Quantifying the Gains from Trade Across Countries with Consumer Heterogeneity *

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Abstract

The workhorse consumer utility model in international trade literature assumes constant elasticity of substitution (CES). The CES assumption, estimates the consumer welfare change by a representative consumer. However the majority consumer groups who are represented by the representative consumer differ across countries such that the bias in the welfare gains in the CES framework differs across countries as well. I connect the CES bias with income distribution to illustrate that comparing welfare gains from international trade by the CES assumption across countries will significantly underestimate the welfare gains differences between developed and developing countries.

(PRELIMINARY AND NOT FOR CITATION)

1 Introduction

Trade economists have developed many theoretical models and empirical proofs from different perspectives to show how important international trade and trade liberalization are. However, when it comes to ask how expensive protectionism is, as said "The answer is a little embarrassing, because standard estimates of the cost of protection are actually very low… the negative effects of U.S. import restrictions on efficiency are therefore much smaller – around one-quarter of 1 percent of U.S. GNP." Krugman (1990). Since then economists tried various ways to extend our understanding of welfare impact from trade liberalization. In these studies, the most popular specification is CES utility (Spence, 1976; Dixit & Stiglitz, 1977) combined with monopolistic competition. In their recent work, Arkolakis, Costinot

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and Rodriguez-Clare(2010) revisited the welfare estimation of trade liberalization and concluded that comparing with autarky, free trade provided the United States benefits as large as 0.7% to 1.4% of US GDP. Their estimates are also based on CES utility with either perfect or monopolistic competition.

Along with its convenience and simplification from CES assumption comes its drawbacks. CES utility assumes that each individual is represented by a representative. Therefore, when I estimate consumer welfare changes with new product or prices change, I will assume each individual will behave the same as the representative consumer. They have the same own price elasticity. Combined with monopolistic competition, each individual will have zero cross price elasticity, exactly the same across all consumers, regardless of the differences in consumer's income, household size etc. Furthermore, own price elasticity is the same across products. All these result in a very simple price elasticity matrix - own price elasticity is captured by the same single parameter for any goods and any consumer; and all cross product price elasticity is equal to zero. Most trade impact analyses were done with these strong elasticity restrictions.

However, *how representative the representative consumer is*? Could the aggregate welfare change due to any shock be accurately represented?

Hausman(1997) argues that the CES will overvalue new goods because of the IIA property. But Nevo (2011) argues that the difference could be positive or negative.

Petrin (2002) follows Berry, Levinsohn, and Pakes(BLP) (1995, 1999, 2004) specification to study the introduction of the minivan in the US. In his paper, as the significant developments in the IO literature on consumer heterogeneity, including the "BLP" papers, among others, Petrin's estimation allows estimated substitution patterns and welfare to reflect demographic-driven differences in tastes for observed product attributes. Since BLP specification allows more accurate substitution pattern and takes into more information and variation in data, it is proved to be closer to the reality. He shows that estimating a model assuming same tastes across individuals can lead to average compensating variations for new goods that are two times as large compared to those from BLP specifications.

Similarly, very recent research by Sheu (2011) used India printers data to analyze where the bias comes from, either from category level data, like customs data or from the ignorance of consumer heterogeneity. She concludes that using aggregate level data is the major source of bias. My paper follows hers paper but differs from hers in the following aspects. First, I am going to use household data, where I not only know market level information for each type of TV but also know each individual household's choice decision. The more detailed data will potentially provide me more credible estimates. I also allow for consumer heterogeneity, but not by imposing distribution of coefficients, i.e., random coefficient. I will interact consumer characteristics with product attributes explicitly, such as, my identification will not come from functional form. Thirdly, my major interest is to see how the potential bias in the CES depends on income distribution.

None of previous papers tells the relationship between the bias in CES estimates of consumer welfare gains and *income distribution*. However these relations will be very important for international trade analysis when I simply use CES assumptions to do welfare comparison across countries.

Bajona et. al. (2010) applies the simple welfare gains formula in Arkolakis et. al. (2010) to estimate the consumer welfare gains for Mexico and China. They find that the other parameters are similar in both countries. They assume the parameter that captures the own price elasticity is the same across all consumers within each country and the same across countries. Given these conditions, they conclude, with simple welfare formula due to CES assumption, both China and Mexico have experienced almost identical gains from their expansion of trade. The extremely simple formula in Arkolakis et. al. (2010) could also be easily applied to any other countries, both developed and developing countries to measure consumer welfare gains due to international trade. But if the CES bias is upward in one country but downward in the other country, the CES welfare estimates will not be comparable across countries. This concern is understated. It could be very serious if these two countries are significantly different in their income distribution.

In my paper, I test the relationship between the CES bias and income distribution in my counterfactural analysis.

My paper applies IO heterogeneous coefficient (HC) specification to first get the CES bias for the U.S. by using a U.S. television data. This specification allows for consumer heterogeneous tastes. These different tastes together with consumer distribution will determine the price elasticity matrix. HC specification provides us with more accurate substitution patterns than the CES. I also describe product in characteristics space following IO literature (McFadden, 1973; Berry, 1994; BLPs, 1995, 1999, 2004; Goldberg, 1995; Nevo, 2000; and Petrin, 2002). This provides me the opportunity to analyze the impact from trade when product variety increases in the context of differentiated products since product attributes could be interpreted as vertical differentiation.

Answering the questions on how the CES bias is related to income distribution makes my paper differ from the IO papers that also allow for consumer heterogeneity. Most of the IO papers focus on a single country to see how the given population is affected by some product attributes change. Their counterfacturals could not answer if the income distribution changed, the CES bias will become larger or smaller.

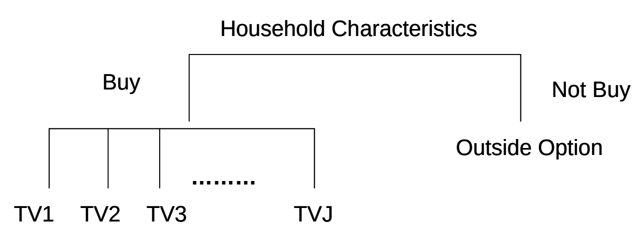
My paper will contribute to the trade literature by suggesting the CES bias when I compare welfare gains among rich countries or between rich and poor countries. I find that when two countries differ dramatically in income distribution, e.g., the U.S. vs China, the CES will overestimate the consumer gains due to the availability of high end products in rich country by *60%* but will underestimate it in China by *20%*. Given these opposite biases, the difference in the consumer welfare gains for these two countries will be underestimated.

My paper also find that the CES bias is larger in magnitude when I analyze the welfare change due to product variety availability than due to price changes. My data is not the classical trade aggregate data. This detailed individual data provides me the opportunity to avoid the unclear "product" definition in classical harmonized system data where more than one products are grouped together. My data only includes well-defined TV products. Given TV attributes, I could accurately control for the change in product variety. Lastly, the addition of heterogeneous coefficients reveals important heterogeneity across types of consumers. The HC compensating variations for the richest consumers is *5* times higher than the CES representative when they lose the high end TV choices; the HC compensating variations for the poorest consumers in only *92* percent lower than the CES representative in this case.

This paper is organized into six sections. In section two, I outline my theory by proving the equivalence between CES utility and discrete choice nested logit model. I will describe my data in section three. Section four describes my estimation strategy and regression results as my benchmark results. Section five includes my counterfactural analysis when I change income distribution. I conclude in section six.

2 Theory Model

Since I am applying IO approach to trade literature, my first task is to connect these two seemingly disparate frameworks. I will apply the nested logit structure. Consumers will first choose between "buy" or "not buy" a current marketed TV. Given their decision of buying a TV, they will choose among marketed TVs.



2.1 CES + product characteristics vs Logit with product Characteristics

Following the idea in Anderson et. al. (1987,1989) and Sheu (2011), I first prove the equivalence between **CES with product characteristics vs Nested Logit with product characteristics.**

1) The CES based framework

Let me start with CES in product characteristics space. Since CES assumes representative consumer, I ignore subscript for consumer i for now.

$$\underset{Z,\ M}{Max}\ U = \left\{ Z^{\frac{\gamma-1}{\gamma}} + M^{\frac{\gamma-1}{\gamma}} \right\}^{\frac{\gamma}{\gamma-1}}$$

$$s.t. \qquad Z + P_m M = Y \qquad given \ \ P_z = 1$$

Where product Z is homogeneous product. M is composite differentiated products. P_m is the price index of this composite product M. $\gamma > 1$ is the elasticity of substitution between Z and M. For the representative consumer in the CES framework, γ is assumed to be the same across all consumers. By solving for the above utility aximization problem, I have the total expenditure on differentiated products:

$$P_m M = \frac{P_m^{1-\gamma}}{1+P_m^{1-\gamma}} Y = wY$$

Then, next, consumers will choose among the $j = 1,,,J$ marketed TVs that are currently available in the market, that is, buying a new TV. The representative consumer will maximize the following utility function:

$$\underset{\{q_j\}_{j=1,,,J}}{Max} \quad M = \left[\sum_{j=1,,,J} \left(\exp(X_j\rho)^{\frac{1}{\sigma}} * q_j^{\frac{\sigma-1}{\sigma}} \right) \right]_j^{\frac{\sigma}{\sigma-1}}$$

$$s.t. \quad \sum_{j=1,,,J} q_j p_j = wy$$

For simplicity, let $b_j = \exp(X_j\rho)$. I get the conditional (on purchase) expenditure share on product j .

$$S_{j \mid purchase} = \frac{p_j^{1-\sigma} * b_j}{\sum_{k=1,,,J} \left[p_k^{1-\sigma} * b_k \right]} \tag{1}$$

The share of expenditure allocated to product j within wy is $S_{j\mid purchcase}=\frac{p_j^{1-\sigma}*b_j}{\sum\limits_{k=1,,,J}\left[p_k^{1-\sigma}*b_k\right]}$.

Meanwhile, $P_m=\left[\sum\limits_{j=1,,,J}p_j^{1-\sigma}*b_j\right]_j^{\frac{1}{1-\sigma}}$ Therefore, the expenditure share on differentiated products becomes

$$S_{purchcase}=w=\frac{\left[\sum\limits_{j=1,,,J}p_j^{1-\sigma}*b_j\right]^{\frac{1-\gamma}{1-\sigma}}}{1+\left[\sum\limits_{j=1,,,J}p_j^{1-\sigma}*b_j\right]^{\frac{1-\gamma}{1-\sigma}}} \tag{2}$$

Combining equation (1) and (2) I get the unconditional expenditure share allocated to product j.

$$S_j\ =S_{j\mid purchase}*S_{purchase}=\frac{p_j^{1-\sigma}*b_j}{\left[1+\left(\sum\limits_{j=1,,,J}p_j^{1-\sigma}*b_j\right)^{\frac{1-\gamma}{1-\sigma}}\right]\left[\sum\limits_{k=1,,,J}p_k^{1-\sigma}*b_k\right]^{\frac{\gamma-\sigma}{1-\sigma}}} \tag{3}$$

2) The Nested Logit based framework

$$\underset{q_j}{Max}\ U_j=\ln q_j+\ln(\exp(X_j\beta))^{\frac{1}{\mu_2}}+\eta_g+\epsilon_j$$

g index groups in nested logit. In my case, I only have two groups, "buy" or "not buy". The η_g is a random draw from a logit distribution with scale parameter μ_1, the group specific error term. The ϵ_j is a random draw from a logit distribution with scale parameter μ_2. q_j is the quantity demanded for product j. $X_j\beta$ represents the quality of product j and has the same meaning as in the CES framework.

This is an entirely static problem, without borrowing or saving. The budget constraint for discrete choice is given by $p_jq_j=y$. $j=0,1,,,J$. Outside option is indexed by $j=0$. The utility function becomes

$$\underset{\{q_j\}_{j=0,1,,,,J}}{Max} \quad U_j = \ln y - \ln p_j + \tfrac{1}{\mu_2}\ln b_j + \eta_g + \epsilon_j$$

Within the same group of purchase, the η_g term drops out, reducing the choice problem to

$$Max\ \{\ln y - \ln p_1 + \tfrac{1}{\mu_2}\ln b_1 + \epsilon_1, , , , \ln y - \ln p_J + \tfrac{1}{\mu_2} b_J + \epsilon_J\}$$

Since the lny will not affect the choice decision among $j = 1, , , , J$ through lny directly, the consumer problem becomes

$$Max\ \{-\ln p_1 + \tfrac{1}{\mu_2}\ln b_1 + \epsilon_1, , , , , , -\ln p_J + \tfrac{1}{\mu_2} b_J + \epsilon_J\}$$

So the probability of buying product j given that she will buy a current TV becomes

$$S_{j\ |\ purchase} = \frac{p_j^{-\frac{1}{\mu_2}} * b_j}{\sum_{k=1,,,J}\left[p_k^{-\frac{1}{\mu_2}} * b_k\right]}$$

In this step I could get the expected maximum utility if the consumer chooses to buy. Given the property of logit model, I will have

$$V_{|\ purchase} = \mu_2 \ln\left[\sum_{k=1,,,J} \exp(u_k)\right]$$
$$\text{where } u_k = p_k^{-\frac{1}{\mu_2}} * b_k$$

So the consumer will

$$Max\ \left\{V_{|\ purchase} + \eta_{purchase},\ V_{|\ not\ purchase} + \eta_{\ not\ purchase}\right\}$$

The probability of purchasing becomes

$$S_{purchase} = \frac{\left[V_{|\ purhase}\right]^{\frac{\mu_2}{\mu_1}}}{1+\left[V_{|\ purhase}\right]^{\frac{\mu_2}{\mu_1}}} \qquad if\ V_{|\ not\ purhase} = 0$$

As long as $\mu_1 = \frac{1}{\gamma-1}$ and $\mu_2 = \frac{1}{\sigma-1}$, $S_{purchase} = \frac{\left[\sum\limits_{j=1,,,J} p_j^{1-\sigma} * b_j\right]^{\frac{1-\gamma}{1-\sigma}}}{1+\left[\sum\limits_{j=1,,,J} p_j^{1-\sigma} * b_j\right]^{\frac{1-\gamma}{1-\sigma}}}$

And

$$S_j \ = S_{j \mid purhase} * S_{purchase} = \frac{p_j^{1-\sigma} * b_j}{\left[1+\left(\sum\limits_{j=1,,,J} p_j^{1-\sigma} * b_j\right)^{\frac{1-\gamma}{1-\sigma}}\right]\left[\sum\limits_{k=1,,,J} p_k^{1-\sigma} * b_k\right]^{\frac{\gamma-\sigma}{1-\sigma}}}$$

It is the same as what I get from CES framework. So from now on, I will work with the logit-based framework since it provides me an estimation equation corresponding to the CES.

$$\underset{q_j}{Max} U_j = -\alpha \ln p_j + X_j \beta + \eta_g + \epsilon_j \tag{4}$$

where $\alpha = \sigma - 1$, $\beta = \rho(\sigma - 1)$.

For heterogeneous coefficient case, I allow α, β, that is σ and ρ to differ across individuals and it becomes

$$\underset{q_j}{Max} \quad U_{ij} = -\alpha_i \ln p_j + X_j \beta_i + \eta_{ig} + \epsilon_{ij} \tag{5}$$

2.2 Own price elasticity

Given this demand function, I have two cases to get own price elasticity: CES+monopolistic competition; HC+monopolistic competition. The firm's interaction is not discussed in this paper and might be included in future work. It is also assumed to be single product firm.

For each case, each single product firm is maximizing its profit by choosing prices given tariff level $\tau \geq 1(\tau = 1$ if no tariff): P_j is consumer price. $\frac{P_j}{\tau}$ is producer price.

$$\underset{\frac{P_j}{\tau}}{Max}\ \Pi_j = (\frac{P_j}{\tau} - MC_j) * D(P_j) - FC_j$$

Firm's first order condition is

$$\frac{P_j}{\tau} = \frac{\eta_{jj}}{1+\eta_{jj}} MC_j \tag{6}$$

where $\eta_{jj} = \frac{\partial D(P_j)}{\partial (P_j)} * \frac{P_j}{D(P_j)}$ is own price elasticity.

The η_{jj} will depend on market structure assumption and consumer utility assumption.

Case I: CES+monopolistic competition (CES+MC)

Monopolistic competitive firms will have unique differentiated products and their measure is zero in the sense that each firm is unique but very small. For this case, consumers are still assumed to be identical, so there is no consumer subscript.

Given demand for product j from equation (3),

$$\eta_{jj} = \frac{\partial (S_j * Y)}{\partial p_j} * \frac{p_j}{(S_j * Y)} = -\,\sigma$$

It shrinks to this simple form is because there is no impact on the *aggregate* expected utility, $V_{|\,purchase}$. Each individual product's price change is not big enough to impact aggregate price index and aggregate consumer welfare given that each firm is very small to have zero metric. Therefore with CES+monopolistic competition, I have the elasticity matrix (e.g. four products).

$$\begin{bmatrix} -\sigma & 0 & 0 & 0 \\ 0 & -\sigma & 0 & 0 \\ 0 & 0 & -\sigma & 0 \\ 0 & 0 & 0 & -\sigma \end{bmatrix}$$

For each firm, its first order condition becomes $\frac{P_j}{\tau} = \frac{\sigma}{\sigma - 1} MC_j$. It means that each firm's profit markup is always fixed at $\frac{-\sigma}{1-\sigma}$. That is, whenever tariff is imposed, consumer prices will increase by the same rate of tariff as long as marginal cost of product j is constant. The second implication for my product barrier counterfactural analysis is that, whatever product I take away, each existing product will not change its price, if MC_j is not affected by the change.

Case II: HC + monopolistic competition (HC+ MC)

I still assume there is no firm interaction but only with consumer tastes variation. In this case, each firm is still very small such that it will not affect and will not be affected by other firms.

Now I allow for consumer heterogeneity by letting y_i, α_i, β_i, that is, y_i, σ_i and ρ_i differ across individuals. The demand equation becomes

$$D_{ij} = S_{ij} \ * y_i = \frac{p_{ij}^{1-\sigma} * b_{ij}}{\left[1+\left(\sum_{j=1,,,J} p_{ij}^{1-\sigma i} * b_{ij}\right)^{\frac{1-\gamma_i}{1-\sigma_i}}\right]\left[\sum_{k=1,,,J} p_{ik}^{1-\sigma} * b_{ik}\right]^{\frac{\gamma_i-\sigma_i}{1-\sigma_i}}} * y_i \tag{7}$$

This demand equation gives me the following elasticity when I still assume monopolistic competition in supply side:

$$\eta_{jj} = \frac{\partial D_j}{\partial p_j} * \frac{p_j}{D_j} = \sum_{i=1}^{I}\left[-(1+\alpha_i) * \frac{D_{ij}^*}{D_j^*}\right]$$

where $\frac{D_{ij}^*}{D_j^*} = \frac{\text{Total expenditure allocated to product j by } \textbf{type i} \text{ consumers}}{\text{Total expenditure allocated to product j by } \textbf{all types} \text{ of consumers}}$. For example, if this product is high end TV. Rich consumers accounts for a majority in all its consumers in terms of total expenditures. And if I know rich consumers are less sensitive to price changes, that is, α_i is smaller, the own price elasticity of this high end TV will be smaller in magnitude. In other words, its consumers are less sensitive to its price change. For cross product price elasticity, given the "zero metric" assumption in firm side, it is still zero.

This differs from the CES+MC. Now in the HC framework, own price elasticity is not the same across all consumers any more. For each individual, it becomes $-\sigma_i$. At the product level, it will vary according to consumer composition.

That is, individual level $i\prime s$ own price elasticity:

$$\begin{bmatrix} -\sigma_i & 0 & 0 & 0 \\ 0 & -\sigma_i & 0 & 0 \\ 0 & 0 & -\sigma_i & 0 \\ 0 & 0 & 0 & -\sigma_i \end{bmatrix}$$

σ_i varies across individuals but not across products. But at the market level for product j, it becomes:

$$\begin{bmatrix} \eta_{11} & 0 & 0 & 0 \\ 0 & \eta_{22} & 0 & 0 \\ 0 & 0 & \eta_{33} & 0 \\ 0 & 0 & 0 & \eta_{44} \end{bmatrix}$$

$\eta_{11} = \eta_{jj}$ only when they have exactly the same types of consumers. Each single product firm will follow the pricing rule defined as $P_j = \frac{\eta_{jj}}{1+\eta_{jj}} MC_j$. It implies that in the HC framework, it is no longer fixed markup as in the CES+MC but now it varies based on

$\frac{\eta_{jj}}{1+\eta_{jj}}$. Before and after policy change, consumer composition might change such that η_{jj} changes. When η_{jj} changes, equilibrium prices might not be changing at the same rate as tariff changes as CES+MC predicts.

In sum, comparison between CES+MC and HC+MC will tell me the role of allowing for heterogenous tastes. The heterogeneous tastes will affect the welfare estimates through the following channels: 1) different consumer has different tastes for marketed products $j = 1,,,J$; 2) different consumer has different probability of purchase given their different expected maximum utility on purchase; 3) different products have different own price elasticity and these elasticities vary when consumer composition changes. It changes the firm's prices.

2.3 Compensating Variation

Choice set before any change is defined as (P^0, X^0), where P^0 is consumer price and $\frac{P^0}{\tau^0}$ is the producer price. My analysis start with $\tau^0 = 1$, that is under free trade. So TV choices in the benchmark situation will be proceeded with (P^0, X^0). After policy changes, such as, tariff increases or trade barrier on products, consumer will make her choice with (P^1, X^1) where 1 indexes new price or new product attributes.

For consumers, given their choice set, they will rank all options and choose the one that gives them the highest utility. So, let me define $V(P^0, X^0)$ as the highest indirect utility given (P^0, X^0). Outside option expected utility is assumed to be 0 as discussed above. Still let $V_{|\,purchase}$ denote the expected maximum utility from her purchase of TV. Then $V^0_{|\,purchase} = \mu_2 \ln \left[\sum_{k=1,,,J} \exp(u^0_k) \right]$. When I calculate the consumer welfare, I could not ignore the lny term any more, $\ln y - \ln p_{_j} + \frac{1}{\mu_2} b_j + \eta_g + \epsilon_j$. Since at the upper level, error term is also distributed as logit, I have

$$Max \left\{ V^0_{|\,purchase} + \ln y + \eta_{purchase},\ \ln y + \eta_{\,not\ purchase} \right\}$$

It implies that unconditional expected maximum utility V^0

$$V^0 = \mu_1 \ln(1 + \exp(V^0_{|\,purchase})) + \ln y$$

I will use compensating variation (Hicks, 1939) (Hicks, J.R. Value and capital: An inquiry into some fundamental principles of economic theory Oxford: Clarendon Press, 1939) to measure consumer welfare change. 'Compensating variation' (CV) refers to the amount of additional money an agent would need to reach its initial utility after a change in prices, or a change in product quality, or the introduction of new products.

Let $I^0 = \mu_1 \ln(1 + \exp(V^0_{|\,purchase}))$

$$V^0(P^0, X^0, y) = V^1(P^1, X^1, y + CV)$$

$$I^0 + \ln y = I^1 + \ln(y + CV)$$
$$CV = [\exp(I^0 - I^1) - 1] * y$$

For the CES case, CV is the consumer welfare change for the representative consumer or each individual consumer.

For the HC case, for each type i consumers:

$$CV_i = [\exp(I^0 - I^1) - 1] * y_i$$

For the HC case, the average consumer welfare changes is defined as

$$Average\ CV = \frac{\sum_{i=1}^{I} [CV_i * POP_i]}{Total\ Population} \tag{8}$$

Where POP_i is the population of type i consumers.

Therefore, consumer incomes and their expected unconditional utility change together affects their welfare level.

3 Data

3.1 US TV industry

Consumer behavior empirical studies focus on automobile analysis (BLP (1995, 1999, 2004), Petrin (2002), Goldberg (1995), among others). Nevo (2001) analyzed cereal. Petrin and Train (2010) provided analysis on how consumer characteristics impact their choices between television reception options, including antenna, cable and satellite dish. Nosko (2010) examined how Intel's development of Core 2Duo affected AMD in computer CPU market.

As one of major consumer durable goods, television is well under analyzed. Based on shipment data from Consumer report and iSuppli company, in 2010, there were 38 millions units of television shipped to US. This number was stable over years. LCD TV alone had the shipment, 25 million in 2008, 32 million in 2009 and 31 million in 2010 in units. It is predicted that LCD TV alone will have more than 40 million unites sold in US in 2014. With total 120 million households, it means one third of households buy a new TV each year. Or in other word, each household buys a new TV every three years on average. Although household expenditure share on television is not high, as a durable good, its re-purchase frequency is relatively high. Ninety-eight percent of American households own at least one television set - likely the highest penetration rate for any single product or good in the world.

But so far, I could not find a complete purchase analysis for television. Part of the reason is the lack of detailed data.

The majority of televisions sold in US is imported. Even the US brand, such as Vizio, also outsourced their production to China. The value of television imports to the US accounted for 7.7% of total commodity imports in 2009.[1] Major country origins include Mexico (42%), China (41%) in 2010 (see details in the Appendix Table 1).

In 2010, the top five companies in the U.S. television set market - Samsung (18%-20%), Sony (14%), Vizio (12%-13%), LG (8%-10%) and Panasonic (8%)[2] - accounted for more than 60% of total units sold. 40-49 inches TVs are the most popular size (40%) and larger TV was becoming more attractive over time.

In 2010, LCD display technology was the leading technology (66% of TV markets). Other display technologies include LED (18%), Plasma(13%) and others. LCD, LED and Plasma are vastly different, particularly how each the screen is lit. In plasma HDTVs, the phosphors that create the image on the screen light up themselves, and don't need any backlighting. For LCD HDTVs, however, the liquid crystal screen does not illuminate, requiring a separate light source. That's where the difference between "regular" LCD screens (also known as CCFL-backlit LCD) and LED-backlit LCD screens (also known as LED-LCD, or just LED screens) come in. Traditional LCD HDTVs use cold cathode fluorescent lights (CCFLs) to illuminate the screen. CCFLs are similar to the fluorescent lights in your lamps and overhead light fixtures. They use a charged gas to produce light. LED screens, like their name implies, use light emitting diodes (LEDs) to illuminate the display. The difference between plasma and LCD wavered for some time, with each offering different economic and visual benefits depending on the model, price, and time in the life cycle of HDTVs. But in the past couple of years, with the advent of increasingly sophisticated LED backlighting, I finally have a true winner. With its unmatched energy efficiency and more lightness, LED is the best flat-panel HDTV technology.

3.2 TV data

I am using two data sets. The data for consumer buyer information comes from the unique U.S. TV Consumer Preference Analysis data by IHS-iSuppli (TV data). Their standard data is collected monthly and report is quarterly. It covers 2010 national wide TV purchase data. It was done as an online survey.

This data is a very unique data set on US TV purchase. It not only has detailed product attributes- technology, such as, LCD, LED, Plasma; size; brand; and price, but also, it provides individual household's characteristics, such as, income, number of adults, attitude to technology, if he/she is the first TV buyer and her motivation to buy the current TV.

[1] US Census Bureau International trade in goods and services report, Series FT 900 Final report. <http://www.census.gov/foreign-trade/Press-Release/2009pr/final_revisions/>.

[2] Based on different data sources, these numbers are reported by range. Sources include Display Search and iSuppli publications.

So far, it is the best data set I know for TV consumer analysis. It provides me with the possibility of capturing consumer's heterogeneity after I control for product attributes for televisions.

I have 2010 full year data which has more than 9,000 household buyers, 66 TV brands.

3.3 Consumer Expenditure Survey (CEX), 2009

I use the CEX data for two reasons. Firstly, I use CEX households weight to correct potential non-response bias due to the online survey. Secondly, I get non-buyer information from CEX.

1) Although this TV data includes rich product and consumer side information, it was done by an online survey. It means even with the randomness in their phone calls, it is likely to suffer from non-responses bias. For example, poor family might not respond proportionally due to the lack of computer or internet at home. Rich people might not have been motived to do the online survey after they answered the phone due to time opportunity cost.

In order to correct this potential non-response bias, I combine consumer expenditure survey (CEX), 2009 with my TV data. In CEX, each household reported their household characteristics, number of TVs at home, where they are living, if they bought a TV within the past three months. Also they have weights for each household to see how many households each represents. I use the most detailed household characteristics to assign their weights to my TV buyer data with the goal of correcting the non-response bias.

Table 1 reports TV buyer income distribution before and after I assign weights from CEX.

Table 1. Comparison between income distribution with / without CEX weights

Income	From TV Data	With CEX weight	Difference
$Under $25,000	11.3	16.2	-4.9
$25,000-$49,999	32.2	23.8	8.4
$50,000-$74,999	24.4	18.9	5.4
$75,000-$99,999	15.1	13.1	2.1
$100,000-$149,999	11.5	14.3	-2.8
$150,000-$199,999	3.3	6.6	-3.3
$200,000 and greater	2.3	7.1	-4.9
Total	100%	100%	

From this table, I do see family with income range $25,000-$99,999 are more likely to respond. Lowest income family ($\leq \$25,000$) and highest income family ($\geqslant \$100,000$) are less likely to do the survey as I expect.

In the TV data, each type of family (quarter-region- income- family size- number of TV) has multiple entries. I divide their total weights from CEX evenly with the assumption that after I control for their household characteristics, their responses rate will be the same across TV product choices. That is, after I control for household characteristics, Sony consumers are not more likely to respond than LG consumers. Although the brand shares are little off (see Appendix Table 2), most of other characteristics with my new assigned weights work well. I would like to think the non-response rate based on household characteristics is more serious. From now on for the TV buyer, I will use my assigned CEX weights.

2) The CEX also provides me the household characteristics information for TV non-buyers (for currently marketed TV). [3]

I append these buyer and non-buyer data to represent whole US population data[4].

3.4 Outside Options

In order to get aggregate welfare estimates and their changes, I need to define consumers' outside option. That is, if they do not buy current TV, what is their alternative choices and what is the utility by consuming the outside option. Consumers will rank their utility based on available marketed TVs and choose the one that gives them the highest utility. If the highest utility from the marketed TVs is still lower than their outside option utility, they will choose not to buy the current one.

For TV buyers, they need these outside options so that when I do counterfactural analysis, I know who might drop out from the current TV market.

For TV non-buyers, I will assume they face the same marketed TVs in each market as TV buyers in my data. I also get outside options for non-buyers. These non-buyers end up with choose outside options.

The studies based on aggregate data (e.g., BLP, 1995) assumes outside option utility is equal to zero for all consumers. Its role is to adjust active market share. Since theirs are not individual data, they do not need to specify the characteristics for outside option. Working with individual data, specifying outside options characteristics becomes a challenge given data limitation. In her paper, Sheu (2011) chose a dot matrix printer, the most common alternative to the laser and inkjet models as outside option assuming that if firms do not buy any laser and inkjet printers, they will buy dot matrix printer.

With the individual data, I will take advantage of two step nested logit model to get around the outside option issue.

I first get estimates within buyers only. Given these estimates, I could get the estimated maximum utility by purchasing the favorite TV given they choose to buy one TV, that is, $V_{|\ purchase}$.

Next, taking advantage of the information on non-buyer characteristics from the CEX data, I will assume the probability of "buy" only depends on consumer characteristics, rather than any product characteristics. After excluding the product characteristics from decision making given expected utility, I do not need to specify outside option characteristics for each individual any more. Therefore, I could follow the idea of assuming outside options will provide zero utility. This could be supported by assuming $P_z = 1$ and b_j (exp($X_0\beta$) is equal

[3] One note is that the TV buyers in given year only accounted for around 5% of total households surveyed in CEX. In order to match with 38 millions units sold in US, we adjust the aggreage weights for buyer to get 1:2 for buyers vs non-buyers.

[4] In the 2010 U.S., there were approximately 115 million households. In order to avoid huge weights, we adjust the total weights by dividing all weights by 4. In this way, the relative shares by income groups will not change.

to 1. Applying these conditions to equation (5) will give me zero outside option utility. I also assume all types of consumers have the same outside option utility.

With zero utility from outside option and given the expected maximum utility from purchase, I run a binary logit model to estimate the probability of choosing purchase. In this way, I get around the need to assign specific product characteristics to outside options.

In short, the key assumptions when I get outside option include:

a) outside option price is normalized to 1 and $b_0 = \exp(X_0\rho) = 1$

b) given available product choice set, the probability of purchase or not depends on consumer characteristics but not directly on product attributes.

c) consumers first choose among "buy" or "not buy" and then choose which one to buy given their choice of purchase, that is, I have nested logit structure.

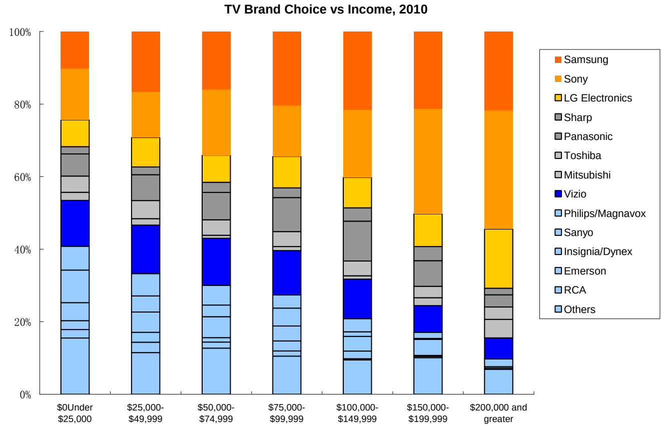
Now I get my full corrected data set where I know both buyer and non-buyer household characteristics, current TV attributes for current buyers and their outside options, that are non-buyers choices. I will use this data to proceed my analysis. Following table group A include the tests on the quality of imputed data; table group B include summary statistics based on my imputed data. (Appendix Table 3 and 4 report the quality of my full data.).

3.5 Summary Statistics for my data

The following tables include the summary statistics based on my imputed data.

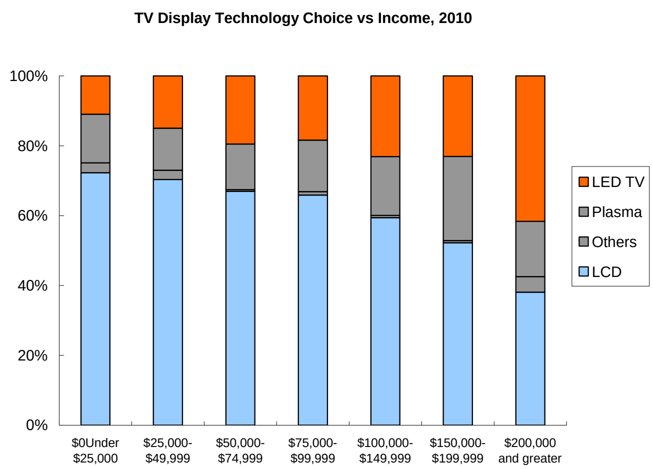
a) The first one shows a trend that rich consumers are more likely to buy the top3 brands: Samsung(orange), Sony(gold) and LG(tan). The brands with grey colors are Sharp, Panasonic, Toshiba and Mitsubishi. There is no significant difference in market share between rich and poor people among these four. Vizio is one of the major brands, whose market share was 12.7%, the third highest in US 2010 TV markets. But I do see poor people are more likely to have Vizio TVs. The other blue groups brands also lose interests from rich people but have their sales to poor households. I will group the top 3 into "TOP3", the grey area brands into "Middle4", Vizio and "Others" which represent the left over blue groups in my further analysis.

Figure 1. Brand Choice by Income Groups



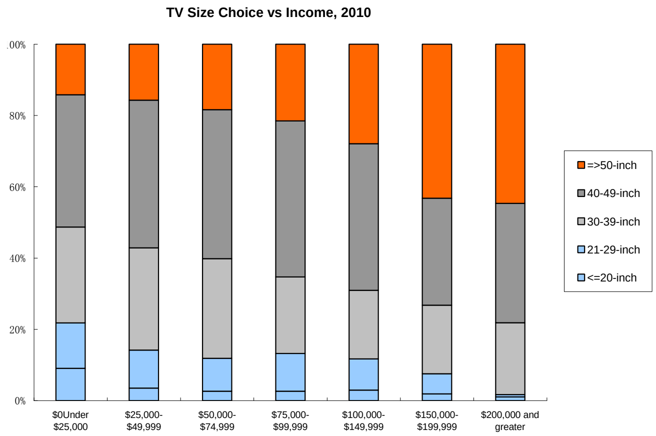
b) Consumer preference for TV display technology varies across income groups. Although the majority consumers like to have LCD TVs, richer consumers are more likely to buy LED TV which is more energy saving and fancier. Plasma and other projection TVs only account for 16% of the full markets and there is no obvious differences between rich and poor buyers

Figure 2. Technology Choice by Income Groups



c) The majority consumers buy a TV 30-50 inches. Rich people have stronger preferences towards $>=$50 inches TV and against smaller TVs, especially $\leq$ 30 inches TVs. However, smaller TVs ($\leq$ 30 inches) accounted for almost 20% of poor household ($\leq \$25,000$) TV choices.

Figure 3. TV size Choice by Income Groups



d) On average, richer households are more willing to pay higher to buy a TV. The richest income group ($\geqslant$ \$100,000) on average pays twice compared to the lowest income group ($\leq \$25,000$).

Table 2. TV Prices by Income Group

	Buyer Price in logs				
	Min	Mean	Exp(Mean)	Max	Std Dev
Under $25,000	4.61	6.65	774	8.3	0.6
$25,000-$49,999	4.82	6.72	825	8.3	0.5
$50,000-$74,999	4.78	6.82	915	8.3	0.6
$75,000-$99,999	4.89	6.93	1022	8.3	0.6
$100,000 and greater	5.33	7.21	1347	8.3	0.6

e) The following table reports consumer preferences within the same brand groups. As mentioned above, I grouped them into 4 major groups: top 3, middle 4, Vizio and others. Share numbers reported are the choices within each income group. For example, for the consumers with income ($\leq \$25,000$) and with a purchase in the top 3 brand group, 17% of them bought larger than 50 inch TV, 15% bought LED TV and on average, they pay \$958 for top3 grouped TVs.

Table 3. TV Consumer Preferences by Income Group

TV Consumer Preferences By Income

Brand Group	Income	Size				Technology				Price
		<=30-inch	30-49-inch	=>50-inch	Total	LCD	Plasma	LED TV	Total	
Top3	⩽ $25,000	13%	70%	17%	100%	68%	17%	15%	100%	958
	⩾ $100,000	4%	55%	41%	100%	47%	17%	36%	100%	1328
Middle4	⩽ $25,000	23%	54%	23%	100%	61%	31%	8%	100%	827
	⩾ $100,000	6%	50%	44%	100%	37%	42%	21%	100%	1122
Vizio	⩽ $25,000	14%	75%	11%	100%	69%	13%	19%	100%	683
	⩾ $100,000	11%	63%	26%	100%	60%	9%	31%	100%	905
Others	⩽ $25,000	31%	60%	10%	100%	81%	12%	7%	100%	592
	⩾ $100,000	23%	62%	14%	100%	81%	14%	5%	100%	658

From this table, I find:

1) Cross Brands: Once a consumer buys larger-sized TV, both rich and poor prefer Better Brands. Or say, once a consumer decides to buy better brands, she will prefer larger sizes

2) Cross Brands: Both rich and poor trust Vizio LED TV, although rich still prefers Top3 LED; Vizio LED is very competitive. Compared with poor people, rich people like to buy LED TV either Top 3 or Vizio.

3) Cross Income: poor is more likely to buy smaller TV, in both <=30 and 30-49 inches; more likely to buy LCD TV; poor is less likely to buy Larger than 50 inches TV,

4) Price: For whatever brand group, poor people are paying less; rich people are paying more; the differences between prices are more significant in better brands

4 Estimation Strategy and Results

Since I have multiple steps regressions, I illustrate the relations between them in Figure 4. I will start description from step 2 and then explain why I need to use instrumental variables and control functions to correct endogeneity in prices. Step 2 is the major step to get the estimated coefficients on tastes for product attributes including prices, size etc. But it is done for current buyers only. With these estimates, I get the expected highest utility for each type of consumers. I use this expected utility as the only one control variable to get the probability of purchase in step 3. Step 4 and step 5 are both based on the estimates from step 2 and step 3 but with trade restrictions - tariffs and imports barriers. Let me from the step 2.

Figure 4. Estimation Roadmap

Step 1:	IV step
	↓
Step 2:	Conditional Logit – Within Buyers
	↓
Step 3:	Binary Logit – Buy or not
	↓
Step 4:	Welfare Change due to trade restrictions the US benchmark
	↓
Step 5:	Welfare Change due to trade restrictions Across Countries

Our regression equations for step 2 are defined in (4) for the CES and (5) for the HC, with α_i and β_i depending on household characteristics. I will use the interaction between income level dummy e.g., $1\{\underline{y} \leq yi \leq \overline{y}\} * \ln price_j$ to capture α_i. The lowest income group is the reference group. Similar treatment to other household characteristics includes number of persons, number of TVs at home. These characteristics not only interact with prices but also interact with other TV attributes to capture individual households heterogeneous tastes for my heterogeneous coefficients estimation (HC). For the corresponding CES estimation, I impose $\alpha_i = \alpha \ \forall i$ and $\beta_i = \beta \ \forall i$, that is, assuming everyone has the same taste.

I have full 2010 data including four quarters and each state information. Prices vary across time (quarters) and also across regions (states). In my data, prices differ differently across regions even with the existence of 20% online purchase through Amazon or online Wal-Mart. Due to the data limitation, I could not get rich enough information to do my analysis at state level. So I grouped some states to get region information. I divide states into four regions: northeast, southeast, west and others (see Appendix Table 5 for details). The definition of "market" is defined as quarter-region (that is, across region and over time).

In step 2: Given individual data, I proceed with conditional logit to maximize the following likelihood for buyers only :

$$\sum_{m=1}^{M}\sum_{j=1}^{J}\sum_{i=1}^{I}1\{HH_i=1\}\ln Prob_{ijm}$$

where

$$Prob_{ijm} \mid purchase \qquad = S_{ijm \mid purchase} = \frac{p_j^{-\alpha_i} * \exp(X_j\beta_i)}{\sum_{k=1,,,J}\left[p_k^{-\alpha_i} * \exp(X_k\beta_i)\right]}$$

m is market, i is index for consumer i and j is type j TV.

Identification in this step comes from the differences across types of TVs within each market.

Endogenous Prices and Instrumental Variables

I will assume that the product characteristics X_j are exogenous. Prices are endogenous variables in the sense that although I have measures of major TV attributes, such as, TV size, display technology, brands and energy saving indicator, I still have unobserved factors that affect prices, such as advertising. If one TV has more advertising than the average, I will expect consumers will be more likely to buy the advertised TV. Meanwhile, advertising causes higher marginal cost and therefore, it will cause the increase in price.

Given my estimation equation, assume I could not observe advertising: δ_{jm}, but consumers could observe them, their true indirect utility function given purchase should be

$$U_{ijm} = -\alpha_i \ln p_{jm} + X_j\beta_i + \delta_{jm} + \epsilon_{ijm} \tag{9}$$

$p_{_{jm}}$ is the price of type j TV in market m; X_j are the time-invariant TV attributes; δ_{jm} is a product - market specific unobserved advertising effect. ϵ_{ijm} is an individual TV type and market specific shock. For the illustration of endogeneity issue, let me ignore individual specific tastes for now. If $cov(p_{_{jm}}, \delta_{jm}) \neq 0$, the OLS estimates will not be unbiased nor consistent. The market share of product j becomes

$$Prob_{j,m} \quad = \frac{p_j^{-\alpha} * \exp(X_j\beta + \delta_{jm})}{\sum\limits_{k=1,,,J} \left[p_k^{-\alpha} * \exp(X_k\beta + \delta_{jm})\right]}$$

The general form of pricing rule for firms is $P_{jm} = \frac{\eta_{jj}}{1+\eta_{jj}}(MC_{jm})$ for both CES+MC and HC+MC. If $\frac{\partial Prob_{j,m}}{\partial \delta_{jm}} > 0$ (the more advertising, the higher possibility to buy it) , $\frac{\partial MC_{jm}}{\partial \delta_{jm}} > 0$ and therefore $\frac{\partial P_{jm}}{\partial \delta_{jm}} > 0$, I will have upwards bias in the coefficient on price in my conditional logit estimation. It will cause the estimate of α biased towards zero. This is the source for endogeneity.

I need to look for cost shifters as instrumental variables for each product j in each market. They need to 1) enter into utility function only through prices (consumers do not care about production costs. they only care about prices); 2) prices will depend on production costs.

I will apply Hausman-Nevo IV strategy. I define each quarter in each region as a single market so that I have data on the prices for the same type of TV in other markets. I take the average of prices for the same type of product size by tech by brand from other markets as the IV for current prices with the assumption that product level cost information is the major/persistent components passed through prices. The quality shocks are not persistent or not as persistent as the product attributes marginal cost. That is, by construction, $MC_{jm} = C_j + C_{jm}$ where C_j is nationwide cost for product j but C_{jm} is market specific cost shock for product j.

More generally speaking, the equation for the price of product j in region r in quarter t as

$$ln(P_{jm}) = \theta_0 + \theta_1 \ln(C_j) + w_{jm}$$

The term θ_0 captures anything that is common to all markets and all products. Cost shocks for each product, $\ln(C_j)$, are common across regions and across quarters. The cost shock has no market subscript, i.e. product cost shocks determine prices in each market through a nationwide component. The error w_{jm} contains both demand and cost shocks, including C_{jm}. By assumption, it is independent across markets.

The key assumption in applying the Hausman-Nevo IV strategy is that the demand errors and cost errors (including C_{jm}) are restricted to be independent across markets (only through the error term w_{jm}) whereas cost errors can be common across markets through $\ln(C_j)$. It is equivalent to assume that any demand shock or local cost shock that affects prices is drawn independently in each market rather than being a nationwide effect. So the identification of IV comes from the nationwide common cost shocks vs the independently drawn demand shocks.

Control Function

Since my demand function is defined as equation (7) which is nonlinear in parameters, I will apply control function approach, following Petrin and Train (2010).

In step 1, I run regression defined as

$$lnP_{jm} = X_j\Phi + \theta ln\bar{P}_{j(-m)} + v_{jm} \tag{10}$$

where $ln\bar{P}_{j(-m)}$ is the average price of same type of TV in other markets. Then I get

$$lnP_{jm} = X_j\hat{\Phi} + \hat{\theta}\ ln\bar{P}_{j(-m)} + \hat{v}_{jm}$$

Instead of plugging in predicted $ln\hat{P}_{jm}$ from the first step, I will take $\hat{v}_{jm}$ as a new regressor in my step 2 demand estimation.

Now my probability function becomes:

$$Prob_{j,m} \quad = \frac{p_j^{-\alpha} * \exp(X_j\beta + \pi\hat{v}_{jm})}{\sum\limits_{k=1,,,J}\left[p_k^{-\alpha} * \exp(X_k\beta + \pi\hat{v}_{km})\right]}$$

I choose to use control function approach over the BLP (Berry, 1994; BLP, 1995) product-market mean product utility approach. As discussed in Petrin & Train (2010), BLP approach has its restrictions in my situation given that in some market some type TVs have almost zero or very small number of purchase observations per product. This causes inconsistency in BLP approach because it requires relatively little sampling error in market shares.

Step 3: After step 1 and step 2, I get estimates on α_i and β_i and the expected maximum utility of purchase for type i consumers: $V_{i(m)}|\ purchase = \mu_2 \ln\left[\sum\limits_{k=1,,,J(m)} \exp(u_k^0)\right] = \frac{1}{\alpha_i}\sum\limits_{k=1,,,J(m)}\left[p_k^{-\alpha_i} * \exp(X_k\beta_i)\right]$. I will assume each type of consumers in each market have the same α_i and β_i. Since each market has different product choice set, $V_{i(m)}|\ purchase$ will differ across markets.

By combing buyer and non-buyer information for each market, I know the probability of purchase for type i consumers. So, I estimate the following binary logit model,

$$Purchase_{i(m)} = \lambda_0 + \lambda_1 V_{i(m)}|purchase + \omega_{im} \tag{11}$$

$Purchase_{i(m)}$ takes 0 or 1 and 1 means the decision of purchase.

For the CES, I only have market level variation, that is, $V_{i(m)}|\ purchase = V_m|\ purchase$. So for the CES, identification in this step comes from variation across markets.

For the HC, identification in this step comes from variation across markets and type of consumers. But λ_1 is assumed to be the same across all markets and all consumers. It is equivalent to assume that, there is no individual difference in shopping behavior if they are given the same expected utility.

In sum, the channels that the consumer heterogeneity impact estimation include:

1) different types of consumers have different tastes for product characteristics, that is, β_i. For example, rich people might prefer high end TV.

2) different types of consumers have different sensitivity to prices, which is captured by α_i. For example, poor people might be more sensible to price changes.

3) therefore different types of consumers might end up with different choices given different utility levels even when they face the same product sets.

4) this results in different expected utilities of purchase for different types of consumers.

5) λ_1 is identified due to the variation across markets and also across individuals, but for the CES, they only come from the variation across markets. Therefore, I will have different λ_1 for the CES and the HC.

4.1 Regression Results

4.1.1 First Step Regressions

In the Table 4 it reports my **step 1** regressions (**equation 10**). Each observation corresponds to each type of TV (size- technology- brands- green) for each market. So I take the average prices over all consumers by TV type in each market.

Table 4. IV step

$\ln(price_{jm})$	(1) tech	(2) size	(3) brand	(4) tech+size	(5) tech+brand	(6) size+brand	(7) size+brand+tech
Hausman IV	0.85***	0.38***	0.82***	0.37***	0.83***	0.29***	0.28***
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)	(0.05)
West Region	0.01	-0.01	-0.00	-0.01	-0.00	-0.02	-0.02
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
North East Region	-0.01	-0.02	-0.01	-0.02	-0.01	-0.03	-0.04
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
South East Region	-0.05	-0.05	-0.06	-0.05	-0.06	-0.07*	-0.07*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Quarter 2	0.05**	0.05***	0.05**	0.05***	0.05**	0.06***	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Quarter 3	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Quarter 4	-0.02**	-0.02**	-0.02*	-0.02**	-0.02**	-0.02*	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
green	0.03	0.08***	0.04	0.09***	0.04	0.10***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
LCD	0.05			0.06*	0.05		0.06*
	(0.04)			(0.04)	(0.04)		(0.04)
LED	0.09**			0.15***	0.08**		0.14***
	(0.04)			(0.04)	(0.04)		(0.04)
30-49 inches		0.54***		0.57***		0.60***	0.63***
		(0.05)		(0.05)		(0.05)	(0.05)
>= 50 inches		0.92***		0.96***		1.04***	1.08***
		(0.08)		(0.08)		(0.09)	(0.09)
Best Top 3 brands			0.15***		0.14***	0.25***	0.23***
			(0.04)		(0.04)	(0.04)	(0.04)
Median 4 brands			0.12***		0.11**	0.17***	0.16***
			(0.04)		(0.04)	(0.04)	(0.04)
vizio			0.02		0.01	0.03	0.01
			(0.04)		(0.04)	(0.04)	(0.04)
Partial R2	0.66	0.12	0.65	0.12	0.64	0.09	0.09
F	229.6	15.0	228.7	14.5	210.8	10.1	10.2
Overid P value	2.95E-186	1.72E-18	1.02E-185	7.86E-18	2.79E-176	3.76E-12	2.78E-12
Observations	808	808	808	808	808	808	808
R-squared	0.672	**0.721**	0.677	**0.727**	0.679	**0.740**	**0.746**

Robust standard errors in parentheses; not weighted
*** p<0.01, ** p<0.05, * p<0.1
Base Groups: for region, other states; quarter 1; Plasma; <=30 inch; Other brands

I apply Hausman-Nevo type price instruments (Hausman 1997). I calculated the price instrument for market m as the average price in other markets for the same type of TV. These instruments will be valid if the prices of the same type of TV in other markets reflect common costs of this type of TV but not common demand shocks. One example for this type of shocks is unobserved local advertising if I assume advertising in local mostly have local impact. Or the relatively weaker assumption is that the common costs of the same type of TV are more persistent than demand shocks.

With these instrumental variables for each type of TV in each market, I regress the log prices on product attributes, quarter dummies and region dummy to get residuals. I do this step regressions for buyers only, without including the outside option.

Markets are defined over regions and quarters. Regions are divided into four regions: west, northeast, southeast and others given the data limitation. Given the large distance among these regions. it decreases the possibility of common shocks.

Key findings:

a) All of these Hausman - Nevo IVs are significant when I control for technology, size, and brand either individually or together.

b) TV size is a major factor affecting prices. It could be shown from the drop in the magnitude of Hausman IV (drop from $0.82 - 0.85$ to less than 0.4) whenever I control for TV size. Meanwhile, the R^2 also shows that, on average, it is 5% higher in the regressions with TV size included than the ones without size.

c) Region dummies are not significant but in quarter 2 prices are significantly higher than in quarter 1; the ones in quarter 4 are significantly lower due to holiday sales.

d) All the estimates on product attributes have expected signs. Energy saving TVs are more expensive; LCD is slightly more expensive than Plasma; LED TVs are significantly more expensive than Plasma TVs; the larger the TVs, the more expensive they become, being a TV larger than 50 inches will increase prices by 1% on average. The median four brands are also more expensive but Vizio is not significant more expensive than the excluded low end TV brands.

e) Partial R2 and F statistics are acceptable but overidentification p-value does not work very well. The reason why I need to check overid is that given the special property in the second stage after correcting endogeneity, I could not add any quarter or region dummies since they do not vary across TVs for the same consumer. That means in this IV stage, I should take quarterly dummies and region dummies as IV as well.

The column (7) includes all TV attributes I have - green technology, size, brand and display technology dummies, which is consistent with the one I will use in my second step. Therefore, residuals from column (7) will be used for my second step analysis. For comparison, I also include residuals from column (5) to show how important to include size in the first step.

4.1.2 Step 2 Regressions

In the second step I run a conditional logit model on all current TV buyers (based on **equation 9**). Each consumer faces the same types of marketed TVs given each quarter in each region. Among these choices, each household will choose the one that gives them the highest utility. Control variables include product attributes, such as, prices, TV size, display technology, green technology status, brands. At the same time, residuals from the IV step will be used to correct endogeneity.

Table 5 reports my key regression results in the second step regression.

Table 5. Conditional Logit for buyers

TV Choice	CES			HC		
C Logit	NO CF	CF5	CF7	NO CF	CF5	CF7
ln (price)	0.02***	-0.31***	**-0.54*** **	-0.47***	-0.81***	**-1.22*** **
	(0.00)	(0.01)	**(0.01)**	(0.01)	(0.01)	**(0.01)**
Income Group X ln(price)						
inc25_50p				0.01	0.03**	0.03**
				(0.01)	(0.01)	(0.01)
inc50_75p				0.30***	0.39***	0.39***
				(0.01)	(0.01)	(0.01)
inc75_100p				0.48***	0.48***	0.48***
				(0.01)	(0.01)	(0.01)
inc100highp				0.60***	0.62***	**0.62*** **
				(0.01)	(0.01)	**(0.01)**
HH size X ln(price)				0.05***	0.05***	0.05***
				(0.00)	(0.00)	(0.00)
TV number X ln(price)				-0.02***	-0.03***	-0.03***
				(0.00)	(0.00)	(0.00)
Best Top 3 brands	0.31***	0.44***	0.49***	-0.17***	0.03***	0.08***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
inc100high				1.12***	1.10***	**1.10*** **
				(0.01)	(0.01)	**(0.01)**
Median 4 brands	-0.65***	-0.57***	-0.53***	-0.96***	-0.86***	-0.78***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
inc100high				0.79***	0.76***	**0.76*** **
				(0.01)	(0.01)	**(0.01)**
Vizio	-0.94***	-0.90***	-0.90***	-1.14***	-1.10***	-1.09***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
inc100high				0.39***	0.39***	**0.39*** **
				(0.01)	(0.01)	**(0.01)**
LCD	1.44***	1.64***	1.95***	1.32***	1.52***	1.99***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
inc100high				-0.44***	-0.41***	**-0.41*** **
				(0.01)	(0.01)	**(0.01)**
LED	0.21***	0.24***	0.29***	-0.33***	-0.31***	-0.23***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
inc100high				0.67***	0.71***	**0.71*** **
				(0.01)	(0.01)	**(0.01)**
30-49 inches	1.44***	1.64***	1.95***	1.32***	1.52***	1.99***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
inc100high				0.21***	0.22***	**0.22*** **
				(0.01)	(0.01)	**(0.01)**
>= 50 inches	0.40***	0.86***	1.29***	0.13***	0.62***	1.32***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
inc100high				0.83***	0.80***	**0.84*** **
				(0.02)	(0.02)	**(0.02)**
green	0.80***	0.82***	0.86***	0.81***	0.84***	0.90***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CF Res 5		0.44***			0.46***	
		(0.01)			(0.01)	
CF Res 7			0.65***			**0.87*** **
			(0.01)			**(0.01)**
Pseudo R2	0.1055	0.1078	0.1078	0.1216	0.1237	0.1237
Number of Observations	7399	7399	7399	7399	7399	7399

Standard errors are reported. Weighted by household weights {should use bootstrap se in pro
* p<0.10 ** p<0.05 *** p<0.01

In the above table, I have two sets of regressions, one for the CES and the other for the HC. When I estimate for the CES, all coefficients are assumed to be the same across different individuals. In the CES estimation without the correction for endogeneity "NO CF" column, price coefficient is positive 0.02. The positive sign proves the existence of endogeneity. As mentioned above, in step 1, I keep two sets of residuals, one without controlling for size, the other with controlling for size. The residuals without controlling for size are reported in the column with title "CF5" under the CES section. Price coefficient becomes negative,

-0.31. The control function residuals are included with name of "CF Res 5" at the bottom of the table also has the expected signs, +0.44. With higher unobserved shocks, consumers are more likely to buy. Both of these, the change in price coefficients and the sign on control variable, support my argument on endogeneity. When I include the residuals "CF Res7" which comes from previous step controlling for TV size, I find that price coefficient is further corrected from being biased towards zero. Now price coefficient becomes -0.54, compared with +0.02 in the regression without correcting endogeneity. The control function variable also takes the expected signs +0.65.

The role of control function is also confirmed when I do the regressions for the HC. Price coefficients become -1.22 from being -0.47 when there is no correction for endogeneity.

I listed the interaction terms right after the price coefficient on the HC section regressions. These interaction terms are interacting between household income and prices they paid. For the base group, the consumers with income less than $25,000 per year have price coefficients as low as -1.22. Based on this, consumers with income higher than $100,000 less sensitive to price by 0.62, so their price coefficient is -1.22+0.62,=-0.60, only 49% of -1.22. It shows that rich people are less sensitive to prices. If I compare across income groups, I find that consumers with income between $25,000 and $50,000 is 0.03 less sensitive to the poorest, 0.39 less for income group $50,000 to $75,000. 0.48 less for income group $75,000 to $100,000. I see a clear pattern: the richer the households, the less they are sensitive to TV prices. I also test if larger family is more likely to buy TV and the positive 0.05 proves this expectation -0.03 on the interaction between how many TVs they have at home excluding the current one, and prices they pay, tells us, the more TVs they have, the less likely they will pay high prices to buy a new one.

I interact household income with all other product attributes, but I only report the highest income group for saving space. Consumers preference for the best brands is only 0.08 for lowest income group, but for richest family, it becomes 1.18 (0.08+1.10), 14.8 times higher. For the median brands, compared with other lower end brands, poorest consumers choose to buy from other lower quality brands. However, richest still prefer to buy the relatively better branded TVs. Compared with other lower end TV brands, poorest prefers them to Vizio. Richest family also has negative coefficient on Vizio, but less negative (-1.09+0.39 vs -1.09). Compared with the poorest, richest does not prefer LCD to Plasma technology. LED TV is very attractive to richest consumers, -0.23 vs -0.23+0.71. All income group consumers love larger TVs, and the richest consumers love the larger TV even more, based on the estimates 1.99 vs 1.99+0.22 for median sized TV and 1.32 vs 1.32+0.84 for the largest TV.

Finally, energy saving TVs, the green technology TV, are attractive.

Comparing the regression for the CES and the HC without endogeneity correction, the coefficients differ dramatically, +0.02 (CES) vs -0.47 (HC). There are two reasons to explain this difference: firstly, controlling for household characteristics, the coefficients on the price without interaction with household characteristics represent the price sensitivity of base group. Now the base group is the poorest consumers. So the -0.47 should only represent the price sensitivity for the poorest consumer in the HC case. But in the CES, it is something weighted average across all consumers. If some other consumers have lower sensitivity to price, the coefficient for CES should be more towards to zero than the one in HC. Secondly, when CES assumes everyone is the same in their tastes for attributes and prices, it throws the interaction term between prices and income into the error term. However, if higher income consumers pay higher and are more likely to buy, it will be positively correlated with the price term in the CES and also positively correlated with the probability of purchase. This is another source for endogeneity and again the price coefficient in the CES will be biased towards zero, which does not happen in the HC specification.

In sum, my major findings include:

a) people do differ. Compared with poorer households, richer ones have less price sensitivity; stronger preferences for larger than 50 inches TV; more likely to buy the most advanced LED TV; and more preferences towards best TV brands.

b) Price coefficients are biased towards zero without correction for endogeneity and my control function works in the right direction.

c) The HC specification not only tells me more about consumer tastes varying across different income groups, but also by construction, to some degree, correct the price endogeneity in the CES specification. When I calculate the weighted average price coefficient across all types of consumers from the HC estimates, it is -0.90. which is larger than -0.54 in magnitude. This is another source that the CES and the HC differ.

I will use the results in the last columns in the CES and the HC sections, respectively, as my benchmark estimates for further analysis.

4.1.3 Step 3 Regression

In this step, I run regressions on the probability of purchase given their expected maximum utility if they bought any new TV, defined by equation (11). Table 6 lists the key results in this step.

Table 6. expected utility and probability of purchase

		Mean	Min	Max	Variation
Expected Utility given purchase	CES	3.02	2.88	3.12	Across markets
	HC	2.03	-2.96	6.92	Across individuals and markets
Coefficient on expected U	CES	0.457			
λ1	HC	0.132			

CES is overestimating the predicted utility from buying a TV and it has higher estimated $\hat{\lambda}_1$. These shows one of the channels how the HC and CES differ.

4.1.4 Implications of CES vs HC

The coefficient estimates on the price term in the step 2 has direct relation to CES's important parameter $\sigma = -1 - \alpha$, It has the same relation for individual level own price elasticity but has $\sigma_i = -1 - \alpha_i$.

Own price elasticity at the individual level:

	CES	**HC**
All consumers	-1.54	-1.90
Income		
$\leq \$25,000$	-1.54	-2.22
$[\$25,000, \$50,000)$	-1.54	-2.19
$[\$50,000, \$75,000)$	-1.54	-1.83
$[\$75,000, \$100,000)$	-1.54	-1.74
$\geqslant \$100,000$	-1.54	-1.60

As explained in above section, the CES is expected to have the same price elasticity for all income groups. Based on regressions in second step, richest consumers have much less sensitivity to prices, -1.60 vs -2.22. The HC weighted average own price elasticity is still larger than the CES one in magnitude, -1.90 vs -1.54 due to endogeneity in the CES.

Product level own price elasticity is listed in the following table (grouped further for simpler illustration. In fact I have 72 different products based on their attributes):

Table 7. Own price elasticity at product level

Own price elasticity at product level

	CES	HC
TV brand groups		
Best Brands	-1.54	-1.83
Median 4	-1.54	-1.87
Vizio	-1.54	-1.91
Others	-1.54	-1.95
TV size		
>=50 inches	-1.54	-1.8
30-49 inches	-1.54	-1.89
<=30 inches	-1.54	-1.95
Display technology		
LED TV	-1.54	-1.81
Plasma	-1.54	-1.87
LCD	-1.54	-1.91
Green TV		
Green TV	-1.54	-1.88
Not Green	-1.54	-1.89

As analyzed in the theory section, CES + MC price elasticity matrix is captured by only one parameter. $-(1+\alpha)$. That is why I see the same elasticity across all products and all consumers. For HC+MC it has $\eta_{jj} = \sum_{i=1}^{I}\left[-(1+\alpha_i) * \frac{D_{ij}^*}{D_j^*}\right]$. It relaxes CES+MC by allowing for own price elasticity to vary across different products but still with cross price elasticity equal to zero for all products. The variation comes from two sources: firstly, different consumers have different price elasticity; secondly, consumer composition is different for different products. These two components combined together provide different own price elasticity for HC+MC. The patterns in the numbers are as expected. For example, looking at the own elasticities according to brands, rich people are the major consumers of the best brands groups and rich people have relatively less sensitivity to prices. These two reasons combined together explains why I have relatively less sensitivity to prices (-1.83) in this group, compared with -1.95 for the lowest end brands.

This similar pattern also holds in other way to categorize quality: largest TV (>=50) has less price sensitivity (-1.80) than smaller TVs (-1.89 and -1.95); LED (-1.81) has smaller own price elasticity than LCD(-1.91) in magnitude. Since any type of consumers prefer green TVs, I do not see significant differences between green and non-green TVs.

4.2 Benchmark - Consumer welfare change for the U.S. consumers

After I finish regressions in step 1, 2, and 3, I am ready to go to step 4, doing counterfacturals for the U.S. consumers. This part analysis will be taken as benchmark since it is using US data. In next section, I will change the income distribution and consumer tastes variation to model China's data. I will test how the CES bias will change in both cases, compared with the US benchmark results.

In the benchmark analysis, I base on the U.S. consumer information to check how the CES differs from the HC estimates in the consumer's welfare change due to the following two types of shocks in the international trade.

Case I: first I let tariff increase by different rates. Since CES+MC has a constant markup (for the HC+MC, the following results also assume prices will increase by the same rate as tariff, which will be relaxed later), whenever tariff increases by t percent, consumer prices will also increase by the same rate.

Case II: Trade barrier makes some varieties not available any more. Such as, due to the environment consideration, US stops imports of some type of TVs. I particularly focus on two types of TVs. "High End TV" include the TVs that are larger than 50 inches, LED display technology, energy saving and produced by the top 3 producers. "Low End TV" include the TVs that are smaller than 30 inches, Plasma, not energy saving and produced by the less famous producer groups (other groups).

Following the formula for $CV = [\exp(I^0 - I^1) - 1] * y$. there are three factors that determine the bias in the compensating variation.

Factor a) consumer income. It will determine the level of CV. I will expect that, given the same $[\exp(I^0 - I^1) - 1]$, higher income consumers will need more CV.

Factor b) expected maximum utility change in $V_{|\ purchase}$ given the consumer will buy a current TV. The magnitude of this change will depend on estimates from step 2 and also depends on who is mainly affected and who is represented.

Factor c) Notice $I = \mu_1 \ln(1 + \exp(V_{|\ purchase}))$ =prob(buy)*exp($V_{|\ purchase}$) So, it is determined by the probability of purchase too. CES reports $\lambda_1 = 0.457$, while HC reports $\lambda_1 = 0.132$ (Table 6, equation 11). If I have the same change in $\exp(V_{|\ purchase})$, the CES estimate on the CV will be larger given that its probability of purchase has higher sensitivity. I also notice that this will only cause the CV differences when I compare between the CES and the HC. It will not cause differences when I focus on the same framework, such as the HC, across different income groups or across different shocks, since they all have the same λ_1.

Given all those estimates from step 2 and step 3, I now need to know who are the major consumers in these counterfactural shocks.

The following distribution Table 8 by income groups for the total population (including current TV buyers and non-buyers), and for current TV buyers only in the second and third columns, separately. For example, 24% (second column) of total population have family income less than $25,000; the poorest households only account for 16% (third column) in current TV buyers. At the bottom of this table, I also include the total number of population and total buyers in my data.

The forth column includes the consumer income distribution within current high end TV buyers. From this column, I could tell that richer consumers are the major consumers for high end TVs. 63% of the high end TV consumers have family income higher than $100,000. High end TVs attracted 3.5% of total buyers. The last column shows that poorest family are major consumers for low end TVs, and they are totally unattractive for richest households. The low end TV only attracted 0.24% of TV buyers. In short, this tables helps me understand which income group will be most affected in different shocks. Therefore, I could tell what is potential consumer welfare estimate bias in the CES relative to the HC under different situations.

Table 8. Distribution by income groups

Income Groups	% Pop	% Buyers	High End % in Buyers	Low End % in Buyers
⩽ $25,000	24%	16%	2%	70%
$25,000-$49,999	25%	24%	7%	27%
$50,000-$74,999	18%	19%	20%	1%
$75,000-$99,999	12%	13%	8%	2%
⩾ $100,000	22%	28%	63%	0%
	Total Pop	Total Buyers	% of total buyers	% of total buyers
Total	3374992	1072821	3.50%	0.24%

Tariff changes

The following Table 9 is one of my major tables, which reports the consumer welfare losses due to international tariff for the CES and the HC frameworks. The first section reports the tariff on all TVs, regardless of TV types. Tariff rates include 5%, 10% and 20% for each case. The CES estimates show that on average, each consumer will be as happy as before if I pay her \$191 when tariff on TVs becomes 5% from free trade. The weighted average HC estimate is \$182. Therefore the difference in the CES and the HC is 105% (191/182). By using the HC framework, I could get more detailed CV on each type of consumers, such as, the richest consumers need CV as high as \$328 but the poorest only need \$64. It seems contradicting with the less sensitivity to prices for the richest people. However, it does not. The reason is that the calculation of CV depends on the above three factors together, the change in the expected utility, probability, and consumers income. The higher loss comes from higher income. I also report the change in the expected utility in the bottom block of this table. Still in the case with 5% tariff on all TVs, the expected utility for poorest consumers change by 0.0051 as percentage of income, but it is only 0.0024 for richest consumers. This difference in the expected utility change reflects the less sensitivity of richest consumers to prices (notice, for each type of consumers, they have the same λ_1). I report the similar analyses also for tariffs on the high end TVs and low end TVs.

Table 9. Consumer Compensating Variation (\$) for the US, Tariff

	Tariff on all TVs			Tariff on High End TVs			Tariff on Low End TVs		
	5%	10%	20%	5%	10%	20%	5%	10%	20%
CES	191	377	733	26	50	94	3	5	9
HC: average	182	360	708	40	76	139	2	4	7
CES/HC	**105%**	**105%**	**103%**	**65%**	**66%**	**68%**	**129%**	**132%**	**135%**
By HC									
$\leqslant$\$25,000	64	125	239	2	4	8	2	4	8
\$25,000-\$49,999	75	146	279	4	9	16	1	2	4
\$50,000-\$74,999	287	572	1130	32	60	110	3	5	9
\$75,000-\$99,999	216	428	836	26	50	90	2	4	8
$\geqslant$ \$100,000	328	655	1302	138	262	478	2	3	6
Expected Utility Change :									
$\leqslant$\$25,000	0.0051	0.0100	0.0190	0.0002	0.0003	0.0006	0.0002	0.0003	0.0006
$\geqslant$ \$100,000	0.0024	0.0048	0.0096	0.0010	0.0019	0.0035	0.0000	0.0000	0.0000

When I compare the CES/HC ratios across different scenarios for tariff, I find the following patterns:

1) When there are tariffs on *all* current TVs, the CES estimate is almost equal to the HC, that is, CES/HC is 103% - 105%.

2) If I only impose tariffs on high end TVs, the CES is underestimating the HC. CES/HC is 65% - 68%.

3) If I only impose tariffs on low end TVs, the CES/HC becomes around 130%.

These three patterns could be explained by checking which factor dominates. The third factor, λ_1, will always tend to drive up the CES estimate given the same expected utility on purchase. I should combine the other two factors since they both include the income impact. For above three scenarios, the differences between the CES and the HC could be explained by the idea of "majority". The CES estimate represents the "majority". Based on the population distribution, 67% of consumers have income less than \$62500 (or say, the range between \$50,000-\$74,999). The full population in my data have income, on average, \$62779. That means, 67% of consumers are the consumers who have less than average income, or relatively poor consumers. Just because of this, the CES estimate is more likely to present the majority, relatively poor consumers. When tariffs are imposed on all TVs, all products prices increase correspondingly by the same rate as the tariff rate. However, poor consumers are more sensitive to the prices based on estimates in second step estimation. So when the CES let these majority speak for the full population, the CES is overestimating the welfare change.

When tariffs imposed on high end TVs, the majority are not the major consumers. 71% of these high end TVs are purchased by rich people. The CES again tends to represent the majority, the relatively poor consumers. But they are less likely to be affected by this shock since they were less likely to buy high end TVs anyway. Therefore CES/HC is significantly smaller than 1. The much lower expected utility dominates and offsets the exaggerating impact from λ_1.

Opposite argument applies to the low end TV tariffs. Now the majority, the poor consumers, get hit very much while the rich consumers do not. When the poor consumers are chosen by the CES on behalf of rich consumers, the welfare loss is overstated by 29% - 35%.

Meanwhile, when I compare the bottom block in the table 9 across tariff scenarios, I find that

4) when all prices change by the same rate, rich consumers have less loss in expected utility (e.g., 0,0024 vs 0.0051) given that they are less sensitive to price changes

5) when tariffs change the prices of the high end TVs only, rich consumers get hit the most. That is why I have higher expected utility loss for rich people (0.0010) for tariff=5%, 5 times higher than the one for poor people (0.0002); 0.0019 vs 0.0003 for tariff=10%, 6 times higher; 0.0035 vs 0.0006, almost 6 times higher. This is caused by both paying higher prices and some of rich consumers quitting from the markets.

Barriers on varieties

The next counterfacturals I do is to assume that some varieties are no longer imported. Such as, for environment concerns, US government bans the imports of low end TVs. Since almost all TVs are produced outside of US, when they are not allowed to be imported, there are no this type of TVs available in the US market, at least in the short time before the US firms set up domestic production line.

Table 10 reports my results. I first look at the consumer welfare change when I take out the high end TVs where rich households are the major consumers. Comparing with the tariff changes, I notice first that expected utility is much larger for both poorest and richest consumers. Richest consumers lose 0.0181 in terms of expected utility, 52 times higher than 0.0035 when tariff on high end TVs is 20%; for poorest consumers, 5 times larger (0.0030 vs 0.0006). Meanwhile, I notice the CES/HC is significantly larger than 1. This does not contradict the majority idea although the majority is still not the major consumers for high end TVs. The reason for overestimate lies in the dominance of λ_1.λ_1 effect reflects the probability of dropping out the markets. As just discussed, now the change in the expected is much higher than the cases of tariffs. The differences between the CES and the HC will be enlarged by the CES λ_1 (0.457) but only 0.132 in the HC. When the magnitude in the expected utility change is large enough, the λ_1 effect dominates. It means that although expected utility change in the CES is small, the probability of dropping out from the market is expected to be very large in the CES. It explains why I have overestimated CV in the CES.

For the low End TV case, expected utility loss for poorest is 0.0031 which is 15 times larger than the expected utility change for richest consumers. As expected, the majority is poor households and they are hit the most. So, CES/HC is larger than 1 due to both the higher expected utility change and the λ_1 impact. It explains why I have much larger CES/HC (287%) than in 20% tariff on low end TV (135%) where λ_1 impact is smaller given smaller expected utility change. These results are very similar to the findings in Sheu (2011) and Petrin (2002) where they find the CES estimate of average compensating variations for new goods are two times as large compared to those from BLP specifications. I separate the varieties into high end and low end varieties. Compared with their findings, I find that the CES is even more overestimating for low end TVs. But for high end TVs, it is not as large as 2 times because the majority is not major consumers for the high end TV.

Table 10. Consumer Compensating Variation ($) for US, varieties

	Take out the High End TVs	Take out the Low End TVs
CES	1012	98
HC: average	714	34
CES/HC	**142%**	**287%**
By HC		
$\leqslant$$25,000	38	39
$25,000-$49,999	78	22
$50,000-$74,999	552	44
$75,000-$99,999	456	41
$\geqslant$ $ 100,000	2473	31
Expected Utility Change :		
$\leqslant$$25,000	0.0030	0.0031
$\geqslant$ $100,000	0.0181	0.0002

4.3 Counterfacturals: Across Countries Comparison

I find the difference between the CES and the HC by using the US data in above section. Does it mean I could apply this relative bias directly to other countries? Such as, I now know, the new high end varieties will provide 42% higher CVs in the CES than in the HC. When I estimate the same shock in China by applying the CES, are I going to still get the overestimate? This is very important for country comparison in the international trade. But it is not answered by the IO literature.

Income distribution

For simplicity, I often use the CES in trade. But the following results show that by applying the CES, when I compare between rich country and poor country on their welfare gains due to trade, I will underestimate the welfare differences across countries.

Table 11. Changing income distribution, CES/HC on CVs

	China	AA	US
Richest Share	5.5%	15%	22%
Poorest Share	42.8%	30%	24%
Tariff 10%			
All products	109%	107%	105%
High End	64%	66%	66%
Low End	119%	132%	132%
Varieties			
High End	**79%**	**118%**	**142%**
Low End	167%	246%	287%

In Table 11, I change the income distribution from my benchmark - US, by changing the households weights in the US data. I keep everything else unchanged. I changed the richest consumers to account for 5.5% and the poorest consumers to account for 42.8% of total population. This is the case for the 2007 of China[5]. The country AA is a case in between where this imaginary country AA has 15% and 30% richest and poorest consumers, respectively.

The second column includes the results for China. When tariff becomes 10% on all products, CES/HC is 109%. The CES is still slightly overestimating the welfare changes. The upward bias is due to the majority consumers in China being poor consumers. When prices increase, due to the larger sensitivity to price change, poor consumers will get worse more seriously than rich consumers. As majority, poor consumers speak for all population in the CES case such that the CES/HC is larger than 1. Compared with 105% in the US, the insignificant decline from China to US in the ratio of CES/HC are supported by the income composition. In the US, although the CES also represents the poor consumers, the proportion of rich consumers are higher than in China. Therefore, rich consumers are taking some role in the estimating even though it is still not the majority. At the same time, rich people are less sensitive to prices, which explains why 105%<109%.

When high end TVs price increase by 10%, I do not see significant differences in the CES bias. China's λ_1 (0.47) is similar to the US's λ_1.(0.45) in the CES case. The majority is also still the poor consumers, who are much less affected by this shock.

[5]Source: http://www.china.com.cn/aboutchina/zhuanti/09zgshxs/content_17101088.htm

When low end TVs price increase by 10%, the CES/HC is still larger than 1 for China. This has similar argument as the one for the US. The poor consumers are hit the most while rich consumers almost have nothing to do with this shock. The CES gives more weights to the majority, so that CES/HC>1. However, this ratio is only 119%, smaller than 132% in the US. The less bias is due to the fact that, in China, given the income distribution, more than 80% of population (vs 67% in US) is below the mean income. The CES now for China in this case is closer to the reality. That explains why the CES/HC is closer to 1.

Comparing with the US, I find more differences in the CES/HC when I take out either high end or low end varieties.

After I take out high end TVs, for China, CES is *underestimating*, only 79% of the HC estimate. This is significantly different from the 142% in US. As explained above, the overestimate of 142% in US comes from two sources: first, expected utility (given purchase) changes more with losing product attributes than with price change; second, the probability of dropping out from market, λ_1 ,is larger in the CES. When the change in the expected utility on purchase is larger, the CES overestimates more. In order to explain the underestimate of the CES in China, I still apply the two factors: expected utility changes given purchase and the overestimating in the dropping out. However, in China, the most hit consumers only account for 5.5% of total population while others are much less affected. When the CES weights individual changes and get the representative consumer welfare change, the expected utility changes given purchase is much smaller. It is so small that even the overestimate in the rate of dropping out could not offset the underestimating. That explains why I have underestimate in the CES for China while overestimate for US.

This difference in the CES/HC delivers very important information when I do welfare comparison across countries. Firstly, developing countries like China benefits the most from the access to high end products (consumer side only, not including firm productivity improvement etc.). To get an accurate welfare estimates for high end products in this context is very important. Secondly, still with this counterfactural, assuming I have the same welfare loss estimate equal to 100 for both US and China by using the CES estimation, I will conclude there is no difference in welfare change in China and in the US. However, given above analysis, welfare loss in China should be 127 while US should be 70. The welfare loss differs by 57! This difference is underestimated by 57 out of 100!

When I take out the low end TVs, the CES is much more overestimating in US (287%) than in China (167%) because US has more rich consumers who are not hit by this change. Following the example where I get welfare loss equal to 100 for both US and China, the real loss should be 35 in US and 60 in China. The difference in the welfare loss is again concealed.

In sum, I find:

1) the CES/HC does not vary significantly across countries when I impose tariffs. Small magnitude in the coefficients (0.54 for US, 0.79 for China) explains the small expected utility change on purchase and therefore small welfare loss.

2) when I take out varieties, the CES/HC is much smaller in developing countries, like China since the CES representative is closer to the real population.

3) the welfare loss when I take out high end TVs is underestimated very much in China,

but overestimated very much in the US by the CES. This bias direction change will conceal the welfare loss differences across countries!

5 Conclusions

CES assumes representative consumer could represent heterogeneous consumers. The "representativeness" differs across countries with different income distribution. In my paper, through the analysis for the benchmark US and for the developing countries, like China, I find that using the CES framework will conceal or underestimate the welfare loss differences across countries. This is very important for international trade across country comparison in welfare gains/losses from trade condition changes.

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7 Appendix

Appendix Table 1: Source of US TV imports

Top Five Countries of Origin For Television Receivers, VCR's & Other Video Equipments

	2002	2005	2008	2009	2010
Mexico	30%	30%	45%	42%	42%
China	19%	31%	37%	42%	41%
Japan	23%	16%	5%	4%	4%
Thailand	5%	4%	2%	2%	3%
Korea, South	5%	4%	1%	1%	2%
Total	82%	85%	91%	92%	90%

Source: U.S. Imports by 5-digit End-Use Code, US Census Bureau

Appendix Table 2. Comparison between adjusted TV data and aggregate market data

	Market Share	
	From Aggregate Market Survey*	**With CEX weight**
Top 5 brands		
Samsung	18.5	17.3
Sony	14.0	17.5
Vizio	12.7	11.7
LG	11.1	8.6
Panasonic	7.9	7.6
Others	35.8	37.2
TV size		
<=20-inch	3.2	3.8
21-29-inch	8.8	9.4
30-39-inch	24.5	24.8
40-49-inch	43.0	39.8
=>50-inch	20.5	22.3
Display Technology		
LCD	66.9	64.4
Plasma	13.5	14.6
LED TV	17.8	19.2
Others	1.8	1.8

Source: * iSuppli Consumer Data Shipment Weight

Appendix Table 3 and Table 4: Quality of my full data a) By comparing with Current Population Survey (2009) , my full data has very similar income distribution to CPS 2009.

Appendix Table 3

	Total Population (buyer+non_buyer)	
Income	**Imputed Data**	**CPS, 2009**
Under $25,000	24.2%	25.0%
$25,000-$49,999	24.6%	25.2%
$50,000-$74,999	18.0%	18.1%
$75,000-$99,999	11.6%	11.5%
$100,000 and greater	21.6%	20.2%
Total	100.0%	100.0%

b) Based on Consumer Expenditure Survey (CEX, 2009), I find the income distribution for TV buyers. However, CEX(2009) TV buyer report rate is only 5%. On average, US markets TV shipments per year is more than 38 millions units (iSuppli, Neilson, Consumer Report). So, I adjust the buyer weights vs non-buyers to 1:2 with the assumption that each Household will buy only one TV given any year. The following table reports buyer will account for 32% and non-buyer will account for 68% in my data. Among buyers, 16% of consumers have income less than $25,000. Among the household with income less than $25,000, 21% of them bought a TV in 2010. The purchase rate increases as income increases. 41% of rich household bought a TV in 2010.

Appendix Table 4

	Imputed Data		
	Income	**Shares**	**Purchase Rate**
Buyer, 32%	Under $25,000	16%	21%
	$25,000-$49,999	24%	31%
	$50,000-$74,999	19%	34%
	$75,000-$99,999	13%	36%
	$100,000 and greater	28%	41%
	Total	100%	
Nonbuyer, 68%	Under $25,000	28%	
	$25,000-$49,999	25%	
	$50,000-$74,999	18%	
	$75,000-$99,999	11%	
	$100,000 and greater	19%	
	Total	100%	

Appendix Figure 1: Definition of Regions