Conspicuous Consumption in the United States and China

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Abstract

How do differences in the motive for conspicuous consumption in the United States and China affect the incidence of taxes in those countries? In this paper I develop a model of conspicuous consumption in which a consumer cares not only about the direct utility she receives from consumption, but also about the way her consumption pattern affects her peer group's belief about her well-being. Estimating the model on American and Chinese data, I find that a Chinese consumer cares 20% more than an American consumer about peer beliefs. I use the estimated model in several experiments related to tax incidence. I find that the 1990-2002 American luxury tax on automobiles led to widespread but small welfare gains, and that the stronger Chinese motive for conspicuous consumption leads to fewer households harmed and larger median welfare gains from a 10% tobacco excise tax.

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1 Introduction

People live, work, and relate to one another in a cultural context, and consumption decisions are naturally also affected by culture.[1] When buying a car or a suit, for example, a consumer considers how her social group will view the new purchase. In some cultures, relative status may be more affected by the purchase of conspicuous goods than in others. A government typically cannot choose the culture of a country it governs, but it can design tax policy. The effects of tax policy on consumption and welfare may depend on the cultural context in which the policy is implemented. This paper aims to quantify one effect of culture, the motive for conspicuous consumption, by developing and estimating a model of conspicuous consumption on American and Chinese data. Using the model, I study how the motive for conspicuous consumption affects the incidence of excise taxes in the two countries.

The model of conspicuous consumption developed in the paper is a partial-equilibrium, heterogeneous-agent structural model in which a consumer's peers infer his wealth after observing a subset of his purchases. Inference about welfare by his peer group causes a consumer to distort his consumption toward the purchase of a visible good. To identify the strength of the motive to conspicuously consume, previous literature has either relied on strong assumptions about the functional form of utility (Heffetz, 2011) or arbitrary assumptions about the way in which observable consumption enters utility (Perez-Truglia, 2012). In the model I develop, households are allowed to have heterogeneous, non-homothetic preferences. A peer group forms beliefs about the household's welfare based on the observable part of the household's consumption. The household cares about these peer group beliefs, and takes them into account when choosing how to allocate its income.

In order to identify this more flexible model, I use differences in the perception of the visibility of good categories across demographic groups, along with differences in how these demographic groups spend their incomes. The estimation uses both a survey on the relative visibility of different categories of goods, and household-level consumption expenditure data. As it is used to calculate purchasing power, expenditure data is available for many countries and time periods. I estimate the model separately using American and Chinese consumption expenditure data. The estimated model fits the data well. I find that the Chinese consumers care 20% more than American consumers about peer group beliefs. That is, through the lens of the model, a Chinese person cares more about how his peers will view his spending decisions than an American person.

The motive to conspicuously consume creates the possibility of welfare improving government policy. If people signal wealth using highly visible goods like cars

[1]There is a large literature studying the role of culture in consumption. For a relatively recent survey, see Arnould and Thompson (2005).

or jewelry, than equilibrium consumption will be skewed toward visible goods. Luxury taxes on these conspicuous goods skew consumption back toward the no-signaling optimum. The welfare effect of tax policies will differ across countries as both utility parameters and the motive to conspicuously consume differ. In a policy experiment based on the estimated model, I find that the actual 1990-2002 American luxury tax on automobiles had a small but positive welfare effect on all but around three in 10,000 American households. In a second policy experiment, I consider the effect of an additional 10% excise tax on cigarettes. I find that increasing the American motive to conspicuously consume to the Chinese level causes a cigarette tax to harm fewer households and raise the median gain in welfare. Conversely, lowering the Chinese motive to conspicuously consume to the American level makes a Chinese cigarette tax harm more households, and lowers the median gain in welfare. In other words, taxes on luxury goods are more welfare enhancing in cultures with a stronger motive for conspicuous consumption.

In order to estimate the model, I must make several stark assumptions. Among these are that I must take a stand on the relevant peer group for peer effects. I assume a consumer's peer group is people of a similar age living in the same region as her. For technical reasons I also assume that each household signals with spending in a single category of goods. This is, of course, a counterfactual assumption, but it is critical to creating an estimable signaling model. Finally due to data limitations, when estimating the Chinese utility function, I must take some estimated parameters from the American data, including how conspicuous is consumption in different goods categories. I will elaborate on these and other identification assumptions in Section 5 below.

2 Literature

This paper is most closely related to an empirical literature on conspicuous consumption (Bloch et al., 2004; Charles et al., 2009; Moav and Neeman, 2010, 2012; Perez-Truglia, 2013), and in particular to recent work on differences in conspicuous consumption between regions (Friehe and Mechtel, 2014).[2] I extend work by Heffetz (2011), who conducts a telephone survey in the United States to determine the visibility of consumption goods. Heffetz analyzes household budget survey data, and finds evidence that the relatively visible goods identified by the survey are being used as a means to signal income. To my knowledge, the only other structural estimation of a utility function including conspicuous consumption is Perez-Truglia (2012). Perez-Truglia follows earlier literature in using a two-good functional form, and a variety of specifications for how non-market goods like sta-

[2]Friehe and Mechtel (2014) contains an interesting discussion of why the Socialist East German system was likely to increase the importance of conspicuous consumption relative to its importance in West Germany. The difference I find between Chinese and American preferences for visible consumption may be related to the Socialist experience of Chinese citizens over the last century.

tus enter utility. My specification below differs from Perez-Truglia's in a few important ways. Some cosmetic differences include that I allow for individual level preference heterogeneity and estimate a many good utility function. Any good can be used for signaling in my model, while in Perez-Truglia's model cars and clothes are the visible goods. More substantively, while Perez-Truglia is focused on the provision of unobservable non-market goods (status), I assume that society cares only about an individual's unobservable welfare. This allows me to consider peer-group beliefs as an equilibrium outcome, rather than assume a functional form for the provision of a non-market good. In line with my paper's findings, Perez-Truglia finds that properly designed taxes on luxury goods benefit everyone a small amount.

There is a related business economics literature which analyzes conspicuous consumption across countries, including comparison of the United States and China (Wong and Ahuvia, 1998). Using surveys with direct questions about conspicuous consumption, an empirical branch of this literature has found mixed results concerning Chinese and US consumers.[3]

This paper is also related to an older empirical literature that support the presence of a peer belief component in the utility function. Consider the ultimatum game in which one player proposes a split of a sum of money, and the other player decides whether to accept or reject. If the second player accepts, the money is allocated according to the split. If the second player rejects, neither player gets anything. There is a long and robust experimental literature showing that if people only care about immediate monetary payoffs, the splits they propose are too fair. Researchers have been careful to pair subjects who do not know each other and are unlikely to have interaction after the experiment, and the result still holds. One explanation is that there is some sort of social component in the utility function. (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000) A second explanation for splits that are too fair comes from the literature on self-reported happiness and relative wealth. Luttmer (2004) finds that relative wealth compared with neighbors has a robust positive correlation with self-reported happiness, controlling for absolute wealth level. It seems hard to explain the behavior in the literature on ultimatum games without some sort of social component in the utility function, and this paper aims to measure one such component.

Finally, there is a relatively large and old related literature estimating what are known as interdependent preferences. Beginning with James Duesenberry's 1949 doctoral thesis (Duesenberry, 1967), researchers have theorized that the consumption of neighbors affects own demand. A typical econometric model in this literature lets household demand parameters depend linearly on the average of the consumption of a reference group. A relationship between neighbor consumption

[3]A nice discussion of the recent literature is found in the discussion section of Podoshen et al. (2011). Podoshen et al. (2011) themselves find that Chinese youth care significantly more about conspicuous consumption and materialism than American youth.

and own consumption is taken to mean that preferences are interdependent. The literature, however, does not take a stand on why consumption neighborhood consumption should be linked in this particular way. More recent contributions more careful about identification include (De Giorgi et al., 2015). A model of conspicuous consumption as developed below takes a stand on why consumption is linked within neighborhoods.

3 An Empirical Model of Conspicuous Consumption

There is a finite set of goods G. Each good has an exogenous price p_g. There is a continuum of consumers I. For each consumer, nature draws an income w_i, a preference type $\boldsymbol{\gamma}_i$, and an observation type $t_i \in G$. The observation type t_i is the category of spending which a consumer's peers are able to observe. A consumer allocates his income to goods in order to maximize his utility. Following previous literature on conspicuous consumption (Ireland, 1994; Heffetz, 2011), I assume a consumer's utility function consists of two additively separable parts.

$$U(\mathbf{C}_i, \boldsymbol{\gamma}_i, t_i) = (1-\alpha)u(C_i, \boldsymbol{\gamma}_i) + \alpha\, u(C_b(c_{t_i}, \boldsymbol{\gamma}_i, t_i), \boldsymbol{\gamma}_i) \tag{1}$$

The first term on the right-hand side of (1) is a fundamental utility $u : \mathbb{R}_+^I \to \mathbb{R}$. Fundamental utility describes the pleasure a consumer gets directly from consuming a bundle of goods. The second term is the belief of a consumer's peer group over his utility. Peer group belief over the utility level of consumer i is based on his expenditure on good category t_i. C_b maps consumption of the observable good, observation type, and preference type to the unobservable full consumption vector. The preference type and observation type of consumer i are known to his peer group.[4]

3.1 Equilibrium Concept

An equilibrium is a social belief function C_b and a consumption function C on (W, Γ, G) such that:

1. For each consumer type $(w_i, \boldsymbol{\gamma}_i, t_i)$, $C(w_i, \boldsymbol{\gamma}_i, t_i)$ solves the consumer's problem.

2. For each consumer type $(w_i, \boldsymbol{\gamma}_i, t_i)$, $C(w_i, \boldsymbol{\gamma}_i, t_i) = C_b(C(w_i, \boldsymbol{\gamma}_i, t_i)_{t_i}, \boldsymbol{\gamma}_i, t_i)$.

The first condition says that a consumer chooses an optimum consumption bundle, and the second condition says that Consumer i's peer group learns his true type.

[4]The peer-group infers the one-dimensional income of a consumer from the one-dimensional observed consumption choice of the observable good. If I allow for more than one observed good, then one-dimensional would be inferred from multi-dimensional consumption. As in a typical multi-dimensional screening model, the equilibrium will be driven by beliefs off the equilibrium path and there will be many possible equilibria.

3.2 Specializing to Cobb-Douglas

Let the fundamental utility function be Cobb-Douglas:

$$u(\mathbf{C}, \boldsymbol{\gamma}) = \sum_{g=1}^{G} \gamma_g \ln(c_g)$$

The model can then be written as a generalization of the Heffetz model to many goods and preference heterogeneity.[5] In what follows I drop subscripts for Consumer i to simplify notation. Let $t \in G$ be Consumer i's observation type, and let c_t^* be Consumer i's equilibrium consumption of the visible good. Equilibrium demand for good $g \neq t$ conditional on spending on the visible good is the standard Cobb-Douglas constant expenditure share:

$$p_g c_g^* = \gamma_g \left(\sum_{j \neq t} \gamma_j \right)^{-1} (w - p_t c_t^*) \tag{2}$$

Using the demands, we can write the utility function as a function of visible good consumption.

$$U(c_t) = (1-\alpha)\left(\hat{\gamma} \ln\left(w - p_t c_t\right) + \gamma_t \ln\left(c_t\right)\right) + \alpha\left(\gamma_t \ln\left(s(c_t)\right) + \gamma_t \ln\left(c_t\right)\right) + \zeta(\mathbf{p}, \boldsymbol{\gamma}) \tag{3}$$

Here $\hat{\gamma} = \sum_{g \neq t} \gamma_g$ and $\zeta(\mathbf{p}, \boldsymbol{\gamma})$ is a constant which depends only on utility parameters and prices. The single-valued function $s(c_t)$ is the belief of the peer group about spending on non-visible goods $w - p_t c_t$.

Consumer i maximizes utility function (3) subject to his budget constraint. The first order condition for an interior solution to his problem can be written:

$$s'(c_t^*) = \frac{1}{\alpha}\left((1-\alpha)\, p_t - \frac{\gamma_t}{\hat{\gamma}} \frac{s(c_t^*)}{c_t^*} \right) \tag{4}$$

This differential equation has the solution:

$$s(c_t^*) = \frac{\hat{\gamma}\,(1-\alpha)}{\gamma_t + \alpha\hat{\gamma}} p_t c_t^* + \frac{\hat{\gamma}\alpha}{\gamma_t + \alpha\hat{\gamma}} \underline{\mathrm{W}} \frac{p_t c_t^{*}}{p_t \underline{\mathrm{c}}}^{-\frac{\gamma_t}{\alpha\hat{\gamma}}} \tag{5}$$

The constant in the solution (5) is pinned down because the lowest possible income type $\underline{\mathrm{W}} > 0$ has no reason to signal in a separating equilibrium. His expenditure on the visible good $\underline{\mathrm{c}}$ is the fraction $\gamma_t / \sum_j \gamma_j$ of his income. As one might expect, the function s is jointly homothetic in c_t^* and $\underline{\mathrm{W}}$.

[5] In the Heffetz version, there are only two goods, one visible and the other not visible to society. In my version, there is one visible good for each observation type, and spending on all the other goods is not observable.

Define equilibrium expenditure share on the visible good category $r = p_t c_t^* / w$, the ratio $\gamma = \gamma_t / \hat{\gamma}$, and normalized income $\hat{w} = \underline{\mathrm{W}}/w$. Substituting in for the s function and dividing by income, we have a simplified equilibrium condition:

$$(1-r)(1+\frac{\gamma}{\alpha}) = \frac{(1-\alpha)}{\alpha} r + \left(r\left(1+\gamma^{-1}\right)\right)^{-\frac{\gamma}{\alpha}} \hat{w}^{1+\frac{\gamma}{\alpha}} \tag{6}$$

4 Description of Data and Sources

This project requires two types of data. We need household-level consumer expenditure data, and we need information about how visible different good categories are relative to each other. Household expenditure data is widely available from national statistical agencies. Information on the visibility of different good categories is taken from a survey conducted in Heffetz (2011).

4.1 Household Expenditures

American household expenditure data is taken from the Harris and Sabelhaus extracts hosted by the National Bureau of Economic Research (National Bureau of Economic Research, 2011). This data set is publicly available, and features a large random sample of American household consumption information for selected years between 1981 and 2002. This data set is ultimately based on the American Consumer Expenditure Survey conducted by the US Census Bureau.[6] In addition to detailed information on household income and expenditures, the NBER data set contains demographic data on household members such as age, race, sex, and location.

There are 47 good categories available in the NBER data set. Following Heffetz (2011) exactly,[7] I aggregate into 29 expenditure categories. The cleaned NBER data set contains 160,617 household observations across 18 years. Households display widely varying consumption behavior. Figure 1 is a scatter plot the 2001 log budget shares by log expenditures. Representative household models in the literature such as those by Heffetz and Ireland cannot replicate this heterogeneity.[8] The heterogeneous preference model estimated in this paper can potentially match the noise observed in the data.

For the Chinese household expenditures, I use data from the Chinese Household Income Project or CHIP (Li, 2002). This data is publically available from the Inter-university Consortium for Political and Social Research at the University of Michigan. CHIP data has been a popular data set among economists studying

[6] While the American Consumer Expenditure Survey has been collected since 2002, I choose to use the harmonized and cleaned National Bureau of Economic Research data as it is well-understood and has been used in several other studies in the literature (Charles et al., 2009; Heffetz, 2011).

[7] Heffetz was kind enough to give me his STATA code.

[8] Heffetz (2011) contains a discussion of this issue.

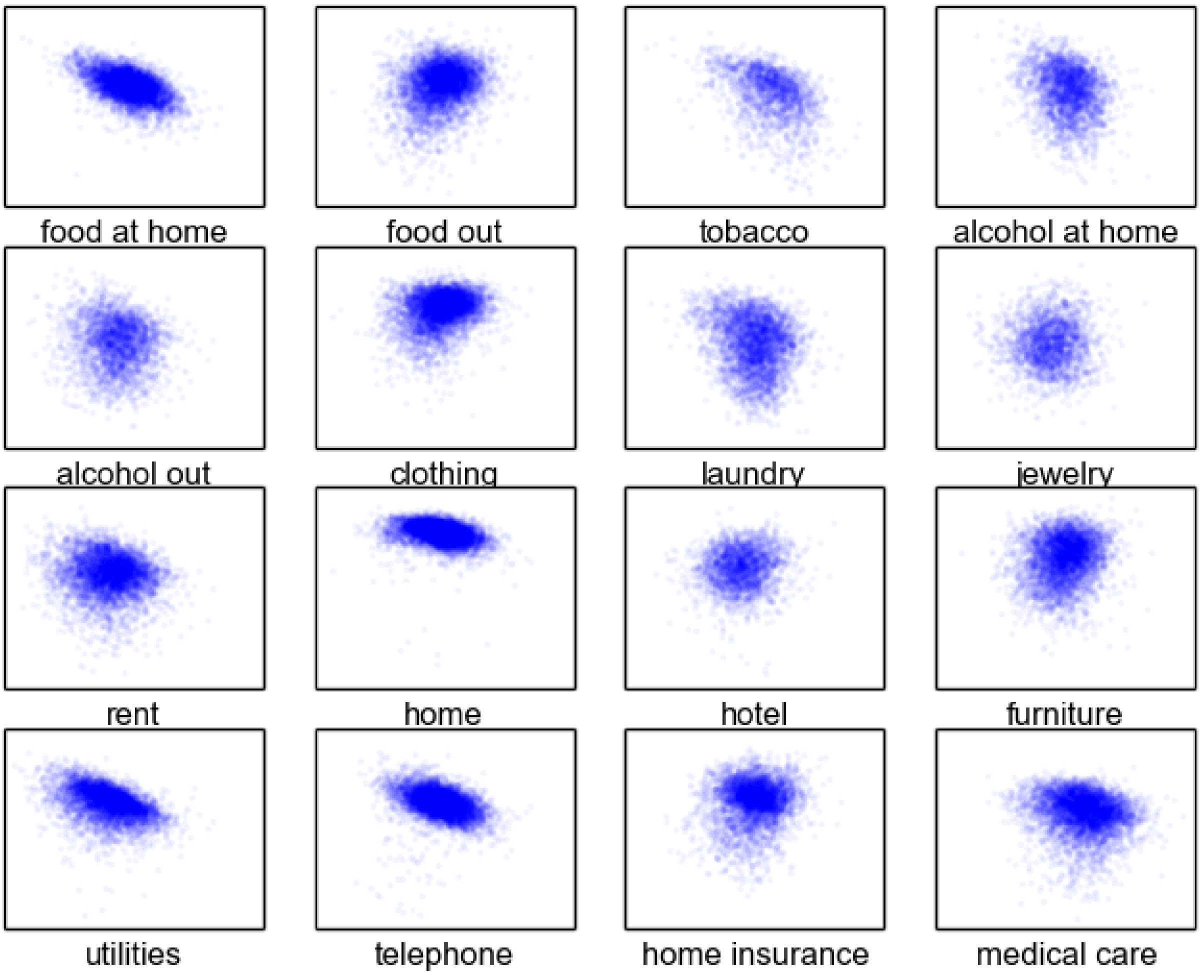

Figure 1: Log expenditure shares (y) by log expenditure (x)

Chinese consumers. As of 2015, the website for the data set lists more than 200 scholarly publications based on the data. Like the American household expenditure data, the CHIP data is comprised of repeated cross-sections of a random selection of Chinese households. The survey sample was drawn from a larger randomized set of urban and rural households collected by the State Statistical Bureau of China. Details on the methodology used in data collection can be found in Khan and Riskin (1998). In this study I use urban households surveyed in 1995 and 2002 for a total of 13,767 observations.[9] I use 14 good categories which correspond to aggregates of those in the American household expenditure survey. Table 1 details the link between the American and Chinese expenditure data. Additional details including Chinese category names is contained in appendix Table A.2.

Summary statistics for household heads in the United States and China are presented in Table 2.[10] Chinese household heads are more likely to be male, and much more likely to be married. These two statistics are linked. Due to gender norms a married couple being interviewed may be more likely to list the husband as the head of household. The marriage rates in China are high, but the household heads are relatively mature with an average age around 50 in both countries. The marriage rates in China are in line with what has been found by other research on marriage in China (Brandt et al., 2008). Americans are more educated than Chinese, both at the high school level and at the college level. The Chinese household size is a bit larger on average than the American household, most likely related to the larger proportion of married couples.

4.2 Visibility Indexes

Data concerning the visibility of good categories is taken from Heffetz (2011). Heffetz bases the index on randomized telephone surveys conducted in the United States in several waves around 2004. Survey respondents were asked how long it would take them to notice if a new acquaintance similar to themselves spent more than average on a particular good category. Respondents chose from five time periods ranging from almost immediately to almost never. Basic demographics similar to those in the consumer expenditure survey were also recorded for respondents.

From the survey responses, Heffetz creates indexes, called vindexes, between zero and one for each category of goods by averaging over survey results. A higher vindex value implies that a good category is more visible. A result of this aggregation methodology is that the index is cardinal rather than ordinal. Two goods with similar index values are similar in visibility. Details on the implementation of the

[9] I restrict the Chinese data to urban households because the level of poverty in rural households in China during this period makes comparisons with American consumers difficult.

[9] Air, Gas, Cmn, Cin

[10] I follow Heffetz (2011) in that if the individual-level data does not contain information on the household head, I use information on the spouse if present.

US Abrev.	US category definition	Chinese category def.
Air	Airline fares for out-of-town trips	Transportation fees
AlO	Alcoholic beverages at restaurants bars, cafeterias, cafes, etc.	Alcohol
AlH	Alcoholic beverages for home use	Alcohol
Bks	Books, including school books, newspapers and magazines, toys, games, and hobbies	Educational materials
Brb	Barbershops, beauty parlors, hair dressers, health clubs, etc.	Home furnishings and services
Bus	Public transportation, both local and long distance, like buses and trains	Transportation fees
CIn	Vehicle insurance, like insurance for cars, trucks, and vans	Transportation fees
CMn	Vehicle maintenance, mechanical and electrical repair and replacement	Transportation fees
Car	The purchase of new and used motor vehicles such as cars, trucks, and vans	Transportation fees
Cha	Contributions to churches or other religious organizations, and other charities	Other products and services
Cig	Tobacco products like cigarettes, cigars, and pipe tobacco	Cigarettes
Clo	Clothing and shoes	Clothes
Edu	Education, from nursery to college, like tuition and other school expenses	Educational expend. - Educational materials
FdH	Food and nonalcoholic beverages at grocery, specialty, and convenience stores	Food-Cig.-Alcohol
FdO	Dine out at restaurants, drive-throughs, etc, excluding alcohol; including food at school	Food-Cig.-Alcohol
Fee	Legal fees, accounting fees, and occupational expenses like tools and licenses	Other products and services
Fur	Home furnishings and household items, like furniture, appliances, tools, and linen	Home furnishings and services
Gas	Gasoline and diesel fuel for motor vehicles	Transportation fees
HIn	Homeowner's insurance, fire insurance, and property insurance	Housing
Hom	Rent, mortgage, or purchase of housing	Housing
Htl	Lodging away from home on trips and housing for someone away at school	Housing
Jwl	Jewelry and watches	Clothing
LIn	Life insurance, endowment, annuities, and other death benefits insurance	Medical and health
Lry	Laundry and dry cleaning	Home furnishings and services
Med	Medical care, including health insurance, drugs, dentists, doctors, hospitals, etc.	Medical and health
Ot1	Computers, games, TVs, video, audio, musical and sports equipment, tapes, CDs	Educ. and entertainment services - Educ.
Ot2	Cable TV, pets and veterinarians, sports, country clubs, movies, and concerts	Educ. and entertainment services - Educ.
Tel	Telephone services	Communication services
Utl	Home utilities such as electricity, gas, and water; garbage collection	Water,elec.,fuel,other

*Category definitions from Heffetz(2011) and translated by author from Chinese survey questionnaire. The minus signs in Chinese categories come from umbrella category from which we subtract a sub-category.

Table 1: Correspondence between Chinese and American category definitions

survey and calculation of the index are available in the original paper. Table A.1 in the appendix presents vindex survey data.

As I do not have a vindex equivalent for China, I use the aggregated American vindex data for the Chinese estimation. Since there are fewer good categories in the Chinese data, I collapse the American vindex by taking the mean over aggregated good categories. The sensitivity of my estimates to this assumption is assessed in Section 8.

	United States	China
Male	44.4%	66.5%
Married	58.7%	94.9%
Avg. Age	52.9	47.0
High Sch.	77.4%	61.5%
College	21.0%	8.9%
Avg. Members	2.3	3.1

Table 2: Summary statistics for household heads

5 Discussion and Identification Assumptions

We are interested in α, the weight given to the peer belief part of the utility function. The key identification issue is that, for a fixed α, *any* consumption bundle can be rationalized by a particular set of utility function parameters $\boldsymbol{\gamma}_i$. In order to separate preferences and conspicuous consumption, we need to take a stand on how utility parameters might be distributed. One natural assumption is that most people's preferences are broadly similar. To operationalize this idea, I assume that preferences for each household and each good category are independently drawn from lognormal distributions. In addition, to rationalize zero expenditure in a good category I assume that with some probability a consumer doesn't derive any pleasure from consumption of a particular category ($\gamma_{ig} = 0$).

A second challenge is that the Cobb-Douglass base utility assumption implies that there are no luxury or inferior goods. Absent any conspicuous consumption, expenditure shares are constant as household income increases. Figure 1 shows that expenditure shares are changing on average as household income increases. The combination of Cobb-Douglass utility and changing expenditure shares in principle identifies α in the model.

The Cobb-Douglass assumption is too strong, however. I want to allow a good like "food at home" to be inferior even without conspicuous consumption effects. To do this, I allow the location of the distribution of utility parameters to drift as a function of normalized income. In particular, the location parameter $\hat{\mu}_g(w_i)$ of the lognormal distribution for good category g is given by (7).

$$\hat{\mu}_g(w_i) = \psi_g \ln\left(\frac{w_i}{\underline{\mathrm{W}}}\right) + \mu_g \tag{7}$$

This 'money-in-the-utility-function' specification is somewhat ad hoc, but it allows us to keep the simple equilibrium condition (6) as well as allowing for rich evolution of expenditure shares with income. This distribution of utility parameters also breaks the simple identification of α from the correlation of household expenditure shares and income.

In order to regain identification, I use differences in observed vindexes across demographics. I assume that all utility parameters γ_i are drawn out of the same distribution, but observation types t_i are drawn with probability weighted by an individual's demographic specific vindex. The size of differences in average consumption between demographic groups are then informative about the weight α of peer group beliefs in the utility function.

In the United States I use visibility indexes for eight different demographic types of household. One dimension of differentiation is the age of the survey respondent (over/under age 40). The other dimension of differentiation is region in the United States (Northeast, Midwest, West, and South). An examination of The visibility probabilities are taken directly from Heffetz and normalized so that they sum to one. Table A.4 in the appendix characterizes observation-type probability distributions for the demographic groups. Standard multivariate statistical tests reported in the appendix reject the null-hypothesis that all eight visibility indexes are the same.

While there is a high correlation in observation-type probabilities across demographics, some reasonable differences between demographic groups emerge from Table A.4. Parents of secondary school and university students will probably not be surprised that younger people are more likely to signal with expenditure on clothing. It is also not surprising that older people are generally more likely to go to expensive medical care providers as a signal of wealth. Expenditures on automobiles are more likely to be used to signal in the Midwest and South, places where people drive everywhere.

I do not have separate vindexes for Chinese demographic categories, so when estimating Chinese preference parameters I cannot use an identification strategy based on the differences across demographic groups. In the Chinese estimation, I take the ψ_g's, the income scaling parameters in equation (7), as data from the American estimation. This assumption implies that luxury and inferior good categories are the same in both China and the United States. Deviations from Chinese expenditure share trends along with vindex probabilities identify α.

There are two issues which using American parameters in the Chinese estimation raises. The first is that Chinese consumers might rank the visibility of goods differently than American consumers. While it would of course be better to have a vindex calculated from Chinese survey data, on average using an average American vindex is likely to be a reasonable approximation to the average Chinese vindex. While the US estimation is based on heterogeneity between demographic groups in observation-type probability, as one might expect, the correlation across groups is still quite high. Jewelry is going to be more visible than insurance payments in any US demographic group. This is likely true in China as well. A second issue is that the correspondence between Chinese and American good categories broken out in Table 1 is not perfect. The categories which households are asked to group expenditures in China and the United States are not exactly the same. For example, the Chinese household is not asked to break out spending on jewelry separately from clothing, and it may in principle include jewelry expenditures in a different consumption category.

If the Chinese do have a very different average vindex compared with Americans, my estimates are likely to be biased downward. In the Chinese estimation, α is identified by the change in expenditure shares with income. If the goods I am assuming have the highest visibilities are actually low visibility goods in China, expenditure shares will be nearly flat in income in those goods. This will cause the estimated Chinese α to be too low. It is more difficult to predict the effect of misclassification of good categories on the estimates. In any case, as a robustness check I reestimate Chinese utility using each demographic-specific American visibility index, as well as randomly shocking the utility slope parameters taken from the American estimation. The results, reported in Section 8 are qualitatively the same, indicating that at least some degree of misclassification is unlikely to drastically alter my results.

The model assumes that each household signals with a single spending category. Modeling in this way is necessary because multi-dimensional signaling models are technically challenging. This paper is not the first to run into this issue. Some papers in the conspicuous consumption literature have relied on models including only one socially observable good (Heffetz, 2011), while others have ex-ante defined an aggregator of several expenditure categories as visible to peers, assuming that other spending is only privately observable (Charles et al., 2009; Perez-Truglia, 2012). In my methodology, any good category can potentially be socially observable, but ultimately each household uses only one expenditure category to signal. In a very loose sense, one might think of my methodology as a reduced form of a more complicated multi-dimensional signaling model. This point should not be overstressed, however, as signaling behavior can change dramatically when multiple signals are available (Matthews and Moore, 1987).

Finally, a key issue in any model of peer effects is to identify the correct peer group. In some studies in the literature, surveys are used to determine the identity of the relevant peer group. In economics, some recent examples from this literature are Conley and Udry (2010) and Christakis et al. (2010). I do not have a direct measure of peer group, so I will assume that a consumer's peer group is drawn from people of the same age, ethnicity, and region.

6 Estimation Procedure

In order to estimate the parameter of interest α, we must jointly estimate the observation type of each household and four preference distribution parameters for each good category. This is a large problem, so I split the estimation into two steps using a 'hard' expectation maximization algorithm. In the first step (maximization), I condition on the observation type of each household and update α and preference distribution parameters. In the second stage, I take α and the preference distribution parameters as given and find the most likely observation type of each household (expectation). The algorithm stops when there is close to no change in α.[11] As the algorithm is standard, I relegate a detailed discussion to Appendix B.

7 Results and an Application to an American Luxury Tax

Chinese care about 20% more than Americans about social beliefs. The weight of social beliefs α in American utility is 0.0266 with standard error 0.0001. In Chinese utility, the weight of social beliefs is 0.0316 with standard error 0.001. Standard errors are bootstrapped by repeatedly redrawing from the data and reestimating the model. All estimated parameters are presented in Appendix C.

The model is capable of simulating data similar to the real data set. Figure 2 is a scatter plot of simulated US data, superimposed on top of the scatter plots of the actual US data in Figure 1. The estimation also does well fitting observation types. The observation type distribution (for a particular demographic) should be the same as the vindex probability distribution. Figure 3 is a scatter plot of the vindex probabilities and the estimated observation type densities. Each point is labeled with the relevant good category, and the colors represent different demographic types (region and age). Although there is not a perfect correlation between vindex probabilities and observation type frequencies, there is a clear trend in the right direction. The model misses the most on good categories "car" and "jewelry". I suspect the problem is that these are durable goods, so that a single year of expenditure is a poor reflection of average expenditure in those categories.

As my model and data are modified from Heffetz (2011), it is useful to compare my results with his. Of course, Heffetz takes a much different approach to estimation. From his model he derives the prediction that a more visible good should have a larger elasticity with respect to income. Using the same American consumer expenditure share data that I use, he first constructs a population-weighted, average elasticity for each good, and then regresses this elasticity on his visibility index. Recall that the vindex is bounded between zero and one. In his baseline regression, he finds that an increase of a good's vindex of 0.1 will result in an increase in elasticity of consumption share of that good with respect to income of 0.18.[12]

Heffetz makes no claim to structurally estimate his model – he is just testing whether one of the model's predictions is borne out in the data. The left hand side of the regression in his test is an average elasticity, for example, while even in his relatively simple model the elasticity of expenditure share of a visible good

[11] Intuitively this algorithm converges because in each step the likelihood must weakly increase. As with other expectation maximization algorithms, the algorithm used here will stop at either a local maximum, or a saddle point.

[12] That is, if apples have a vindex of 0.5, and bananas have a vindex of 0.6, we should expect that a doubling of income will raise the consumption share of bananas 18% more than the consumption share of apples.

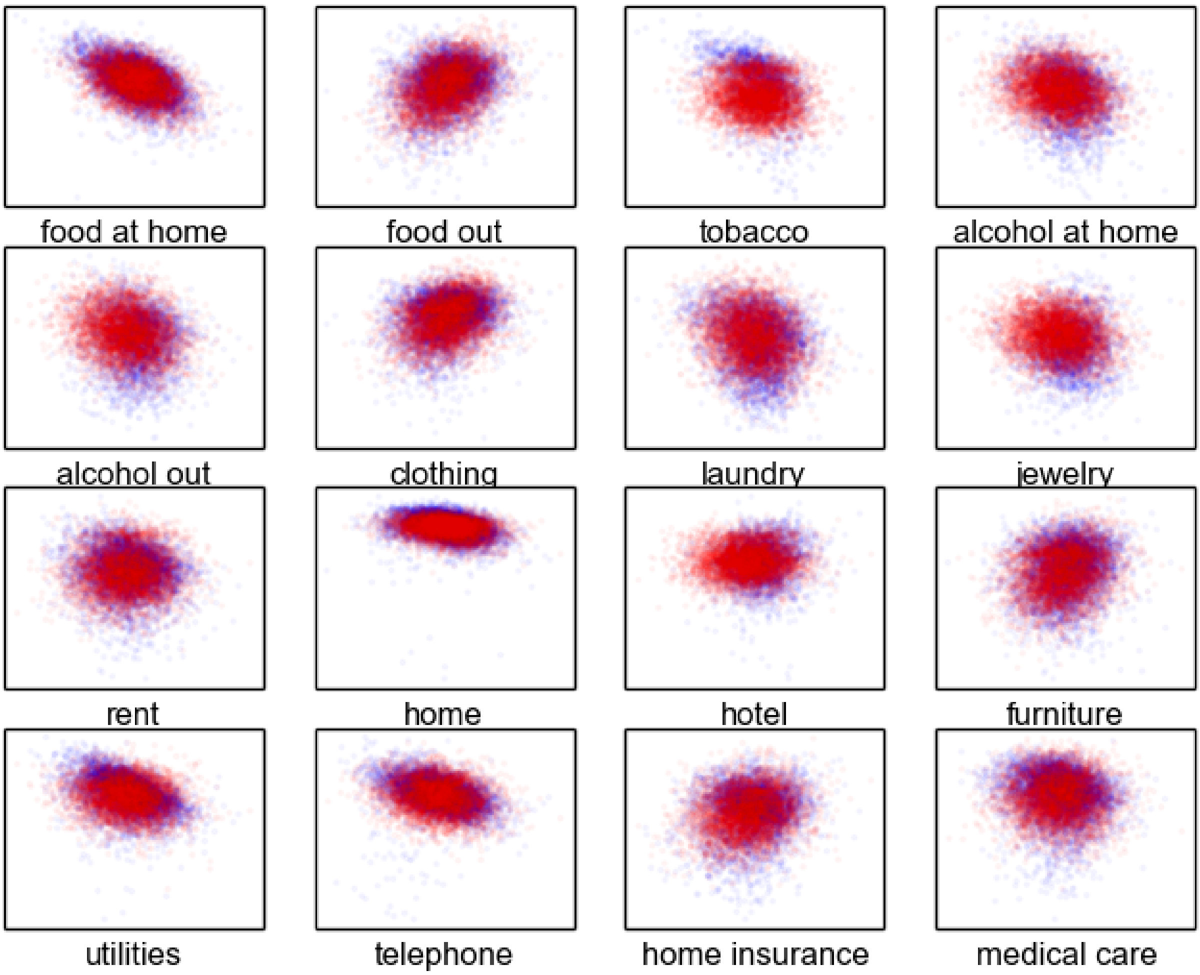

Figure 2: Log expenditure shares (y) by log expenditure (x), sim=red, dat=blue

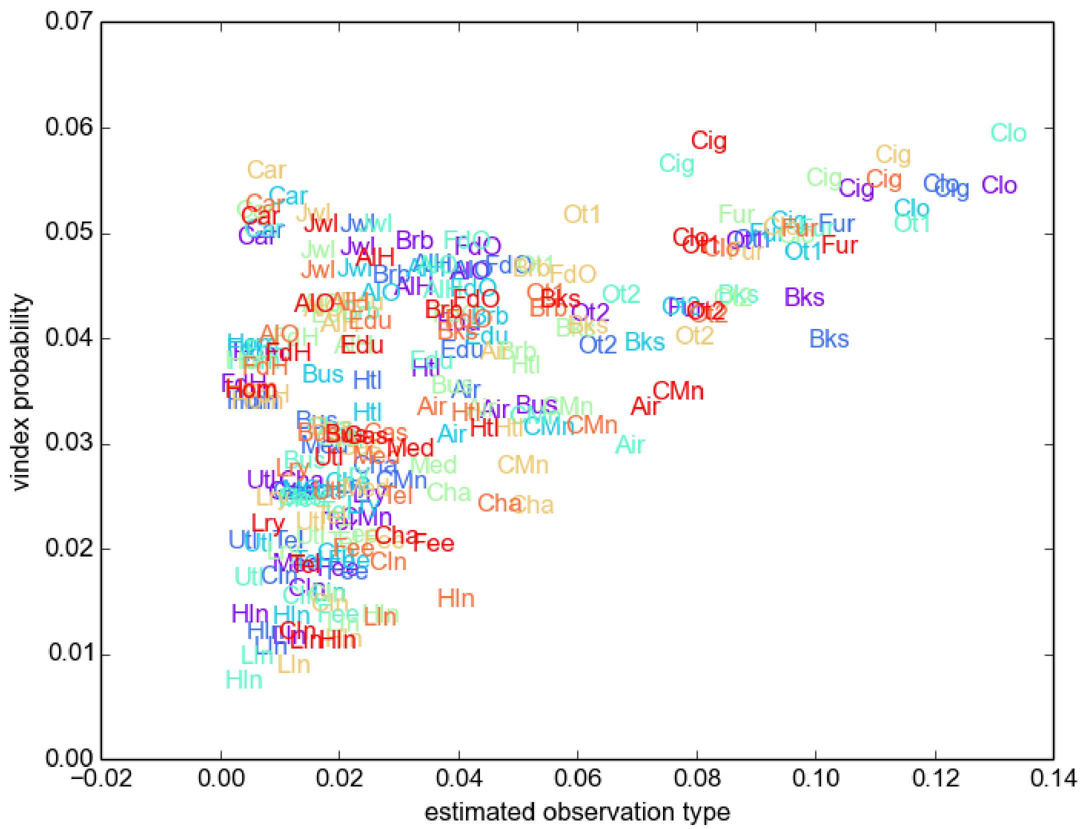

Figure 3: Estimated observation type frequencies vindex probabilities, by demographic

decreases with income.[13] As one might expect with the amount of flexibility in my model, simulations do an excellent job of replicating the expenditure share data, suggesting that a replication of the Heffetz methodology on my simulated data would be reasonably close to the original estimates.

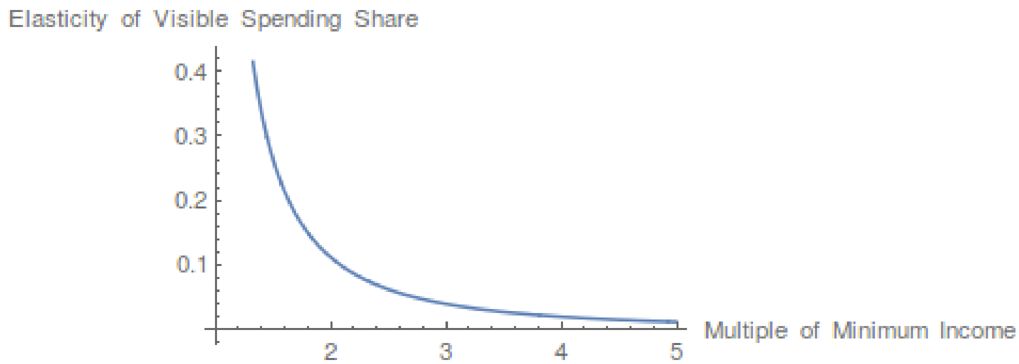

Figure 4: Elasticity of visible good share with respect to income as a multiple of lowest possible income

Rather than replicating the Heffetz regressions on my simulated data, it is maybe more interesting to consider the elasticity of visible good expenditure with respect to the income of a household in my estimated model. In my model, a household only signals with one expenditure category. The consumption share elasticity with respect to income of all other categories is slightly less than zero, as an increase in income causes a relative spending increase in the visible category. We can get the elasticity of the visible good share with respect to income by implicitly differentiating (6) with respect to income. Solving for the derivative of visible good consumption share r with respect to income, multiplying by income and dividing by r gives us an expression for the elasticity of the expenditure share on the visible good with respect to income:

$$\frac{\alpha+\gamma}{r\left(1+\gamma\right)\hat{w}^{-\frac{\alpha+\gamma}{\alpha}}\left(\left(1+\frac{1}{\gamma}\right)r\right)^{\frac{\gamma}{\alpha}}-\gamma} \tag{8}$$

The elasticity is not constant, but but falls as income increases.[14] The strength of signaling in utility as estimated ($\alpha = 0.027$). Further assuming equal utility weights ($\gamma = \frac{1}{28}$) and using (6) to get the share of spending on the visible good r for any given normalized income level $\hat{w}$, I numerically plot the elasticity of visible good share with respect to income as a multiple of lowest possible income in Figure 4.

[13]This is shown in Figure 1 of the working paper version of Heffetz (2004).

[14]Recall that normalized income is the minimum income level divided by the household's income level. It decreases as income rises. Thus the denominator of (8) approaches infinity as income grows, and the elasticity goes to zero.

The elasticity falls dramatically with income, and is equal to 18% (the Heffetz gain in elasticity from a 0.1 increase in vindex) when income is a little under twice the minimum income level.

7.1 Policy Analysis: Sales Taxes

In the model developed above, a consumer distorts his full-information utility-maximizing consumption bundle in order to signal his income. The signal is on expenditures, however, not on physical goods. In principle, a social planner could impose a sales tax on a highly visible good category in order to reduce physical consumption. In the real world, such a tax is sometimes known as a luxury tax. In this section I consider the welfare implications of two such tax schemes. The first is an American luxury tax on automobiles, and the second a sales tax on tobacco products in both China and the United States.

7.1.1 Application: Welfare Effect of US Automotive Luxury Taxes

In 1990, President George H.W. Bush signed the Omnibus Budget Reconciliation Act into law.[15] The OBRA contained a provision for a luxury tax on automobiles, as well as jewelry, furs, yachts, and personal aircraft. The tax on autos was 10% of the price exceeding $30,000. As one might imagine, the luxury tax did not go over well at campaign fundraisers and was repealed in 1993 for all goods except automobiles.[16] Congress finally scrapped the auto tax in 2002.

In this section, I measure the welfare effects of a 10% tax on automobiles, redistributed lump-sum as a proportion of wealth. Redistributing the tax proportionally to wealth conveniently abstracts from the welfare effect of a transfer from the rich to the poor. In addition, taxes redistributed this way change neither the individual nor aggregate fraction of wealth optimally allocated to any particular good category, as relative wealth remains unchanged.

My luxury tax will be 10% of spending on automobiles. Let $\tau = 0.1/1.1$ be the fraction of spending on autos taken by the government, let s be the fraction by which the government increases wealth levels, let l_i be the equilibrium fraction of auto expenditure in consumer i's total expenditures, and let L be the aggregate fraction of spending on automobiles. Condition (9) balances the budget.

$$\begin{aligned} (1+s)\tau \sum_i w_i l_i &= s \sum_i w_i \\ s &= \frac{\tau L}{1-\tau L} \end{aligned} \tag{9}$$

[15]Some readers might remember that this act proved television to be a poor medium for lip-reading.

[16]A cynical political realist might observe that luxury vehicles are often imported from Europe.

An individual's welfare change for a tax on automobiles is:

$$\Delta u_i = \sum_{g \in G} \gamma_{ig} \ln(1+s) + \gamma_{il} \ln(1-\tau) \tag{10}$$

Using (9), it can be shown that $\ln(1+s) + \ln(1-\tau) \leq 0$ with the inequality strict when the aggregate share of spending on automobiles L is less than one. Thus, it is impossible to have a truly Pareto sales tax in my environment. That is, it is always possible that some unlucky consumer will have all zero γ_{ig}'s in non-automobile expenditure categories, ensuring he will be harmed by a luxury tax. A sales tax on a luxury good can, however, potentially benefit all but a small fraction of consumers. The fraction of consumers harmed and average welfare gains will depend on the distribution of utility parameters the government faces.

The relationship between α and the tax scheme here is through the share of expenditures households spend on automobiles, a relatively visible good category. Since many households have automobiles as an observation type, fixing preference parameters and the tax level τ, all else equal the higher is α the more distortion there will be from signaling and the higher will be government subsidies s to consumers.

Figure 5 displays a histogram of percentage welfare changes resulting from a 10% automobile luxury tax, calculated for one million American households simulated using estimated model parameters from Section 7. Only three in 100,000 households are harmed by the auto luxury tax. The vast majority of households benefit from the automobile luxury tax. In contrast, a similar 10% sales tax on food at home harms 98% of households.

7.1.2 Comparison of tobacco sales tax in the United States and China

In this section, I compare the effect of a tobacco sales tax in the United States and China. Excise taxes on cigarettes are a popular policy tool in much of the Western world to discourage smoking. The median US state tax on cigarettes is 40% of the retail price.[17] As tobacco is also the most visible good category, expenditures on tobacco are often used for conspicuous consumption.[18] We perform the experiment on tobacco because it is the most visible good, but also because it is broken out separately in the Chinese data. Spending on automobiles, for example, is aggregated into a larger transportation category in the Chinese data, so it would be hard to compare a luxury tax on automobiles across countries.

[17] Data from the American Centers for Disease Control and Prevention https://chronicdata.cdc.gov/Policy/The-Tax-Burden-on-Tobacco-Volume-49-1970-2014.

[18] In author's personal experience, smokers with high social status in China often smoke expensive brands of cigarette. One popular brand is "Panda", the favored cigarette of Mao Zedong. According to the blog "China Whisper", a carton went for 1200 RMB or about 190 USD in 2013. http://www.chinawhisper.com/the-10-most-expensive-cigarettes-in-china/

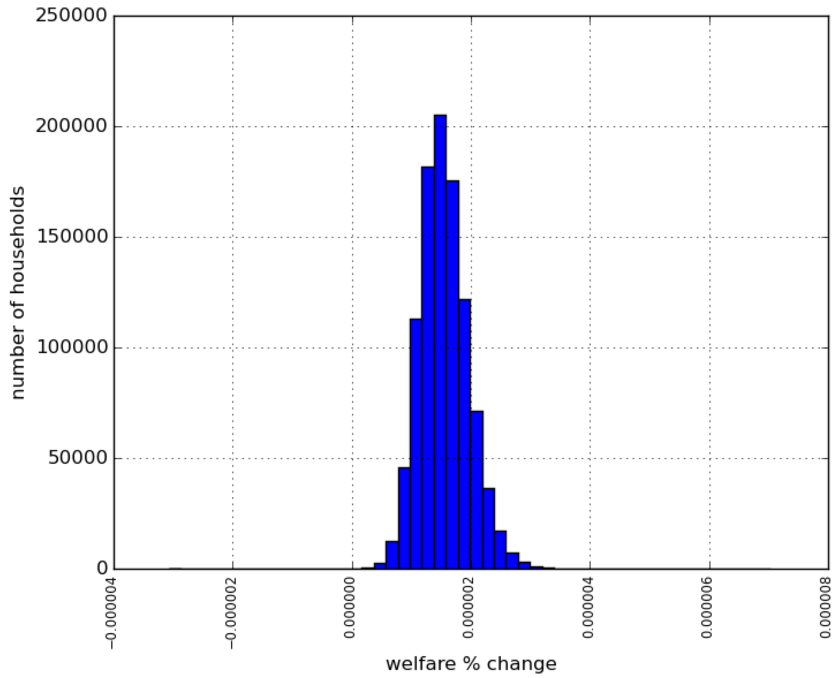

Figure 5: Histogram of American welfare changes from a 10% luxury auto tax

Chinese and American taxes will have different effects for a number of reasons, including strength of the conspicuous consumption motive, different utility parameters, and the different expenditure categories which enter utility. We want to isolate the effect of the motive for conspicuous consumption as measured by the parameter α in the model. To that end, we simulate an American cigarette tax twice, once with the estimated American level of α, and once with the larger estimated Chinese level of α. We repeat the experiment by simulating a Chinese cigarette tax with both the American and Chinese levels of α. We expect that increasing the motive for conspicuous consumption will increase the welfare benefits of the tax by moving consumption closer to the optimum level in the absence of signaling.

Data	α	Fraction harmed	% Δ	Med. wel. chng.	% Δ
US	US	0.3164		6.1294e-07	
US	CHN	0.3143	-0.0064	6.2862e-07	0.0256
CHN	US	0.3598		7.2322e-07	
CHN	CHN	0.3558	-0.0110	7.4763e-07	0.0338

Table 3: Effects of an (additional) 10% sales tax on cigarettes

Results are reported in Table 3. In line with the intuition from the model, if the

US had the Chinese level of motive for conspicuous consumption, around 1% fewer households would be hurt by a 10% increase in the cigarette sales tax, and median welfare gains would rise by around 3%. Likewise, should China have had the American level of motive for conspicuous consumption, around 1% more household would have been harmed by a 10% cigarette sales tax, and median welfare gains would have been around 3% lower. The fraction of households harmed in both countries by a tax on cigarettes is quite high at more than 30%. This is because while most people spend nothing on tobacco, those that smoke spend a relatively large fraction of expenditures on it. Because many people spend nothing, the revenue raised by a tobacco tax is low in an aggregate sense and the lump-sum rebates to each household from the tax are small. Since households which smoke and do not signal with tobacco spend a large share of expenditures on tobacco, the small rebate is not enough to compensate for the loss of tobacco consumption. When we raise α, people who signal with tobacco distort their consumption further by spending more on tobacco. Since the distortion is worse, a tax causes a greater increase in welfare. Moreover, because there is more spending on tobacco products, revenues of the tax are higher and we reduce the number of households harmed by the tax.

In summary, both the luxury tax on automobiles and a tobacco sales tax are shown to lead to median welfare gains, although the gains are not as widespread for a tobacco sales tax. An American automobile luxury tax, however, leads to gains for nearly all households. The effects of the tax are small, which is to be expected, as the intervention is only a tax on a single good category and is rebated lump-sum in proportion to wealth. In line with the model intuition, in both China and the United States gains from an excise tax on cigarettes are larger when the motive for conspicuous consumption is stronger. The lesson for policy makers is that tax incidence depends upon cultural values, and in particular the motive for conspicuous consumption.[19]

8 Robustness

The policy conclusions found in the last section are dependent upon several modeling assumptions. One of these assumptions is that Chinese consumers have the average visibility index of American consumers. A second assumption is that if an expenditure category is inferior in the United States, it is also inferior in China. More precisely, Chinese and American utilities deliver identically sloped no-signaling Engels curves. These assumption are necessary to identify the model, since the Chi-

[19]My empirical exercise is about culture across countries, but one could imagine that within a country cultural differences between groups could also lead to differences in the incidence of luxury or other excise taxes. Charles et al. (2009) finds that blacks and whites in the United States spend markedly different shares of total expenditure on visible goods. Excise taxes might affect these communities differently.

nese data is more limited than the American data. In this section, I perform two robustness exercises. In the first, I reestimate Chinese utility parameters with all eight demographically differentiated American vindexes. In the second, I randomly perturb the Chinese utility terms ψ, which govern the slope of Engels curves, up to 25% around the estimated American levels. I then report the variation in the new parameter estimates. Most parameter estimates are qualitatively robust to these experiments.

demographic	alpha
be40northeast	0.034317
be40midwest	0.031809
be40west	0.031306
be40south	0.032268
up40northeast	0.033234
up40midwest	0.032587
up40west	0.033645
up40south	0.031813
mean	0.032622
std. dev.	0.001033

Table 4: Demographic videxes and Chinese conspicuous consumption motive

Table 4 contains estimated Chinese conspicuous consumption motives α using each of the eight demographically differentiated American vindexes. The estimates do vary a bit from 0.031306 to 0.034317, but they are qualitatively similar, with the mean of 0.032622 about one standard deviation higher than the baseline estimated Chinese α of 0.031638. All of the estimates are higher than the estimated American α of 0.026632.

In the second robustness exercise, American slope parameters ψ were shocked randomly up to 25% of their absolute value. The Chinese utility parameters were then reestimated using the shocked parameters. This was done one hundred times. Table 5 contains the standard deviation of the estimated utility parameters as well as the baseline estimated parameters. Some parameters are more sensitive than others. For example, the probability of zero consumption z is not sensitive at all, while the average weight of alcohol in utility μ for Alh/AlO has a standard error more than twice as large as the its estimated baseline value.[20] Our main parameter of interest, the conspicuous consumption motive α, is little affected by the experiment. On the whole, the estimated parameters seem fairly robust to deviations from the American slope parameters.

[20]It can be seen from Table C.2 that this parameter is estimated with little precision.

Cat	std dev μ	baseline μ	std dev σ	baseline σ	std err z	baseline z
Fdh/Fdo	0.003537	3.79	0.000290	0.13	0.000000	0.00
Cig	0.074227	0.70	0.004457	1.08	0.000016	0.47
Alh/Alo	0.171268	0.08	0.029300	3.72	0.000062	0.10
Clo/Jwl	0.016124	2.02	0.000638	0.72	0.000016	0.01
Ot1/Ot2	0.078940	0.54	0.015542	1.34	0.000016	0.03
Fur/Lry/Brb	0.038842	1.38	0.009454	1.62	0.000016	0.03
Med/Lin	0.035551	1.02	0.003489	2.06	0.000030	0.07
Bus/Car/Gas/	0.040814	-0.50	0.005457	1.44	0.000016	0.17
Tel	0.136319	1.27	0.013318	1.79	0.000016	0.30
Edu	0.023848	0.98	0.001506	1.32	0.000016	0.25
Bks	0.059662	-0.72	0.004651	0.79	0.000016	0.55
Hom/Htl/Hin	0.057353	-0.08	0.002447	1.87	0.000016	0.51
Utl	0.105151	2.10	0.002615	0.59	0.000016	0.01
Fee/Cha	0.021170	1.61	0.003278	1.41	0.000040	0.01
α	0.000156	0.032				

Table 5: Standard deviation of estimated parameters (and baseline estimated parameters), randomly shocking ψ up to 25%

9 Summary

I develop a structural conspicuous consumption model with preference heterogeneity estimable from consumption expenditure data and information on the visibility of expenditures. Using the model, I estimate the motive to conspicuously consume in both China and the United States. I find that Chinese have a stronger motivation to conspicuously consume. I use the estimated model to show that a 1990's luxury tax on automobiles in the United States had broad but small welfare benefits, harming very few people. In another experiment, I show that raising the level of the conspicuous consumption motive from the US level to the Chinese level reduces the fraction of people harmed by a tobacco sales tax, and increases the median welfare gains. This result holds in both the United States and China.

One strong assumption in the model is that a household's peer group sees only consumption expenditures on one good category. While a single-dimensional signal generates a unique and simple equilibrium solution in my model, it is clearly counterfactual. In the real world, one's peer group sees a full, noisy vector of consumption expenditures. Future research might focus on relaxing this stark assumption about the observability of consumption.

References

Arnould, E. J. and Thompson, C. J. (2005). Consumer culture theory (CCT): Twenty years of research. *Journal of consumer research*, 31(4):868–882.

Bloch, F., Rao, V., and Desai, S. (2004). Wedding Celebrations as Conspicuous Consumption. *Journal of Human Resources*, 39(3):675–695.

Bolton, G. and Ockenfels, A. (2000). ERC: A theory of equity, reciprocity, and competition. *The American Economic Review*, pages 166–193.

Brandt, L., Siow, A., and Vogel, C. (2008). Large shocks and small changes in the marriage market for famine born cohorts in china. *Working paper*.

Charles, K. K., Hurst, E., and Roussanov, N. (2009). Conspicuous Consumption and Race. *The Quarterly Journal of Economics*, 124(2):425–467.

Christakis, N. A., Fowler, J. H., Imbens, G. W., and Kalyanaraman, K. (2010). An empirical model for strategic network formation. *National Bureau of Economic Research*.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in ghana. *The American Economic Review*, pages 35–69.

De Giorgi, G., Frederiksen, A., and Pistaferri, L. (2015). Consumption network effects. *Working paper*.

Duesenberry, J. S. (1967). *Income, Saving, and the Theory of Consumer Behavior*. Oxford University Press.

Fehr, E. and Schmidt, K. (1999). A Theory of Fairness, Competition, and Cooperation. *The Quarterly Journal of Economics*, 114(3):817–868.

Friehe, T. and Mechtel, M. (2014). Conspicuous consumption and political regimes: Evidence from east and west germany. *European Economic Review*, 67:62–81.

Heffetz, O. (2004). Conspicuous consumption and the visibility of consumer expenditures. *Department of Economics, Princeton University*.

Heffetz, O. (2011). A test of conspicuous consumption: Visibility and income elasticities. *Review of Economics and Statistics*, 93(4):1101–1117.

Ireland, N. J. (1994). On Limiting the Market for Status Signals. *Journal of Public Economics*, 53:91–110.

Khan, A. R. and Riskin, C. (1998). Income and inequality in china: composition, distribution and growth of household income, 1988 to 1995. *The China Quarterly*, 154:221–253.

Li, S. (2002). Chinese Household Income Project. *Inter-university consortium for Political and Social Research*.

Luttmer, E. (2004). Neighbors as Negatives: Relative Earnings and Well-being. *National Bureau of Economic Research*.

Matthews, S. and Moore, J. (1987). Monopoly provision of quality and warranties: An exploration in the theory of multidimensional screening. *Econometrica: Journal of the Econometric Society*, pages 441–467.

Moav, O. and Neeman, Z. (2010). Status and Poverty. *Journal of the European Economic Association*, 8:413–420.

Moav, O. and Neeman, Z. (2012). Saving Rates and Poverty: The Role of Conspicuous Consumption and Human Capital. *The Economic Journal*, 122:933–956.

National Bureau of Economic Research (2011). Consumer Expenditure Survey Family-Level Extracts. http://www.nber.org/data/ces_cbo.html.

Perez-Truglia, R. (2012). Measuring the market value of non-market goods: The case of conspicuous consumption. *Working paper*.

Perez-Truglia, R. (2013). A test of the conspicuous-consumption model using subjective well-being data. *Available at SSRN 1934007*.

Podoshen, J. S., Li, L., and Zhang, J. (2011). Materialism and conspicuous consumption in china: A cross-cultural examination. *International Journal of Consumer Studies*, 35(1):17–25.

Wong, N. Y. and Ahuvia, A. C. (1998). Personal taste and family face: Luxury consumption in confucian and western societies. *Psychology and Marketing*, 15(5):423–441.

A Vindex Tables and Data details

Category	Vindex	SE
cigarettes	0.76	(0.014)
cars	0.72	(0.012)
clothing	0.70	(0.013)
furniture	0.68	(0.012)
jewelry	0.67	(0.015)
recreation 1	0.66	(0.012)
food out	0.61	(0.012)
alcohol home	0.60	(0.014)
barbers etc	0.60	(0.014)
alcohol out	0.59	(0.014)
recreation 2	0.57	(0.013)
books etc	0.57	(0.013)
education	0.56	(0.014)
food home	0.51	(0.014)
rent/home	0.49	(0.016)
cell phone	0.46	(0.016)
air travel	0.46	(0.014)
hotels etc	0.45	(0.013)
public trans	0.44	(0.015)
car repair	0.42	(0.014)
gasoline	0.39	(0.016)
health care	0.36	(0.014)
charities	0.34	(0.014)
laundry	0.33	(0.015)
home utilities	0.31	(0.015)
home phone	0.29	(0.015)
legal fees	0.26	(0.013)
car insur	0.22	(0.014)
home insur	0.16	(0.012)
life insur	0.16	(0.011)
underwear	0.12	(0.011)

Table A.1: Aggregate Vindex

US Cat	1995 Chn Cat	2002 Chn Cat	2002 Chn Cat Name	Translation
Fdh,Fdo	h27	e1-e152-e153	食品 - 烟草类 - 酒类	Food-Cig.-Alcohol
Alh,Alo	h30-h31	e153	酒类	Alcohol
Cig	h31	e152	烟草类	Cigarettes
Bks	h37	f631	教材	Educational materials
Edu	h38 to h42	f63-f631	教育支出 - 教材	Educational expend. - Educational materials
Bus,Car[21]	h44	f514	交通费	Transportation fees
Utl	h45 to h46	f72	水电燃料及其他	Water,elec.,fuel,other
Tel	h47	f522	通信服务	Communication services
Clo,Jwl	h32	f2	衣着	Clothes
Ot1,Ot2	h33	f6-f63	教育文化娱乐服务 - 教育支出	Educ. and entertainment services - Educ.
Fur,Lry,Brb	h34,h36	f3	家庭设备用品及服务	Home furnishings and services
Med,Lin	h48	f4	医疗保健	Medical and health
Hom,Htl,Hin	h64	f71	住房	Housing
Fee,Cha	h35	f8	杂项商品和服务支出	Other products and services

Table A.2: US-China Consumption Category Correspondence

Abbrev.	Category definition*	Interviewee age under 40				Interviewee age over 40			
		NEast	South	MWest	West	NEast	South	Mwest	West
Air	Airline fares for out-of-town trips	3.2	3.0	3.4	2.9	3.2	3.2	3.7	3.2
AlO	Alcoholic beverages at restaurants bars, cafeterias, cafes, etc.	4.4	4.5	4.6	4.3	3.8	4.2	4.0	4.6
AlH	Alcoholic beverages for home use	4.5	4.3	4.5	4.6	4.2	3.9	4.2	4.2
Bks	Books, including school books, newspapers and magazines, toys, games, and hobbies	4.3	3.8	3.9	4.3	4.0	3.9	4.0	4.2
Brb	Barbershops, beauty parlors, hair dressers, health clubs, etc.	4.8	4.1	4.5	4.1	3.8	4.2	4.5	4.1
Bus	Public transportation, both local and long distance, like buses and trains	3.2	3.5	3.1	2.7	3.4	3.0	3.0	3.0
CIn	Vehicle insurance, like insurance for cars, trucks, and vans	1.5	1.8	1.6	1.4	1.4	1.7	1.4	1.1
CMn	Vehicle maintenance, mechanical and electrical repair and replacement	2.2	3.0	2.5	3.1	3.2	3.0	2.7	3.4
Car	The purchase of new and used motor vehicles such as cars, trucks, and vans	4.8	5.2	4.9	4.9	5.1	5.2	5.5	5.0
Cha	Contributions to churches or other religious organizations, and other charities	2.5	2.5	2.7	3.0	2.4	2.3	2.3	2.0
Cig	Tobacco products like cigarettes, cigars, and pipe tobacco	5.3	5.0	5.3	5.5	5.4	5.4	5.6	5.7
Clo	Clothing and shoes	5.3	5.1	5.3	5.8	4.9	4.7	4.9	4.8
Edu	Education, from nursery to college, like tuition and other school expenses	4.0	3.9	3.8	3.7	4.1	4.0	4.2	3.8
FdH	Food and nonalcoholic beverages at grocery, specialty, and convenience stores	3.4	3.8	3.3	3.8	3.9	3.6	3.3	3.7
FdO	Dine out at restaurants, drive-throughs, etc, excluding alcohol; including food at school	4.7	4.3	4.6	4.8	4.1	4.1	4.5	4.2
Fee	Legal fees, accounting fees, and occupational expenses like tools and licenses	1.7	1.8	1.7	1.3	2.0	1.9	2.0	1.9
Fur	Home furnishings and household items, like furniture, appliances, tools, and linen	4.2	4.9	5.0	4.9	5.0	4.9	4.7	4.8
Gas	Gasoline and diesel fuel for motor vehicles	2.4	2.4	2.4	2.4	2.9	3.0	2.8	2.9
HIn	Homeowner's insurance, fire insurance, and property insurance	1.3	1.2	1.1	0.6	1.3	1.4	1.0	1.0
Hom	Rent, mortgage, or purchase of housing	3.7	3.8	3.3	3.7	3.7	3.4	3.3	3.4
Htl	Lodging away from home on trips and housing for someone away at school	3.6	3.2	3.5	2.9	3.6	3.2	3.0	3.0
Jwl	Jewelry and watches	4.7	4.5	5.0	5.0	4.7	4.5	5.1	5.0
LIn	Life insurance, endowment, annuities, and other death benefits insurance	1.0	1.5	1.0	0.9	1.2	1.2	0.8	1.0
Lry	Laundry and dry cleaning	2.4	2.3	2.5	2.6	1.9	2.6	2.4	2.1
Med	Medical care, including health insurance, drugs, dentists, doctors, hospitals, etc.	1.7	2.4	2.9	2.3	2.7	2.8	2.4	2.8
Ot1	Computers, games, TVs, video, audio, musical and sports equipment, tapes, CDs	4.8	4.7	4.8	5.0	4.6	4.3	5.0	4.8
Ot2	Cable TV, pets and veterinarians, sports, country clubs, movies, and concerts	4.1	4.2	3.8	4.3	4.3	4.1	3.9	4.1
Tel	Telephone services	2.1	1.8	2.0	2.2	1.9	2.4	2.2	1.7
Utl	Home utilities such as electricity, gas, and water; garbage collection	2.5	1.9	2.0	1.6	2.0	2.4	2.1	2.7

*Category definitions from Heffetz(2011)

Table A.3: Observation type probabilities by demographic category

Test	Statistic	F	Prob > F
Wilks' lambda	0.5150	1.42	0.001
Pillai's trace	0.6259	1.42	0.001
Lawley-Hotelling trace	0.7047	1.43	0.001
Roy's largest root	0.1875	2.70	0.000

Table A.4: Test for equality of vindexes (Stata's mvtest)

B Details on Estimation Algorithm

In this section I discuss the estimation algorithm in detail.

B.1 Maximization: Updating α and Preference Distribution Parameters

B.1.1 Overview

In the maximization step, I condition the likelihood function on the observation type t_i of each household and update α and lognormal preference distribution parameters μ_g, σ_g, income-scaling parameter ψ_g, and a zero probability z_g. The outer structure of the maximization step uses a numerical optimizer to maximize the conditional likelihood over α, treating the likelihood-maximizing preference parameters and preference distribution parameters as functions of α. Given α, the preference parameters $\boldsymbol{\gamma}_i$ of each household can be quickly calculated using observed consumption shares. Once we have preference parameters for each household, we can analytically calculate the most likely lognormal preference distribution and zero consumption parameters.

B.1.2 Recovering Household Preference Parameters Given α

Taking observation type t_i and α as given, there is a mapping from observed consumption shares directly to household preference parameters. Consider a household of observed income type w, observed consumption vector C, and observation type t. Rearranging (2), γ_g for $g \neq t$ are given by :

$$
\begin{aligned}
p_g c_g &= \frac{\gamma_g}{\sum_{g \neq t} \gamma_g} (w - p_t c_t) \\
\gamma_g &= \frac{p_g c_g}{(w - p_t c_t)}
\end{aligned}
\tag{11}
$$

We can solve for the 28 non-observation type γ_g's up to a scaling factor $\sum_{g \neq t} \gamma_g = 1$. Using (11) and the equilibrium condition (4) we can then solve for γ_t. Unfortunately, (4) is non-linear and in principle needs to be solved numerically for each household. To decrease estimation time, in practice I solve (4) on a 1000 point grid of visible consumption shares and incomes, and then linearly interpolate to find household specific γ_t's.

B.1.3 Updating Preference Distribution Parameters

Given α and household preference parameters $\boldsymbol{\gamma}_i$ for each household $i \in I$, the most likely zero probability z_g^* for good category g is the fraction of zero γ_{ig}'s:

$$
z_g^* = \frac{1}{\|I\|} \sum_i \mathbf{1}_{\gamma_{ig}=0}
$$

Let an upper bar denote sample means over non-zero γ_i's, and let m_i refer to normalized income, $m_i = w_i/\underline{\mathrm{W}}$. The other likelihood-maximizing preference parameters are:

$$
\begin{aligned}
\psi_g^* &= \frac{\hat{\text{cov}}(\ln m, \ln \gamma)}{\hat{\text{var}}(\ln m)} \\
\mu_g^* &= \overline{\ln \gamma} - \psi_g^* \overline{\ln m} \\
\sigma_g^{2*} &= \overline{\left(\ln \gamma - \psi_g^* \ln m - \mu_g^*\right)^2}
\end{aligned} \tag{12}
$$

B.1.4 Full Conditional Likelihood Function

I have shown how, given observation types, it is straight-forward to calculate preference parameters and likelihood maximizing preference distribution parameters as a function of α. Let ϕ be the log-normal probability density function. The maximization step conditional log-likelihood function is given in (13). All preference parameters and preference distribution parameters are implicitly functions of α.

$$
l^1(\alpha) = \sum_{ig} \Big(\mathbf{1}_{\{\gamma_{ig}=0\}} \ln(z_g) + \mathbf{1}_{\{\gamma_{ig}\neq 0\}} \left(\ln(1-z_g) + \ln \phi(\gamma_{ig}, m_i | \mu_g, \sigma_g, \psi_g)\right) \Big) \tag{13}
$$

Likelihood (13) is the objective function used by the numerical solver in the search for α. This completes the characterization of the maximization step in the algorithm.

B.2 Expectation: Updating Observation Type t_i

Given the utility weight of social beliefs α and a set of preference distribution parameters, we find the most likely observation type for each household. Now preference parameters γ_{ig} are a function of observation type t and are calculated exactly as in Section B.1.2. $\mathbf{v}_i$ is the household-specific vector of observation type probabilities. Household i's (unnormalized) probability of being observation type $t \in G$ is given by (14).

$$
l_i^2(t) = \ln(v_{it}) + \sum_{g} \Big(\mathbf{1}_{\{\gamma_{ig}=0\}} \ln(z_g) + \mathbf{1}_{\{\gamma_{ig}\neq 0\}} \left(\ln(1-z_g) + \ln \phi(\gamma_{ig}, m_i | \mu_g, \sigma_g, \psi_g)\right) \Big) \tag{14}
$$

For each household, I assign the observation type giving the highest probability. This concludes the discussion of the estimation routine.

C Detailed Results

Good Cat	μ	std err	σ	std err	ψ	std err	z	std err
FdH	3.98	(0.011)	0.22	(0.002)	0.44	(0.003)	0.00	(0.000)
FdO	-0.48	(0.025)	0.82	(0.007)	-0.42	(0.006)	0.06	(0.001)
Cig	0.92	(0.020)	0.38	(0.003)	0.22	(0.005)	0.64	(0.001)
AlH	0.94	(0.016)	0.68	(0.006)	0.37	(0.005)	0.47	(0.002)
AlO	1.05	(0.026)	1.19	(0.007)	0.48	(0.008)	0.46	(0.002)
Clo	-0.81	(0.027)	1.01	(0.011)	-0.42	(0.006)	0.05	(0.000)
Lry	0.79	(0.031)	1.24	(0.010)	0.47	(0.009)	0.31	(0.002)
Jwl	0.61	(0.021)	0.90	(0.008)	0.32	(0.006)	0.57	(0.002)
Brb	0.07	(0.020)	0.64	(0.006)	0.11	(0.005)	0.09	(0.001)
Hom	4.17	(0.011)	0.19	(0.001)	0.23	(0.003)	0.00	(0.000)
Htl	0.09	(0.019)	0.60	(0.010)	0.06	(0.006)	0.52	(0.002)
Fur	-0.87	(0.032)	1.45	(0.015)	-0.29	(0.009)	0.17	(0.001)
Utl	2.50	(0.020)	0.31	(0.002)	0.27	(0.005)	0.04	(0.001)
Tel	2.12	(0.024)	0.45	(0.006)	0.37	(0.006)	0.01	(0.000)
HIn	-0.61	(0.032)	1.18	(0.008)	-0.22	(0.008)	0.19	(0.001)
Med	2.03	(0.030)	1.35	(0.014)	0.16	(0.008)	0.05	(0.001)
Fee	0.13	(0.027)	1.25	(0.012)	0.15	(0.007)	0.25	(0.002)
LIn	0.38	(0.023)	0.73	(0.006)	0.06	(0.006)	0.45	(0.001)
Car	-2.31	(0.028)	1.06	(0.008)	-0.86	(0.008)	0.76	(0.001)
CMn	-0.45	(0.023)	1.40	(0.012)	-0.23	(0.006)	0.13	(0.001)
Gas	0.92	(0.024)	0.53	(0.005)	-0.04	(0.006)	0.07	(0.001)
CIn	0.62	(0.018)	0.44	(0.005)	-0.02	(0.005)	0.22	(0.001)
Bus	0.78	(0.025)	0.99	(0.008)	0.33	(0.008)	0.63	(0.001)
Air	0.02	(0.014)	0.41	(0.008)	0.00	(0.004)	0.67	(0.002)
Bks	-0.75	(0.026)	0.89	(0.008)	-0.16	(0.007)	0.07	(0.000)
Ot1	-0.27	(0.027)	1.36	(0.012)	-0.04	(0.007)	0.29	(0.001)
Ot2	-0.72	(0.034)	0.89	(0.009)	-0.40	(0.009)	0.07	(0.001)
Edu	-0.21	(0.017)	0.86	(0.009)	-0.06	(0.005)	0.70	(0.002)
Cha	-0.06	(0.031)	1.35	(0.011)	-0.04	(0.009)	0.41	(0.001)
α	0.026632	(0.000)						

Table C.1: US Parameter Estimates

Good Cat	μ	std err	σ	std err	ψ	z	std err
Fdh/Fdo	3.79	(0.111)	0.13	(0.889)	0.01	0.00	(0.007)
Cig	0.70	(0.111)	1.08	(0.889)	0.22	0.47	(0.007)
Alh/Alo	0.08	(0.077)	3.72	(0.571)	0.42	0.10	(0.004)
Clo/Jwl	2.02	(0.013)	0.72	(0.017)	-0.04	0.01	(0.001)
Ot1/Ot2	0.54	(0.022)	1.34	(0.050)	-0.22	0.03	(0.002)
Fur/Lry/Brb	1.38	(0.020)	1.62	(0.040)	0.09	0.03	(0.002)
Med/Lin	1.02	(0.071)	2.06	(0.488)	0.11	0.07	(0.003)
Bus/Car/Gas/	-0.50	(0.022)	1.44	(0.046)	-0.13	0.17	(0.005)
Tel	1.27	(0.117)	1.79	(1.142)	0.37	0.30	(0.006)
Edu	0.98	(0.021)	1.32	(0.038)	-0.06	0.25	(0.006)
Bks	-0.72	(0.035)	0.79	(0.085)	-0.16	0.55	(0.007)
Hom/Htl/Hin	-0.08	(0.062)	1.87	(0.267)	0.15	0.51	(0.007)
Utl	2.10	(0.011)	0.59	(0.012)	0.27	0.01	(0.001)
Fee/Cha	1.61	(0.018)	1.41	(0.032)	0.05	0.01	(0.001)
α	0.031638	(0.001)					

Table C.2: Chinese Parameter Estimates