbag is shipped from outside the U.S. it will be more expensive. The F statistics are significant in both estimations, rejecting the null hypothesis that the coefficients are jointly zero. The adjusted R squared are 0.73-0.88, indicating a good fit.

1.4.3 Robustness and Generalizability

To check the robustness and generalizability of our results, we collected the data from another website Tradesy. Tradesy is an e-commerce mobile app and website that facilitates the sales of private items online. Tradesy, launched on October 24, 2012, is a comparatively new website that is not as well-known as eBay.com. Only pre-owned items are offered for sale on this website. All goods are sold at their list price (BuyITNow) and there are no auctions. Similar to our eBay.com data, we collected transaction data on 1,020 handbags, among which 966 were Monogram handbag and 54 were DE handbags.

On the Tradesy, the seller evaluation system is different. Every seller is like a blogger and she can list several items for sale simultaneously. If users look at an item and like it, they can click “save this to favorites” and others can see how many other users save this item. In addition, if users like this seller and want to look at what the seller posts once she lists an item, they can choose to follow that individual seller. Others can also see how many people follow this seller, which reflects whether the seller is popular or not in some context. Hence, *Likes* and *followers* is an evaluation system for seller’s reputation. Similar measures have been used in prior studies (Bakshy et al 2010). Consumers can see this information, which may influence both their willingness to pay. The number of items a seller lists can tell us some information about each seller's experience. Therefore, we collected data on the number of items a seller sells (*items),* the number of likes - how many people save the item (*likes)* and how many followers the seller has (*followers)*.

Table 1.6 presents the distribution of prices by conditions that is similar to the eBay.com data. However, we note that handbags sold on Tradesy have a higher condition level than those sold on eBay.com, but loud handbags still have a lower condition level. Loud handbags sold are in poorer condition on both eBay.com and Tradesy. Table 1.7 presents the descriptive statistics and correlation matrix.

Table 1.8 presents the estimation results. For both models, the estimates for DE variable are consistent in terms of sign and significance, demonstrating the robustness of our results. For model 1, the coefficient of DE is positive and significant (α=135, $p < 0.001$), indicating that consumers have higher willingness to pay for quiet bags. On Tradesy, the quiet bags are $135 more expensive than loud handbags which is about 35% of the price of loud handbags (the average price of all loud bags is $408.9) and about 20% of the price of quiet handbags (the average price of all quiet bags is $715.6). The results provide further support to H1. For model 2, the coefficient of *DE* is positive and significant (α=151.3, $p < 0.001$), but the coefficient of *DE*Condition* is negative and insignificant (α = -7.38). This is consistent with the estimation results using eBay.com data where the coefficient for the interaction term is also insignificant in the estimation with the BuyItNow subset data. Because Tradesy does not have auctions, H3 cannot be tested.

1.5 Concluding Remarks

Luxury good market is a fast-growing market. Nowadays, in addition to the wealthy consumers who buy luxury goods, there are more customer segments in this market, and there are more reasons for consumers of buying luxury goods. Buying luxury goods is not only to signal wealthy and status but also signal their culture capital and social capital. Hence, it is of great importance to examine different consumer behaviors. Using a carefully chosen pair of loud and quiet products, a loud we collected data from online markets and compare their transaction prices and the price premiums between the loud and quiet products.

We find that the price of quiet handbags is around $150 higher than that of loud handbags on eBay.com and is around $135 on Tradesy, suggesting that consumer’s willingness to pay for quiet luxury goods is higher than that for loud luxury goods. This result provides empirical evidence that supports the conclusions from Carbajal et al. (2015), Berger and Ward (2010) and Han et al. (2010) that consumers with high social capital are willing to pay more for quiet luxury goods.

We find that that the premium of consumer’s willingness to pay for quiet luxury goods is decreasing as the condition is getting worse. The decrease in the price premium by each condition is around $7. This result complements prior studies on conspicuous consumption by extending their research setting to pre-owned luxury market where consumers may be less wealthy and who buy lower condition level luxury handbags. As discussed earlier, consumers who are not sufficiently wealthy to afford luxury goods but have low social capital and high desire to signal status tend to use loud counterfeits to emulate the wealthy group of consumers they desire to be recognized with (Han et al. 2010). Alternatively, they may buy pre-owned handbags of lower conditions that are sold for cheaper prices. Our finding suggests that for the consumers who are not sufficiently wealthy to afford luxury goods but have high social capital, they also would like to pay more to buy quiet luxury goods rather than loud luxury goods in order to distinguish themselves from the less connected peers and imitate the wealthy and well-connected consumers.

We also find that the premium of consumer's willingness to pay for quiet luxury goods using BuyItNow option is around $48 greater than that of auction option. This result suggests that consumers who are less price sensitive are willing to pay more for quiet handbags than for loud handbags.

Our findings have important managerial implications. Although managers may be aware that consumers have different willingness to pay on quiet luxury goods and loud luxury goods, they may not have the means to know how much on average the difference is. Our estimation offers managers a quantitative modeling process that can help them obtain an approximation of the price premium that can be charged on quiet handbags. For LV speedy bags, that premium is about $135 which is about 13% as much as the new handbag price.

Our study has limitations that provide future research directions. We find that that consumers buy luxury bags is not only to signal their wealthy and status but also signal a third dimension, but we do not know which third dimension is more appropriate. Berger and Ward

(2010) explain third dimension as culture capital. Carbajal, Hall, and Li (2015) think third dimension as social capital. Due to the limitation of data we do not have information about consumers, so it is difficult to tell what the third dimension is, social capital, culture capital or others. Future research can collect data about consumers and examine what the third dimension is and verify whether our findings hold in comparing between different types of consumers. If the social capital or the cultural capital can be quantified, future research can examine how these capitals influence consumers' behavior (e.g. the consumption on luxury goods) quantitatively.

1.6 References

Aiken, L. S., West, S. G., & Reno, R. R. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Ait-Sahalia, Y., J.A. Parker, and M.Yogo. 2004. Luxury goods and the equity premium. *The Journal of Finance*, 59(6), pp.2959-3004.

Amaldoss, W., & Jain, S. (2005). Pricing of conspicuous goods: A competitive analysis of social effects. *Journal of Marketing Research*, *42*(1), 30-42.

Bagwell, L. S. and B. D. Bernheim .1996. Vehlen Effects in a Theory of Conspicuous Consumption, *The American Economic Review*, 86 (June), 349-73.
Bajari, P., A. Hortacsu, 2003. The winner's curse, reserve prices, and endogenous entry: Empirical insights from eBay.com auctions. *RAND Journal of Economics*, 329-355.

Bakshy, E., J. M. Hofman, W. A. Mason, and D. J. Watts. 2011. Everyone's an influencer: quantifying influence on twitter. In *Proceedings of the fourth ACM international conference on Web search and data mining* (pp. 65-74). ACM.

Berger, J., and Ward, M. 2010. Subtle signals of inconspicuous consumption. *Journal of Consumer Research*, *37*(4), 555-569.

Berry, C.J. 1994. The idea of luxury – a conceptual and historical investigation, *Cambridge University Press.*

Cabral, L., A. Hortaçsu. 2010. The dynamics of seller reputation: Evidence from eBay.com. The *Journal of Industrial Economics* 58(1) 54–78.

Carbajal, J. C., J. Hall, H. Li. 2015. *Inconspicuous Conspicuous Consumption* (No. 2015-38).

Cavender, B., K., Der Arslanian, and C. Chan. 2014. Luxury in China: The End of Bling. In *Luxury Brands in Emerging Markets* (pp. 148-154). Palgrave Macmillan, London.

Chao, A., J. B. Schor. 1998. Empirical tests of status consumption: Evidence from women's cosmetics. *Journal of Economic Psychology*, *19*(1), 107-131.

Chaudhuri R. H., S. Mazumdar, A. Ghoshal. 2011. Conspicuous consumption orientation: Conceptualisation, scale development and validation. *Journal of Consumer Behaviour*, 10(4), 216-224.

Duesenberry, J. S. 1949. Income, saving, and the theory of consumer behavior.

Duran, H. B. 2017 Unbranded luxury goods give consumers the look without a lable. *https://www.alistdaily.com/strategy/unbranded-luxury-goods-give-consumers-the-look-without-a-label/.*

Eckhardt, G. M., R. W. Belk, and J. A. Wilson. 2015. The rise of inconspicuous consumption. *Journal of Marketing Management*, *31*(7-8), 807-826.

eBay.com. 2018c. Item conditions by category. *http://pages.eBay.com.com/help/sell/item-condition.html#tech*. Accessed March 1.

Frank, R. H. 1985. The demand for unobservable and other nonpositional goods. *The American Economic Review*, *75*(1), 101-116.

Ghosh, A., S. Varshney. 2013. Luxury goods consumption: A conceptual framework based on literature review. *South Asian Journal of Management*, *20*(2), 146.

Han, Y. J., J. C. Nunes, X. Drèze. 2010. Signaling status with luxury goods: The role of brand prominence. *Journal of Marketing*, *74*(4), 15-30.

Han, J. M., H. J. Suk, and K. W. Chung. 2008. The influence of logo exposure in purchasing counterfeit luxury goods. In *DMI Conference, Essec* (pp. 14-15).

Hirsch, F. 1976. Social Limits to Growth. Harvard University Press, Cambridge, Massachusetts.

Ireland, N. J. 1994. On limiting the market for status signals. *Journal of public Economics*, *53*(1), 91-110.

Jaramillo, F., F. Moizeau. 2003. Conspicuous consumption and social segmentation. *Journal of Public Economic Theory*, *5*(1), 1-24.

Kapferer, J. N. 2010. Luxury after the crisis: Pro logo or no logo. *The European Business Review*, (September-October), 42-46.

Kapferer, J. N., G. Laurent. 2016. Where do consumers think luxury begins? A study of perceived minimum price for 21 luxury goods in 7 countries. *Journal of Business Researc*h, 69(1), pp.332-340.

Krabtree, J. 2016. No-logo: why un-branded luxury goods are on the rise.

Leibenstein, H. 1950. Bandwagon, Snob and Veblen Effects in the Theory of Consumer's Demand, *Quarterly Journal of Economics*, 64 (May), pp. 183-207.

Mathews, T., K. Brett. 2006. "The Role of Varying Risk Attitudes in an Auction with a Buyout Option." *Economic Theory* 27: 597-613.

O'cass, A., H. McEwen. 2004. Exploring consumer status and conspicuous consumption. *Journal of Consumer Behaviour: An International Research Review*, *4*(1), 25-39.

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood. 2006. The value of reputation on eBay.com: A controlled experiment. *Experimental economics*, *9*(2), 79-101.

Roth, A. E., A. Ockenfels. 2002. Last-minute bidding and the rules for ending second-price auctions: Evidence from eBay.com and Amazon auctions on the Internet. *American economic review*, *92*(4), 1093-1103.

Shukla, P. 2008. Conspicuous consumption among middle age consumers: psychological and brand antecedents. *Journal of Product & Brand Management*, *17*(1), 25-36.

Veblen, T. 1965. *The theory of the leisure class. 1899*. AM Kelley, bookseller.

Veblen, T. 1899. The Theory of the Leisure Class: an Economic Study of Institutions, *Unwin Books*, London (reprinted Dover Publications (1994), New York, NY).

Vickrey, W. 1961. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance*, *16*(1), 8-37.

Wernerfelt, B. 1990. Advertising content when brand choice is a signal. *Journal of Business*, 91-98.

Truong, Y., R. McColl. 2011. Intrinsic motivations, self-esteem, and luxury goods consumption. *Journal of Retailing and Consumer Services*, *18*(6), 555-561.

Yeoman, I., U. McMahon-Beattie. 2006. Luxury markets and premium pricing. *Journal of Revenue and Pricing Management*, *4*(4), 319-328.

1.7 Tables and Figures

Table 1.1: Loud and Quiet LV Handbags

LV Monogram Speedy 30	**LV Damier Ebene Speedy 30**
30 x 21 x 17 cm (length x height x width)	30 x 21 x 17 cm (length x height x width)
11.8 x 8.2 x 6.6 in	11.8 x 8.2 x 6.6 in
Golden color metallic pieces	Golden color metallic pieces
Elegant hand carry	Textile lining
Rounded handles and trimmings in natural cowhide leather	Leather trimmings
	
https://us.louisvuitton.com/eng-us/products/speedy-30-monogram-008784	https://us.louisvuitton.com/eng-us/products/speedy-30-damier-ebene-008788

Table 1.2: Evaluation of the Handbag Conditions

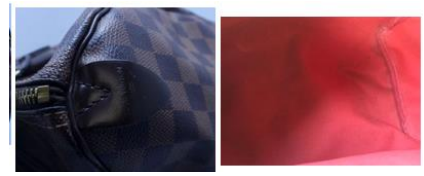
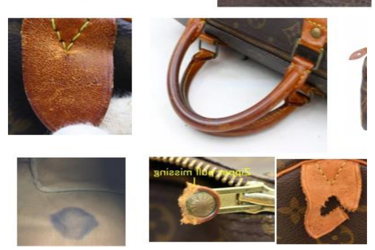
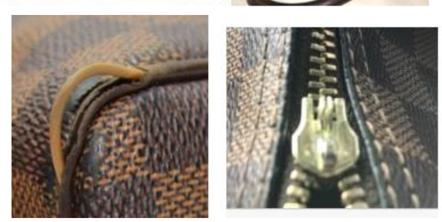
Condition Level	Condition Description	LV Monogram Speedy 30	LV Damier Ebene Speedy 30
1	Excellent, less frequently used handbag		
2	Very good, appears to be a little used but is in beautiful condition		
3	Good, only minor damage		
4	OK, some noticeable scratches and dirt		
5	Fair, many noticeable scratches and dirt		
6	Poor, many heavy noticeable scratches and dirt with some damage		
7	Junk, in need of repair		

Table 1.3: Price Distribution by Conditions and Sale Options (eBay.com)

	Monogram (Loud) Handbags						DE (Quiet) Handbags					
	Auction			BuyItNow			Auction			BuyItNow		
Condition	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N	Mean	S.D.	N
1	740.3	230.4	13	785.5	119.2	31	722.7	79.13	38	804.7	56.61	69
2	552.5	99.87	33	578.8	88.57	77	614.2	59.9	57	690.8	85.23	77
3	381.3	76.56	142	424.6	85.1	178	533.8	76.13	34	601.2	79.72	41
4	258.1	54.65	280	299.6	62.06	270	452.4	78.94	24	523.2	88.85	13
5	204.7	36.99	618	240.7	42.01	495	382.6	55.53	5	521.8	89.24	5
6	156.5	34.55	513	181.6	40.76	407	347.9	75.04	6	283.3	76.38	3
7	98.62	29.21	103	121.1	36.55	40	255	0	1	-	-	-
Total	218.1	106.1	1,702	283.1	141	1499	580.2	129.2	165	690.5	128	208

Table 1.4: Descriptive Statistics and Correlation Matrix (eBay.com) (N=3,538)

Table 1.4: Descriptive Statistics and Correlation Matrix (N=3,538)

		Summary Statistics					Correlation Matrix							
		N	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8
1	Price	3,538	287.22	174.16	40	989.95	1							
2	DE	3,538	0.1	0.3	0	1	0.68***	1						
3	BuyItNow	3,538	0.48	0.5	0	1	0.23***	0.06***	1					
4	Condition	3,538	4.6	1.45	1	7	0.89***	-0.53***	0.15***	1				
5	Free Shipping	3,538	0.6	0.49	0	1	0.22***	0.25***	0.01	0.15***	1			
6	US Location	3,538	0.27	0.44	0	1	0.59***	0.48***	0.09***	-0.47***	0.54***	1		
7	Reputation	3,538	99.32	2.73	10	100	0.04*	0	-0.03	-0.04*	0.01	-0.01	1	
8	Experience	3,538	5938.02	18913	0	628324	0.44***	0.40***	0.13***	0.36***	0.43***	0.61***	0.01	1

** $p < 0.05$; ** $p < 0.01$; ***$p<0.001$*

Table 1.5: Regression Results (eBay.com)

(Robust Standard Errors in Parentheses)

	(I) Model 1 All	(II) Model 2 All	(III) Model 2 Auction	(IV) Model 2 BuyItNow	(V) Monogram Handbags	(VI) DE Handbags
DE	149.6***	189.0***	167.1***	170.0***		
	(4.22)	(8.29)	(11.43)	(11.59)		
BuyItNow	37.90***	33.07***			32.95***	73.30***
	(2.07)	(2.16)			(2.09)	(8.25)
Condition	-79.24***	-78.24***	-70.57***	-85.04***	-77.96***	-86.40***
	(0.88)	(0.92)	(1.22)	(1.37)	(0.90)	(3.22)
Free shipping	13.91***	13.84***	18.75***	14.56***	12.84***	24.72*
	(2.53)	(2.51)	(3.58)	(4.06)	(2.53)	(10.95)
US location	67.93***	69.96***	65.15***	70.39***	73.14***	23.94
	(3.19)	(3.18)	(4.21)	(4.91)	(3.19)	(15.22)
Reputation	0.609	0.595	0.366	0.971	0.458	1.447
	(0.37)	(0.37)	(0.48)	(0.57)	(0.39)	(1.17)
Experience	4.57E-05	4.18E-05	-8.28E-05**	5.42E-05	4.21E-05	-5.3E-05
	(5.49 E-05)	(5.44E-05)	(3.14E-05)	(5.9E-05)	(5.29E-05)	(8.6E-04)
DExCondition		-7.34**	-9.637**	-6.624		
		(2.77)	(3.52)	(4.28)		
DExBuyItNow		47.73***				
		(6.91)				
_cons	569.3***	563.0***	517.9***	556.9***	575.2***	704.6***
	(37.77)	(37.53)	(48.15)	(57.29)	(39.36)	(118.30)
Model Statistics						
N	3538	3538	1849	1689	3183	355
F statistic	3651.5	2895.8	1596.9	1914.4	1929.7	156.7
R-sq	0.879	0.881	0.859	0.889	0.785	0.73

$* p < 0.05$; $** p < 0.01$; $***p<0.001$

Table 1.6: Price Distribution by Conditions and Sale Options (Tradesy)

	Monogram (Loud) Handbags			DE (Quiet) Handbags		
Condition	Mean	S.D.	N	Mean	S.D.	N
1	774.9	97.16	42	868.3	104.7	9
2	617.9	70.62	136	735.3	87.3	29
3	489	80.61	200	592.3	93.17	8
4	384.7	71.98	168	571.8	109.3	5
5	315.1	68.66	164	470	0	1
6	223.6	64.4	197	395.9	0	1
7	166.2	51.09	46	.	.	0
Total	408.9	184.8	966	715.6	145.6	54

Table 1.7: Descriptive Statistics and Correlation Matrix (Tradesy) (N=968)

Table 1.7: Descriptive Statistics and Correlation Matrix (Tradesy) (N=968)

		Summary Statistics					Correlation Matrix						
		N	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7
1	Price	968	418.1	192.3	78	1040.5	1						
2	DE	968	0.05	0.22	0	1	0.35***	1					
3	Condition	968	3.95	1.68	1	7	0.90***	-0.24***	1				
4	Free Shipping	968	0.26	0.44	0	1	0.15***	-0.11***	0.19***	1			
5	Items	968	570.6	1350.2	0	6900	-0.07*	-0.02	0.09**	-0.02	1		
6	Loves	968	114.6	348.5	0	4000	0.11***	-0.01	-0.04	-0.02	-0.09**	1	
7	Followers	968	644.8	974.7	0	5100	0.23***	-0.06	0.24***	0.01	0.87***	-0.09**	1

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p<0.001$

Table 1.8: Regression Results (Tradesy)

(Robust Standard Errors in Parentheses)

	(I) Model 1 All	(II) Model 2 All	(III) Monogram Handbags	(IV) DE Handbags
DE	135.0***	151.3***		
	(13.55)	(35.32)		
Condition	-97.87***	-97.73***	-97.70***	-98.24***
	(2.00)	(2.02)	(2.02)	(15.53)
Free shipping	13.18*	13.04*	11.61*	130.2**
	(5.69)	(5.69)	(5.70)	(40.35)
Items	0.0169***	0.0170***	0.0172***	-0.0148
	(0.0049)	(0.0049)	(0.0049)	(0.0292)
Loves	0.0394***	0.0393***	0.0393***	0.0484
	(0.0081)	(0.0081)	(0.0081)	(0.0795)
Followers	-0.0227***	-0.0229***	-0.0227***	0.0102
	(0.0068)	(0.0068)	(0.0068)	(0.0403)
DExCondition		-7.38		
		(14.51)		
_cons	801.8***	801.3***	801.4***	932.5***
	(8.45)	(8.53)	(8.52)	(38.92)
Model Statistics				
N	968	968	921	47
F statistic	725.87	625.84	709.96	18.51
R-sq	0.847	0.847	0.83	0.624

* p < 0.05; ** p < 0.01; ***p<0.001

Chapter 2: Peer Effects on Consumption: Conformism or Snobbism?

2.1 Introduction

Consumers' purchase decisions are influenced not only by themselves, but also through their interactions with others. An example is the fashion industry, where one person buys an item because another person is buying the same thing. In this paper, we want to figure out how people interact with others when making a purchase decision. Research on the social impacts of consumer behavior in economics has a long history. Veblen (1899) proposed the theory of conspicuous consumption and its relationship to social status.[6] People purchase conspicuous goods to signal their social status. Veblen's work marked an important economic study about social factors affecting consumer behavior.

Additional important research was conducted by Leibenstein (1950), who classified the motivations of demand for consumer goods and services into two perspectives: functional and nonfunctional. According to Leibenstein, "by functional demand it is meant that part of the demand for a commodity which is due to the qualities inherent in the commodity itself. By nonfunctional demand it is meant that a portion of the demand for a consumer's good which is due to factors other than the qualities inherent in the commodity." In particular, he describes the external effects on utility as being the most important kind of nonfunctional demand. He initially identified three external effects on utility: the bandwagon (conformism) effect, the snobbism effect, and the Veblen effect. The bandwagon effect describes a situation in which the demand

[6] Conspicuous consumption is the spending of money on and the acquiring of luxury goods and services to publicly display economic power—of the income or of the accumulated wealth of the buyer.

for the good increases because others are buying the same good. The snobbism effect is the opposite: demand decreases because others are purchasing the good. Finally, the Veblen effect refers to the increasing demand for a good due to a higher price. Whereas the first two effects reflect the influence of others' consumption, the Veblen effect shows that demand is a function of the price. Inspired by the idea of Leibenstein (1950), our current study will focus on the first two effects to explore how the purchase decision of a consumer is affected by others' consumption. Data on clothes and footwear will be used to analyze whether the conformism effect or snobbism effect plays a dominant role in making consumption decisions and whether this conclusion is different for different categories of goods.

Based on the conformism and snobbism effects that Leibenstein (1950) proposed, Pollak (1976) suggested a general theoretical approach to analyze interdependent preferences, which becomes the basis of empirical research in estimating peer effects. He developed the linear expenditure system with others' past consumption as the specification of the source of interdependent preferences. The basic assumption is that the demand function of one individual is a linear function of other people's consumption. The model of Pollak (1976) also informs the theoretical model in this paper.

In the empirical literature, there are many studies estimating peer effects in different areas. Sacerdote (2011) summarized the recent literature on peer effects in education. Cawley and Ruhm (2011) summarized the literature on peer effects in risky health behaviors such as smoking. However, there are few studies estimating peer effects on consumer goods. Furthermore, existing studies that estimate peer effects on consumer goods do not explain the estimation results using the framework developed by Leibenstein (1950). For example, Birch (1980) used experimental data from 39 preschool children to estimate the peer effects on their food and eating consumption behaviors. Moretti (2011) collected the data of box-office sales from the firm ACNielsen-EDI and found the social multiplier effect on movie consumption. However, the peer effects on movie consumption come from a learning mechanism that includes receiving information from peers, rather than a preference mechanism that involves others' demand behavior as in the snobbism or conformism effect.

Thus, although there are several theoretical studies about the conformism or snobbism effect on consumer behavior, there is no empirical research focused on these two effects. Our research will fill this gap, by using data on the consumption of clothes to analyze whether the conformism effect or snobbism effect exists in the real world. We will use data from the Consumer Expenditure Surveys (CEX) in the U.S. to estimate peer effects.

There are two main econometric challenges in our paper. First, there is an endogeneity problem in the regression. For example, it is difficult to distinguish empirically between peer effects that are driven by individuals' backgrounds and driven by individuals' behavior. To address the endogeneity problem, we use an instrumental variable method. Second, the data on expenditures are naturally censored with many zeros. To address this problem, we use the two-part model. The empirical strategy is described further in Section 4. In this paper, we find that there are significant conformism effect on outerwear and footwear, which can be easily observed by peers and have insignificant peer effect on underwear, which cannot be observed by others.

The paper proceeds as follows. In Section 2, a theoretical model is introduced. Subsequently, in Sections 3 and 4 we describe the data and the empirical strategy. In Sections 5 and 6 we describe the empirical results, while conclusions will be drawn in Section 7.

2.2 Theoretical Model

In this section, we will use an economic model to examine the interaction among consumers. In particular, we will examine how the external effects, snobbism or conformism, influence demand. We use the general model from Becker and Murphy (2009). The utility function is as follows: U=U (*x*, *y*; S), where *x* is the consumption of the good, y is the numeraire, and S represents social influences. Assume S equals the average of the *x*'s chosen by all members of the same social group: S $=\frac{1}{N}\sum x^i$, where the sum is over $i \in G,$ where G denotes the group. A typical member of group G chooses x^i to maximize the utility. Here we assume that G is large enough that the change in an individual's x^i will not influence S. So, each person takes S as exogenous to his own choices. Let each person of a population maximizes utility under this budget constraint, $p_x x + y \leq I$. We assume that p_x , the price of x, is fixed, and I is income. Then we can get this formula below:[7]

$$\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{D}$$

This formula is derived in the appendix, where D=$U_{xx} - 2p_x U_{xy} + {p_x}^2 U_{yy}$. However, there is one important difference between our analysis and Becker and Murphy (2009). In their analysis, it is assumed that S and *x* are complements: $U_{xS} > 0$. But in our analysis, we relax this assumption. According to Leibenstein (1950), consumer behavior is conformist if the utility of the good grows when it is more widely consumed, and it is snobbish if the utility is instead enhanced by its rarity. Applying this theory, the increase in S raises the marginal utility from x if conformism is present ($U_{xS} > 0$) and decreases the marginal utility from *x* if snobbism is present ($U_{xS} < 0$).

[7] Becker,G.S.,&Murphy,K.M.(2009). Social economics: Market behavior in a social environment. Harvard University Press.P11.

The assumption of Becker and Murphy (2009) is the first case.

Next, we solve the utility maximization problem under the budget constraint and take the derivative of the consumption of the good *x* on social influences *S*. From the result above, that $\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{D}$, we will get the following predictions:

Prediction 1: *If the conformism effect dominates, an increase in peers' consumption will lead to an increase in individual i's consumption.*

When *S* increases, according to the definition of conformism effect, the marginal utility from *x* will increase, therefore the partial derivative of utility function with respect to variable *x* and S is positive, $U_{xS} > 0$. Assume that *y* and *S* are not related, therefore the partial derivative of utility function with respect to variable y and S is zero, $U_{yS} = 0$. If the conformism effect dominates, $U_{xS} > 0$ and $U_{yS} = 0$, therefore the first derivative of *x* on S is positive.

$$\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{D} > 0$$

Prediction 2: *If the snobbism effect dominates, an increase in peers' consumption will lead to a decrease in individual i's consumption.*

When *S* increases, according to the definition of snobbism effect, the marginal utility from *x* will decrease, therefore the partial derivative of utility function with respect to variable *x* and S is negative, $U_{xS} < 0$. Assume that *y* and *S* are not related, therefore the partial derivative of utility function with respect to variable y and S is zero, $U_{yS} = 0$. If the snobbism effect dominates, $U_{xS} < 0$ and $U_{yS} = 0$, therefore the first derivative of *x* on S is negative.

$$\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{D} < 0$$

Also, in this analysis, we assume that p_x is exogenous and we ignore the price effect.

2.3 Data

2.3.1 Dataset Description

In this paper, we use the Consumer Expenditure Surveys (CEX) data from the Bureau of Labor Statistics. Because the primary sampling unit (PSU) categories changed in 2015, we use data from 2011 to 2014. The Bureau of Labor Statistics collects data every three months, so in total we have 16 time periods. Our analytical dataset includes 21 PSUs[8] in total (see Figure 2.1). These PSU areas have an urban "core" plus the adjacent counties that have a high degree of social and economic integration with the core as measured by commuting ties. Because people living in these core and adjacent counties have many similar characteristics, we will use the PSUs to define peer groups. The dataset includes households' demographic characteristics, income, and consumption information. The sample has 32,716 household by quarter observations in total. It is an unbalanced panel that has 14,619 different consumer units (i.e., households). Any observations without PSU information are excluded.

2.3.2 Key Variables of Interest

The key outcome variables are the expenditures on different categories of goods. We pick three representative categories: outerwear, underwear, and footwear. Each household may have consumed several items from the same category in one period, and we see how much the household

[8] According to the Bureau of Labor Statistics website, "the selection of households for the survey begins with the definition and selection of primary sampling units (PSUs), which consist of counties (or parts thereof), groups of counties, or independent cities. The sample of PSUs currently used in the survey consists of 105 geographic areas, of which 87 are urban geographic areas." https://www.bls.gov/opub/hom/cex/design.htm

spent on each item. For example, one household may purchase three coats during one period. In the raw data there would be three observations for this household on coats purchases, which show how much was spent on each coat. We combine these records within each time period (quarter) so that each household has only one observation containing the sum of their expenditure in each category. We use this total to conduct the main analysis.

The key explanatory variable is the consumption spending of other people within the peer group. We define peer groups using the PSU, education level, and age groups. We define four age groups according to the reference person's age: 0 to 17 years old, 18 to 39 years old, 40 to 64 years old, and 65 to 100 years old. There are 387 observations in the first age group, 92,605 in the second group, 133,965 in the third group and 30,602 in the last group. We also define two education groups by whether the reference person has any education beyond high school ("any college") or not. We assume that no matter who the reference person is, his/her education level shows the education level of the family because when people choose spouses, they are more likely to choose those who have similar education levels. We include 21 PSUs, so we have 168 (=21*4*2) total peer groups. We calculate the mean consumption within household *i*'s peer group, excluding the consumption of the household *i*. If there is only one group member, we cannot calculate the group mean; therefore, we drop those observations with only one observation in the peer group. If there are only two group members and we exclude one person, the group mean will be exactly the consumption of the other person, which causes some extreme values. Therefore, we also exclude those observations if there are two observations in the peer group. After dropping these observations, we have 140 groups left in total.

After these restrictions, the final sample has 29,249 quarterly observations. Other control variables include age, race, education level, family type (single or not; have children or not), and income. We also calculate the mean of each control variable within each peer group to use as instruments. In the next section, we explain more about the empirical strategy and instrumental variables.

2.3.3 Summary Statistics

Table 2.1 shows the summary statistics of key variables. We use expenditures on outerwear, underwear, and footwear as the outcome variables. Figure 2.2 shows the histogram regarding these variables. There are many zero values in these expenditure observations. We think that zero is a meaningful amount, so we do not drop zero values in the analysis. However, because there are many zero values, we use a two-part model for the main analysis.

2.4 Empirical Strategy

2.4.1 General

In this paper we want to estimate the influence of peers' consumption on individuals' consumption. We will learn that if the peers' average consumption increases by one unit, how much the individual's consumption will increase or decrease, controlling for other variables. A very popular approach to estimate peer effects in economic research is to fit a linear regression of individuals' outcomes on the average outcomes of their peers. We will use Manski (1993)'s linear in means model as the basic specification. However, because there are many zero values, we will use a two-part model as the main specification. The first part of the model is a probit regression for any expenditures. The second part is a linear regression for the log of expenditure, only for those observations with positive expenditures. We use same regressors in the first and second part, including the peers' average consumption. Thus, that model is:

$$Pr(C_{ikt} > 0) = \Phi(\alpha_0 + \alpha_1 C_{G_i kt} + \alpha_2 X_{ikt} + \lambda_k + S_t)$$

$$Ln(C_{ikt}) = \beta_0 + \beta_1 C_{G_i kt} + \beta_2 X_{ikt} + \delta_k + S_t + \varepsilon_{ikt}$$

C_{ikt} is the consumption of each household *i* in PSU *k* at time *t*, with a peer group G_i, on outerwear, underwear and footwear. $C_{G_i kt}$ is the average consumption of group G_i. $C_{G_i kt} = \frac{\sum_{j \in G_i, j \neq i} C_{ijt}}{N_{G_i} - 1}$, N_{G_i} is the number of peers of household *i*. X_{ikt} is a vector of households' characteristics, and λ_k and δ_k are PSU fixed effects in order to control fixed PSU characteristics. S_t controls for the seasonal variation. We are interested in the marginal effect of $C_{G_i kt}$. If marginal effect of the average consumption is bigger than zero, according to our prediction, it shows that conformism dominates, and if the marginal effect is smaller than zero, snobbism dominates.

However, as detailed in Manski (1993), the estimators of peer effects face several problems. The first problem is the self-selection. Individuals generally self-select into groups because of some unobserved characteristics. In this paper, our groups are based on metro area, age, and education level, which help us to solve this problem. Second is the simultaneity problem. Two individuals in one group can affect each other simultaneously, and it is difficult to separate out the actual causal effect that individual i's outcome has on j's outcome. Third is the correlation of unobservables. It is difficult to distinguish empirically between peer effects that are driven by individuals' backgrounds (correlated effects) and peer effects that are driven by individuals' behavior (endogenous effects). We will use an instrumental variable (IV) method to solve the last two problems.

There are many other researchers who use IV methods to deal with these endogeneity problems. For example, Evans, Oates and Schwab (1992) use metropolitan area characteristics as instruments. Case and Katz (1991) and Gaviria and Raphael (2001) use the average behavior of the peers' parents as instruments. Borjas (1992) uses the average human capital in the prior generation of one's ethnic group as the instrument. Many authors also adjust for group fixed effects and use instrumental variables to solve the endogenous problem (see e.g., Bramoullé et al. (2007); Trogdon et al. (2008); Carrell et al. (2009)) .

In this paper we regress individuals' outcomes on the average outcomes of their peers using instrumental variables and controlling for PSU fix effects, to see what the peer effect is, and to learn if snobbism or conformism dominates in this market. We assume that social effects only include snobbism and conformism. In our regression we also control for seasonal effects because we can expect that consumers' consumption will be different in different seasons.

2.4.2 Instrumental Variables Approach

Due to the endogeneity problem, we want to find instruments that will change households' consumption expenditure only through variable *x* and aside from the indirect route via *x*. Here we use the peers' characteristics as the instrument. We assume that peers' characteristics do not affect the individual's consumption behavior directly. For example, the average education level of this group will influence individual consumption through the path of group consumption. And it is obvious that peers' characteristics are correlated with group consumption. The instrumental variable Z_{G_ikt} in this case is equal to $\overline{X_{G_ikt}}$.

Furthermore, by including fixed effects, we control for the average differences across PSU in any observable or unobservable predictors and this helps us to avoid omitted variable bias. People in the same PSU face the same prices, so the fixed effects also help control prices.

For the first part we use the IVprobit model with continuous endogenous regressors[9]:

$$C_{G_ikt} = \alpha_0 + \alpha_1 Z_{G_ikt} + \alpha_2 X_{ikt} + \lambda_k + \mathrm{S}_t + \eta_{G_ikt}$$

$$C_{ikt} *= \beta_0 + \beta_1 C_{G_ikt} + \beta_2 X_{ikt} + \delta_k + \mathrm{S}_t + \varepsilon_{ikt}$$

C_{G_ikt} is the average consumption of group G_i, in PSU k, time period t and C_{G_ikt} is endogenous. Z_{G_ikt} is the instrument that is a vector of group characteristics; X_{ikt} is a vector of household characteristics, and λ_k, δ_k are PSU fixed effects in order to control fixed PSU characteristics. Note that C_{G_ikt} appears in the equation for $C_{ikt} *$, but $\mathrm{C}_{ikt} *$ does not appear in the equation for C_{G_ikt} . We do not observe $C_{ikt} *$, ; instead, we observe

$$\mathrm{C}_{ikt} \quad \begin{cases} 0 & \mathrm{C}_{ikt} * < 0 \\ 1 & \mathrm{C}_{ikt} * > 0 \end{cases}$$

Then the maximum likelihood method is used to estimate this model.

For the second part, we use the two stage least square method.

The first-stage regression for the peer group is

$$C_{G_ik} = \alpha_0 + \alpha_1 Z_{G_ikt} + \alpha_2 X_{ikt} + \lambda_k + \mathrm{S}_t + \eta_{G_ikt}$$

The second-stage regression is

$$Ln(\mathrm{C}_{ikt}) = \beta_0 + \beta_1 \widehat{\mathrm{C}_{G_ikt}} + \beta_2 \mathrm{X}_{ikt} + \delta_k + \mathrm{S}_t + \varepsilon_{ikt}$$

[9] Rivers, D., & Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. Journal of econometrics, 39(3), 347-366.

2.4.3 Two-part Model

There are many zeros in our data set in the outcome variables, so we also use two-part models which may provide a better fit to the data. In a two-part model, the censoring mechanism and outcome are modeled using separate processes. For example, in explaining individual outerwear consumption, one process will determine purchase outerwear or not and a second process explains consequent outerwear expenditure.

To model the two-part process, let an individual with a positive expenditure be called a participant in the activity being studied. Define a binary indicator variable d =1 for participants and d =0 for nonparticipants. In our paper, d=1 means that consumers buy the goods and they will have positive expenditures *y>0*. And d=0 means that consumers do not buy the goods and the observation will have a zero expenditure. *y =0* is observed for nonparticipants. For nonparticipants, those who have zero expenditures, we observe only Pr [d =0]. For participants, those who have positive expenditures, the conditional density of y given $y > 0$ is specified to be f (y|d =1), for some choice of density f (·). The two-part model for y is then given by

$$f(y|x) \begin{cases} \Pr[\mathrm{d} = 0|\mathrm{x}] & \text{if } y=0 \\ \Pr[\mathrm{d} = 1|\mathrm{x}] * \mathrm{f}(y|\mathrm{d} = 1, \mathrm{x}) & \text{if } y>0 \end{cases}$$

We calculate marginal effect manually and use bootstrap method in order to get the standard error of marginal effect. (See appendix)

2.5 Empirical Results

Table 2.2 presents the estimated peer effects for outerwear, underwear and footwear using different specifications (for full results, see Appendix Table 2.3 - Table 2.5). From this table, we observe that the estimates for outerwear and footwear are significant, which shows that peer effects exist. The estimated coefficients are positive which indicates that the peer effects are due to conformism effects. The marginal effects of outerwear and footwear are around 0.64 and 0.61, which are substantial, implying that a $1.00 increase in peers' average consumption will lead to a $0.60 increase in individual *i*'s consumption on average. The peer effects for underwear are not significant. We conclude from these results that people only have significant peer effects on those categories that can be observed by their peers, for example outerwear and footwear. For outerwear and footwear, people can observe each other's consumption easily. However, the consumption of underwear cannot be observed by their peers. That is why the consumption of underwear does not have significant peer effects.

The first row in Table 2.2 shows the OLS results, and the second row shows the results of adding PSU dummies to control the unobserved characteristics. After a comparison of these two rows, we find that the marginal effects of the OLS regression with PSU dummies are smaller than the OLS results. This means that the PSU unobserved characteristics do influence people's consumption behavior. These unobserved characteristics may make individuals self-select into groups. We control for PSU fixed effects in other specifications. Additionally, for each specification, we present robust standard errors and clustered standard errors.

The third row in Table 2.2 shows the two-stage least squares estimation results. The endogeneity problem causes an increase in the results because the measurement error problem leads to a downward bias. When adding the instrumental variables, we find that marginal effects increase, which also addresses the measurement error problem. Thus, the OLS results actually underestimate the peer effects.

The fourth and fifth rows in Table 2.2 shows the results from the two-part model and the IV two-part model. When we use the two-part model with fixed effects, the results for outerwear and footwear are similar to the results for the OLS with fixed effects. Comparing the two-part model and the two-part model with instrumental variables, we get the same conclusion as comparing OLS with 2SLS. The estimates without instrumental variables underestimate the peer effects. The results for outerwear and footwear are significant. The results for underwear are not significant. We conclude that people have a significant conformism effect on those obviously observed consumptions and have an insignificant peer effect on the unobserved consumptions.

2.6 Conclusion

People's consumption behavior is influenced by their peers. To examine peer effects on consumption, we develop a theoretical model based on Becker and Murphy (2009), which includes the peers' average consumption in the utility function. We then use a more general dataset, the Consumer Expenditure Survey (CEX) from the Bureau of Labor Statistics (BLS), to estimate the magnitude of peer effect using a two-part model with instrument variables to overcome the endogeneity and censored data issues. The empirical results show that a \$1.00 increase in peers' average consumption leads to a \$0.60 increase on average in the individual's consumption for outerwear and footwear significantly. The coefficients are positive, which means that the conformism effect dominates. People tend to conform to the behavior of their social networks. People will increase their expenditures, when their peers increase expenditures.

The snobbism effect may exist at the level of the brand rather than category. For example, perhaps if others purchase a Louis Vuitton handbag, a person will purchase a Gucci handbag rather than a Louis Vuitton handbag. His expenditure on luxury handbags increases, which shows the results from this paper: when peers' expenditures on luxury handbags increase, that person's own expenditures also increase. But the snobbism effect also exists here when the market demand for the Louis Vuitton handbag decreases because others are purchasing the Louis Vuitton handbag. In our paper, because of the limited data, we can only examine peer effects on expenditures at the level of the category for outerwear, footwear and underwear. To figure out whether a snobbism effect exists at the level of the brand, we would need data with information on brand to conduct this further research.

2.7 References

Becker, G. S. (1991). A note on restaurant pricing and other examples of social influences on price. *Journal of political economy*, 99(5), 1109-1116.

Becker, G. S., & Murphy, K. M. (2009). *Social economics: Market behavior in a social environment.* Harvard University Press.

Bernheim, B. D. (1994). A theory of conformity. *Journal of political Economy*, 102(5), 841-877.

Birch, L. L. (1980). Effects of peer models' food choices and eating behaviors on preschoolers' food preferences. *Child development*, 489-496.

Borjas, G. J. (1992). Ethnic capital and intergenerational mobility. *The Quarterly journal of economics*, 107(1), 123-150.

Bramoullé, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of econometrics*, 150(1), 41-55.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Carrell, S. E., Fullerton, R. L., & West, J. E. (2009). Does your cohort matter? Measuring peer effects in college achievement. *Journal of Labor Economics*, 27(3), 439-464.

Case, A. C. (1991). Spatial patterns in household demand. *Econometrica: Journal of the Econometric Society*, 953-965.

Case, A. C., & Katz, L. F. (1991). The company you keep: The effects of family and neighborhood on disadvantaged youths(No. w3705). *National Bureau of Economic Research*.

Cawley, J., & Ruhm, C. J. (2011). The economics of risky health behaviors. In *Handbook of health economics* (Vol. 2, pp. 95-199). Elsevier.

Duan, N. (1983). Smearing estimate: a nonparametric retransformation method. *Journal of the American Statistical Association*, 78(383), 605-610.

Evans, W. N., Oates, W. E., & Schwab, R. M. (1992). Measuring peer group effects: A study of teenage behavior. *Journal of Political Economy*, 100(5), 966-991.

Gaviria, A., & Raphael, S. (2001). School-based peer effects and juvenile behavior. *The review of economics and statistics*, 83(2), 257-268.

Leibenstein, H. (1950). Bandwagon, snob, and Veblen effects in the theory of consumers' demand. *The quarterly journal of economics*, 64(2), 183-207.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3), 531-542.

Moretti, E. (2011). Social learning and peer effects in consumption: Evidence from movie sales. *The Review of Economic Studies*, 78(1), 356-393.

Pollak, R. A. (1976). Interdependent preferences. *The American Economic Review*, 66(3), 309-320.

Sacerdote, B. (2011). Peer effects in education: How might they work, how big are they and how much do we know thus far?. In *Handbook of the Economics of Education* (Vol. 3, pp. 249-277). Elsevier.

Trogdon, J. G., Nonnemaker, J., & Pais, J. (2008). Peer effects in adolescent overweight. *Journal of health economics*, 27(5), 1388-1399.

Veblen, T. (1899). *The theory of the leisure class: An economic study in the evolution of institutions*. Macmillan.

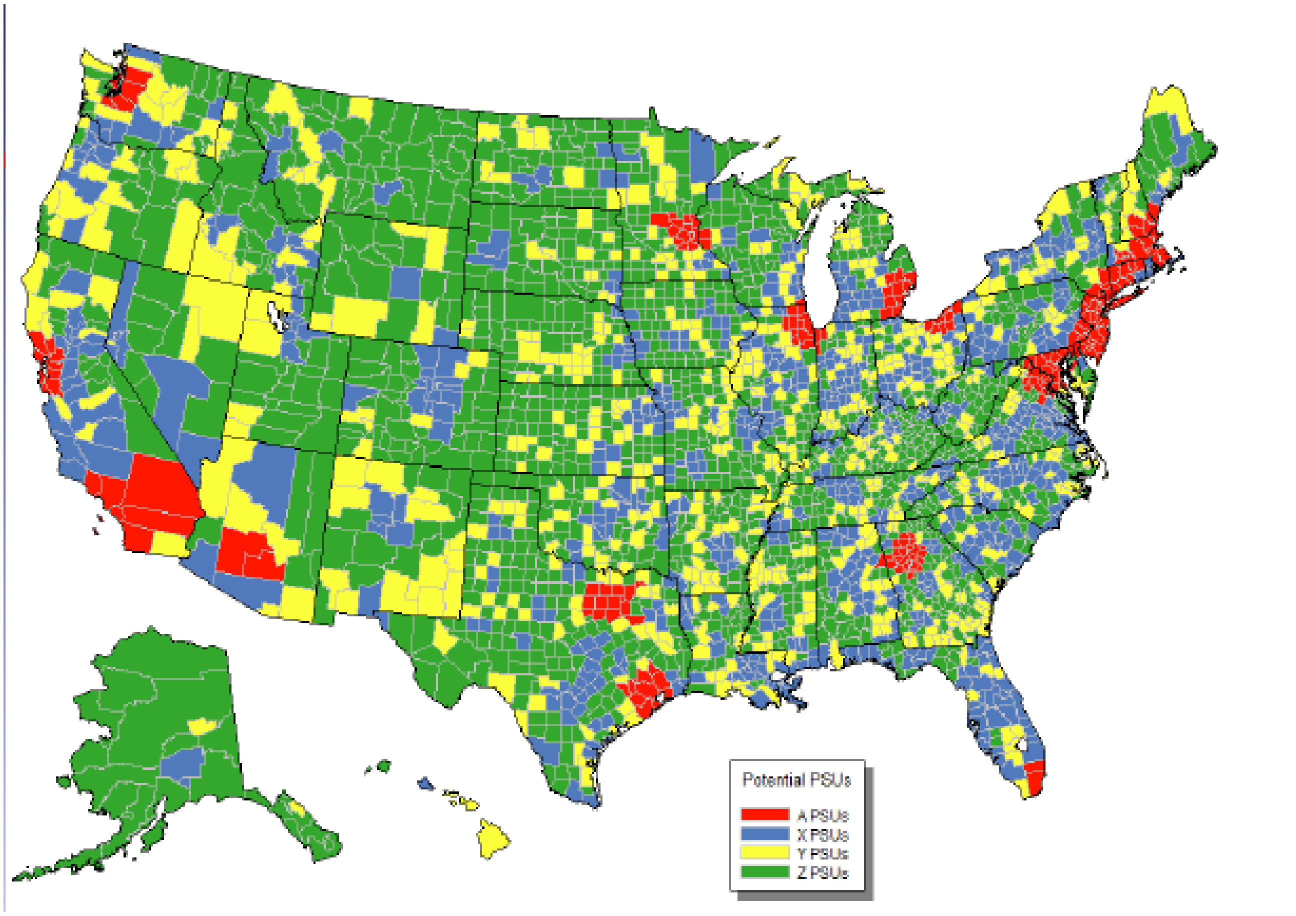
2.8 Tables and Figures

Table 2.1: Summary Statistics

Variable	Mean	Std. Dev.	percentage of zeros
Dependent Variable			
Outerwear expenditure ($)	257.99	549.94	0.21
Underwear expenditure ($)	28.37	74.47	0.65
Footwear expenditure ($)	83.42	164.58	0.47
Individual Characteristics			
College: education level of reference person *(Any college above or not)*	0.7	0.46	0.3
Age: age of reference person	46.01	15.02	0
Male: sex of reference person (male or not)	0.47	0.5	0.53
Black: race of reference person (black or not)	0.12	0.32	0.88
Asian: race of reference person (Asian or not)	0.08	0.28	0.92
Other: race of reference person (Other or not)	0.02	0.14	0.98
Hispanic: Hispanic origin of reference person	0.18	0.39	0.82
Single: familytype (single person/single parent or not)	0.23	0.42	0.77
Children: have children or not	0.39	0.49	0.61
Lnincome: log of family income	10.76	1.29	0
Number of peers	421	265	0

Number of peers	Percentiles	
	1%	50
	5%	88
	10%	124
	25%	203
	50%	372
	75%	632
	90%	805
	95%	994
	99%	1097

Figure 2.1: Picture of PSU



Primary Sampling Unit
CODED
1109 New York, NY
1110 New York, Connecticut suburbs
1111 New Jersey suburbs
1102 Philadelphia – Wilmington – Atlantic City, PA – NJ – DE - MD
1103 Boston – Brockton – Nashua, MA – NH – ME - CT
1207 Chicago – Gary – Kenosha, IL – IN - WI
1208 Detroit – Ann Arbor – Flint, MI
1210 Cleveland – Akron, OH
1211 Minneapolis – St. Paul, MN – WI
1312 Washington, DC – MD – VA – WV
1313 Baltimore, MD
1316 Dallas – Ft. Worth, TX
1318 Houston – Galveston – Brazoria, TX
1319 Atlanta, GA
1320 Miami – Ft. Lauderdale, FL
1419 Los Angeles – Orange, CA
1420 Los Angeles suburbs, CA
1422 San Francisco – Oakland – San Jose, CA
1423 Seattle – Tacoma – Bremerton, WA
1424 San Diego, CA
1429 Phoenix – Mesa, AZ

Picture is from BLS website: https://www.bls.gov/cex/sampling-methods.pdf

We are going to use the A PSUs in this picture which has the population more than 2,700,000. There are 21 A PSUs, 5 Northeast, 4 midwest, 6 South, and 6 West.

Figure 2.2: Histogram of Group Mean of Consumption

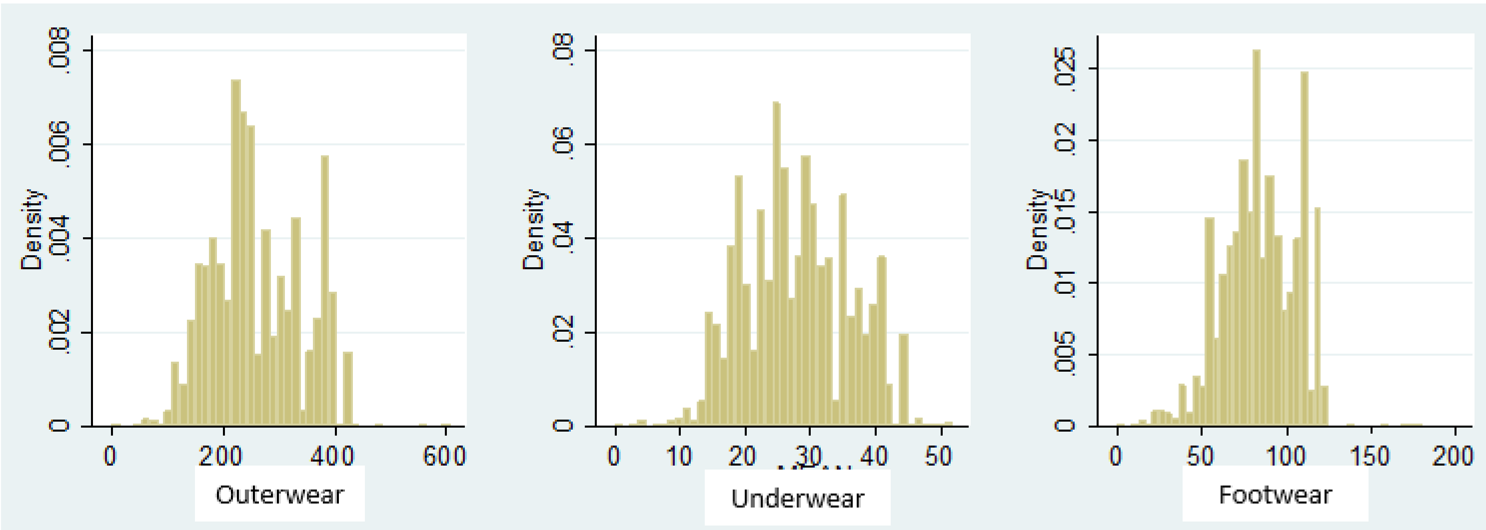
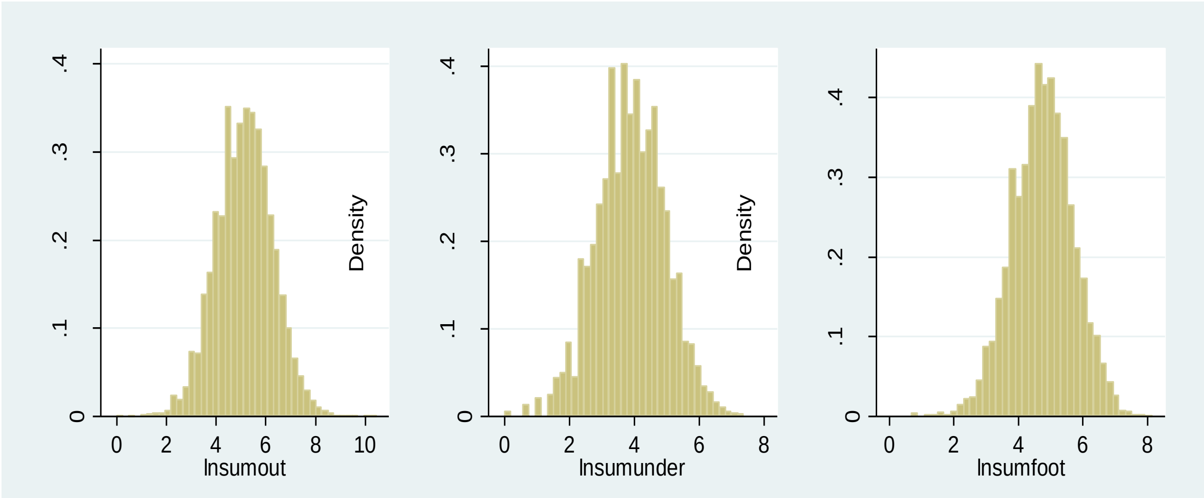


Table 2.2: Peer Effects on Outerwear, Underwear, Footwear Consumption

	outwear	underwear	footwear
OLS	0.68	0.53	0.57
(Robust S.E)	(0.05)	(0.06)	(0.06)
(Cluster S.E)	(0.07)	(0.08)	(0.05)
OLS with FIX effect	0.28	0.12	0.38
(Robust S.E)	(0.09)	(0.11)	(0.09)
(Cluster S.E)	(0.09)	(0.11)	(0.09)
2SLS with FIX effect	0.42	0.58	0.46
(Robust S.E)	(0.17)	(0.25)	(0.1)
(Cluster S.E)	(0.14)	(0.14)	(0.08)
Two-Part Model	0.28	0.13	0.39
(Bootstrap S.E)	(0.06)	(0.08)	(0.05)
Two-Part Model with IV	0.64	0.35	0.61
(Bootstrap S.E)	(0.15)	(0.22)	(0.11)

Notes: Each cell shows the marginal effects of average consumption of group from separate models. Standard Errors in the parentheses. All models include households' characteristic explanatory variables *college, age, male, black, Asian, other, Hispanic, single and children*. All models include seasonal effects. All two-part models control for the PSU fix effects.

Figure 2.3: Histogram of Log Expenditure (exclude zeros)



2.9 Appendix

2.9.1 Maximization Process

Suppose the household utility function is as follows:

$$U=U(x, y; S).$$

Assume S is exogenous, we want to maximize the utility by choosing x and y under the following budget constraint:

$$P_x x + y \leq I$$

To solve this maximization problem, we get this Lagrange function below:

$$L = U(x, y, S) + \lambda(I - P_x x - y)$$

Now we let the partial derivatives of L equal to zero in order to find the local maximum of utility function.

$$\begin{cases} \dfrac{\partial L}{\partial x} = U_x - \lambda P_x = 0 \\ \dfrac{\partial L}{\partial y} = U_y - \lambda = 0 \end{cases}$$

Solving these equations, we get

$$U_x = P_x U_y$$

Then we take full differential on both sides and we will get equation (1).

$$d(U_x) = d(P_x U_y)$$

$$U_{xx}\frac{\partial x}{\partial s}\mathrm{ds} + U_{xy}\frac{\partial y}{\partial s}\mathrm{ds} + U_{xS}\mathrm{ds} = P_x U_{yx}\frac{\partial x}{\partial s}\mathrm{ds} + P_x U_{yy}\frac{\partial y}{\partial s}\mathrm{ds} + P_x U_{yS} ds \quad (1)$$

According to the budget constraint,

$$P_x x + y \leq I$$

$$y = I - P_x x$$

Taking the derivation of S on both sides, we get equation (2).

$$\frac{\partial y}{\partial s} = -P_x \frac{\partial x}{\partial s} \quad (2)$$

Now we plug equation (2) into equation (1), we get the following equation

$$\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{U_{xx} - 2p_x U_{xy} + {p_x}^2 U_{yy}}$$

Denoting D=$U_{xx} - 2p_x U_{xy} + {p_x}^2 U_{yy}$, we get the same equation which is in the book of Becker and Murphy (2009)

$$\frac{dx}{dS} = \frac{p_x U_{yS} - U_{xS}}{D}$$ [10]

Next, we want to show that D is smaller than zero. To test a twice-differentiable function is quasiconcave, we can examine the determinants of matrices of the utility function, known as "bordered Hessians".

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[10] Becker, G. S., & Murphy, K. M. (2009). *Social economics: Market behavior in a social environment*. Harvard University Press. P11.

$$\begin{pmatrix} \frac{\partial^2 L}{\partial \lambda^2} & \frac{\partial^2 L}{\partial \lambda \partial x} & \frac{\partial^2 L}{\partial \lambda \partial y} \\ \frac{\partial^2 L}{\partial x \partial \lambda} & \frac{\partial^2 L}{\partial x^2} & \frac{\partial^2 L}{\partial x \partial y} \\ \frac{\partial^2 L}{\partial y \partial \lambda} & \frac{\partial^2 L}{\partial y^2} & \frac{\partial^2 L}{\partial y \partial x} \end{pmatrix} = \begin{pmatrix} 0 & -P_X & -1 \\ -P_X & U_{xx} & U_{xy} \\ -1 & U_{yx} & U_{yy} \end{pmatrix}$$

If it is strictly quasiconcave,

$$\begin{vmatrix} 0 & -P_X & -1 \\ -P_X & U_{xx} & U_{xy} \\ -1 & U_{yx} & U_{yy} \end{vmatrix} > 0,$$

So, we get that D= $U_{xx} - 2p_x U_{xy} + {p_x}^2 U_{yy} < 0$

2.9.2 Marginal Effects for Two-part Model

First part:

Using a Probit model for the first stage, we therefore have

$$\mathrm{P}_r(\mathrm{Y} > 0) = \mathrm{P_r}(\mathrm{I} = 1) = \Phi(x_i{}'\beta_1)$$

The Probit model is estimated on the full sample.

Second part:

To model the second stage, we need to account for skewness in E(Y | Y>0, X), so use the log transformation:

$$\log(\mathrm{Y}|\mathrm{I} = 1) = x_i'\beta_2 + \varepsilon_{2i}$$

Log OLS model is estimated on the sample with positive expenditures.

To re-transform the estimates back to the raw (dollar) scale we must apply a factor, *the smearing factor*

$$\mathrm{E}(\mathrm{Y}|\mathrm{I} = 1, \mathrm{X}) = \phi_s \exp(x_i'\beta_2)$$

Where $\phi_s = \mathrm{E}(\mathrm{e}^{\varepsilon}|\mathrm{X}) \equiv \exp(\sigma^2/2)$

Together:

Putting it all together we get:

$$\mathrm{E}(\mathrm{Y}|\mathrm{X}) = \mathrm{P}_r(\mathrm{I} = 1)\mathrm{E}(\mathrm{Y} > 0|\mathrm{X}) + \mathrm{P}_r(\mathrm{I} = 0)\mathrm{E}(\mathrm{Y} = 0|\mathrm{X})$$

$$\mathrm{E}(\mathrm{Y}|\mathrm{X}) = \Phi(x_i{}'\beta_1)\phi_s \exp(x_i'\beta_2)$$

E(Y|X) is estimated on the full sample (everyone has a predicted probability of positive expenditures)

For this case Duan[11] developed the following nonparametric estimate of ϕ_s and we use this in our calculation.

$$\widehat{\phi_s} = \frac{1}{n}\sum_i \exp(\widehat{\varepsilon_{2\iota}})$$

Where $\widehat{\varepsilon_{2\iota}}$ are the estimated residuals from the second stage of the model.

And we take the derivative of x_1 for E(Y|X), which is the marginal effect of x_1.

For continuous variable x_1, we will get:

$$\frac{\partial E(Y|X)}{\partial x_1} = \Phi(x_i'\beta_1)\beta_{11}\phi_s \exp(x_i'\beta_2) + \Phi(x_i{}'\beta_1)\phi_s \exp(x_i'\beta_2)\beta_{21}$$

β_{11} is the coefficient of x_1 in first part, Probit model.

β_{21} is the coefficient of x_1 in second part, OLS model

[11] Duan, N. (1983). Smearing estimate: a nonparametric retransformation method. *Journal of the American Statistical Association*, *78*(383), 605-610.

2.9.3 Bootstrap Method

Bootstrap was introduced by Efron (1979) and it has several advantages. For example, it requires no theoretical calculations, is not based on asymptotic results, and no matter how complicated the estimator $\hat{\theta}$ is, we can use it to get the standard error. A bootstrap sample is defined to be a random sample of size n drawn from the dataset. If $\hat{\theta} = s(x)$, $x = (x_1, x_2 \dots x_n)$ is a random sample. For each bootstrap sample x* there is a bootstrap replicate of $\hat{\theta}$, $\widehat{\theta^*} = s(x^*)$. If we pick B independent bootstrap samples, each consisting of n data values drawing with replacement from x. Then we evaluate the bootstrap replication corresponding to each bootstrap sample $\widehat{\theta^*}(b) = s(x_b{}^*)$, b = 1, ..., B. Then we estimate the standard error se $(\hat{\theta})$ by the sample standard error of the B replicates $\widehat{se}_B = \left[\frac{1}{B-1}\sum_{b=1}^{B}\{\widehat{\theta^*}(b) - B^{-1}\sum_{b=1}^{B}\widehat{\theta^*}(b)\}^2\right]^{1/2}$. And using this method we get the bootstrap standard error of marginal effect for the two-part model.[12]

[12] Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

2.9.4 Appendix Tables

Table 2.3: Peer Effects on Outerwear

	(1)	(2)	(3)		(4)		(5)			
	default	fixed effect	2sls		Two-part model		IV Two-part model			
					first part:probit	second part: ols	first part:ivprobit		second part: 2sls	
			first stage	second stage			first stage	second stage	first stage	second stage
groupMEAN	0.68	0.28		0.42	0.0011	0.0007		0.0024		0.0017
(Robust SE)	(0.05)	(0.09)		(0.17)	(0.0002)	(0.0002)		(0.0006)		(0.0005)
(Cluster SE)	(0.07)	(0.09)		(0.14)						
male	-15.25	-14.60	-0.32	-14.52	-0.06	0.01	-0.32	-0.06	-0.07	0.01
(Robust SE)	(6.96)	(9.30)	(0.38)	(6.99)	(0.02)	(0.01)	(0.38)	(0.02)	(0.42)	(0.01)
(Cluster SE)	(9.11)	(9.30)	(0.30)	(9.02)						
black	-13.01	-16.42	-0.55	-16.49	-0.09	0.03	-0.55	-0.09	-1.05	0.03
(Robust SE)	(7.81)	(10.74)	(0.58)	(7.82)	(0.03)	(0.02)	(0.62)	(0.03)	(0.71)	(0.02)
(Cluster SE)	(11.09)	(10.74)	(0.49)	(10.46)						
asian	10.94	9.25	0.30	8.94	0.07	-0.06	0.30	0.07	0.38	-0.06
(Robust SE)	(17.28)	(27.55)	(0.70)	(17.74)	(0.03)	(0.03)	(0.70)	(0.03)	(0.77)	(0.03)
(Cluster SE)	(26.30)	(27.55)	(0.26)	(26.67)						
other	-48.05	-45.00	0.01	-45.19	-0.13	-0.12	0.01	-0.13	-1.23	-0.12
(Robust SE)	(13.13)	(12.59)	(1.49)	(13.13)	(0.06)	(0.05)	(1.35)	(0.06)	(1.55)	(0.05)
(Cluster SE)	(12.28)	(12.59)	(1.02)	(12.42)						
hisp	-19.45	-20.19	-0.15	-20.58	0.02	-0.01	-0.14	0.01	-0.61	-0.01
(Robust SE)	(7.16)	(12.43)	(0.61)	(8.50)	(0.03)	(0.02)	(0.57)	(0.03)	(0.64)	(0.02)
(Cluster SE)	(10.73)	(12.43)	(0.35)	(11.82)						
college	12.13	13.58	4.30	13.13	-0.01	0.11	4.29	-0.01	4.06	0.11
(Robust SE)	(9.00)	(6.02)	(1.35)	(8.97)	(0.03)	(0.03)	(0.85)	(0.03)	(0.97)	(0.03)
(Cluster SE)	(4.99)	(6.02)	(14.28)	(4.74)						
child	41.52	45.68	0.14	44.55	0.18	0.24	0.14	0.17	0.78	0.23
(Robust SE)	(7.45)	(9.26)	(0.40)	(7.58)	(0.02)	(0.01)	(0.42)	(0.02)	(0.46)	(0.02)
(Cluster SE)	(8.78)	(9.26)	(0.17)	(9.70)						
single	-14.80	-13.68	0.24	-14.03	0.01	-0.04	0.24	0.00	0.44	-0.04
(Robust SE)	(6.79)	(7.36)	(0.46)	(6.88)	(0.02)	(0.02)	(0.46)	(0.02)	(0.52)	(0.02)
(Cluster SE)	(7.26)	(7.36)	(0.28)	(7.22)						
lnFIN	64.18	64.58	0.53	64.45	0.08	0.20	0.53	0.08	0.44	0.20
(Robust SE)	(3.47)	(4.82)	(0.16)	(3.44)	(0.01)	(0.01)	(0.16)	(0.01)	(0.17)	(0.01)
(Cluster SE)	(4.78)	(4.82)	(0.12)	(4.64)						
groupFIN	-33.63	25.76	124.90	4.34	0.07	0.04	124.90	-0.12	126.40	-0.10
(Robust SE)	(13.19)	(14.13)	(1.74)	(25.53)	(0.05)	(0.04)	(0.99)	(0.10)	(1.12)	(0.08)
(Cluster SE)	(14.02)	(14.13)	(12.51)	(21.00)						
summer	-71.88	-71.98	0.29	-71.99	-0.05	-0.25	0.29	-0.05	0.33	-0.25
(Robust SE)	(7.32)	(9.28)	(0.52)	(7.33)	(0.02)	(0.02)	(0.52)	(0.02)	(0.59)	(0.02)
(Cluster SE)	(9.23)	(9.28)	(0.27)	(9.03)						
fall	-51.93	-52.30	0.11	-52.28	-0.02	-0.16	0.11	-0.02	0.37	-0.16
(Robust SE)	(7.23)	(7.14)	(0.52)	(7.23)	(0.02)	(0.02)	(0.52)	(0.02)	(0.59)	(0.02)

(Cluster SE)	(7.12)	(7.14)	(0.34)	(6.95)						
winter	137.80	137.70	0.00	137.70	0.18	0.38	0.00	0.18	-0.01	0.38
(Robust SE)	(10.72)	(7.67)	(0.52)	(10.72)	(0.02)	(0.02)	(0.52)	(0.02)	(0.57)	(0.02)
(Cluster SE)	(7.64)	(7.67)	(0.27)	(7.47)						
groupMALE			-92.64				-92.64		-89.83	
(Robust SE)			(5.73)				(3.46)		(3.95)	
(Cluster SE)			(60.96)							
groupBLACK			-141.00				-141.04		-151.00	
(Robust SE)			(8.95)				(5.44)		(6.20)	
(Cluster SE)			(80.09)							
groupASIAN			-58.95				-58.95		-63.90	
(Robust SE)			(5.97)				(5.33)		(6.14)	
(Cluster SE)			(49.76)							
groupOTHER			-92.60				-92.60		-81.69	
(Robust SE)			(20.80)				(13.07)		(15.00)	
(Cluster SE)			(228.50)							
groupHISP			-97.58				-97.58		-99.38	
(Robust SE)			(4.13)				(3.26)		(3.72)	
(Cluster SE)			(53.66)							
groupCHILD			128.70				128.69		126.30	
(Robust SE)			(3.22)				(2.42)		(2.73)	
(Cluster SE)			(43.21)							
groupSIN			-28.73				-28.73		-17.76	
(Robust SE)			(8.61)				(4.07)		(4.62)	
(Cluster SE)			(69.30)							
_cons	-247.60	-810.90			-1.15	2.19	-1079.48	0.62		
	(139.90)	(161.20)			(0.49)	(0.43)	(10.38)	(0.92)		
	(145.70)	(161.20)								
N	29249	29249	29249	29249	29249	23121	29249	29249	23121	23121
margin					0.28			0.64		
(Bootstrap S.E)					0.06			0.15		
Number of psu	21	21	21	21	21	21	21	21	21	21

Note: Standard Errors in parentheses

Table 2.4: Peer Effects on Underwear

	(1) default	(2) fixed effect	(3) 2sls		(4) Two-part model		(5) IV Two-part model			
					first part:probit	second part: ols	first part:ivprobit		second part: 2sls	
			first stage	second stage			first stage	second stage	first stage	second stage
groupMEAN	0.53	0.12		0.58	0.0015	0.0032		-0.0022		0.0147
(Robust SE)	(0.06)	(0.11)		(0.25)	(0.0016)	(0.0023)		(0.0047)		(0.0062)
(Cluster SE)	(0.08)	(0.11)		(0.14)						
male	-6.95	-6.89	-0.01	-6.83	-0.16	-0.08	-0.01	-0.16	-0.07	-0.08
(Robust SE)	(0.87)	(1.03)	(0.05)	(0.87)	(0.02)	(0.02)	(0.05)	(0.02)	(0.09)	(0.02)
(Cluster SE)	(1.00)	(1.03)	(0.04)	(0.99)						
black	1.86	2.11	-0.06	2.11	0.02	0.02	-0.06	0.02	-0.06	0.02
(Robust SE)	(1.46)	(1.91)	(0.09)	(1.48)	(0.03)	(0.03)	(0.09)	(0.03)	(0.14)	(0.03)
(Cluster SE)	(1.93)	(1.91)	(0.06)	(1.87)						
asian	-5.41	-5.77	-0.06	-5.61	-0.10	-0.13	-0.06	-0.10	-0.18	-0.12
(Robust SE)	(1.52)	(2.03)	(0.09)	(1.57)	(0.03)	(0.04)	(0.10)	(0.03)	(0.17)	(0.04)
(Cluster SE)	(1.99)	(2.03)	(0.07)	(1.92)						
other	-2.41	-2.60	-0.03	-2.56	0.06	-0.10	-0.03	0.06	-0.12	-0.10
(Robust SE)	(2.60)	(3.22)	(0.19)	(2.59)	(0.05)	(0.07)	(0.19)	(0.05)	(0.30)	(0.07)
(Cluster SE)	(3.20)	(3.22)	(0.16)	(3.08)						
hisp	-2.27	-1.73	-0.04	-1.62	-0.06	0.03	-0.04	-0.06	0.11	0.03
(Robust SE)	(1.12)	(1.61)	(0.08)	(1.18)	(0.02)	(0.03)	(0.08)	(0.02)	(0.13)	(0.03)
(Cluster SE)	(1.73)	(1.61)	(0.05)	(1.54)						
college	-0.38	-1.22	-3.11	0.53	-0.06	0.09	-3.11	-0.07	-2.83	0.13
(Robust SE)	(1.42)	(1.65)	(0.18)	(1.81)	(0.03)	(0.04)	(0.12)	(0.03)	(0.20)	(0.04)
(Cluster SE)	(1.32)	(1.65)	(2.67)	(1.10)						
child	5.90	6.19	0.02	6.03	0.08	0.13	0.02	0.08	0.00	0.12
(Robust SE)	(1.00)	(1.71)	(0.05)	(1.00)	(0.02)	(0.02)	(0.06)	(0.02)	(0.10)	(0.02)
(Cluster SE)	(1.66)	(1.71)	(0.02)	(1.66)						
single	-0.29	-0.32	-0.01	-0.33	0.00	-0.03	-0.01	0.00	-0.05	-0.03
(Robust SE)	(1.09)	(1.11)	(0.06)	(1.10)	(0.02)	(0.02)	(0.06)	(0.02)	(0.11)	(0.03)
(Cluster SE)	(1.10)	(1.11)	(0.03)	(1.08)						
lnFIN	5.06	5.11	0.00	5.10	0.04	0.13	0.00	0.04	0.06	0.13
(Robust SE)	(0.37)	(0.63)	(0.02)	(0.37)	(0.01)	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)
(Cluster SE)	(0.62)	(0.63)	(0.02)	(0.61)						
groupFIN	0.83	5.67	12.80	-0.89	0.09	0.01	12.80	0.14	12.35	-0.15
(Robust SE)	(1.72)	(2.39)	(0.18)	(3.95)	(0.04)	(0.05)	(0.14)	(0.07)	(0.23)	(0.10)
(Cluster SE)	(2.18)	(2.39)	(1.97)	(2.24)						
summer	-8.92	-8.89	0.01	-8.89	-0.07	-0.23	0.01	-0.07	-0.01	-0.23
(Robust SE)	(1.11)	(1.35)	(0.07)	(1.11)	(0.02)	(0.03)	(0.07)	(0.02)	(0.12)	(0.03)
(Cluster SE)	(1.35)	(1.35)	(0.04)	(1.33)						
fall	-6.57	-6.58	0.06	-6.59	-0.04	-0.17	0.06	-0.04	0.11	-0.17
(Robust SE)	(1.12)	(0.93)	(0.07)	(1.12)	(0.02)	(0.03)	(0.07)	(0.02)	(0.12)	(0.03)

(Cluster SE)	(0.93)	(0.93)	(0.05)	(0.91)						
winter	12.72	12.71	-0.02	12.73	0.09	0.28	-0.02	0.09	0.00	0.28
(Robust SE)	(1.43)	(1.28)	(0.07)	(1.44)	(0.02)	(0.03)	(0.07)	(0.02)	(0.12)	(0.03)
(Cluster SE)	(1.29)	(1.28)	(0.05)	(1.26)						
groupMALE			-18.14				-18.14		-17.77	
(Robust SE)			(0.76)				(0.48)		(0.81)	
(Cluster SE)			(7.84)							
groupBLACK			-4.70				-4.70		-3.68	
(Robust SE)			(1.14)				(0.75)		(1.29)	
(Cluster SE)			(13.67)							
groupASIAN			-31.66				-31.66		-30.93	
(Robust SE)			(0.91)				(0.73)		(1.25)	
(Cluster SE)			(13.71)							
groupOTHER			14.99				14.99		17.10	
(Robust SE)			(2.55)				(1.80)		(3.03)	
(Cluster SE)			(32.45)							
groupHISP			-12.72				-12.72		-13.28	
(Robust SE)			(0.64)				(0.45)		(0.77)	
(Cluster SE)			(7.56)							
groupCHILD			10.74				10.74		11.60	
(Robust SE)			(0.44)				(0.33)		(0.57)	
(Cluster SE)			(5.03)							
groupSIN			-3.86				-3.86		-4.47	
(Robust SE)			(0.90)				(0.56)		(0.96)	
(Cluster SE)			(5.90)							
_cons	-47.81	-90.02					-100.33	-2.21		
	(17.23)	(26.53)					(1.43)	(0.67)		
	(20.12)	(26.53)								
N	29249	29249	29249	29249	29249	10267	29249	29249	10267	10267
margin					0.13			0.35		
(Bootstrap S.E)					(0.08)			(0.22)		
Number of psu	21	21	21	21	21	21	21	21	21	21

Note: Standard Errors in parentheses

Table 2.5: Peer Effects on Footwear

	(1)	(2)	(3)		(4)		(5)			
	default	fixed effect	2sls		Two-part model		IV Two-part model			
					first part:probit	second part: ols	first part:ivprobit		second part: 2sls	
			first stage	secon d stage			first stage	second stage	first stage	second stage
groupMEAN	0.57	0.38		0.46	0.0016	0.0035		0.0034		0.0048
(Robust SE)	(0.06)	(0.09)		(0.11)	(0.0005)	(0.0005)		(0.0010)		(0.0010)
(Cluster SE)	(0.05)	(0.09)		(0.08)						
male	-2.95	-2.74	-0.10	-2.73	-0.07	0.06	-0.10	-0.07	0.08	0.06
(Robust SE)	(1.95)	(2.47)	(0.14)	(1.96)	(0.02)	(0.02)	(0.14)	(0.02)	(0.20)	(0.02)
(Cluster SE)	(2.43)	(2.47)	(0.14)	(2.40)						
black	15.89	16.11	-0.23	16.06	0.08	0.13	-0.23	0.07	-0.31	0.13
(Robust SE)	(3.20)	(5.48)	(0.21)	(3.22)	(0.02)	(0.02)	(0.22)	(0.02)	(0.32)	(0.02)
(Cluster SE)	(5.41)	(5.48)	(0.16)	(5.32)						
asian	-10.53	-11.22	-0.10	-11.29	-0.05	-0.12	-0.10	-0.06	0.01	-0.12
(Robust SE)	(3.56)	(4.02)	(0.22)	(3.78)	(0.03)	(0.03)	(0.25)	(0.03)	(0.37)	(0.03)
(Cluster SE)	(3.58)	(4.02)	(0.09)	(3.88)						
other	-10.17	-9.84	-0.26	-9.90	-0.04	-0.06	-0.26	-0.04	-0.32	-0.06
(Robust SE)	(5.04)	(5.47)	(0.47)	(5.05)	(0.05)	(0.06)	(0.49)	(0.05)	(0.71)	(0.05)
(Cluster SE)	(5.51)	(5.47)	(0.40)	(5.38)						
hisp	4.37	3.81	-0.01	3.65	0.09	0.03	-0.01	0.09	-0.02	0.03
(Robust SE)	(2.41)	(3.67)	(0.22)	(2.74)	(0.02)	(0.02)	(0.21)	(0.02)	(0.29)	(0.02)
(Cluster SE)	(3.23)	(3.67)	(0.17)	(3.49)						
college	3.57	0.23	-7.79	1.13	-0.05	0.05	-7.78	-0.03	-8.78	0.06
(Robust SE)	(2.89)	(2.16)	(0.91)	(3.35)	(0.03)	(0.03)	(0.31)	(0.03)	(0.45)	(0.03)
(Cluster SE)	(2.27)	(2.16)	(5.85)	(1.78)						
child	20.17	21.25	0.13	20.90	0.25	0.07	0.13	0.24	0.40	0.06
(Robust SE)	(2.14)	(2.33)	(0.13)	(2.25)	(0.02)	(0.02)	(0.15)	(0.02)	(0.21)	(0.02)
(Cluster SE)	(2.15)	(2.33)	(0.07)	(2.43)						
single	-0.70	-0.49	0.02	-0.61	0.02	-0.02	0.02	0.01	0.04	-0.02
(Robust SE)	(2.31)	(2.59)	(0.17)	(2.31)	(0.02)	(0.02)	(0.17)	(0.02)	(0.24)	(0.02)
(Cluster SE)	(2.55)	(2.59)	(0.08)	(2.46)						
lnFIN	14.62	14.73	0.10	14.71	0.06	0.13	0.10	0.06	0.19	0.13
(Robust SE)	(0.94)	(1.16)	(0.06)	(0.94)	(0.01)	(0.01)	(0.06)	(0.01)	(0.08)	(0.01)
(Cluster SE)	(1.15)	(1.16)	(0.06)	(1.12)						
groupFIN	-2.63	7.94	36.95	4.45	0.14	0.03	36.95	0.05	35.67	-0.02
(Robust SE)	(3.94)	(5.33)	(1.29)	(6.47)	(0.04)	(0.04)	(0.36)	(0.06)	(0.52)	(0.05)
(Cluster SE)	(3.36)	(5.33)	(4.07)	(4.55)						
summer	-17.87	-17.86	0.02	-17.85	0.04	-0.23	0.02	0.04	0.07	-0.23
(Robust SE)	(2.39)	(2.44)	(0.18)	(2.39)	(0.02)	(0.02)	(0.19)	(0.02)	(0.28)	(0.02)
(Cluster SE)	(2.42)	(2.44)	(0.11)	(2.38)						

fall	-5.54	-5.58	0.17	-5.58	0.11	-0.10	0.17	0.11	0.33	-0.10
(Robust SE)	(2.49)	(2.43)	(0.19)	(2.50)	(0.02)	(0.02)	(0.19)	(0.02)	(0.27)	(0.02)
(Cluster SE)	(2.41)	(2.43)	(0.15)	(2.37)						
winter	26.15	26.16	0.07	26.15	0.01	0.25	0.07	0.01	0.03	0.25
(Robust SE)	(3.14)	(2.89)	(0.19)	(3.14)	(0.02)	(0.02)	(0.19)	(0.02)	(0.27)	(0.02)
(Cluster SE)	(2.87)	(2.89)	(0.14)	(2.81)						
groupMALE			-54.42				-54.42		-58.56	
(Robust SE)			(2.16)				(1.25)		(1.88)	
(Cluster SE)			(19.13)							
groupBLACK			-48.90				-48.90		-71.45	
(Robust SE)			(5.57)				(1.97)		(2.99)	
(Cluster SE)			(27.37)							
groupASIAN			-45.16				-45.16		-43.37	
(Robust SE)			(2.74)				(1.93)		(2.95)	
(Cluster SE)			(21.58)							
groupOTHER			13.75				13.75		-1.50	
(Robust SE)			(9.80)				(4.73)		(6.87)	
(Cluster SE)			(94.50)							
groupHISP			-40.17				-40.17		-46.37	
(Robust SE)			(1.84)				(1.18)		(1.73)	
(Cluster SE)			(21.89)							
groupCHILD			59.08				59.08		61.27	
(Robust SE)			(1.21)				(0.87)		(1.28)	
(Cluster SE)			(11.83)							
groupSIN			2.28				2.28		7.36	
(Robust SE)			(5.37)				(1.47)		(2.17)	
(Cluster SE)			(19.56)							
_cons	-103.50	-204.80			-2.28	2.49		-1.48		
	(38.72)	(49.85)			(0.41)	(0.39)		(0.54)		
	(37.03)	(49.85)								
N	29249	29249	29249	29249	29249	15370		29249	15370	15370
margin					0.39			0.61		
(Bootstrap S.E)					(0.05)			(0.11)		
Number of psu	21	21	21	21	21	21	21	21	21	21

Note: Standard Errors in parentheses

Chapter 3: Interaction of Household Consumption: Evidence from US Households

3.1 Introduction

Consumers' purchase decisions are influenced through their interactions with others. There is a long history of research on social impacts. Veblen (1899) proposes the theory of conspicuous consumption to address the importance of social influence on consumption. His study lays the foundation for economics research on social interactions. In the previous chapter, "Peer effects on consumption: conformism or snobbism," we present empirical evidence showing significant peer effects in consumption.

Family is the smallest social unit. Social interactions also exist between family members. Browning et al. (2014) introduce many popular models to analyze family economics and have developed influential research papers in the area of family economics in recent years. Three fundamental models can explain the family utility maximization problem: the unitary model, the cooperative model, and the noncooperative model. In this paper, we examine which of these theoretical models is more accurate when applied to US households.

The unitary model explains one extreme situation. In the unitary model, the family is considered as a single entity and has one utility function. There are different explanations for this theory. For example, Samuelson (1956) thinks the common preference ordering may be the outcome of a consensus among the family members, and Becker (1974) shows that the dominant family member makes decisions for the whole family.[13]

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[13] Another extreme situation is that each family member only thinks about his/her utility, which is called the non-cooperative model. Browning, Chiappori, and Weiss (2014) also introduce this model in their book. In this model, family members maximize their own utility functions. Because whether people are family members or not has no effect on their decision-making process in this model, we ignore this extreme

The cooperative model explains the more general cases in real-world situations. This model attempts to incorporate divergent and conflicting preferences of individual family members into an economic analysis. Several models use different methods to deal with the divergence. The examples are the bargaining models, which include cooperative bargaining (e.g., Manser and Brown 1980; McElroy and Horney 1981; Lundberg and Pollak 1993) and non-cooperative bargaining (e.g., Kanbur and Haddad 1994; Lundberg and Pollak 1994; Bergstrom 1996). A generic "collective" approach avoids specifying a particular model of intrafamily allocation but assumes that family allocations obey a Pareto-efficient sharing rule (e.g., Chiappori 1988, 1992). In this paper, we conduct the theoretical analysis based on this collective approach.

In the empirical literature, researchers want to figure out which theoretical model is more accurately explains real-world phenomena. Some empirical studies challenge the models whereas others provide support for the models. Browning (2014) reviews the empirical studies in Chapter 5 of *Economics of the Family*, reviewing, for example, studies providing evidence against the unitary model (e.g., Browning and Chiappori 1998; Kapan 2009; Tomas 1990; Lundberg et al 1997; Duflo 2003; Ward-Batts 2008), supporting the collective model (e.g., Chiappori 1998; Dauphin et al. 2009; Kapan 2009), and estimating the collective model (e.g., Browning et al 1994; Browning and Bonke 2009). In this paper, we aim to provide some evidence from US households.

Our estimates show that when a wife's relative salary compared to her husband's salary increases, womenswear consumption will increase while menswear consumption will decrease. The paper proceeds as follows. In section 2, a theoretical model will be introduced. Subsequently,

situation in our later empirical analysis.

in sections 3 and 4, we will describe the data and the empirical strategy. In section 5, we describe the empirical results, while conclusions will be drawn in section 6.

3.2 Theoretical Model

3.2.1 Unitary and Cooperative Model

In this section, we use a simple framework to explain the interaction of consumption within households. To simplify the analysis, we assume that each family has two family members: a husband and a wife.[14] The model we use in this chapter is based on Samuelson's (1956) work. In this model, one natural assumption, according to Samuelson (1956), is to impose on the household utility function that it respects individual preferences in the sense that:

$$\widetilde{U}(x_H, x_W, S) = \mathrm{W}(\mathrm{U}^a(x_H, \mathrm{S}), \mathrm{U}^b(\, x_W, \mathrm{S}))$$

x_H is the quantity of private good x consumed by husband and x_W is the quantity of private good x consumed by wife. S is the quantity of public goods. W is a utility weighting function which is strictly increasing in the individual utilities. The key difference between the unitary model and the cooperative model is the weight. For the unitary model, all family members think of the family as a whole, which indicates that the weight in the unitary model should be fixed. However, in the cooperative model, the weight changes along with the distribution factors. For example, a family member who gets more income has more weight in the family utility function. In our empirical analysis, the income ratio is the distribution factor influencing the weight. We next explain the unitary model and the cooperative model in more detail.

[14] These models apply to same-sex couples as well.

In the unitary model, based on the following utility function given by Samuelson (1956),

$$\widetilde{U}(x_H x_W, \mathrm{S}) = \mathrm{W}(\mathrm{U}^a(x_H, \mathrm{S}), \mathrm{U}^b(x_W, \mathrm{S}))$$

we define a household utility function over market goods as:

$$U(x, \mathrm{S}) = \max\widetilde{U}(x_H, x - x_H, \mathrm{S})$$

Given this household utility function we can derive market demands in the usual way —namely, maximize the family utility function $\mathrm{U}(x_H, x_W, \mathrm{S})$ under the family budget constraint $P_x(x_H + x_W) + P_S S \leq I$. P_x is the price of good x. P_S is the price of good S. I is family income which is also the budget constraint.

In the cooperative model, husbands' and wives' consumption of private goods influence their utilities. Each household has a unique decision-making process. The key assumption of this approach is that the outcomes of such a process are efficient. Another important assumption in the cooperative model is the distribution factors. Among the various factors that can influence household behavior, many have a direct impact on either preferences or the budget constraint. A more subtle influence occurs indirectly through the decision-making process. A change in the economic environment may not affect either the preferences or the budget opportunities but can still affect the decision-making process. This idea is incorporated into this model by introducing distribution factors. Any variable that has an impact on the decision-making process but affects neither preferences nor budget constraints is termed a distribution factor. The decision process is as follows:

$$\text{Max U} = \mu U_H(x_H, S) + (1 - \mu) U_W(x_W, S)$$
$$P_x(x_H + x_W) + P_S S \leq I$$

The detailed proof is in *Economics of the Family* by Browning, Chiappori, and Weiss (2014, p. 105). The coefficient μ indicates the Pareto weight for the husband. This shows that a Pareto-efficient outcome always maximizes a weighted sum of the two individual utilities. Moreover μ should be a function of (P_x, S, I, z), where z is the distribution factor.

3.2.2 Pareto Weight Identification

The maximization problem is as follows. Family members maximize the family utility by choosing the quantity of private consumption of each family member, under the family budget constraint:

$$\text{Max U} = \mu U_H\ (x_H, S) + (1-\mu) U_W\ (\ x_W, S)$$
$$P_x(x_H + x_W) + P_S S \le I$$

We assume the Pareto weight μ has a linear form $\mu = \mu^0 + \ \mu^z z$, Where z is a K-vector of distribution factors (for example, the income ratio). To solve this maximization problem, we suppose utility function is a linear expenditure system (LES) form,[15]

$$U_H\ (x_H, \mathrm{S}) = \alpha_1^H \log(x_H) + \alpha_2^H \log(S)$$
$$U_W\ (x_W, \mathrm{S}) = \alpha_1^W \log(x_W) + \alpha_2^W \log(S)$$

Using this utility function to solve the linear expenditure system, we can get following demand functions,[16]

[15] One popular demand system is called the linear expenditure system (LES), And this demand system is derived from a simple modification of Cobb-Douglas utility function. And the LES utility function has this form: $U = \prod_{i=1}^{n} (C_i - \theta_i)^{\mu_i}$ where $\sum_{i=1}^{n} \mu_i = 1$.

[16] For the process of solving the demand, see Pollak and Wales (1969)
Pollak, R. A., & Wales, T. J. (1969). Estimation of the linear expenditure system. Econometrica: Journal of the Econometric Society, 611-628.

$$Y_H = P_H x_H = \alpha_1^H(\mu^0 + \mu^z z)I$$
$$Y_W = P_W x_W = \alpha_1^W[1-(\mu^0 + \mu^z z)]I$$

These demand functions show the relationship between private goods expenditures (Y_H, Y_W), family income (I) and distribution factors (z). The left side is private goods expenditure, and the right side includes income and the interaction term of income and the distribution factor. We can rewrite the equations into the following forms, where we use βs to denote the coefficient of each variable. Also, using these equations, we can compare with the empirical models.

$$Y_H = \alpha_1^H\mu^0 * I + \alpha_1^H\mu^z * z * I$$
$$Y_W = \alpha_1^W * I - \alpha_1^w\mu^0 * I - \alpha_1^W\mu^z * z * I = (\alpha_1^W - \alpha_1^W\mu^0) * I - \alpha_1^W\mu^z * z * I$$

$$Y_H = \beta_0 + \beta_1 * I + \beta_2 * z * I$$
$$Y_W = \gamma_0 + \gamma_1 * I + \gamma_2 * z * I$$

Where $\beta_1 = \alpha_1^H\mu^0$, $\beta_2 = \alpha_1^H\mu^z$, $\gamma_1 = \alpha_1^W - \alpha_1^W\mu^0$, $\gamma_2 = \alpha_1^W\mu^z$.

To identify the parameters in the Pareto weight function, we can regress the husband's and wife's private goods expenditures on the family income and the interaction of distribution factors and family income. We will get the estimated coefficients $\widehat{\beta_1}$,$\widehat{\beta_2}$, $\widehat{\gamma_1}$, $\widehat{\gamma_2}$ by doing the regression. Then we can do some transformations to recover all the parameters in the Pareto weight function. Combining the above equations and assuming $\mu^z \neq 0$, we have

$$\frac{\beta_1}{\beta_2} = \frac{\mu^0}{\mu^z}\ \frac{\gamma_1}{\gamma_2} = \frac{1-\mu^0}{\mu^z}$$

Therefore,

$$\mu^0 = \frac{\beta_1\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2}$$
$$\mu^z = \frac{\beta_2\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2}$$

The value of μ^z will enable us to distinguish between the unitary model and the cooperative model. For the unitary version, $\mu^z = 0 = \beta_2 = \gamma_2$ and for the cooperative model $\mu^z \neq 0$.

3.3 Data

3.3.1 Dataset Description

In this paper, we use Consumer Expenditure Surveys (CEX) data from the Bureau of Labor Statistics. Because the primary sampling unit (PSU) categories changed in 2015, we use data from 2011 to 2014. The Bureau of Labor Statistics collects data every three months, so in total, we have 16 different periods. Our analytic dataset includes 21 PSUs in total (see Figure 2.1).[17] The family dataset includes households' demographic characteristics, family income, and expenditure information. The family member's dataset includes family member's characteristics and salary information. We combine the family dataset and the family member dataset. Any observations without family information or family member's information are excluded.

[17] According to the Bureau of Labor Statistics website, "the selection of households for the survey begins with the definition and selection of primary sampling units (PSUs), which consist of counties (or parts thereof), groups of counties, or independent cities. The sample of PSUs currently used in the survey consists of 105 geographic areas, of which 87 are urban geographic areas."

3.3.2 Key Variables of Interest

The key outcome variables are two private consumption expenditures, the expenditures on womenswear and menswear. The key explanatory variable is family income and the ratio of wife's salary to husband's salary. Family income also includes some investment interest or other transfer payments and is not equal to the sum of husband's and wife's salary. We use the salary ratio as the distribution factor in our analysis, which is equal to the wife's salary divided by husband's salary (ratio= $\frac{Wife\ Salary}{Husband\ Salary}$). This influences how the family will distribute their income.

Figure 3.1 shows histograms of womenswear expenditure, menswear expenditure, income, and salary ratio. There are around 80% zero values in the outcome variables. We think that zero is a meaningful amount, so we do not drop zero values during the analysis. However, these inflated zero values will bias our estimates if we use the OLS regression. We instead use a two-part model for the main analysis. We also observe the histograms of positive values of outcome variables which are right-skewed. Therefore, for the second part of the two-part model, we use a log-linear regression.

For the variable salary ratio, the mean value is 0.72 in Table 3.1, which is smaller than one. This mean value shows that in most families, the wife has a lower salary than the husband. By looking at the histogram in Figure 3.1, we find some extreme values. The reason for these extreme values is that in some families one member has a very high salary and the other member has a very low salary. We next look at the detailed percentile summary of the variable *ratio* in Table 3.1. The 99th percentile has a very large value (40). Thus, we drop the extreme values bigger than 95th percentile. For the income variable, we also see the right-skewed histogram graph and the variation is large, so we use the log of income as the explanatory variable.

Table 3.2 shows the summary statistics after dropping extreme values. Figure 3.2 shows the histogram of key variables after transformation (log of womenswear expenditure and log of menswear expenditure after dropping the zeros, log of income and salary ratio after dropping the extreme values). The max salary of husband and wife is 292,304 because the upper topcode value is 292,304. Furthermore, since family income also includes some investment income and other income, family income is not equal to the sum of husband's salary and wife's salary. The correlation between the family income and the sum of husband's salary and wife's salary is 0.93.

3.4 Empirical Strategy

3.4.1 Two-part Model

In this paper, we want to estimate the parameters in the Pareto weight function. One possible problem is that some determinants of the process are not observed, which is the unobserved heterogeneity problem. For example, different tastes for consumption across households may make the regression results biased. In this case the different consumption allocation is not due to the different proportion of salary; instead, it is due to the different tastes. We can control for the PSU fix effects to address some of this heterogeneity problem.

Second, because we also observe many zero values in the dependent variable, the womenswear expenditure and menswear expenditure, we will use a two-part model to address the inflated zero problem. The first part of the model is a probit regression for any expenditures. The second part is a linear regression for the log of expenditure, only for those observations with positive expenditures. We use the same regressors in the first and second part. Thus, the model is:

$$Pr((Y_H)_{ikt} > 0) = \Phi(\alpha_0 + \alpha_1 * I_{ikt} + \alpha_2 * \ z_{ikt} * I_{ikt} + \alpha_3 * \ z_{ikt} + \alpha_4 \mathrm{X}_{Hikt} + \lambda_k)$$
$$Ln((Y_H)_{ikt} > 0) = \beta_0 + \beta_1 * I_{ikt} + \beta_2 * \ z_{ikt} * I_{ikt} + \beta_3 * \ z_{ikt} + \beta_4 \mathrm{X}_{Hikt} + \pi_k$$

$$Pr((Y_W)_{ikt} > 0) = \Phi(\gamma_0 + \gamma_1 * I_{ikt} + \gamma_2 * \ z_{ikt} * I_{ikt} + \gamma_3 * \ z_{ikt} + \gamma_4 \mathrm{X}_{Wikt} + \varphi_k)$$
$$Ln((Y_W)_{ikt} > 0) = \delta_0 + \delta_1 * I_{ikt} + \delta_2 * \ z_{ikt} * I_{ikt} + \delta_3 * \ z_{ikt} + \delta_4 \mathrm{X}_{Wikt} + \omega_k$$

$(Y_H)_{ikt}$ is the husband consumption of each family i in PSU k at time t. ${p_W x_W}_{ikt}$ is the wife consumption of each family i in PSU k at time t. X_{Hikt} is a vector of husband characteristics, for example, age, race and education level, X_{Wikt} is a vector of wife characteristics and $\lambda_k, \pi_k, \varphi_k, \omega_k$ are PSU fixed effects in order to control fixed PSU characteristics. We can calculate the marginal effects of log income (M_1) and marginal effects of the interaction term (M_2) using the DUAN method and use the bootstrap method to get standard errors for these marginal effects.[18]

3.4.2 Pareto Weight Identification

Recall the theoretical model. We have the following equations**.**

$$Y_H = \beta_0 + \beta_1 * I + \beta_2 * \ z * I$$
$$Y_W = \gamma_0 + \gamma_1 * I + \gamma_2 * \ z * I$$

Where $\beta_1 = \ \alpha_1^H \mu^0, \ \ \beta_2 = \alpha_1^H \ \mu^z, \ \gamma_1 = \alpha_1^W - \alpha_1^W \mu^0, \ \gamma_2 = \alpha_1^W \ \mu^z$.

$$\mu^0 = \frac{\beta_1 \gamma_2}{\beta_2 \gamma_1 + \beta_1 \gamma_2}$$
$$\mu^z = \frac{\beta_2 \gamma_2}{\beta_2 \gamma_1 + \beta_1 \gamma_2}$$

[18] Duan, N. (1983). Smearing estimate: a nonparametric retransformation method. *Journal of the American Statistical Association*, *78*(383), 605-610.

By using the two-part model, we can get the marginal effects of the log of income and the interaction of log of income and the income ratio. We can use the following equation to show the relationships

$$Y_H = M_{0H} + M_{1H} * ln(I) + M_{2H} * \ z * ln(I) \ + \varepsilon_H$$
$$Y_W = M_{0W} + M_{1W} * ln(I) + M_{2W} * \ z * ln(I) + \varepsilon_W$$

We find the following results. The detailed derivation is shown in the appendix.

$$\mu^0 = \frac{\beta_1\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} = \frac{M_{1H} * M_{2W}}{M_{2H} * \ M_{1W} + M_{1H} * \ M_{2W}}$$
$$\mu^z = \frac{\beta_2\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} = \frac{M_{2H} * M_{2W}}{M_{2H} * \ M_{1W} + M_{1H} * \ M_{2W}}$$

We can use the bootstrap method to get the standard errors of μ^0 and μ^z.

3.5 Empirical Results

Table 3.3 presents the estimation results, and Table 3.4 shows the estimated marginal effects. The first column in Table 3.3 shows the parameters of the first part probit regression of menswear, and the first column in Table 3.4 shows the corresponding marginal effects. The estimates imply that if the salary ratio increases by one unit, while keeping other variables unchanged, at the mean of *lnincome*, the probability of buying menswear will increase by 0.009.[19] We also calculate the marginal effects if *lnincome* at the 25th and 10th percentile level and find that, when *lnincome* is at the 25th percentile, this effect is still positive but it becomes negative at

[19] 0.009=0.009*11.6-0.095, which is the product of marginal effect of the interaction term *ln(income)*ratio* and the mean of *lnincome* plus the marginal effect of *ratio.* 11.6 is the mean and also the median of *lnincome*.

the 10th percentile. [20] As the ratio is the wife's salary divided by the husband's salary, the ratio increases when the wife's salary becomes relatively higher. If the marginal effect of the ratio is negative, it means that when wife's salary becomes relatively higher, the probability of buying menswear decreases. We should also note that, in the real world, the ratio and the family income always change together. If the *lnincome* increases by one unit while keeping other variables unchanged, at the mean of *ratio*, the probability of buying menswear will increase by 0.045. [21] As the sign of the marginal effect of income and the sign of the marginal effect of the interaction term are both positive, the effect of income should always be positive. When family income increases, the probability of buying menswear increases as well.

The second column in Table 3.3 shows the parameters of the second part linear regression of menswear, and the second column in Table 3.4 shows the corresponding marginal effects. The estimates imply that, if the salary ratio increases by one unit while keeping other variables unchanged, at the mean of *lnincome*, the menswear expenditure will decrease by 0.041%.[22] We also calculate the marginal effects at different percentiles and the effects are all negative. A negative effect implies that, when the wife's salary becomes relatively larger, the menswear expenditure will decrease. If the *lnincome* increases by one unit while keeping other variables unchanged, at the mean of *ratio*, the menswear expenditure will increase by 0.448.[23]

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[20] When *lnincome* is at the 25th percentile the effect is -0.004 and at the 10th percentile, the effect is 0.006.
-0.004=0.009*10.07-0.095.
0.006=0.009*11.18-0.095.

[21] 0.045=0.038+0.009*0.81, which is the product of marginal effect of the interaction term *ln(income)*ratio* and the mean of *ratio* plus the marginal effect of *lnincome*.

[22] 0.041=0.273-0.020*11.6, which is the product of marginal effect of the interaction term *ln(income)*ratio* and the mean of *lnincome* plus the marginal effect of *ratio*.

[23] 0.448=0.432+0.020*0.81, which is the product of marginal effect of the interaction term *ln(income)*ratio* and the mean of *ratio* plus the marginal effect of *lnincome*.

Next, we combine these two parts. If the ratio increases one unit, the menswear expenditure will increase by $0.242.[24] We also calculate the marginal effects if *lnincome* at the 25th and 10th percentile levels and find that, when *lnincome* is at the 25th percentile, this effect is still positive but it becomes negative at the 10th percentile. When family income is low, the increase of *ratio* decreases the menswear expenditure. When family income is high, the increase of ratio increases the menswear expenditure. If *lnincome* increases one unit, the menswear expenditure will increase by 18.77 percentage points at the mean of *ratio*.[25]

The third column in Table 3.3 shows the parameters of the first part probit regression of womenswear, and the third column in Table 3.4 shows the corresponding marginal effects. The estimates imply that if the salary ratio increases by one unit while keeping other variables unchanged, at the mean of *lnincome*, the probability of buying womenswear will increase by 0.009.[26] We try all percentiles and the effects are always positive. Positive effect implies that when the wife's salary becomes relatively higher, the probability of buying womenswear increases. If the *lnincome* increases by one unit while keeping other variables unchanged, at the mean of *ratio*, the probability of buying womenswear will increase by 0.048.[27]

The Fourth column shows the second part regression of womenswear. The estimates imply that, if *the* salary ratio increases by one unit keeping other variables unchanged, at the mean of *linincome*, the womenswear expenditure will increase by 0.0518.[28] When the *ratio* increases, the wife's salary becomes relatively higher, and the consumption of womenswear increases. We try all percentiles and the effects are always positive. If the income increases by 1%, the womenswear

[24] 0.242=1.87*11.6-21.45.
[25] 18.77=17.26+1.87*0.81.
[26] 0.009=0.044-0.003*11.626.
[27] 0.048=0.051-0.003*0.81.
[28] 0.0518=0.423-0.032*11.6.

expenditure will increase by 0.38%.[29]

Last, we combine these two parts. If ratio increase one unit, at the mean of *lnincome*, the womenswear expenditure will increase by $3.8.[30] The effects are positive for all percentiles. If the *lnincome* increases by one unit while keeping other variables unchanged, at the mean of *ratio*, the womenswear expenditure will increase by 24.06.[31]

Table 3.5 provides the estimation results for μ^0 and μ^z. Recall our theoretical model, U=$\mu U_H\,(x_H, y)$ + $(1-\mu)U_W\,(\,x_W, y)$. Because we specify $\mu = \mu^0 + \mu^z z$, the results mean that, if the ratio increases by one unit, the pareto weight will decrease by 0.34. That is to say, when a wife's relative salary compared to her husband's salary increases, the weight of the wife's utility in the family's utility will increase, and the weight of husband's utility in the family's utility will decrease. This conclusion is consistent with the cooperative model. However, the estimated value of μ^z is not statistically significant.

3.6 Conclusion

The estimation indicates that, when the wife's relative salary compared to the husband's salary increases, womenswear consumption increases while menswear consumption decreases. When the wife's salary increases, both the family income and ratio change. The increasing income changes womenswear consumption through both the increased budget constraint and the distribution factor. Using our model, we can estimate different effects through these two paths. By using the US Consumer Expenditure Survey data, we estimate the Pareto weight to be negatively

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29 0.38=0.408-0.032*0.81.

30 3.8=26.00-1.91*11.6.

31 24.06 =25.63-1.91*0.81.

correlated with the ratio of the wife's salary to the husband's salary. When the wife's salary increases, the ratio increases whereas the weight of the husband's utility decreases. However, in our results, these estimations are insignificant, which means that μ^z is not significantly different from zero. If μ^z is not significantly different from zero, the unitary model is more appropriate for explaining the situation in the US.

Our research faces some limitations. For example, we only include one distribution factor: the salary ratio. There might exist other distribution factors that have a significant influence on the Pareto weight. In addition, we assume that the Pareto weight and the distribution factors have a linear relationship. In reality, they may have more complicated relationships, such as a quadratic function form. In future research, we can relax the assumptions when making the estimations. We can also conduct some interesting further research related to this topic. For example, people with different education levels, ages, and races may perceive things in different ways. We can examine how their education, age, or race influences the way that they make decisions related to family consumption. For example, family members with a higher education level might care more about themselves than the whole family; as people get older, they love their spouses more and might be more likely to use the unitary model to make decisions; and people from cultures with very strong family values might be more likely to use the unitary model to make decisions.

3.7 References

Becker, G. S. (1974). A theory of social interactions. *Journal of political economy*, *82*(6), 1063-1093.

Bergstrom, T. C. (1996). Economics in a family way. *Journal of Economic Literature*, *34*(4), 1903-1934.

Browning, M., Bourguignon, F., Chiappori, P. A., & Lechene, V. (1994). Income and outcomes: A structural model of intrahousehold allocation. *Journal of political Economy*, *102*(6), 1067-1096.

Browning, M., & Chiappori, P. A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, 1241-1278.

Bonke, J., & Browning, M. (2009). The allocation of expenditures within the household: A new survey. *Fiscal Studies*, *30*(3-4), 461-481.

Browning, M., Chiappori, P. A., & Weiss, Y. (2014). *Economics of the Family*. Cambridge University Press. Samuelson, P. A. (1956). Social indifference curves. *The Quarterly Journal of Economics*, *70*(1), 1-22.

Chiappori, P. A. (1988). Nash-bargained households decisions: a comment. *International Economic Review*, *29*(4), 791-796.

Chiappori, P. A. (1992). Collective labor supply and welfare. *Journal of political Economy*, *100*(3), 437-467.

Chiappori, P. A. (2011). Collective labor supply with many consumption goods. *Review of Economics of the Household*, *9*(2), 207-220.

Dauphin, A., El Lahga, A. R., Fortin, B., & Lacroix, G. (2011). Are children decision-makers within the household?. *The Economic Journal*, *121*(553), 871-903.

Duflo, E. (2003). Grandmothers and granddaughters: old-age pensions and intrahousehold allocation in South Africa. *The World Bank Economic Review*, *17*(1), 1-25.

Kanbur, R., & Haddad, L. (1994). Are better off households more unequal or less unequal?. *Oxford Economic Papers*, *46*(3), 445-458.

Kapan, T. (2009). Essays in household behavior. *PhD diss. Columbia Univ*.

Lundberg, S., & Pollak, R. A. (1993). Separate spheres bargaining and the marriage market. *Journal of political Economy*, *101*(6), 988-1010.

Lundberg, S. J., Pollak, R. A., & Wales, T. J. (1997). Do husbands and wives pool their resources? Evidence from the United Kingdom child benefit. *Journal of Human resources*, *32*(3), 463-481.

Lundberg, S., & Pollak, R. A. (1994). Noncooperative bargaining models of marriage. *The American Economic Review*, *84*(2), 132-137Veblen, T. (1899). *The theory of the leisure class: An economic study in the evolution of institutions*. Macmillan.

Manser, M., & Brown, M. (1980). Marriage and household decision-making: A bargaining analysis. *International economic review*, 31-44.

McElroy, M. B., & Horney, M. J. (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International economic review*, 333-349.

Thomas, D. (1990). Intra-household resource allocation: An inferential approach. *Journal of human resources*, 635-664.

Veblen, T. (2017). *The theory of the leisure class*. Routledge.

Ward-Batts, J. (2008). Out of the wallet and into the purse using micro data to test income pooling. *Journal of human resources, 43*(2), 325-351.

3.8 Tables and Figures

Table 3.1: Summary Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max	Percentage of Zeros
Womenswear expenditure ($)	7,183	43	142.47	0	3971	0.75
Menswear expenditure ($)	7,183	28	124.34	0	3536	0.82
Income ($)	7,183	136349	103671.5	2	1110485	0
Wife Salary ($)	7,183	49222	48173.5	1	292304	0
Husband Salary ($)	7,183	75502	66230.03	1	292304	0
Income Ratio (wife's salary/ husband's salary)	7,183	59.23	1703.99	0	58000	0

Income Ratio (wife's salary/ husband's salary)		Percentiles
	1%	0.01
	5%	0.05
	10%	0.11
	25%	0.34
	50%	0.72
	75%	1.09
	90%	2.20
	95%	4.07
	99%	40

Note: The minimum of income Income Ratio is a positive number and round to zero

Figure 3.1: Histogram of Key Variables

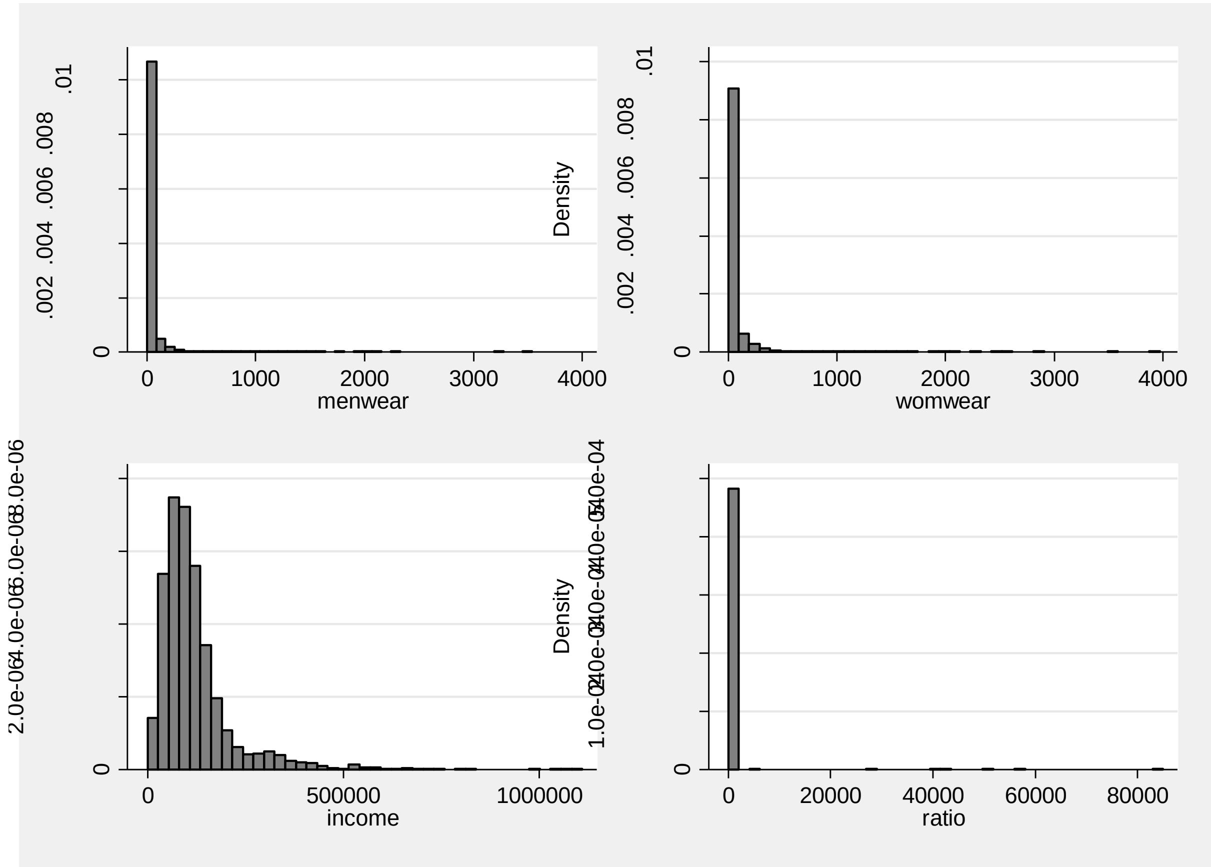

Table 3.2: Summary Statistics (After dropping)

Variable	Observation	Mean	Std. Dev.	Min	Max	Percentage of Zeros
Womenswear expenditure ($)	6,824	43	143.76	0	3971	0.75
Menswear expenditure ($)	6,824	28	116.43	0	3200	0.82
Income ($)	6,824	138554	104121.20	2	1110485	0
Wife Salary ($)	6,824	48038	46666.31	1	292304	0
Husband Salary ($)	6,824	79058	66009.59	1	292304	0
Income Ratio (wife's salary/ husband's salary)	6,824	0.81	0.69	0	4.06	0
Log income	6,824	11.60	0.73	0.69	13.92	
Income Ratio (wife's salary/ husband's salary)		Percentiles				
	1%	0.01				
	5%	0.04				
	10%	0.11				
	25%	0.33				
	50%	0.69				
	75%	1.00				
	90%	1.61				
	95%	2.22				
	99%	3.40				

Note: The minimum of income Income Ratio is a positive number and round to zero

Figure 3.2: Histogram of Key Variables (After Transformation)

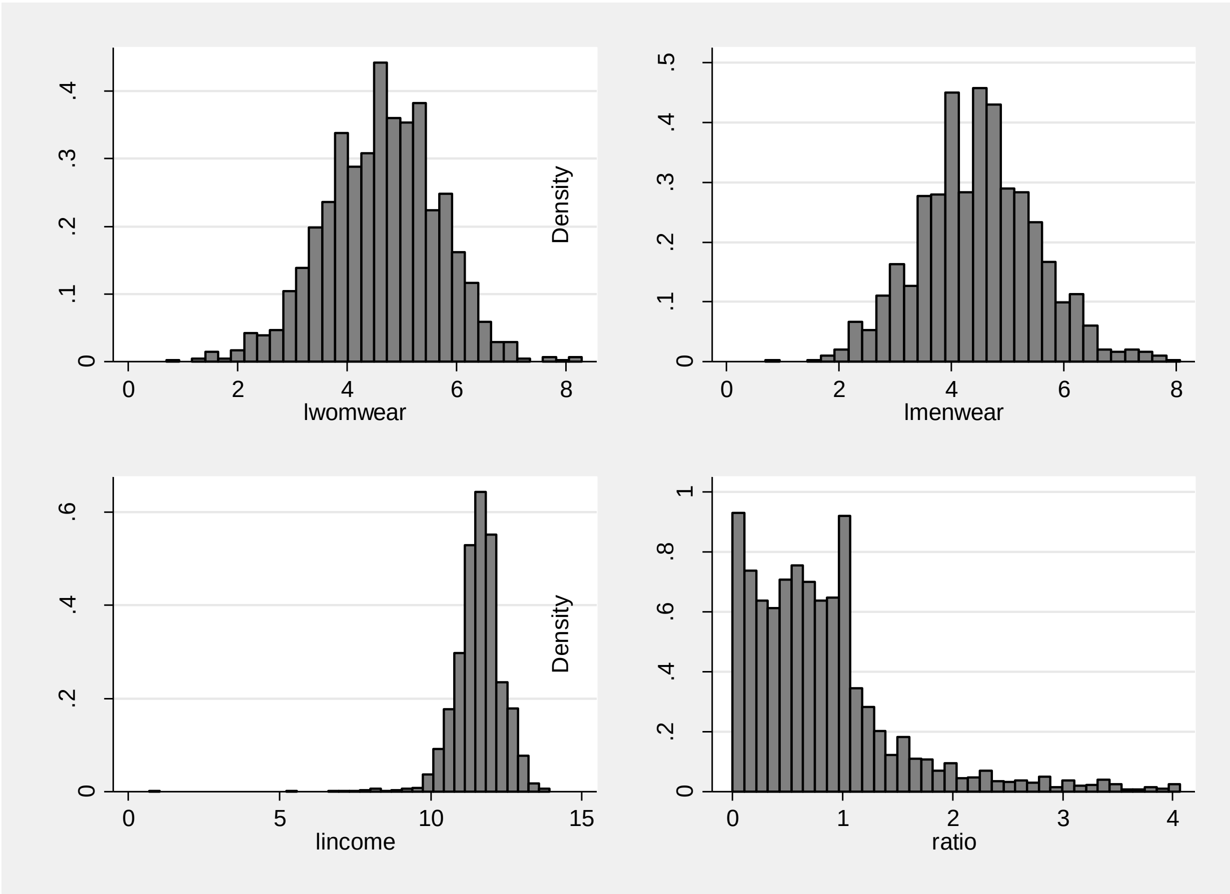

Table 3.3: Estimation Results of Menswear and Womenswear

	Menswear		Womenswear	
	Probit	Linear	Probit	Linear
ln(income)	0.148***	0.432***	0.155***	0.408***
	(0.039)	(0.066)	(0.036)	(0.052)
ln(income)*ratio	0.035	0.020	-0.010	-0.032
	(0.033)	(0.054)	(0.030)	(0.043)
ratio	-0.371	-0.273	0.149	0.423
	(0.390)	(0.639)	(0.351)	(0.510)
age	-0.002	0.003	0.003*	0.008***
	(0.002)	(0.003)	(0.002)	(0.002)
college	0.072*	0.205***	0.114***	0.271***
	(0.038)	(0.060)	(0.035)	(0.049)
white	-0.070	-0.275	0.086	0.052
	(0.139)	(0.211)	(0.135)	(0.198)
black	-0.136	0.023	-0.002	0.183
	(0.154)	(0.238)	(0.148)	(0.217)
Asian	-0.108	-0.469**	0.020	-0.087
	(0.149)	(0.230)	(0.144)	(0.211)
_cons	-2.498***	-0.745	-2.692***	-0.976
	(0.475)	(0.787)	(0.434)	(0.633)
N	6824	1220	6824	1697

Standard errors in parentheses

* p<0.1 ** p<0.05 *** p<0.01

Table 3.4: Marginal Effects Estimation

	Menswear		Womenswear	
	Probit	Linear	Probit	Linear
ln(income)	0.038***	0.432***	0.051***	0.408***
	(0.010)	(0.066)	(0.011)	(0.052)
ln(income)*ratio	0.009	0.020	-0.003	-0.032
	(0.009)	(0.054)	(0.009)	(0.043)
ratio	-0.095	-0.273	0.044	0.423
	(0.100)	(0.639)	(0.110)	(0.510)
Two-Part Marginal Effect dy/dx (ln(income))	17.26***		25.63***	
	(2.51)		(4.26)	
Two-Part Marginal Effect dy/dx (ln(income)*ratio)	1.87		-1.91	
	(1.91)		(2.73)	
Two-Part Marginal Effect dy/dx (ratio)	-21.45		26.00	
	(22.29)		(32.22)	

Standard errors in parentheses

* p<0.1 ** p<0.05 *** p<0.01

Table 3.5: Estimation Results of μ^0 and μ^z

μ^0	-3.22
	(8.86)
μ^z	-0.35
	(0.42)

3.9 Appendix

Pareto Weight Identification

Recall the theoretical model, we have these following equations**.**

$$Y_H = \beta_0 + \beta_1 * I + \beta_2 * \ z * I \quad (1)$$

$$Y_W = \gamma_0 + \gamma_1 * I + \gamma_2 * \ z * I \quad (2)$$

Where $\beta_1 = \ \alpha_1^H \mu^0, \quad \beta_2 = \alpha_1^H \ \mu^z, \ \ \gamma_1 = \alpha_1^w - \alpha_1^w \mu^0, \ \gamma_2 = \alpha_1^W \ \mu^z$.

$$\mu^0 = \frac{\beta_1\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} \quad (3)$$

$$\mu^z = \frac{\beta_2\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} \quad (4)$$

By using the two-part model, we can get the marginal effects of log of income and the marginal effects of the interaction term of log income and income ratio. We can use the following equation to show the relationships

$$Y_H = M_{0H} + M_{1H} * ln(I) + M_{2H} * \ z * ln(I) \ + \varepsilon_H \quad (5)$$

$$Y_W = M_{0W} + M_{1W} * ln(I) + M_{2W} * \ z * ln(I) + \varepsilon_W \ (6)$$

In equation (1), if *I* increase one unit, the y_H will increase by ($\beta_1 + \beta_2 * \ z$) units. And in equation (5), if *I* increase on unit, the y_H will increase by $M_{1H} * [ln(I+1) - ln(I)] + M_{2H} * [ln(I+1) - ln(I)] \ * z$. Due to this relationship we can get that $\beta_1 = M_{1H} * \ ln(1 + \frac{1}{I}), \ \beta_2 =$

$M_{2H} * \ ln(1+\frac{1}{I})$. And use same logic on equation (2) and (6), we will get $\gamma_1 = \ M_{1W} * \ ln(1+\frac{1}{I})$, $\gamma_2 = M_{2W} * \ ln(1+\frac{1}{I})$.

And if we plug these marginal effects in the μ^0 equation we will find that the term $ln(1+\frac{1}{I})$ will be canceled out.

$$\mu^0 = \frac{\beta_1\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} = \frac{M_{1H} * \ ln(1+\frac{1}{I}) * M_{2W} * \ ln(1+\frac{1}{I})}{M_{2H} * \ ln(1+\frac{1}{I})M_{1W} * \ ln(1+\frac{1}{I}) + M_{1H} * \ ln(1+\frac{1}{I})M_{2W} * \ ln(1+\frac{1}{I})}$$

$$\mu^0 = \frac{\beta_1\gamma_2}{\beta_2\gamma_1 + \beta_1\gamma_2} = \frac{M_{1H} * M_{2W}}{M_{2H} * \ M_{1W} + M_{1H} * \ M_{2W}}$$

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COURSES TAUGHT

MBA497: Quantitative Elements (1-MBA Core Course)
Teaching Evaluations: 4.48/5 (Average score of All 21 Questions)
4.07/5 (Average score of Four Key Questions[32])

[32] Four Key Questions from the Course Evaluation at Lehigh University:

1. Overall, the instructor's teaching was effective
2. Overall, the quality of the course was good
3. I learned a great deal in this course
4. I would recommend this course to other students.

ECO 045: Statistical Method (Undergraduate Core Course)
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Project Lead, Undergraduate Research & Innovation Program, "Impact of Monetary Policy on the Welfare of Farmers", Central University of Finance and Economics, 11/2011-4/2013

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College of Business & Economics Graduate Life Leadership Award
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Third Awards, Social Practice Prize
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Third Prize Scholarship
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