Three Essays in Applied Economics on Household Consumption

by

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Abstract

This dissertation consists of three essays in applied economics on household consumption. Common to each essay is the use of aggregate data. Understanding how economic theory and model of household consumption are employed for different goods and services around the whole world, and what factors determine household consumption and expenditure, is critical for developing policies to improve consumer wellbeing and economic growth.

In the first study, we revisit this issue with rural area household data in China during the post economic reform regime (1978-2009) as well as the postwar US data for comparison. The in-sample analysis provides strong evidence against the Permanent Income Hypothesis (PIH) for both countries. Out-of-sample forecast exercises also reveal that consumption changes are highly predictable. The vector autoregressive (VAR) model analysis also shows significantly positive responses of consumption to income shocks, and non-negligible proportions of variations in consumption are explained by innovations in income.

The second study empirically investigates potential effects of economic recessions on consumer's decision making process for recreational activities using the Consumer Expenditure Survey (CES) data during the Great Recession. I employ the Probit model to study the propensity of making non-zero expenditures on entertainment activities. I also use the Tobit model to correct for the bias from using the ordinary least squares (OLS) method in presence of censored observations. I find overall significantly negative effects of recessions either through decreases in intercept or in the income coefficient estimates.

In the third study, I revisit the work of Edelstein and Kilian (2009) who point out that the oil price shock involves a reduction in consumer spending, which results in a decrease in the demand for goods and services. The present study empirically evaluates this argument by investigating effects of the oil price shock on six CPI sub-indices in the US. I find substantial decreases in the relative price in less energy-intensive sectors, but not in energy-intensive sectors. The findings are consistent with those of Edelstein and Kilian (2009) in the sense that spending adjustments play an important role in price dynamics.

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List of Abbreviations

PIH	Permanent Income Hypothesis
VAR	Vector Autoregressive Model
FRED	Federal Reserve Bank of St. Louis
ADF	Augmented Dickey-Fuller Test
GMM	Generalized Method of Moments
DMM	Diebold-Mariano-West Statistics
RRMSPE	Root Mean Square Prediction Error
CES	Consumer Expenditure Survey
OLS	Ordinary Least Squares
F&A	Fees and Admissions
TRS	Televisions, Radios and Sound Equipment
OES	Other Equipment and Services
CPI	Consumer Price Index
GNP	Gross National Product
FRED	Federal Reserve Economic Data
WTI	Western Texas Intermediate
PCE	Personal Consumption Expenditures
OIRF	Orthogonalized Impulse-response Function

GIRF	Generalized Impulse-response Function
GDP	Gross Domestic Product

Chapter 1. Introduction

Household decisions about consumption affect the way the economy as a whole behaves both in the long run and in the short run. The consumption decision is critical for long-run analysis for its role in economic growth. In my first study, the permanent income hypothesis (PIH), proposed by Friedman (1957) and restated by Darby (1974) implies that consumption is largely determined by the annuity value of one's lifetime resources.[1] The PIH has been examined by an array of researches, to name a few, Hall (1978), Flavin (1981), Campbell and Mankiw (1990), Sommer (2007), and Carroll, Slacalek, and Sommer (2011), which find mixed evidence of the PIH.

Chow (1985) reported strong evidence in favor of the PIH using annual observations in China from 1953 to 1982. This paper revisits this issue by investigating the predictability of consumption changes for rural area household data in China as well as the postwar US data for comparison. We use samples from 1978 to 2009, omitting all observations before 1978 when China implemented economic reform toward a market-oriented economy.

A number of studies have examined consumer's decision making processes for entertainment and leisure activities. Travel expenditure patterns are identified to examine the likelihood of travel expenditures in the U.S. (Sung et al., 2001; Hong et al., 2005, Zheng & Zhang, 2011). The determinants of leisure satisfaction are estimated through ordered Probit models (Ateca-Amestoy, Serrano-del-Rosalet & Vera-Toscano, 2008). Leisure value is calculated with a time allocation model by Jara-Díaz et al. (2008). Additionally, fishing and

[1] Wang (2006) proposes a generalized version of the PIH.

hunting leisure spending shares in the U.S. are examined with a bivariate censored demand system by Bilgic et al. (2008).

Leisure development is also related with the general social and social psychological processes (Moore et al., 1995), leisure activities are supposed to provide life satisfaction and improve personal wellbeing (Weagley & Huh, 2004b; van der Meer, 2008). Patterns of work and leisure have changed dramatically during the past decades in the U.S. (Weagley & Huh, 2004a; Bilgic et al., 2008). Economic and social environment changes have influenced leisure activities and expenditure in the U.S. (Dardis, Soberon-Ferrer & Patro, 1994).

The objectives in this dissertation are to (1) revisit Chow's argument about the permanent income hypothesis (PIH) with rural area household data in China during the post economic reform regime (1978-2009) as well as the postwar US data for comparison, (2) investigate potential effects of economic recessions on consumer's decision making process for recreational activities using the Consumer Expenditure Survey (CES) data, and (3) reveal effects of the oil price shock on the demand for goods and services in the U.S.

In Chapter 2, I use rural China data excluding urban consumers, because rural consumers have been a dominant majority. About 82% of the consumers resided in rural areas in 1978. Although substantial migration toward urban areas began in 2000, rural consumers maintained the majority even in 2009. Further, the population structure in rural areas is a lot more stable than those in urban areas.

I employ not only the in-sample analysis framework by Campbell and Mankiw (1990) but also out-of-sample forecast exercises using the Diebold-Mariano-West test (Diebold and Mariano, 1995; West, 1996), which is a direct test for predictability of changes in consumption. We obtain very weak evidence of the PIH especially from rural China compared with results from the US.

I further investigate dynamic implications of the PIH on consumption changes over time via the vector autoregressive (VAR) model analysis. I obtain stronger responses of consumption to income shocks in rural China than those from the U.S. data. I also find that income shocks in rural China contribute more to variations in future consumption, while we find a lot weaker contributions of income shocks in the U.S.

In Chapter 3, I investigate potential effects of economic recessions on the U.S. household expenditures on entertainment activities using the Consumer Expenditure Survey (CES) data in 2003, 2006, 2008, and 2010. In this study, I investigate whether economic downturns influence the consumption function for entertainment goods and services. For this purpose, we use 2008 and 2010 CES data for recession years, while 2003 and 2006 CES data were used as economic booms years.

I note substantial degree censored observations in all years, which led me to employ the Tobit model instead of the ordinary least squares (OLS) estimator. Even though the Tobit model is useful to quantify the effects of socio-economic variables on the expenditure on entertainment activities, it does not answer the question of how those variables affect the propensity of paying (or not paying) for entertainment activities. To answer this question, we also employ the Probit model by transforming the expenditure data into a dichotomous variable.

I find overall negative effects of recessions on recreational activities via changes in income coefficient estimates and intercept both in Probit and Tobit models. For example, income coefficients become smaller during recession years for two out of the three recreation expenditure categories, while substantial decreases in intercept estimates were observed for the Fees and Admissions (F&A) in 2008 and 2010 relative to 2003 and 2006, which imply exogenous changes across those years outside our model specification. I also find non-negligible changes in coefficients of some socio-economic variables including the number of children, family size, and the marital status.

The third study in Chapter 4 is focused on the impact of oil price shocks on the demand for goods and services. As Barsky and Kilian (2002) argue, oil price shocks are unambiguously inflationary, especially when one uses the consumer price index (CPI) inflation rate to measure the pass-through effect of the shock. On the other hand, Edelstein and Kilian (2009) point out that oil price shocks may have a substantial income effect on the demand for goods and services. This study estimates the pass-through effect of the oil price shock on six CPI sub-indices in the U.S.

I find strong evidence of spending adjustment effects that limit the pass-through effect of the shock on the apparel, food, housing, and medical care price indices (less energy-intensive sectors), but not on the energy and transportation price indices. That is, consumer welfare loss is primarily driven by a strong pass-through effect in energy-intensive sectors.

Then, we further investigate possibilities of regime-specific responses of CPI sub-indices to an oil price shock. These greater responses during the low growth regime seem consistent with Edelstein and Kilian (2009), because the negative income effect would become greater when the economy is bad, resulting in weaker responses of less energy-intensive product prices compared with those of more energy-intensive goods prices.

Chapter 2. Revisiting the Empirical Inconsistency of the Permanent Income Hypothesis: Evidence from Rural China

Abstract

Chow (1985, 2010) reports indirect evidence in favor of the permanent income hypothesis (PIH) using time series observations in China. We revisit this issue by addressing direct evidence on the predictability of consumption growth employing rural area household data in China during the post economic reform regime (1978-2009) as well as the postwar U.S. data for comparison. The in-sample analysis provides strong evidence against the PIH for both countries. Out-of-sample forecast exercises reveal that consumption changes are highly predictable. The vector autoregressive (VAR) model analysis also shows significantly positive responses of consumption to income shocks, and non-negligible proportions of variations in consumption are explained by innovations in income.

1. Introduction

The permanent income hypothesis (PIH), proposed by Friedman (1957) and restated by Darby (1974) implies that consumption is largely determined by the annuity value of one's lifetime resources. Wang (2006) proposes a generalized version of the PIH. The PIH has been examined by an array of researches, to name a few, Hall (1978), Flavin (1981), Campbell and Mankiw (1990), Sommer (2007), and Carroll, Slacalek, and Sommer (2011), which found mixed evidence of the PIH.

The PIH implies that consumption obeys a random walk process (or a martingale process with i.i.d. noise) under quite general framework (Hall, 1978). Put it differently, consumption changes are not predictable. Campbell and Mankiw (1990) empirically test this claim by employing an instrumental variables estimation method, which provides strong, but indirect evidence against the PIH.

Attfield (1980) and Ermini (1993), among others, report favorable evidence of the PIH when transitory income or measurement error problems are taken care of in the model. DeJuan and Seater, and Wirjanto (2004) and DeJuan and Seater (2007) also find some supporting evidence. Kim (1996) argues that the PIH approximates the postwar US consumption data fairly well. Engsted (2002), however, finds weaker evidence of the PIH when he uses an alternative test to Kim's (1996).

In his early study, Chow (1985) reported strong evidence in favor of the PIH using annual observations in China from 1953 to 1982. Later, Chow (2010) extended his previous model for the data from 1978 to 2006, then provided the same conclusion. It should be noted, however, that his analysis focuses on the coefficient of lagged consumption in an autoregressive model for consumption. Finding the coefficient estimate to be almost exactly 1, that is, the conventional confidence band includes 1, he suggested that the PIH is consistent with Chinese annual data. His statistical inference is based on the standard normal approximation which may not be valid when consumption is an integrated variable. Further, his evidence evaluates the validity of the PIH only indirectly without addressing the predictability of consumption growth.

This paper revisits this issue by investigating the predictability of consumption changes for rural area household data in China as well as the postwar US data for comparison. We use samples from 1978 to 2009, omitting all observations before 1978 when China implemented economic reform toward a market-oriented economy.

We use rural China data excluding urban consumers, because rural consumers have been a dominant majority. About 82% of the consumers resided in rural areas in 1978. Although substantial migration toward urban areas began in 2000, rural consumers maintained the majority even in 2009. Further, the population structure in rural areas is a lot more stable than those in urban areas.

We employ not only the in-sample analysis framework by Campbell and Mankiw (1990) but also out-of-sample forecast exercises using the Diebold-Mariano-West test (Diebold and Mariano, 1995; West, 1996), which is a direct test for predictability of changes in consumption.[2] We obtain very weak evidence of the PIH especially from rural China compared with results from the US.

We further investigate dynamic implications of the PIH on consumption changes over time via the vector autoregressive (VAR) model analysis. We obtain stronger responses of consumption to income shocks in rural China than those from the US data. We also find that income shocks in rural China contribute more to variations in future consumption, while we find a lot weaker contributions of income shocks in the US.

[2] For similar out-of-sample forecast exercises in OECD countries, see Everaert and Pozzi (forthcoming).

The rest of the study is organized as follows. In section 1, we present economic theory. Section 2 provides a data description and preliminary test results. In Section 3, we provide our main empirical findings from in-sample and out-of-sample tests. Section 4 presents dynamic aspects of the PIH via a VAR model. Section 5 concludes.

2. Economic Theory

We use a simple infinite period utility maximization problem by a unit mass of identical households who faces stochastic lifetime earning processes (Romer, 2006). The representative consumer maximizes his/her lifetime utility,

$$U = \sum_{t=0}^{\infty} \beta^t u(C_t) , \qquad u'(\bullet)>0, \quad u''(\bullet)<0, \tag{1}$$

where $u(C_t)$ is the instantaneous utility function, $0< \beta <1$ is the subjective discount factor, C_t is consumption at time *t*. We assume that consumers have nice convex preferences.

Assume that the representative household is uncertain about its future income stream. At time $\mathrm{t} = 0$, the consumer maximizes the following expected lifetime utility.

$$E_0 \sum_{t=0}^{\infty} \beta^t u(C_t), \tag{2}$$

subject to the given initial wealth of A_0 and stochastic labor income sequence $\{Y_t\}_{t=0}^{\infty}$, that is, the individual's flow budget constraint is

$$A_{t+1} = A_t(1 + r) + Y_t - C_t, \quad 0 \leq t \leq \infty \tag{3}$$

The consumer cannot choose the entire path of consumption at time 0 due to uncertainty, but the consumer can only choose C_0 and contingency plans for C_t, $\mathrm{t} \geq 1$, where the plans are contingent of the realizations of Y_t. We assume that a proper transversality condition is satisfied.

To solve the consumer's problem, we would set up the following Lagrangian.

$$L = E_0 \sum_{t=0}^{\infty} \beta^t \{ u(C_t) + \lambda_t [A_t(1+r) + Y_t - C_t - A_{t+1}]\}, \quad (4)$$

where each period budget constraint is treated as a separate constraint, and has a separate Lagrange multiplier.

Then, we can get the equation as follows:

$$u'(C_t) = \beta (1+r) E_t \lambda_{t+1} = \beta (1+r) E_t u'(C_{t+1}) \quad (5)$$

The principle theoretical results are presented in a series of corollaries as follows:

As a special case, suppose ρ = r ($\beta = \frac{1}{1+r}$), that is subjective time preference parameter equals objective time preference parameter and we have $E_t u'(C_{t+1}) = u'(C_t)$, so that the marginal utility of consumption follows a martingale process (or a random walk process with additional assumption on second moments).

Consider the quadratic utility function u(C) = $C - \frac{1}{2} aC^2$, implying that $u'(C_t) = 1 - aC$. If we consider the case of ρ = r, then, implies,

$$E_t C_{t+1} = C_t \quad (6)$$

This implies $C_{t+1} = C_t + \varepsilon_{t+1}$,

Where $\varepsilon_{t+1} = C_{t+1} - C_t = C_{t+1} - E_t C_{t+1}$. That is, consumption is a random walk (more generally, a martingale). In the deterministic case, consumption is perfectly equalized for all *t*. Here, the household chooses to have a consumption path which has no predictable changes.

When uncertainty is resolved, the consumer will adjust its consumption, but it always does it in a way that implies that any future changes are unpredictable.

3. Data and Preliminary Analysis

We obtain per capita disposable income (y_t) and consumption expenditure (c_t) of rural households from China Statistical Yearbook (2010). Observations are annual and span from 1978 to 2009. China began their major economic reforms in 1978, so observations prior to 1978 are not used. Per capita disposable income and consumption expenditures on nondurables and services in the US are from the Federal Reserve Bank of St. Louis (FRED). The data is quarterly and covers the period from 1952:Q1 to 2011:Q4. We deflate the data using the consumer price index in each country and all data are expressed in natural logarithms.

We first present two scatter plot diagrams of ΔC_t and ΔY_t in each country in Figure 1. If consumption is not predictable, as the PIH implies (e.g., Hall, 1978; Campbell and Mankiw, 1990), one should not find any strong systematic pattern from these diagrams, because the consumption responds only to the extent that there is a change in permanent income. We find a clearly positive relation in both diagrams, which may be at odds with the PIH.

We next implement the augmented Dickey-Fuller (ADF) test for these variables to make sure that our instrument and/or explanatory variables are valid. Results are reported in Table 1.

The valid and stationary instrumental variables are employed to test the stationary of time series. The augmented Dickey–Fuller (ADF) statistic in the test is a negative number (Table 1). The more negative it is the stronger rejection of the hypothesis that there is a unit root at some level of confidence.

$$\Delta y_t = \gamma y_{t-1} + a + \delta t + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t \quad (7)$$

Where α is a constant, p is the lag order of the autoregressive process, u_t is the random disturbance term, δ is the coefficient on a time trend. According to the data we select, we will test ADF with constant term only or ADF with both constant and time trend for the unit root test function. The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. If the test statistic is less than the critical value, then the null hypothesis of $\gamma = 0$ is rejected and no unit root is present, and vice versa.

We chose the number of lags by the Akaike Information Criteria with a maximum 8 and 2 lags, for the US (quarterly) and rural China (annual), respectively. The ADF test rejects the null of non-stationary only for differenced series with an exception of y_t in rural China, which may imply a trend stationary process. Overall, our test results imply that consumption and income are integrated series.

4. Empirical findings

4.1 In-Sample Analysis

Campbell and Mankiw (1990) test the empirical validity of Hall's (1978) famous claim that consumption follows a random walk process under the PIH. They assume that a constant fraction of consumers (λ) does not obey the PIH, because they are liquidity constrained, therefore are not capable of smoothing consumption over time. For these consumers, consumption changes should simply reflect income changes, that is, $\Delta C_t = \Delta Y_t$. For the rest of consumers, type 2 consumers, we assume that their consumption is consistent with the PIH, which implies $\Delta C_t = \varepsilon_t$. Aggregating consumptions yields the following estimable equation.

$$\Delta C_t = \lambda \Delta Y_t + u_t, \tag{8}$$

where $u_t = (1-\lambda)\varepsilon_t$. Campbell and Mankiw (1990) report significantly positive estimate using the US data for 1953 to 1986, which implies strong evidence against the PIH. Similarly strong evidence is also reported by Flavin (1981).

We employ Campbell and Mankiw's method for the rural China data. To deal with the endogeneity bias in (1), we use the iterative efficient Generalized Method of Moments (GMM) estimation method (Hansen, 1982) and report a formal specification test results in Table 2.[3] We also report similar estimates from the US data for 1952 to 2011 in Table 3.

The first column provides sets of instrumental variables used in each regression.[4] The second column reports λ estimates along with their robust standard errors. The third column reports specification test results along with the *p*-value of each *J* test statistic.

As we can see in Tables 2 and 3, all λ estimates are positive and statistically significant at the 5% level, which provides strong empirical evidence against the PIH. Our model specification seems reasonable as the *p*-value of the *J* test statistics is less than 0.05 in all regressions.

We also note that the λ estimates are overall bigger in rural China compared with those of the US. The value varies from 0.611 to 0.879 in China, while it ranges from 0.287 to 0.769 in the US. This seems plausible because λ is a fraction of liquidity constrained consumers and households in rural China are more likely to be such consumers.

4.2 Out-of-Sample Predictability

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[3] Campbell and Mankiw (1990) use the instrumental variable estimator, which is a special case of the GMM. They didn't report a formal specification test.

[4] Following Campbell and Mankiw (1990), we do not use first lagged variables, because the US data is quarterly and first lagged variables are still likely to be correlated with errors.

We next implement a more direct test for the PIH via the out-of-sample forecast test proposed by Diebold and Mariano (1995) and West (1996). We evaluate predictability of lagged variables for consumption changes relative to that of the random walk model, which is consistent with the PIH (Hall, 1978), serving as a benchmark. The test is implemented as follows.

The random walk model of C_t implies,

$$C^R_{t+1|t} \;=\; C_t, \tag{9}$$

where $C^R_{t+1|t}$ is the *1*-step ahead consumption forecast by the random walk model given information set at time *t*. The competing model using a vector of lagged variables as the explanatory variables (X_t) is based on the following least squares regression

$$\Delta C_{t+1} = \; \beta' \Delta X_t + \; u_t \tag{10}$$

Note that we use difference filter for the consistency of the least squares estimator. Given the least squares coefficient estimate, we construct the *1*-step ahead forecast by such an alternative model $C^A_{t+1|t}$ as follows.

$$C^A_{t+1|t} \;=\; \Delta\widehat{C_{t+1}}_{|t} + C_t, \tag{11}$$

where $\Delta\widehat{C_{t+1}}_{|t}$ is the fitted value from (3) and C_t is the actual realized observation at time *t*.

We obtain the following differential loss function,

$$d_t = L(\varepsilon^R_{t+1|t}) - L((\varepsilon^A_{t+1|t}),$$

where $L(\varepsilon^{j}_{t+k|t})$, $j = R, A$ is a loss function and forecast errors are, [5]

$$\varepsilon^{R}_{t+1|t} = C_{t+1} - C^{R}_{t+1|t}, \qquad \varepsilon^{A}_{t+1|t} = C_{t+1} - C^{A}_{t+1|t}$$

The Diebold-Mariano-West statistic (*DMW*) with the null of equal predictive accuracy, $H_0: Ed_t = 0$, is given,

$$DMW = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}} \tag{12}$$

where $\bar{d} = \frac{1}{T-T_0}\sum_{t=T_o+1}^{T} d_t$, and $\widehat{Avar}(\bar{d})$ is the asymptotic variance of $\bar{d}$, $\frac{1}{T-T_0}\sum_{j=-q}^{q} k(j,q)\hat{\Gamma}_j$, where $k(\cdot)$ denotes a kernel function where $k(\cdot) = 0, j > q$, and $\hat{\Gamma}_j$ is the j^{th} autocovariance function estimate.[6] Since the DMW statistic is severely under-sized with asymptotic critical values when competing models are nested, we use critical values by McCracken (2007) to correct it.[7]

We carried out forecasting recursively by sequentially adding one additional observation from *P* percent initial observations toward the end of observations. We re-estimate coefficients (β) for each recursive sample. The ratio of the root mean square prediction error (*RRMSPE*) is defined as the root mean square error of the random walk model relative to that of the competing model. Therefore, a greater value of *RRMSPE* than one implies some evidence against the PIH, because the explanatory variables have predictive power. We seek for more rigorous evidence via the *DMW* statistics with McCracken's (2007) critical values.

We report out-of-sample forecast exercise results in Tables 4 and 5 for rural China and

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[5] We use the conventional squared error loss function, $(\varepsilon^{j}_{t+1|t})^2$, $j = R, A$.

[6] Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

[7] Note that the alternative model nests the random walk model when β is a null vector.

the US, respectively. All RRMSPE values exceed one for both rural China and the US. We reject the null of equal predictability of the DMW test at any conventional significance level. Our results are quite robust to size of initial split ratio.[8] Again, we obtain very strong empirical evidence against the PIH via more direct out-of-sample forecast analysis.

5. Vector Autoregressive Analysis

5.1 Impulse-Response Function

We supplement our analysis on the predictability of consumption changes by the vector autoregressive (VAR) model analysis. That is, we propose the following conventional VAR model for the consumption and income growth rates.

$$x_t = A(L)x_{t-1} + B\epsilon_t, \tag{13}$$

where $x_t = [\Delta Y_t, \Delta C_t]'$, B is a lower-triangular matrix, and ϵ_t is a vector of normalized and orthogonalized structural income and consumption shocks ($\mathrm{E}(\epsilon_t \epsilon_t') = I$). The shape of B implies that income is not contemporaneously affected by unexpected consumption changes. We used two lags by the Akaike Information Criteria, and construct nonparametric bootstrap confidence bands from 5,000 bootstrap simulations using empirical distributions. We report the accumulated responses of the level variables, Y_t and C_t, to each structural shock in Figure 2.

Note that Hall's (1978) extension of the PIH predicts that consumption responds to income changes only by the extent of the change in permanent income. In rural China, consumption increases about 0.5% at the impact when there is a 1% income shock. After growing rapidly for about two years, consumption growth slows down and stabilizes to around

[8] The forecast performance may depend of the size of initial number of observations used in the estimation relative to the remaining observations for evaluations. That is, if one uses the first half observations for estimation, the split ratio is 0.5. We report results with three split sizes in each Table.

2% overall increase from the beginning. Similar but a lot weaker responses are observed in the US, which implies stronger evidence against the PIH in rural China. We also note that the response function estimates are significant at the 5%.

We observe that income negatively responds to a consumption shock, which is insignificant at the 5% but significant at the 10% (not reported here) in rural China. On the other hand, significantly positive responses are observed for the US. That is, unexpectedly high consumption growth rates in rural China may reduce their income over time, which may happen if economic capacity shrinks as saving declines. On the contrary, consumption is a virtue, not a vice, in the US.

5.2 Variance Decomposition Analysis

We next implement the variance decomposition analysis to illustrate how much variations of consumption changes in the future can be explained by exogenous shocks to each variable. Results are reported in Tables 6 and 7, for rural China and the US, respectively.

We again observe very different patterns. In rural China, both income shocks and consumption shocks play virtually equally important roles in explaining future changes in consumption. In the US, a little less than 25% contributions of income shocks are observed for all time horizons we consider. These findings imply a weaker evidence of the PIH in rural China compared with the US, while we fail to see strong empirical evidence of the PIH in any of these countries.

6. Concluding Remarks

This paper revisits the empirical inconsistency of the Permanent Income Hypothesis using rural area household data in China along with the postwar US data as a benchmark. We view rural area residents as representative consumers in China since this group of consumers has been a dominant majority until recently. Further, rural China and the US make good contrasting groups of consumers.

We present strong evidence against the PIH in the sense that consumption growth is highly predictable, which is in contrast to the work by Chow (1985, 2010) who reported favorable indirect evidence using conventional normal approximation based tests.

Our in-sample analysis based on Campbell and Mankiw (1990) implies a lot weaker evidence in favor of the PIH when the rural China data is used instead of the US data. The λ point estimate ranges from 0.611 to 0.879 for rural China, while much smaller values were obtained when we use the US data, which seem reasonable because λ is a fraction of consumers who are liquidity constrained.

Our out-of-sample forecasting exercises directly deal with the predictability issue from the PIH. We obtain very strong results against the PIH in the sense that explanatory variables have substantial predictive contents for consumption growth, which is robust to the choice of sample split.

Our dynamic analysis with VAR framework also provides empirical results that are consistent with the previous findings. Consumption responds to an income shock highly significantly in both countries, but we observed a lot stronger responses from rural China than the US. The variance decomposition analysis shows that roughly 50% of consumption changes are explained by income shocks in rural China, while income shocks explain less than 25% of consumption changes in the U.S.

Table 1. ADF Test Results

Rural China

Variable	ADF_c	ADF_t
C_t	0.053	-2.113
Y_t	-0.166	-3.438*
ΔC_t	-3.553*	-3.474†
ΔY_t	-3.342*	-3.170†

US

Variable	ADF_c	ADF_t
C_t	-1.839	-0.688
Y_t	-2.093	-0.503
ΔC_t	-4.966*	-5.280*
ΔY_t	-9.416*	-14.62*

Note: ADF_c and ADF_t denote the ADF *t*-statistic with an intercept and with an intercept and time trend, respectively. We chose the number of lags by the Akaike Information Criteria with a maximum 8 lags for quarterly US data, while a maximum 2 lags were used for annual rural China data. * denotes stationary at the 5% significance level, † denotes stationary at 10% significance level.

Table 2. GMM Estimation Results: Rural China

Instruments (Z)	λ (s.e)	J (p-value)
None (OLS)	0.730 (0.092)	
$\Delta Y_{t-1}, \Delta Y_{t-2}$	0.731 (0.163)	0.908 (0.341)
$\Delta Y_{t-1}, \ \ldots, \ \Delta Y_{t-4}$	0.611 (0.245)	3.257 (0.354)
$\Delta C_{t-1}, \Delta C_{t-2}$	0.766 (0.140)	2.322 (0.128)
$\Delta C_{t-1}, \ \ldots, \ \Delta C_{t-4}$	0.730 (0.235)	4.070 (0.254)
$\Delta Y_{t-1}, \ \Delta Y_{t-2}, \ \Delta C_{t-2}, \Delta C_{t-2}$	0.778 (0.118)	2.831 (0.418)
$\Delta Y_{t-1}, \ \ldots, \ \Delta Y_{t-4}, \ \Delta C_{t-1}, \ \ldots, \Delta C_{t-4}$	0.879 (0.133)	5.409 (0.610)

Note: Annual observations span from 1978 to 2009. This table reports iterative efficient GMM estimates of $\Delta C_t = \lambda Y_t + u_t$, using an array of instrumental variables Z. Numbers in parentheses in column 2 are standard errors for the λ estimate. Numbers in parentheses in column 3 are *p*-values for the *J*-test statistic that follows the chi-square distribution. All λ estimates are significant at the 5% level. The *J*-test supports the specification of our model at any conventional significance levels.

Table 3. GMM Estimation Results: US Nondurable and Services

Instruments (Z)	λ (s.e)	J (p-value)
None (OLS)	0.287 (0.045)	
$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	0.769 (0.282)	1.240 (0.538)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-6}$	0.447 (0.157)	4.989 (0.288)
$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	0.628 (0.137)	5.885 (0.053)
$\Delta C_{t-2}, \ldots, \Delta C_{t-6}$	0.664 (0.132)	8.291 (0.082)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-4}, \Delta C_{t-2}, \ldots, \Delta C_{t-4}$	0.487 (0.112)	9.902 (0.078)
$\Delta Y_{t-2}, \ldots, \Delta Y_{t-6}, \Delta C_{t-2}, \ldots, \Delta C_{t-6}$	0.505 (0.094)	13.06 (0.160)

Note: Observations are quarterly and span from 1952:Q1 to 2011:Q4. This table reports iterative efficient GMM estimates of $\Delta C_t = \lambda Y_t + u_t$, using an array of instrumental variables Z. Numbers in parentheses in column 2 are standard errors for the λ estimate. Numbers in parentheses in column 3 are p-values for the J-test statistic that follows the chi-square distribution. All λ estimates are significant at the 5% level. The J-test supports the specification of our model at the 5% significance level.

Table 4. Out-of-Sample Forecast: Rural China

Split Ratio	Explanatory Variables	*RRMSPE*	*DMW*
0.50	ΔY_t	1.6670	6.4453*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.5121	5.5638*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.6606	6.5673*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.6377	5.3142*
0.66	ΔY_t	1.8764	7.1839*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.6249	10.288*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.7243	9.3049*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.7647	10.931*
0.81	ΔY_t	1.9118	10.956*
	$\Delta C_{t-1}, \Delta C_{t-2}$	1.5886	11.565*
	$\Delta Y_{t-1}, \Delta Y_{t-2}$	1.6889	29.985*
	$\Delta C_{t-1}, \Delta C_{t-2}, \Delta Y_{t-1}, \Delta Y_{t-2}$	1.7863	16.006*

Note: Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from *P*% initial observations toward the end of observations. Split ratio denotes the number for *P*, that is, 0.66 implies that 66% initial observations are used to start recursive forecasting. *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesis to the competing model. *DMW* denotes the test statistics of Diebold and Mariano (1995) and West (1996). * denotes rejection of the null hypothesis of equal predictability at the 1% significance levels.

Table 5. Out-of-Sample Forecast Analysis: US

Split Ratio	Explanatory Variables	*RRMSPE*	*DMW*
0.50	ΔY_t	1.8411	10.322*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	2.0158	10.806*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.9177	10.602*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	2.0068	10.642*
0.65	ΔY_t	1.7986	9.8501*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	2.0615	10.660*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.8993	9.9372*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	2.0824	10.892*
0.81	ΔY_t	1.4856	5.4806*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4}$	1.7480	6.9882*
	$\Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.5825	5.9971*
	$\Delta C_{t-2}, \Delta C_{t-3}, \Delta C_{t-4} \Delta Y_{t-2}, \Delta Y_{t-3}, \Delta Y_{t-4}$	1.7572	7.1435*

Note: Out-of-sample forecasting was recursively implemented by sequentially adding one additional observation from *P*% initial observations toward the end of observations. Split ratio denotes the number for *P*, that is, 0.66 implies that 66% initial observations are used to start recursive forecasting. *RRMSPE* denotes the ratio of the root mean squared prediction error of the random walk hypothesis to the competing model. *DMW* denotes the test statistics of Diebold and Mariano (1995) and West (1996). * denotes rejection of the null hypothesis of equal predictability at the 1% significance levels.

Table 6. Variance Decomposition of $\hat{E}_t(\Delta C_{t+k})$: Rural China

k	Income	Consumption	Standard Error
1	68.165	31.834	0.0312
2	52.974	47.025	0.0354
3	50.480	49.519	0.0400
4	50.916	49.083	0.0413
5	50.465	49.534	0.0415
6	50.187	49.812	0.0416
7	50.003	49.996	0.0417
8	49.943	50.057	0.0418
9	49.917	50.082	0.0418
10	49.903	50.096	0.0418

Note: The variance decomposition is based on a bivariate VAR with ΔY_t and ΔC_t. ΔY_t is ordered first. $\hat{E}_t(\Delta C_{t+k})$ denotes the least squares projection for *k*-period ahead consumption changes using available information at time *t*.

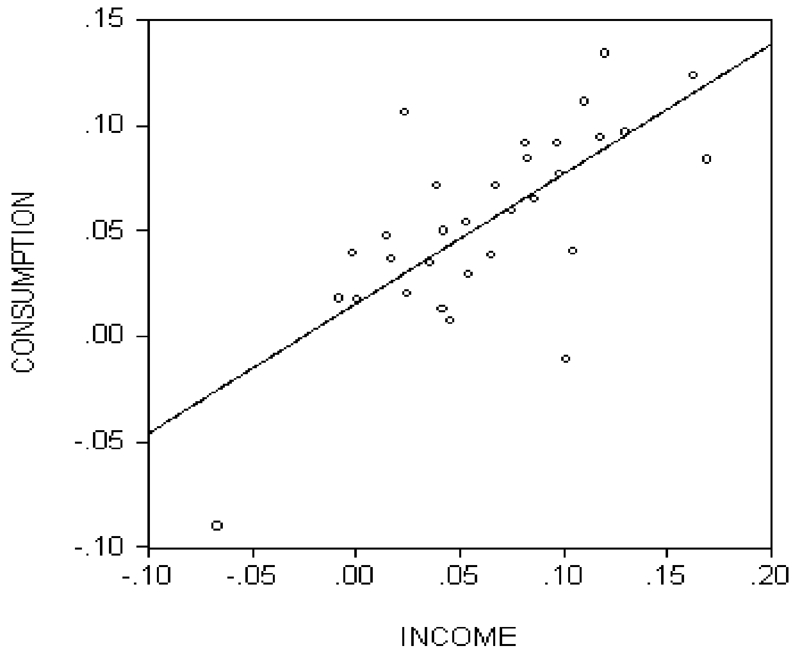
Table 7. Variance Decomposition of $\hat{E}_t(\Delta C_{t+k})$: U.S.

k	Consumption	Income	Standard Error
1	78.5724	21.4276	0.0042
2	75.1206	24.8794	0.0046
3	76.2049	23.7951	0.0047
4	76.1455	23.8545	0.0048
5	76.2113	23.7887	0.0048
6	76.2157	23.7843	0.0048
7	76.2212	23.7788	0.0048
8	76.2223	23.7777	0.0048
9	76.2228	23.7772	0.0048
10	76.2230	23.7770	0.0048

Note: The variance decomposition is based on a bivariate VAR with ΔY_t and ΔC_t. ΔY_t is ordered first. $\hat{E}_t(\Delta C_{t+k})$ denotes the least squares projection for *k*-period ahead consumption changes using available information at time *t*.

Figure 1. Scatter Plot Diagrams of ΔC_t and ΔY_t

(a) Rural China



(b) US

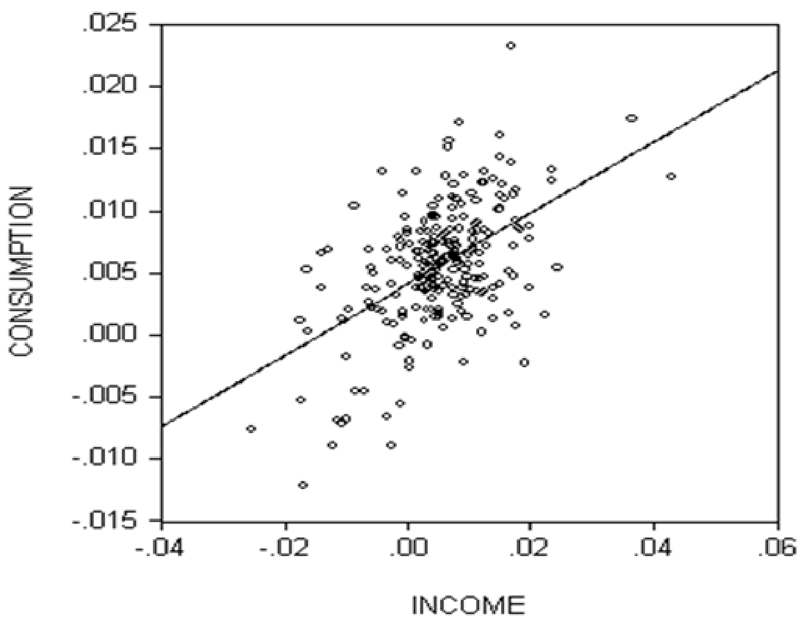
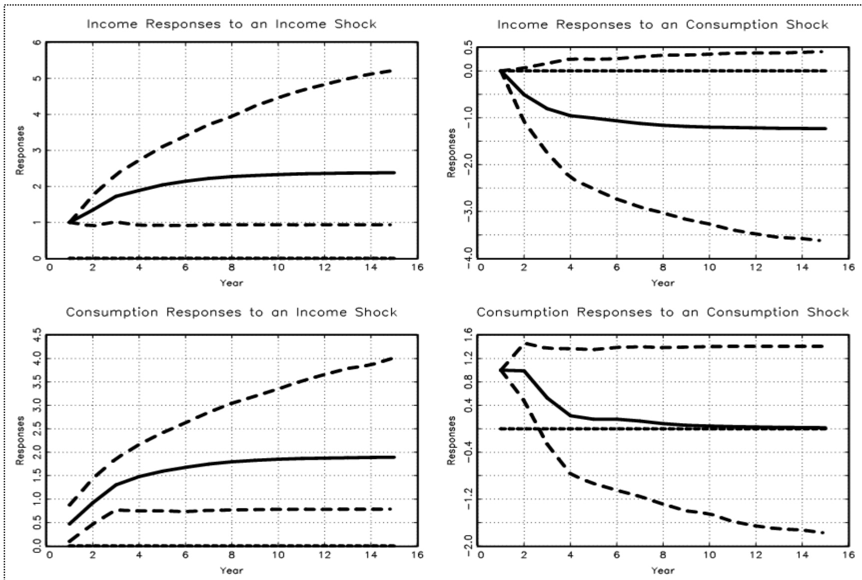
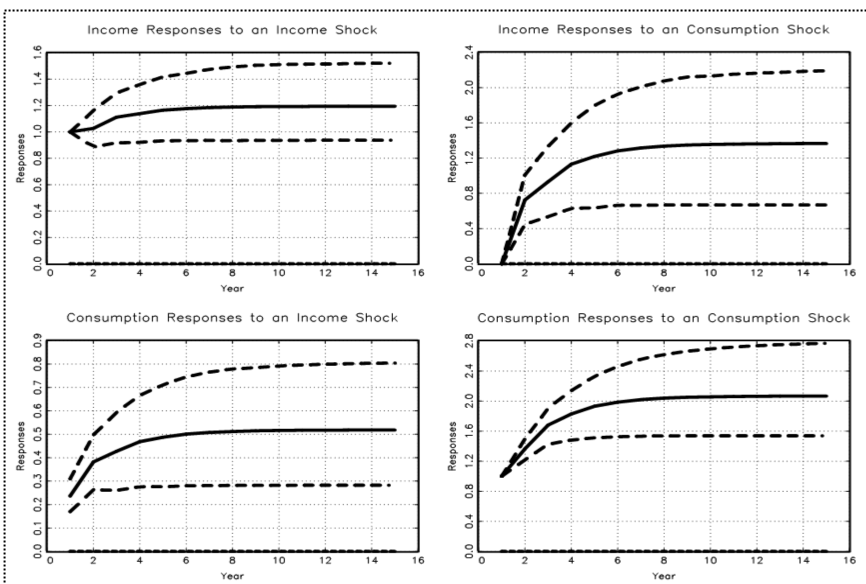


Figure 2. Orthogonalized Impulse Response Function Estimates

(a) Rural China



(b) US



Note: 95% confidence bands are constructed by 5,000 nonparametric bootstrap simulations. ΔY_t is ordered first so that it is not contemporaneously affected by innovations in ΔC_t. Responses are accumulated to make statistical inferences on the level variables, Y_t and C_t, instead of the growth variables.

Chapter 3. On the Effect of the Great Recession on US Household Expenditures on Entertainment

Abstract

This paper empirically investigates potential effects of economic recessions on consumer's decision making process for recreational activities using the Consumer Expenditure Survey (CES) data during the Great Recession. We employ the Probit model to study the propensity of making non-zero expenditures on entertainment activities. We also use the Tobit model to correct for the bias from using the ordinary least squares (OLS) method in presence of censored observations. We find overall significantly negative effects of recessions either through decreases in intercept or in the income coefficient estimates.

1. Introduction

This paper empirically investigates potential effects of economic recessions on US household expenditures on entertainment activities using the Consumer Expenditure Survey (CES) data in 2003, 2006, 2008, and 2010.

A number of studies have examined consumer's decision making processes for entertainment and leisure activities. Travel expenditure patterns are identified to examine the likelihood of travel expenditures in the U.S. (Sung et al., 2001; Hong et al., 2005, Zheng & Zhang, 2011). The determinants of leisure satisfaction are estimated through ordered Probit models (Ateca-Amestoy, Serrano-del-Rosalet & Vera-Toscano, 2008). Leisure value is calculated with a time allocation model by Jara-Díaz et al. (2008). Additionally, fishing and hunting leisure spending shares in the U.S. are examined with a bivariate censored demand system by Bilgic et al. (2008).

Leisure development is also related with the general social and social psychological processes (Moore et al., 1995), leisure activities are supposed to provide life satisfaction and improve personal wellbeing (Weagley & Huh, 2004b; van der Meer, 2008). Patterns of work and leisure have changed dramatically during the past decades in the U.S. (Weagley & Huh, 2004a; Bilgic et al., 2008). Economic and social environment changes have influenced leisure activities and expenditure in the U.S. (Dardis, Soberon-Ferrer & Patro, 1994).

In this paper, we investigate whether economic downturns influence the consumption function for entertainment goods and services. For this purpose, we use 2008 and 2010 CES data for recession years, while 2003 and 2006 CES data were used as economic booms years.

We note substantial degree censored observations in all year, which led us to employ the Tobit model instead of the ordinary least squares (OLS) estimator. Even though the Tobit model is useful to quantify the effects of socio-economic variables on the expenditure for entertainment activities, it does not answer to the question of how those variables affect the propensity of paying (or not paying) for entertainment activities. To answer this question, we also employ the Probit model by transforming the expenditure data to a dichotomous variable.

We find overall negative effects of recessions on recreational activities via changes in income coefficient estimates and intercept both in Probit and Tobit models. For example, income coefficients become smaller during recession years for two out of the three recreation expenditure categories, while substantial decreases in intercept estimates were observed for the Fees and Admissions (F&A) in 2008 and 2010 relative to 2003 and 2006, which imply exogenous changes across those years outside our model specification. We also find non-negligible changes in coefficients of some socio-economic variables including the number of children, family size, and the marital status.

The rest of the present paper is organized as follows. Section 2 provides a data description and preliminary test results. In Section 3, we provide our main empirical findings from Probit and Tobit model. We conclude in section 4.

2. Data

We noticed that the level of entertainment expenditures declined substantially in 2010 in both real and nominal terms. As we can see in Table 8, we observed overall increases in expenditures in 2008 from 2006 both in real and nominal terms except F&A in real term. Furthermore, median nominal household income decreased from 2008 to 2010 but not in 2008 from 2006, while decreases in real income were observed in both years. As we can see in Figure 3, GDP per capita actually exhibited a positive growth rate in 2008 and in 2010, while median household income slowed down in 2008 and became negative in 2009 and 2010. So it is not clear if the Great Recession in 2008 is consistent with dynamics of the US household income. This concern leads us to use 2010 as well as 2008 as recession years relative to 2003 and 2006 as boom years.[9]

We obtain data from the Consumer Expenditure Survey (CES) of the Bureau of Labor Statistics by the U.S. Census Bureau. “Household” is used instead of “consumer unit” in the CES. In the survey, household disposal income is assessed as the personal income after federal, state, and local taxes for all persons in the household in the CES. To examine the entertainment expenditure, the present paper uses the CES data in 2003, 2006, 2008, and 2010, which covers five quarters in each year.

The dependent variable is household expenditures on entertainment. Entertainment expenditures are classified into the following three: (1) Fees and Admissions (F&A); (2) Televisions, Radios and Sound Equipment (TRS); (3) Other Equipment and Services (OES). See Table 9 for details.

We provide preliminary statistics of entertainment expenditures of sampled households in 2003, 2006, 2008, and 2010 in Tables 10 and 11, respectively. Overall, TRS expenditures account for about 40% of the total entertainment expenditures, and about the same proportion of expenditures were made for OES. F&A accounts for about 25% of the total entertainment expenditures.

A family with child accounts approximately 30% of the total. White population accounts for about 80% of the total population. More than 90% of the total population resides in urban area. Majority households are married and with higher education

The most notable characteristic is an issue about high degree censored observations as we can see in Figure 4. We find that over 50% households spent no money for F&A activities. As to

[9] We do not report results in 2006 to save space. All results are available upon request.

TRS, 18.26%, 15%, and 16.59% households report \$0 in 2003, 2008, and 2010, respectively. About 45% households did not spend any money for OES activities.

Clearly, estimated kernel densities are quite different from estimated distribution with a normal density assumption, which implies a severe bias in ordinary least squares (OLS) estimates. To correct for the bias, we employ the Tobit model and report coefficient estimates of explanatory variables in comparison with those of the OLS method. In what follows, however, we first study what variables affect the propensity of spending non-zero expenditures on entertainment activities employing the Probit model, because non-negligible, sometimes majority households report zero expenditures for these recreational activities.

3. Empirical findings

To deal with censored observations, we first employ the Probit model to estimate the likelihood of non-zero expenditures on entertainment, and marginal effects of explanatory variables on the probability, which measures changes in the probability due to a one unit change in explanatory variables. Then, we report Tobit analysis results in comparison with the OLS.

3.1 Probit model

Let $u_{1,i}$ denote an unobservable level of utility of an agent i from spending a strictly positive amount of money on recreational activities, while $u_{0,i}$ is the level of utility when the agent does not consume any entertainment services. Employing the random utility model framework, we describe consumers' decision making processes as follows.

$$y_i^* = u_{1,i} - u_{0,i} = x_i\beta + \varepsilon_i, \tag{1}$$

where x_i is a $k \times 1$ vector of characteristic variables of i including an intercept, β is its associated vector of coefficients, and ε_i is assumed to be normally distributed. Then, realized outcome (y_i) is the following.

$$y_i = \begin{cases} 1, & if \quad y_i^* > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

We first estimate β in the latent equation (1) by the conventional Probit model estimation method in what follows. We also report the marginal effect that measures the effect of changes in x_i on the change in the probability of $y_i = 1$. Since the marginal effect changes depending on the location of i, we report average marginal effects. All results are provided in Tables 12, 13, and 14.

For F&A category, we find intercept decreases in 2008 and 2010, recession years, compared with the boom year (2003), which implies that there was negative effect of variables that are not included in our model. The income coefficient estimates in recession years are substantially lower than that of 2003 for TRS and OES categories. We find a little higher intercepts for these types of expenditures in 2008 and 2010, which seems to be interesting since people prefer to stay at home during the Great Recession.

As expected (Table 12), income has a statistically significant positive impact on F&A. Those household with more persons older than age 64 are more likely to spend on F&A in 2003 and 2010. Those with more children are likely to spend more on F&A in 2008. Family size is only significantly negative related with F&A in 2008 and 2010. Age is supposed to have a nonlinear relationship with expenditures, thus results may not be reliable.

All other remaining factors have the same effect in these three years, and they are all significantly positive related with F&A. For example, Family with children spends more on F&A than Family without children. Male is likely to spend more on F&A than Female.

To examine the exact probability of independent variables on depend variables, we also report the marginal effect of the Probit model. With one unit increasing of income, the probability of spending on F&A goes up by about 0.22%, 0.22%, and 0.21% in 2003, 2008, and 2010. Household with one more adult older than 64 makes the probability of expenditure rising by about 1.24% in 2003 and 0.35% in 2008. Household with one more child has the probability of increasing expenditures by about 1.40% in 2008. However, one more unit of family size causes the probability of spending on F&A going down by about 1.32% in 2008 and 1.01% in 2010.

Moreover, family with children, being married (Married), white people (White), and people with college education (College), being male (Male), or being urban (Urban) increases the probability of spending on F&A, but with different degree. Such as, male has higher probability about 3.28%, 1.43%, and 1.4% higher than female in 2003, 2008, and 2010, respectively.

For TRS category (Table 13), intercept is not significant in 2003, but it decreases from 2008 to 2010, under the 5% significant level, there will be potential overlapping part, but if we use 1% as the significant level, this definitely confirms the decreasing trend. Income coefficient is the same for 2008 and 2010, which is lower than that in 2003. Thus, the Great Recession in 2010 was somewhat influencing expenditure in this category.

As expected, income has a statistically significant positive impact on TRS category in all three years. Those household with person older than 64 year old are less likely to spend on TRS in 2003 and 2008. To our surprise, Male is less likely to spend on TRS than Female, but only significant in 2008 and 2010. Urban is more likely to spend on TRS in 2008, but less likely to spend in 2010.

Others have the same effect in these three years, and they are all significantly positive related with TRS (except No. of children). For example, Family with children spends more on TRS than Family without children.

To examine the exact probability of independent variables on dependent variables, we employ the marginal effect of the Probit model (Table 13). With one unit increasing of income, the probability of spending on TRS goes up by about 0.16%, 0.12%, and 0.13% in 2003, 2008, and 2010. But household with one more adult older than 64 year old makes the probability of expenditure decreasing by about 1.84% in 2003 and 1.14% in 2008. Male exhibits a lower probability about 1.47% in 2008 and about 1.66% in 2010, compared with Female for expenditure spending on TRS. Urban shows a higher probability (approximately 2.02%) than Rural only in 2003.

What's more, Family with children, being married (Married), white people (White), and people with college education (College), or being male (Male) increases the probability of spending on TRS, but with different degree. However, with one more children will decrease the probability of expenditure on TRS about 2.82%, 2.10%, and 1.55% for 2003, 2008, and 2010, respectively.

For OES category (Table 14), income in 2010 is similar with that in 2008, which is less than that in 2003, but intercept in 2008 is larger than that in 2003, but that in 2010 is a little bit lower than that in 2011. The Great Recession effect is more obvious in 2010 than that in 2008.

As expected, income has a statistically significant positive impact on OES category in all three years. It is noted that only No. of children of all main influencing factors is different in three years. Those household with children are more likely to spend on OES entertainment, but it's only significant in 2003.

All the remaining has the same effect in these three years. We further find the negative relationship for No. of adults older than 64 year old, Male, and Urban, and the positive relationship for others.

To examine the exact probability of independent variables on depend variables, we employ the marginal effect of the Probit model. With one unit increasing of income, the probability of spending on OES goes up by about 0.18%, 0.12%, and 0.13% in 2003, 2008, and 2010. But household with one more adult older than 64 year old makes the probability of expenditure decreasing by about 2.86% in 2003, 4.42% in 2008, and 3.34% in 2010. With one more children, household will have a probability about 0.76% in 2003, which is not significant in 2008 and 2010.

And the marginal effect is negative for No. of adults older than 64 year old, Male, and Urban, and but positive for others. For example, White people have a higher probability about 17.56%, 19.27%, and 17% than non-White people for 2003, 2008, and 2010 respectively. Urban resident shows a lower probability about 5.64%, 8.31%, and 3.98% than Rural resident for 2003, 2008, and 2010, respectively.

3.2 Tobit model

We also employ the Tobit model to investigate quantitative effects of changes in the characteristic variables on the amount of expenditures on recreational activities. We employ the model described in equation (1) but modify the determination of the realized outcome (y_i) as follows.

$$y_i = \begin{cases} y_i^* , & if \quad y_i^* > 0 \\ 0 & \quad\quad \text{Otherwise} \end{cases} \tag{2}$$

Note that the ordinary least squares (OLS) estimator is biased due to censored observation. In presence of substantial degree censoring, the OLS tends to underestimate the true coefficients. We report and compare estimates for β using both the Tobit and the OLS methods in what follows.

In contrast to the Tobit model, we also analyze the data with the OLS regression for all entertainment expenditure and report results in Tables 15, 16, and 17. Intercept in OLS is obviously larger than that in the Tobit model, which shows a biased estimate actually. Coefficients in OLS are mainly smaller than that of the Tobit model, which tells the underestimated estimates. Since the OLS method doesn't include the observations with zero values in the model, the results will be biased and unreliable. Thus we employ the Tobit model to explain the entertainment activities in our results for all three years.

Intercept decreases in 2008 and 2010 from 2003, which implies the Great Recession effect on F&A in 2008 and 2010 (Table 15). The similar results of income coefficient confirm the recession effect. We find that income shows a statistically significant positive impact on F&A expenditure. For all three years, only factor that No. of adults older than 64 year old is different and significant only in 2010 in the Tobit model. Age and Family size have a negative relationship with F&A. All others exhibit a positive relationship with F&A.

For TRS category in three years, the results are only different for Family with children and Urban in the Tobit model (Table 16). Family with children is significant positively related with TRS in 2003 and 2008, but it's not significant in 2010. And Urban is significantly positive related with TRS only in 2003 and 2010.

All others exhibit the similar relationships with TRS among these three years. We observe that No. of adults older than 64 year old and No. of children are negatively related with TRS, and the mainly remaining are positively related with TRS.

Income coefficient decreases a little bit from 2003 to 2010 for TRS. But intercepts increases from 2003 to 2010, it's not significant in 2008. This implies that the effect of Great Recession is obvious in 2008 and 2010 if not covering intercept, but we are not sure the effect of recession if we consider the intercept.

We find that income shows a statistically significant positive impact on OES expenditure (Table 17). For all three years, only that Family with children is different for all these three years in the Tobit model. Family with children is significant positively related with OES only in 2003.

All others exhibit the similar relationships with OES among these three years. We notice that No. of adults older than 64 year old, Male, and Urban are negatively related with OES, and the mainly remaining are positively related with this expenditure.

The coefficient of income decreases in 2008 and 2010 from 2003, which implies somewhat cautious expenditures on OES activities during recession years.

4. Conclusions

This paper examines potential effects of the Great Recession on household consumption for entertainment activities in the U.S. using the CES data in 2003, 2006, 2008, and 2010. We estimate consumer's decision making process by estimating consumption functions in recession years, 2008 and 2010, in comparison with 2003 and 2006 as the benchmark.

Probit analysis is implemented to study what socio-economic variables affect the propensity to paying for entertainment activities during economic booms and recessions. We report both the estimated coefficients and marginal effects of economic variables that affect such decision, which is characterized as a latent equation. The Tobit and the OLS models are also employed to estimate quantitative effects of changes in relevant variables on actual expenditures in entertainment activities. Intercept and coefficient of the OLS are shown biased and underestimated results, which is due to severe degree censored observations.

Income has significantly positive coefficients for all three types of entertainment activities across all years. However, recessionary effects were found either in intercept (F&A) or in the income coefficient (TRS and OES) during recession years. That is, we find substantial decreases in intercept for F&A activities in 2008 and 2010 compared with those in 2003 and 2006. As to TRS and OES, we note substantial decreases in the income coefficient in recession years.

Table 8. Recreation Expenditures and Household Income

	Nominal				*Real*			
	2003	2006	2008	2010	2003	2006	2008	2010
F&A	130	156	161	148	130	142	137	125
TV	191	235	256	240	191	214	218	203
Other	183	190	225	193	183	173	193	163
Income	41,694	48,261	49,737	49,485	41,694	44,007	42,515	41,751

Table 9. Definition of Entertainment Expenditures

Entertainment
Fees and admissions
Miscellaneous recreational expenses on out-of-town trips
Membership fees for clubs, swimming pools, social or other recreational organizations, service
Fees for participant sports, participant sports on out-of-town trips, recreational lessons or other instructions
Management fees for recreational facilities
Admission fees for entertainment activities, sporting events on out-of-town trips
Entertainment expenses on out-of-town trips
Admission fees to sporting events (single admissions and season tickets)
Miscellaneous entertainment services on out-of-town trips
Televisions, radios, and sound equipment
Cable, satellite, or community antenna service, satellite radio service, satellite dishes
Televisions, video cassettes, tapes, and discs, video and computer game hardware and software
Streaming or downloaded video files, radio, tape recorder and player, digital audio players
Sound components, component systems, and compact disc sound systems
Accessories and other sound equipment including phonographs
Records, CDs, audio tapes, streaming or downloaded audio files
Repair of television, radio, and sound equipment, excluding installed in vehicles
Rental of televisions, VCR, radio, and sound equipment
Musical instruments, supplies, and accessories
Rental and repair of musical instruments, supplies, and accessories
Installation for TVs, satellite TV equipment, sound systems, other video or sound systems
Other equipment and services
Toys, games, arts, crafts, tricycles, and battery powered riders, playground equipment
Pets, pet supplies and medicine for pets, pet services, veterinarian expenses for pets
Docking and landing fees for boats and planes
Rental of non camper-type trailer, boat or non camper-type trailer
Outboard motor, boat without motor or non camper-type trailer, boat with motor (net outlay), bicycles
Trailer-type or other attachable-type camper (net outlay)
Purchase of motor home, other vehicle
Ping-Pong, pool tables, other similar recreation room items
Hunting and fishing, winter/water/other sports, health and exercise equipment
Photographic film, film processing, photographic equipment, professional photography fees
Rental and repair of photographic equipment, sports, and recreation equipment
Rental of all boats and outboard motors, motor home, other RV's
Rental of all campers, other vehicles on out-of-town trips
Online entertainment and games, live entertainment for catered affairs

Reference: Consumer Expenditure Survey.

Table 10. Summary of the variables in 2003 and 2006

Variable	2003 (N=40374)	2006 (N=35832)
	Mean (Std Dev)	Mean (Std Dev)
Total entertainment expenditure (in dollars)	503.12 (1656.64)	580.36(1563.03)
Fees and admissions	129.75 (429.76)	234.85 (475.56)
Televisions, radios, and sound equipment	190.82 (383.59)	189.82 (392.30)
Other equipment and services	182.54 (1496.61)	182.54 (1357.15)
Income after tax (in dollars)	41694.00 (47255.95)	48260.95 (55544.85)
Family size	2.53 (1.50)	2.55 (1.51)
No. of adult>64 years old	0.31 (0.61)	0.31 (0.61)
No. of children	0.68 (1.09)	0.67 (1.08)
Age	48.48 (17.55)	49.03 (17.27)
	Frequency (%)	Frequency (%)
Family type		
Family with child	12828 (31.77)	11412 (31.85)
Family without child	27546 (68.23)	24420 (68.15)
Marital status		
Married	21285 (52.72)	19165 (53.49)
Not-married	19089 (47.28)	16667 (46.51)
Gender		
Male	20317 (50.32)	16627 (46.40)
Female	20057 (49.68)	19205 (53.60)
Race		
White	33431 (82.80)	29433 (82.14)
Not-White	6943 (17.20)	6399 (17.86)
Education		
Attend college	23272 (57.64)	21086 (58.85)
Never attend college	17102 (42.36)	14746 (41.15)
Location		
Urban	36616 (90.69)	33774 (94.26)
Rural	3758 (9.31)	2058 (5.74)
Season		
1st quarter	8086 (20.03)	7786 (21.73)
2nd quarter	8196 (20.30)	7009 (19.56)
3rd quarter	8072 (19.99)	6988 (19.50)
4th quarter	8044 (19.92)	7084 (19.77)
5th quarter	7976 (19.76)	6965 (19.44)

Note: standard deviation and percentage of frequency are in parenthesis.

Table 11. Summary of the variables in 2008 and 2010

Variable	2008 (N=34485)	2010 (N=35298)
	Mean (Std Dev)	Mean (Std Dev)
Total entertainment expenditure (in dollars)	641.52 (1429.30)	580.58 (1518.27)
Fees and admissions	160.57 (498.72)	147.78 (571.05)
Televisions, radios, and sound equipment	255.54 (415.48)	240.08 (323.20)
Other equipment and services	225.41 (1184.24)	192.72 (1289.13)
Income after tax (in dollars)	49736.83 (58141.69)	49484.55 (59900.82)
Family size	2.52 (1.49)	2.51(1.53)
No. of adult>64 years old	0.33 (0.63)	0.33(0.62)
No. of children	0.65 (1.08)	0.63 (1.07)
Age	49.63 (17.33)	49.64 (17.38)
	Frequency (%)	Frequency (%)
Family type		
Family with child	10699 (31.03)	10338 (29.29)
Family without child	23786 (68.97)	24960 (70.71)
Marital status		
Married	18414 (53.40)	18013 (51.03)
Not-married	16071 (46.60)	17285 (48.97)
Gender		
Male	161519 (46.83)	16543 (46.87)
Female	18334 (53.17)	18755 (53.13)
Race		
White	28199 (81.77)	28390 (80.43)
Not-White	6286 (18.23)	6908 (19.57)
Education		
Attend college	208499 (60.46)	21352 (60.49)
Never attend college	13636 (39.54)	13946 (39.51)
Location		
Urban	32515 (94.29)	33395 (94.61)
Rural	1970 (5.71)	1903 (5.39)
Season		
1st quarter	6914 (20.05)	7198 (20.39)
2nd quarter	6942 (20.13)	7135 (20.21)
3rd quarter	6794 (19.70)	7059 (20.00)
4th quarter	6895 (19.99)	7037 (19.94)
5th quarter	6940 (20.12)	6869 (19.46)

Note: standard deviation and percentage of frequency are in parenthesis.

Table 12. Probit Model Estimations: Fees and Admissions

Variable	$Probit_{03}$	ME_{03}	$Probit_{06}$	ME_{06}	$Probit_{08}$	ME_{08}	$Probit_{10}$	ME_{10}
Income	0.0063	0.0022	0.0063	0.0022	0.0063	0.0022	0.0061	0.0021
	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)
No. of adults>64	0.0357	0.0124	-0.0353	-0.0122	0.0101	0.0035	0.0381	0.0131
years old	(0.0153)	(0.0022)	(0.0161)	(0.0022)	(0.0161)	(0.0007)	(0.0158)	(0.0025)
No. of children	-0.0125	-0.0043	0.0086	0.0030	0.0408	0.0140	0.0186	0.0064
	(0.0130)	(0.0008)	(0.0133)	(0.0005)	(0.0140)	(0.0027)	(0.0134)	(0.0012)
Age	-0.0093	-0.0032	-0.0076	-0.0026	-0.0070	-0.0024	-0.0086	-0.0030
	(0.0005)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
Family size	0.0016	0.0006	-0.0218	-0.0075	-0.0383	-0.0132	-0.0293	-0.0101
	(0.0097)	(0.0001)	(0.0097)	(0.0014)	(0.0103)	(0.0025)	(0.0094)	(0.0019)
Family with	0.1733	0.0601	0.1212	0.0420	0.1437	0.0494	0.1521	0.0524
children	(0.0194)	(0.0105)	(0.0203)	(0.0077)	(0.0214)	(0.0094)	(0.0210)	(0.0099)
Male	0.0945	0.0328	0.0390	0.0135	0.0415	0.0143	0.0406	0.0140
	(0.0136)	(0.0057)	(0.0143)	(0.0025)	(0.0146)	(0.0027)	(0.0144)	(0.0026)
Married	0.0406	0.0141	0.0927	0.0321	0.1037	0.0356	0.0961	0.0331
	(0.0177)	(0.0025)	(0.0183)	(0.0059)	(0.0189)	(0.0068)	(0.0184)	(0.0062)
White	0.3859	0.1338	0.3406	0.1179	0.3528	0.1213	0.2979	0.1026
	(0.0181)	(0.0234)	(0.0189)	(0.0215)	(0.0191)	(0.0230)	(0.0183)	(0.0193)
College	0.5886	0.2041	0.5569	0.1928	0.5648	0.1941	0.5780	0.1991
	(0.0139)	(0.0357)	(0.0148)	(0.0352)	(0.0153)	(0.0368)	(0.0152)	(0.0375)
Urban	0.2243	0.0778	0.1507	0.0522	0.1891	0.0650	0.3188	0.1098
	(0.0231)	(0.0136)	(0.0305)	(0.0095)	(0.0316)	(0.0123)	(0.0326)	(0.0207)
1st quarter	0.1143	0.0396	0.0386	0.0134	0.0171	0.0059	0.0909	0.0313
	(0.0209)	(0.0069)	(0.0218)	(0.0024)	(0.0226)	(0.0011)	(0.0224)	(0.0059)
2ed quarter	-0.0378	-0.0131	0.0390	0.0135	-0.0250	-0.0086	0.0383	0.0132
	(0.0208)	(0.0023)	(0.0224)	(0.0025)	(0.0226)	(0.0016)	(0.0225)	(0.0025)
3rd quarter	0.0164	0.0057	0.1254	0.0434	0.0804	0.0276	0.0882	0.0304
	(0.0209)	(0.0010)	(0.0224)	(0.0079)	(0.0227)	(0.0052)	(0.0225)	(0.0057)
4th quarter	0.0277	0.0096	0.0651	0.0226	0.0351	0.0121	0.0587	0.0202
	(0.0209)	(0.0017)	(0.0223)	(0.0041)	(0.0226)	(0.0023)	(0.0225)	(0.0038)
Intercept	-0.8506		-0.8369		-0.9240		-0.9746	
	(0.0436)	-	(0.0501)	-	(0.0514)	-	(0.0511)	-

Note: Standard errors are in parenthesis.

Table 13. Probit Model Estimations: Televisions, Radios, and Sound Equipment

Variable	$Probit_{03}$	ME_{03}	$Probit_{06}$	ME_{06}	$Probit_{08}$	ME_{08}	$Probit_{10}$	ME_{10}
Income	0.0067	0.0016	0.0076	0.0017	0.0056	0.0012	0.0056	0.0013
	(0.0003)	(0.0006)	(0.0003)	(0.0008)	(0.0002)	(0.0005)	(0.0002)	(0.0005)
No. of adults>64	-0.0752	-0.0184	0.0004	0.0001	-0.0521	-0.0114	0.0135	0.0032
years old	(0.0177)	(0.0071)	(0.0194)	(0.0000)	(0.0195)	(0.0045)	(0.0191)	(0.0012)
No. of children	-0.1153	-0.0282	-0.1193	-0.0268	-0.0958	-0.0210	-0.0663	-0.0155
	(0.0161)	(0.0109)	(0.0167)	(0.0118)	(0.0177)	(0.0083)	(0.0160)	(0.0057)
Age	0.0005	0.0001	-0.0013	-0.0003	0.0016	0.0003	0.0027	0.0006
	(0.0006)	(0.0000)	(0.0007)	(0.0001)	(0.0007)	(0.0001)	(0.0006)	(0.0002)
Family size	0.1137	0.0277	0.0776	0.0174	0.0843	0.0185	0.0637	0.0149
	(0.0119)	(0.0108)	(0.0121)	(0.0076)	(0.0128)	(0.0073)	(0.0112)	(0.0055)
Family with children	0.1199	0.0293	0.1048	0.0235	0.0792	0.0173	0.0632	0.0147
	(0.0239)	(0.0113)	(0.0259)	(0.0103)	(0.0272)	(0.0069)	(0.0258)	(0.0055)
Male	0.0145	0.0035	-0.0563	-0.0126	-0.0673	-0.0147	-0.0710	-0.0166
	(0.0158)	(0.0014)	(0.0173)	(0.0056)	(0.0176)	(0.0058)	(0.0169)	(0.0061)
Married	0.1607	0.0392	0.2359	0.0529	0.1769	0.0388	0.1900	0.0443
	(0.0207)	(0.0152)	(0.0219)	(0.0233)	(0.0229)	(0.0153)	(0.0217)	(0.0164)
White	0.2127	0.0519	0.1632	0.0366	0.2355	0.0516	0.2072	0.0483
	(0.0193)	(0.0201)	(0.0210)	(0.0161)	(0.0209)	(0.0204)	(0.0200)	(0.0179)
College	0.3064	0.0748	0.2737	0.0614	0.2303	0.0505	0.2580	0.0602
	(0.0159)	(0.0290)	(0.0174)	(0.0270)	(0.0180)	(0.0199)	(0.0174)	(0.0223)
Urban	0.0826	0.0202	0.0427	0.0096	-0.0632	-0.0139	-0.0283	-0.0066
	(0.0254)	(0.0078)	(0.0348)	(0.0042)	(0.0372)	(0.0055)	(0.0363)	(0.0024)
1^{st} quarter	0.0560	0.0137	0.0285	0.0064	-0.0745	-0.0163	0.0435	0.0101
	(0.0246)	(0.0053)	(0.0262)	(0.0028)	(0.0273)	(0.0065)	(0.0265)	(0.0038)
2^{ed} quarter	-0.0603	-0.0147	-0.0447	-0.0100	-0.0526	-0.0115	-0.0021	-0.0005
	(0.0240)	(0.0057)	(0.0266)	(0.0044)	(0.0274)	(0.0046)	(0.0263)	(0.0002)
3^{rd} quarter	-0.0849	-0.0207	-0.0192	-0.0043	-0.1075	-0.0236	-0.0662	-0.0154
	(0.0240)	(0.0080)	(0.0268)	(0.0019)	(0.0273)	(0.0093)	(0.0261)	(0.0057)
4^{th} quarter	-0.0642	-0.0157	-0.0031	-0.0007	-0.0869	-0.0190	-0.0419	-0.0098
	(0.0241)	(0.0061)	(0.0267)	(0.0003)	(0.0272)	(0.0075)	(0.0262)	(0.0036)
Intercept	-0.0106		0.2321		0.3410		0.1621	
	(0.0490)	-	(0.0578)	-	(0.0601)	-	(0.0573)	-

Note: Standard errors are in parenthesis.

Table 14. Probit Model Estimations: Other Equipment and Services

Variable	$Probit_{03}$	ME_{03}	$Probit_{06}$	ME_{06}	$Probit_{08}$	ME_{08}	$Probit_{10}$	ME_{10}
Income	0.0050	0.0018	0.0035	0.0013	0.0035	0.0012	0.0037	0.0013
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
No. of adults>64	-0.0811	-0.0286	-0.1075	-0.0386	-0.1256	-0.0442	-0.0930	-0.0334
years old	(0.0151)	(0.0047)	(0.0157)	(0.0054)	(0.0157)	(0.0072)	(0.0154)	(0.0048)
No. of children	0.0217	0.0076	-0.0096	-0.0034	0.0084	0.0030	0.0014	0.0005
	(0.0130)	(0.0012)	(0.0131)	(0.0005)	(0.0140)	(0.0005)	(0.0132)	(0.0001)
Age	-0.0041	-0.0014	-0.0047	-0.0017	-0.0046	-0.0016	-0.0048	-0.0017
	(0.0005)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0003)	(0.0006)	(0.0002)
Family size	0.0439	0.0155	0.0684	0.0245	0.0659	0.0232	0.0618	0.0222
	(0.0096)	(0.0025)	(0.0095)	(0.0034)	(0.0102)	(0.0038)	(0.0092)	(0.0032)
Family with	0.1694	0.0598	0.0904	0.0324	0.1137	0.0400	0.1126	0.0405
children	(0.0194)	(0.0098)	(0.0201)	(0.0045)	(0.0214)	(0.0065)	(0.0208)	(0.0058)
Male	-0.1120	-0.0395	-0.1118	-0.0401	-0.1402	-0.0493	-0.1395	-0.0501
	(0.0136)	(0.0065)	(0.0142)	(0.0056)	(0.0145)	(0.0080)	(0.0142)	(0.0072)
Married	0.2529	0.0892	0.2405	0.0863	0.2597	0.0914	0.2528	0.0908
	(0.0175)	(0.0146)	(0.0179)	(0.0120)	(0.0185)	(0.0148)	(0.0179)	(0.0130)
White	0.4979	0.1756	0.5840	0.2095	0.5479	0.1927	0.4731	0.1700
	(0.0178)	(0.0287)	(0.0187)	(0.0291)	(0.0188)	(0.0313)	(0.0179)	(0.0243)
College	0.3153	0.1112	0.2672	0.0959	0.2841	0.0999	0.2166	0.0778
	(0.0139)	(0.0182)	(0.0147)	(0.0133)	(0.0152)	(0.0162)	(0.0149)	(0.0111)
Urban	-0.1598	-0.0564	-0.1304	-0.0468	-0.2363	-0.0831	-0.1107	-0.0398
	(0.0227)	(0.0092)	(0.0298)	(0.0065)	(0.0312)	(0.0135)	(0.0309)	(0.0057)
1^{st} quarter	0.1265	0.0446	0.0390	0.0140	0.0124	0.0044	0.0100	0.0036
	(0.0209)	(0.0073)	(0.0215)	(0.0019)	(0.0225)	(0.0007)	(0.0221)	(0.0005)
2^{ed} quarter	-0.1810	-0.0638	-0.1227	-0.0440	-0.2136	-0.0751	-0.1892	-0.0680
	(0.0207)	(0.0104)	(0.0221)	(0.0061)	(0.0224)	(0.0122)	(0.0221)	(0.0097)
3^{rd} quarter	-0.1582	-0.0558	-0.1244	-0.0446	-0.1338	-0.0471	-0.1762	-0.0633
	(0.0208)	(0.0091)	(0.0221)	(0.0062)	(0.0225)	(0.0076)	(0.0221)	(0.0090)
4^{th} quarter	-0.1464	-0.0516	-0.1722	-0.1618	-0.1822	-0.0641	-0.1953	-0.0702
	(0.0208)	(0.0084)	(0.0220)	(0.0086)	(0.0224)	(0.0104)	(0.0221)	(0.0100)
Intercept	-0.5162		-0.5989		-0.3379		-0.3594	
	(0.0431)	-	(0.0492)	-	(0.0507)	-	(0.0494)	-

Note: Standard errors are in parenthesis.

Table 15. Tobit Model Estimations: Fees and Admissions

Variable	$Tobit_{03}$	OLS_{03}	$Tobit_{06}$	OLS_{06}	$Tobit_{08}$	OLS_{08}	$Tobit_{10}$	OLS_{10}
Income	0.0036	0.0022	0.0041	0.0025	0.0040	0.0023	0.0046	0.0027
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
No. of adults>64 years	0.0038	-0.0066	-0.0143	0.0002	-0.0135	-0.0133	0.0388	0.0203
old	(0.0085)	(0.0048)	(0.0100)	(0.0054)	(0.0106)	(0.0057)	(0.0120)	(0.0065)
No. of children	0.0184	0.0276	0.0423	0.0438	0.0523	0.0407	0.0445	0.0415
	(0.0070)	(0.0040)	(0.0081)	(0.0045)	(0.0090)	(0.0049)	(0.0099)	(0.0055)
Age	-0.0019	0.0011	-0.0017	0.0011	-0.0009	0.0017	-0.0033	0.0006
	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Family size	-0.0060	-0.0127	-0.0231	-0.0226	-0.0279	-0.0206	-0.0247	-0.0213
	(0.0053)	(0.0030)	(0.0060)	(0.0033)	(0.0067)	(0.0036)	(0.0071)	(0.0038)
Family with children	0.0792	0.0284	0.0528	0.0184	0.0999	0.0495	0.1033	0.0427
	(0.0106)	(0.0061)	(0.0123)	(0.0069)	(0.0137)	(0.0076)	(0.0154)	(0.0086)
Male	0.0539	0.0179	0.0323	0.0152	0.0204	0.0013	0.0261	0.0039
	(0.0074)	(0.0042)	(0.0087)	(0.0048)	(0.0094)	(0.0052)	(0.0107)	(0.0059)
Married	0.0570	0.0267	0.0878	0.0309	0.0985	0.0361	0.0777	0.0145
	(0.0098)	(0.0055)	(0.0113)	(0.0062)	(0.0123)	(0.0067)	(0.0138)	(0.0075)
White	0.1871	0.0446	0.1949	0.0484	0.1948	0.0392	0.1748	0.0270
	(0.0103)	(0.0055)	(0.0120)	(0.0063)	(0.0129)	(0.0067)	(0.0140)	(0.0074)
College	0.2897	0.0763	0.3197	0.0841	0.3585	0.0973	0.3844	0.0785
	(0.0080)	(0.0044)	(0.0094)	(0.0050)	(0.0104)	(0.0055)	(0.0119)	(0.0062)
Urban	0.1366	0.0468	0.1284	0.0519	0.1683	0.0596	0.2343	0.0520
	(0.0132)	(0.0071)	(0.0194)	(0.0102)	(0.0216)	(0.0110)	(0.0258)	(0.0129)
1^{st} quarter	0.0298	-0.0004	0.0134	0.0030	0.0245	0.0119	0.0333	-0.0038
	(0.0113)	(0.0065)	(0.0134)	(0.0074)	(0.0146)	(0.0080)	(0.0167)	(0.0091)
2^{ed} quarter	-0.0168	-0.0044	0.0203	0.0085	0.0046	0.0091	0.0529	0.0252
	(0.0114)	(0.0065)	(0.0137)	(0.0075)	(0.0146)	(0.0080)	(0.0167)	(0.0092)
3^{rd} quarter	0.0201	0.0117	0.0748	0.0302	0.0717	0.0339	0.0553	0.0156
	(0.0114)	(0.0065)	(0.0136)	(0.0075)	(0.0146)	(0.0080)	(0.0167)	(0.0092)
4^{th} quarter	0.0127	0.0034	0.0366	0.0143	0.0419	0.0203	0.0435	0.0133
	(0.0114)	(0.0065)	(0.0136)	(0.0075)	(0.0146)	(0.0080)	(0.0168)	(0.0092)
Sigma	0.6243		0.6930		0.7337		0.8384	
	(0.0033)	-	(0.0039)	-	(0.0042)	-	(0.0048)	-
Intercept	-0.7925	-0.1559	-0.8732	-0.1709	-1.0174	-0.2081	-1.0843	-0.1442
	(0.0246)	(0.0135)	(0.0315)	(0.0168)	(0.0347)	(0.0181)	(0.0397)	(0.0206)

Note: Standard errors are in parenthesis.

Table 16. Tobit Model Estimations: Televisions, Radios, and Sound Equipment

Variable	$Tobit_{03}$	OLS_{03}	$Tobit_{06}$	OLS_{06}	$Tobit_{08}$	OLS_{08}	$Tobit_{10}$	OLS_{10}
Income	0.0016	0.0013	0.0016	0.0013	0.0014	0.0012	0.0011	0.0009
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. of adults>64 years	-0.0296	-0.0231	-0.0157	-0.0160	-0.0176	-0.0139	-0.0208	-0.0206
old	(0.0051)	(0.0044)	(0.0053)	(0.0046)	(0.0056)	(0.0049)	(0.0043)	(0.0037)
No. of children	-0.0178	-0.0063	-0.0241	-0.0126	-0.0212	-0.0129	-0.0121	-0.0068
	(0.0043)	(0.0037)	(0.0044)	(0.0038)	(0.0048)	(0.0043)	(0.0037)	(0.0031)
Age	0.0001	0.0002	-0.0004	-0.0002	0.0001	0.0001	0.0010	0.0007
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Family size	0.0297	0.0175	0.0236	0.0146	0.0266	0.0181	0.0206	0.0144
	(0.0032)	(0.0027)	(0.0032)	(0.0028)	(0.0036)	(0.0031)	(0.0026)	(0.0022)
Family with children	0.0221	0.0155	0.0329	0.0278	0.0203	0.0172	0.0070	0.0043
	(0.0064)	(0.0055)	(0.0067)	(0.0059)	(0.0074)	(0.0065)	(0.0057)	(0.0050)
Male	0.0165	0.0138	0.0069	0.0105	0.0098	0.0135	0.0107	0.0138
	(0.0045)	(0.0039)	(0.0047)	(0.0041)	(0.0051)	(0.0045)	(0.0039)	(0.0034)
Married	0.0319	0.0144	0.0476	0.0255	0.0526	0.0363	0.0547	0.0414
	(0.0059)	(0.0050)	(0.0060)	(0.0053)	(0.0066)	(0.0058)	(0.0050)	(0.0043)
White	0.0405	0.0182	0.0339	0.0170	0.0547	0.0317	0.0332	0.0176
	(0.0060)	(0.0050)	(0.0062)	(0.0053)	(0.0066)	(0.0057)	(0.0050)	(0.0043)
College	0.0627	0.0326	0.0655	0.0393	0.0625	0.0416	0.0599	0.0408
	(0.0047)	(0.0040)	(0.0050)	(0.0043)	(0.0054)	(0.0047)	(0.0042)	(0.0036)
Urban	0.0361	0.0266	0.0361	0.0305	0.0117	0.0160	0.0186	0.0197
	(0.0076)	(0.0065)	(0.0101)	(0.0087)	(0.0108)	(0.0095)	(0.0087)	(0.0074)
1st quarter	0.0028	-0.0015	-0.0052	-0.0065	-0.0019	0.0023	0.0087	0.0059
	(0.0069)	(0.0059)	(0.0072)	(0.0063)	(0.0078)	(0.0069)	(0.0061)	(0.0053)
2ed quarter	-0.0591	-0.0519	-0.0621	-0.0561	-0.0618	-0.0562	-0.0444	-0.0427
	(0.0069)	(0.0059)	(0.0074)	(0.0064)	(0.0078)	(0.0069)	(0.0061)	(0.0053)
3rd quarter	-0.0615	-0.0521	-0.0640	-0.0595	-0.0648	-0.0551	-0.0513	-0.0455
	(0.0069)	(0.0059)	(0.0074)	(0.0064)	(0.0079)	(0.0069)	(0.0062)	(0.0053)
4th quarter	-0.0398	-0.0333	-0.0469	-0.0442	-0.0511	-0.0435	-0.0455	-0.0413
	(0.0069)	(0.0059)	(0.0074)	(0.0064)	(0.0078)	(0.0069)	(0.0062)	(0.0053)
Sigma	0.4245		0.4259		0.4506		0.3548	
	(0.0017)	-	(0.0018)	-	(0.0019)	-	(0.0015)	-
Intercept	-0.0984	0.0421	-0.0144	0.0939	-0.0113	0.0956	-0.0278	0.0722
	(0.0145)	(0.0123)	(0.0165)	(0.0143)	(0.0179)	(0.0156)	(0.0139)	(0.0119)

Note: Standard errors are in parenthesis.

Table 17. Tobit Model Estimations: Other Equipment and Services

Variable	$Tobit_{03}$	OLS_{03}	$Tobit_{06}$	OLS_{06}	$Tobit_{08}$	OLS_{08}	$Tobit_{10}$	OLS_{10}
Income	0.0067	0.0028	0.0054	0.0026	0.0035	0.0016	0.0047	0.0023
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
No. of adults>64	-0.0614	0.0087	-0.1599	-0.0429	-0.1201	-0.0227	-0.1321	-0.0410
years old	(0.0279)	(0.0174)	(0.0276)	(0.0164)	(0.0229)	(0.0143)	(0.0247)	(0.0153)
No. of children	0.0043	0.0182	-0.0190	0.0177	0.0281	0.0429	0.0229	0.0408
	(0.0231)	(0.0147)	(0.0221)	(0.0135)	(0.0192)	(0.0124)	(0.0203)	(0.0129)
Age	-0.0060	-0.0003	-0.0055	0.0002	-0.0045	-0.0001	-0.0046	0.0003
	(0.0010)	(0.0006)	(0.0010)	(0.0006)	(0.0008)	(0.0005)	(0.0009)	(0.0006)
Family size	0.0629	-0.0039	0.0770	-0.0071	0.0610	-0.0061	0.0612	-0.0081
	(0.0174)	(0.0109)	(0.0164)	(0.0099)	(0.0144)	(0.0091)	(0.0145)	(0.0091)
Family with children	0.1061	-0.0166	0.0382	-0.0155	0.0277	-0.0158	-0.0044	-0.0580
	(0.0342)	(0.0220)	(0.0337)	(0.0208)	(0.0292)	(0.0190)	(0.0315)	(0.0203)
Male	-0.0778	0.0145	-0.1024	-0.0042	-0.1088	-0.0117	-0.1189	-0.0081
	(0.0245)	(0.0154)	(0.0243)	(0.0146)	(0.0205)	(0.0130)	(0.0223)	(0.0139)
Married	0.3280	0.0539	0.3053	0.0492	0.3341	0.1103	0.3124	0.0729
	(0.0319)	(0.0200)	(0.0311)	(0.0187)	(0.0265)	(0.0168)	(0.0284)	(0.0178)
White	0.6462	0.0796	0.7650	0.1050	0.6312	0.1309	0.5346	0.0763
	(0.0344)	(0.0200)	(0.0345)	(0.0189)	(0.0285)	(0.0167)	(0.0297)	(0.0174)
College	0.3905	0.0522	0.3046	0.0255	0.3100	0.0701	0.2587	0.0465
	(0.0256)	(0.0159)	(0.0257)	(0.0152)	(0.0219)	(0.0137)	(0.0238)	(0.0147)
Urban	-0.2270	-0.0585	-0.1852	-0.0549	-0.2175	-0.0550	-0.1048	-0.0150
	(0.0404)	(0.0257)	(0.0504)	(0.0309)	(0.0425)	(0.0276)	(0.0482)	(0.0304)
1^{st} quarter	0.1333	0.0219	0.0786	0.0380	0.0235	0.0080	0.0193	0.0086
	(0.0368)	(0.0235)	(0.0365)	(0.0222)	(0.0311)	(0.0200)	(0.0340)	(0.0216)
2^{ed} quarter	-0.2514	-0.0644	-0.0958	0.0134	-0.1744	-0.0261	-0.1778	-0.0244
	(0.0375)	(0.0234)	(0.0379)	(0.0228)	(0.0316)	(0.0199)	(0.0346)	(0.0216)
3^{rd} quarter	-0.1784	-0.0265	-0.0960	0.0163	-0.0544	0.0242	-0.1765	-0.0311
	(0.0375)	(0.0235)	(0.0380)	(0.0228)	(0.0315)	(0.0200)	(0.0347)	(0.0217)
4^{th} quarter	-0.1913	-0.0452	-0.1582	0.0004	-0.1683	-0.0341	-0.1724	-0.0164
	(0.0375)	(0.0235)	(0.0380)	(0.0227)	(0.0316)	(0.0200)	(0.0347)	(0.0217)
Sigma	1.6466		1.9524		1.6461		1.8052	
	(0.0102)	-	(0.0104)	-	(0.0086)	-	(0.0094)	-
Intercept	-1.5696	0.0235	-1.6378	-0.0072	-1.1567	0.0065	-1.2719	-0.0068
	(0.0792)	(0.0489)	(0.0860)	(0.0509)	(0.0724)	(0.0453)	(0.0786)	(0.0487)

Note: Standard errors are in parenthesis.

Figure 3: US Income Growth Rates

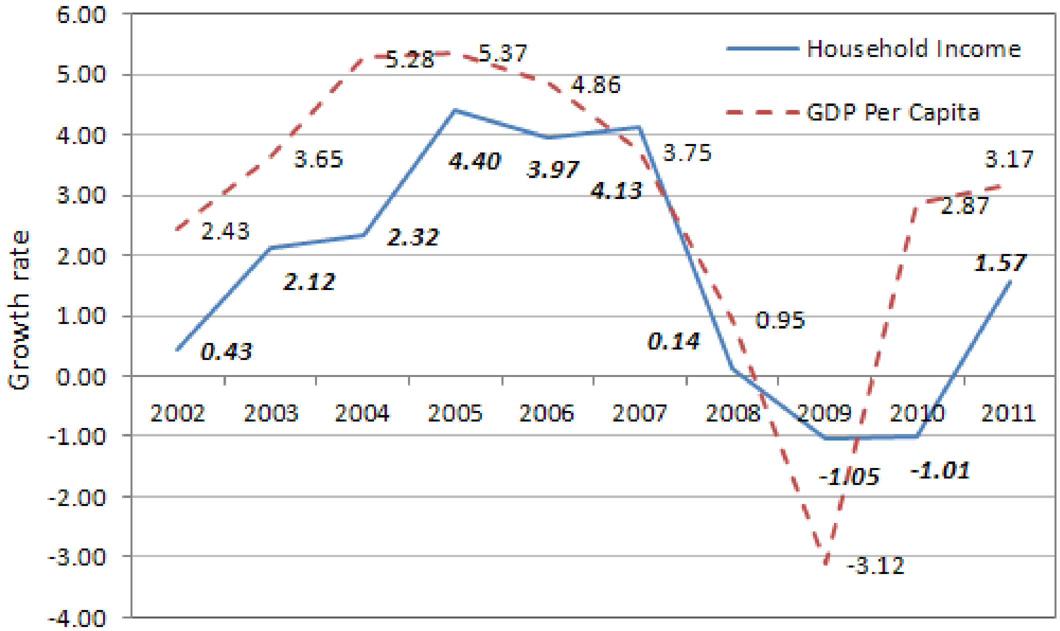
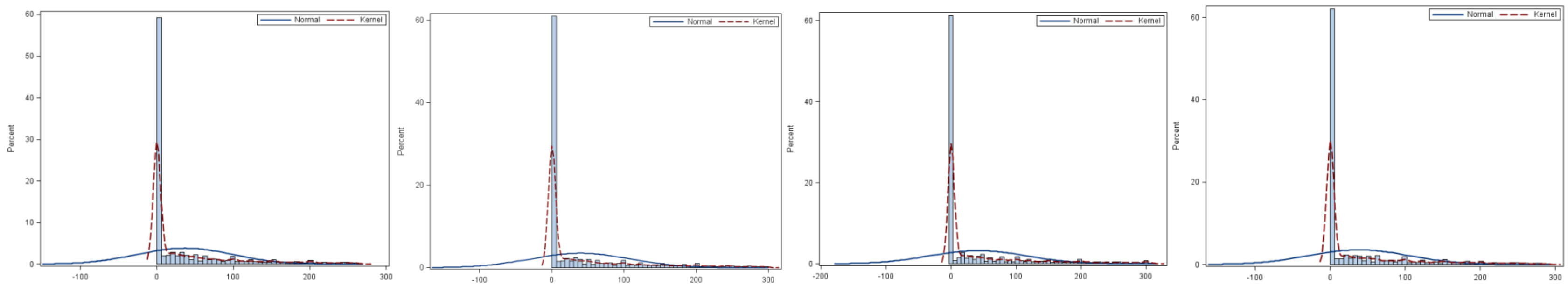
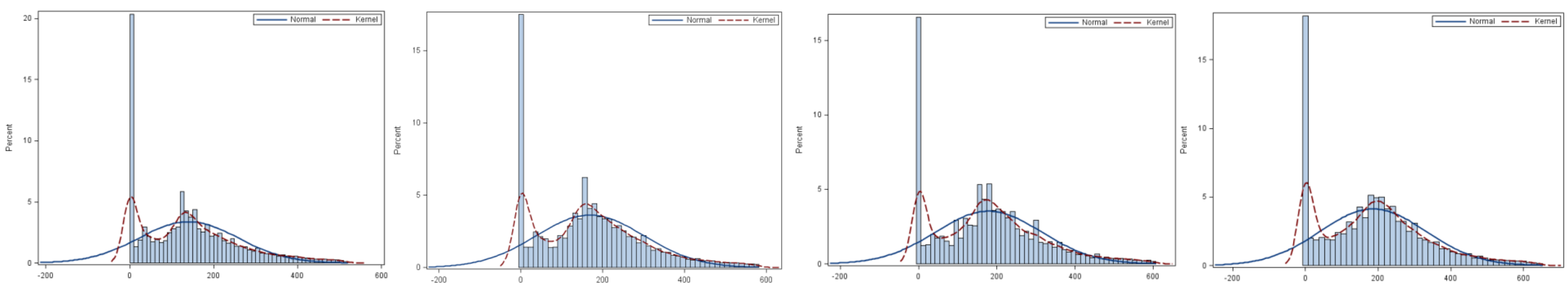


Figure 4. Kernel Densities of Expenditures in 2003 (left), 2006 (left-middle), 2008 (right-middle), and 2010(right)

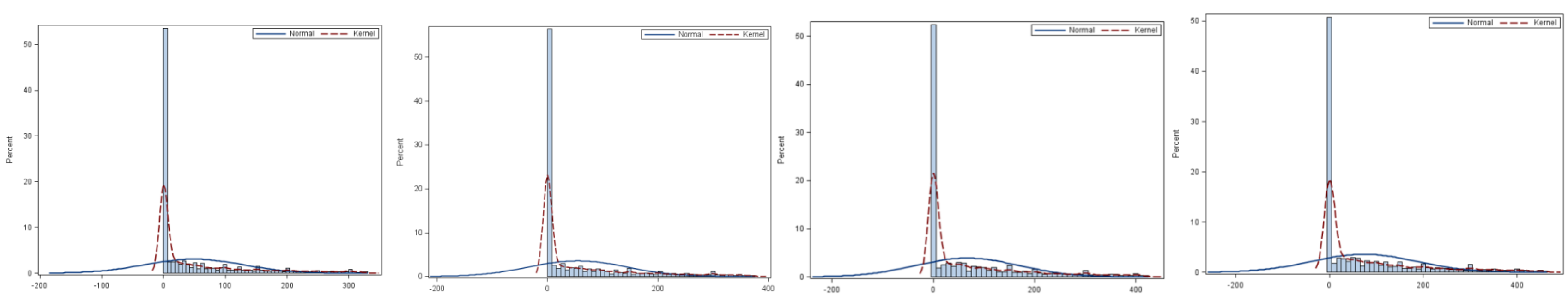
(a) Fee



(b) Television



(c) Other equipment and services



Chapter 4. How does the oil price shock affect consumers?

Abstract

This paper evaluates the degree of the pass-through effect of the oil price shock to six CPI sub-indices in the US. We report substantially weaker pass-through effects in less energy-intensive sectors compared with those in more energy-intensive sectors. We attempt to find an explanation for this from the role of spending adjustments when there's an unexpected change in the oil price. Using linear and nonlinear framework, we find substantial decreases in the relative price in less energy-intensive sectors, but not in energy-intensive sectors, which may be due to a substantial decrease in the demand for goods and services in those CPI sub-baskets. Our findings are consistent with those of Edelstein and Kilian (2009) in the sense that spending adjustments play an important role in price dynamics in response to unexpected changes in the oil price.

1. Introduction

As Barsky and Kilian (2002) argue that oil price shocks are unambiguously inflationary, especially when one use the consumer price index (CPI) inflation rate to measure the pass-through effect of the shock. On the other hand, Edelstein and Kilian (2009) point out that the oil price shock may have a substantial income effect on the demand for goods and services.

Hamilton (1996) observes that oil prices have behaved radically differently after 1986 than before, and oil price is found to affect the macro economy primarily by depressing demand for key consumption and investment goods. Many researches have been investigated the oil price shock to macro-economy and the related industries theoretically and empirically in different counties. (See, for example, Ferderer (1996), Bernanke et al. (1997), Colognia & Manera (2008), Kilian (2009), Korhonen & Ledyaeva (2010), Kilian & Lewis (2011), Archanskaïa et al. (2012), Zhang (2012), and references therein.).

It is widely believed that the increase in the real price of oil will cause the inflation and recession both in the United States and abroad, which will also lead to an adverse shift in the aggregate supply curve that produces a higher price level and lower output (Mork & Hall, 1980; Darby, 1982). Oil price have both real effects and inflationary effects, which shift the supply curve causes large real effects but weak direct price effect, and monetary policy shifts the demand curve causing strong price effects but long-run neutrality with respect to real GNP (Gisser & Goodwin, 1986).

Increases in oil prices are responsible for economic recessions, excessive inflation, reduced productivity and lower economic growth, and the evidence that lead many economists to ascribe a central role to exogenous political events in modeling the oil market is examined by Barsky & Kilian (2004). Kilian & Lewis (2011) show that there is no credible evidence that monetary policy responses to oil price shocks caused large aggregate fluctuations in the 1970s and 1980s or more recently.

This paper estimates the pass-through effect of the oil price shock on six CPI sub-indices in the US. We find strong evidence of spending adjustment effects that *limit* the pass-through effect of the shock on the apparel, food, housing, and medical care price indices (less energy-intensive sectors), but not on the energy and transportation price indices. That is, consumer welfare loss is primarily driven by a strong pass-through effect in *energy-intensive* sectors.

The rest of our manuscript is organized as follows. Section 2 provides a data description and preliminary findings. In Section 3, we provide our main findings. Section 4 concludes.

2. Data Descriptions and Preliminary Findings

We obtained all data from Federal Reserve Economic Data (FRED). The oil price is the spot western Texas intermediate (WTI). Six CPI sub-indices include: Apparel (CPIAPPSL), Energy (CPIENGSL), Food (CPIUFDSL), Housing (CPIHOSSL), Medical Care (CPIMEDSL), and Transportations (CPITRNSL).[10] Observations are monthly and span from 1974 M1 to 2011 M3.[11] We also use Personal Consumption Expenditures (PCE) to investigate expenditure adjustment effects in augmented models.

We first report the impulse response function of the US CPI to an oil price shock in Figure 5 as a benchmark.[12] As in Barsky and Kilian (2002), we observe a strong and significant pass-through effect on aggregate CPI. It should be noted, however, that relatively weak pass-through

[10] We omit the Food and Beverage index because we obtained similar results as that from the Food index. Other categories such as Education and Recreations are omitted due to lack of observations.
[11] Observations prior to 1974 are not used due to the collapse of the Bretton Woods system in 1973 that creates a structural break in oil price dynamics. We are not interested in this particular issue.
[12] We obtain the *accumulated* impulse-response function from a bivariate vector autoregressive model with differenced variables. The oil price inflation is ordered first with an assumption that the US CPI inflation does not contemporaneously affect the oil price inflation within one month.

effects are observed for some CPI sub-indices as we can see in Figure 6. We obtain insignificant responses for the apparel, food, and medical care indices, while strong and significantly positive responses are observed for the energy and transportation indices. The significant positive effect on the housing price, however, was short term and lasts only for about one year.

3. Responses of the Relative Price

Let op_t and x_t be the spot oil price and a CPI sub-index, respectively. All variables are expressed in natural logarithms and deflated by the aggregate US CPI. That is, we construct the following bivariate VAR(p) model for relative prices with deterministic trends.[13]

$$\boldsymbol{y}_t = \boldsymbol{A}\boldsymbol{d}_t + \boldsymbol{B}(L)\boldsymbol{y}_{t-1} + \boldsymbol{C}\boldsymbol{u}_{t,} \tag{1}$$

where

$$\boldsymbol{y}_t = \begin{bmatrix} op_t \\ x_t \end{bmatrix}, \boldsymbol{d}_t = \begin{bmatrix} 1 \\ t \end{bmatrix},$$

$\boldsymbol{A}$ is a coefficient matrix for the deterministic terms, $\boldsymbol{B}(L)$ denotes the lag polynomial matrix, $\boldsymbol{u}_t$ is a vector of normalized underlying shocks, and $\boldsymbol{C}$ is a matrix that describes the contemporaneous relationships among op_t and x_t. We obtain the conventional orthogonalized impulse-response function (OIRF) by Sims (1980) and the variance decomposition analysis is implemented from this framework.[14]

Assuming invertibility of the system, (1) can be rewritten as the following infinite order vector moving average representation.[15]

[13] All eigenvalues are within the unit circle, implying the system is jointly trend stationary.
[14] Kim (2012) shows that the OIRF is the same as the generalized impulse-response function (GIRF) by Pesaran and Shin (1998) for the response to the variable ordered first, which is the oil price in our model.
[15] The system is invertible and thus can be represented as a moving average process when all eigenvalues of the companion matrix of (1) are less than one in norm. See any time-series econometrics textbook such as Hamilton (1994)

$$\widetilde{\boldsymbol{y}}_t = \boldsymbol{D}(L)\boldsymbol{C}\boldsymbol{u}_t = \sum_{s=0}^{\infty} \boldsymbol{D}_s \boldsymbol{C}\boldsymbol{u}_{t-s} \quad (2)$$

Where $\widetilde{\boldsymbol{y}}_t$ is a vector of demeaned and detrended variables, $\boldsymbol{D}(L) = (\boldsymbol{I} - \boldsymbol{B}(L))^{-1}$, $\boldsymbol{D}_{\mathbf{0}} = \boldsymbol{I}$, and $\boldsymbol{D}(L)\boldsymbol{C}$ is the moving average polynomials matrix that provides impulse-response functions.

Kim (2012) shows that the conventional orthogonalized impulse-response function (OIRF) by Sims (1980) is the same as the generalized impulse-response function (GIRF) by Pesaran and Shin (1998) for the response to the oil price in (2). We use the following scaled n-period ahead GIRF,

$$GIRF_j(n) = \sigma_{jj}^{-1} \boldsymbol{D}_n \boldsymbol{\Sigma} \mathbf{e}_{\mathrm{j}},\ j = 1{,}2 \quad (3)$$

where $\boldsymbol{\Sigma}$ denotes the least suqares variance-covariance matrix, σ_{jj} is the j^{th} diagonal element of $\boldsymbol{\Sigma}$, and $\mathbf{e}_{\mathbf{j}}$ is a 2×1 selection vector with 1 as its j^{th} element and zero elsewhere. For the variance decomposition analysis for the k-period ahead forecast $E_t x_{t+k}$ at time *t*, we employ the OIRF because the sum of variances may not be bounded by 1 if the GIRF is used (see Pesaran and Shin (1998) for details).

Responses to the oil price shock are reported in Figure 7. We note that the relative price (price share) exhibits significantly negative movements at least in the short-run for the apparel, food, housing, and medical care sub-indices. We observed very persistent upward movements of relative prices in energy-intensive sectors.

Our findings are consistent with that of Edelstein and Kilian (2009) in the sense that the spending adjustment effect plays an important role in determining the price dynamics. Unexpected changes in the oil price shift not only the supply but also the *demand* curve of goods and services to the left due to a decrease in purchasing power of discretionary income. If the oil shock results in

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for details.

negative GDP growth, consumer spending will be further depressed over time. When the demand responds substantially, relative price in that sector is likely to fall, which might explain a limited pass-through effect on prices in less energy-intensive sectors.

We also implement the variance decomposition analysis to see how much variations of each sub-index are explained by the oil price shock (see Table 18). We observe a dominant role of the oil shock only for the energy and transportation sub-indices, while limited roles of the shock were observed for the apparel, food, housing, and medical care sub-indices especially in the short-run. For example, the oil price perturbation explains only 1.2% of variations in the one-period ahead forecast of the apparel sub-index, whereas it explains 17.8% for the energy sub-index. Furthermore, the former is insignificant at the 5% level, while the latter is significant at any conventional levels. In the longer-run, the oil price shock explains 13.7% of 5-year ahead forecast of the food sub-index, while 72.3% for the transportation sub-index.

Next, we augment the current system to a trivariate VAR model by adding the personal consumption expenditures (PCE) deflated by the CPI ($\mathrm{rcm_t}$), replacing $\mathrm{x_t}$ in equation (2) by $\mathrm{x_t} = [\mathrm{rop_t}, \mathrm{rsp_t}, \mathrm{rcm_t}]$, to see if the oil price shock results in a non-negligible adjustment effect in consumer spending.

We note that all response function estimates of relative prices in Figure 7 are qualitatively similar to those from the bivariate model. More importantly, we observe significantly negative responses of the real consumption expenditures in response to the oil price shock for all cases.[16] These findings provide further evidence of substantial role of the negative income effect.[17] The variance decomposition analysis from this trivariate VAR models is reported in Table 19, which is also

[16] We further experimented with an augmented VAR with the industrial production. Results confirm prolonged recessionary effects over time. All results are available upon request from authors.

[17] The variance decomposition analysis results with trivariate VAR models are available upon request. We obtained similar results as those from bivariate models.

consistent with that of the bivariate model.

Variance decomposition analysis in Table 18 illustrates that oil price explains not much of variations of the forecast for food and housing, within one year forecast horizon it is estimated to account for about 17.7% and 15.3 % respectively. The result is consistent in the long run and statistically significant. In contrast, oil price shock contributes about 23.7% for apparel in the short run, but in the long-run we found quite sizable explanations around 58.4% for apparel. For medical care, it is 37.5% explained by the oil price shock. For those with positive IRF responses, it explains a lot more such as energy, and transportation with 83.3% and 63.0% respectively in the one year horizon.

Table 19 tells the variance decomposition analysis from the tri-variate VAR model, that yields the similar results as that got the bivariate VAR model. The results are robust. It is worthy to note that the real industrial production is consistent with results shown in share response functions (Figure 8). Especially, all models exhibit negative responses of the industrial production to an oil price shock, which may cause negative responses of certain relative price variables due to a recessionary effect of oil shocks.

4. Regime-Specific Responses of the Relative Price

We further investigate possibilities of regime-specific responses of CPI sub-indices to the oil price shock. For this purpose, we employ the following simple threshold trivariate VAR model.

$$\boldsymbol{x}_t = \boldsymbol{A}\boldsymbol{d}_t + \mathbf{1}(\tau_{t-d} > \tau^*)\boldsymbol{B}_+(L)\boldsymbol{x}_{t-1} + \mathbf{1}(\tau_{t-d} \leq \tau^*)\boldsymbol{B}_-(L)\boldsymbol{x}_{t-1} + \boldsymbol{C}\boldsymbol{u}_{t,} \tag{3}$$

where $\boldsymbol{x}_t = [rop_t, rsp_t, rcm_t]$, $\mathbf{1}(\cdot)$ is an indicator function, τ_{t-d} is a d-period lagged threshold variable, τ^* is the chosen threshold value, and $\boldsymbol{B}_+(L)$ and $\boldsymbol{B}_-(L)$ denote lag polynomials in the upper and the lower regime, respectively.

We use the growth rate of the real industrial production (IP) for the threshold variable and set $d = 1$ which is a conventional value. We employed a grid search method by choosing τ_{t-1} that minimizes the determinant of the variance-covariance matrix. We trimmed off the upper and lower 10% of the distribution of IP prior to estimation. Coefficient estimates in the lower and upper regimes are reported in Table 20, and we also demonstrate regime-specific response function estimates in Figure 9.[18]

Note two things about the estimated threshold values. First, estimates are roughly similar to each other with an exception of the system with the energy sub-index. Second, the majority of observations belong to the upper regime for most cases except the VAR with the energy sub-index.

The one-period lagged oil price affects 4 and 3 sub-indices significantly at the 5% level in the upper and lower regime, respectively. The effect of the lagged oil price is quantitatively larger in the lower regime for the energy and the transportation sub-indexes, which seems reasonable because the income effect may play a more important role when the economy is relatively worse. Likewise, the lagged oil price has a bigger coefficient in absolute value for the medical sub-index, which implies that the medical sub-index rises more slowly than the total CPI when the economy enters a period of downturns. For other sub-indices, we obtained insignificant contemporaneous effects. We investigate dynamic effects over time via the impulse-response function estimates in Figure 9.

Regime-specific conditional impulse-response functions during upper regimes (solid lines) are overall consistent with those from the linear bivariate and trivariate models. This result is not

[18] We report these regime-specific responses instead of the generalized impulse-response function analysis proposed by Koop et al. (1996) for more intuitive explanations. These regime-specific responses are conditional response function estimates from each regime based on an assumption that perturbations are small enough not to result in changes in regimes during transition period.

surprising since about 80% of observations belong to the upper regime.

Several interesting results from response function estimates are as follows. There are greater responses during the lower growth regime (dashed) compared with those during the upper growth regime for the energy sub-index. Since observations are split about 42% and 57% in the lower and higher regime for this index, one cannot ignore the different response estimates. These greater responses during the low growth regime seem consistent with Edelstein and Kilian (2009), because the negative income effect would become greater when the economy is bad, resulting in weaker responses of less energy-intensive product prices compared with those of more energy-intensive goods prices. The transportation sub-index also exhibit similar estimates.

The medical care and the food sub-indices overall show greater decreases relative to the total CPI during the lower regime than the upper regime, which is again consistent with the income adjustment hypothesis. The response estimates for the apparel and the housing sub-indices during the low growth regime seem somewhat inconsistent with previous estimates from linear models. However, since observations during the lower regime for these indices are only around 20%, we do not attempt to understand these results.

5. Concluding Remarks

This paper empirically evaluates the role of spending adjustments when there is an oil price shock using six CPI sub-indices in the US. We find limited pass-through effects of the oil price shock on the apparel, food, housing, and medical care CPI sub-indices compared with those on more energy-intensive industry indices such as the energy and transportation prices.

We propose an explanation for such heterogeneous responses from spending adjustment effects based on the work of Edelstein and Kilian (2009), who point out a negative income effect caused by unexpected changes in the oil price. That is, unexpected increases in the oil price may result in a decrease in the demand for non-energy goods and services when the demand for energy is inelastic. Decreases in the demand for those goods then would suppress the degree of the pass-through effect of the oil price shock for those less energy intensive sector prices but not in more energy intensive sub-indices.

Our study shows that energy and transportation reacts positively to the oil price shock, which is consistent with the common sense and closely related with the oil price.

The influence of oil price is substantial for energy and transportation in the earlier period, and then offsets gradually by the economic recession caused by oil price changes in the long run (Figure 6-Figure 8).

Even the results demonstrate that oil price will definitely play an important role in CPI, which implies the consumption expenditure is affected accordingly. But, for each individual CPI component, not all is affected that much as shown on the total consumption. For example, food and housing is exerted a least influence by the oil price shock, followed by apparel and medical care.

Moreover, share response functions in tri-variate model exhibit negative responses of the industrial production to an oil price shock, which may cause negative responses of certain relative price variables due to a recessionary effect of oil shocks. The oil price shock may lead to the lower output and economic growth, the reason is demonstrated by Ferderer (1996).

Oil price shock is seen to account for large proportion of energy and transportation, and small proportion of food and housing. This suggests that energy and transportation is highly related with oil price, thus oil price plays an important role in their related changes. In contrast, food and housing are less affected by the oil price shock.

Table 18. Variance Decomposition Analysis: Bivariate Models

	Apparel				*Energy*		
k	Oil	$E_t x_{t+k}$	se	k	Oil	$E_t x_{t+k}$	se
1	0.012	0.988	0.011	1	0.178	0.822	0.037
3	0.076	0.924	0.030	3	0.563	0.437	0.047
6	0.140	0.860	0.046	6	0.729	0.271	0.050
12	0.237	0.763	0.072	12	0.833	0.167	0.056
24	0.383	0.617	0.115	24	0.896	0.104	0.060
36	0.479	0.521	0.141	36	0.916	0.084	0.060
48	0.542	0.458	0.155	48	0.925	0.075	0.061
60	0.584	0.416	0.163	60	0.930	0.070	0.061
	Food				*Housing*		
k	Oil	$E_t x_{t+k}$	se	k	Oil	$E_t x_{t+k}$	se
1	0.039	0.961	0.019	1	0.026	0.974	0.017
3	0.129	0.871	0.039	3	0.146	0.854	0.042
6	0.168	0.832	0.051	6	0.179	0.821	0.052
12	0.177	0.823	0.064	12	0.153	0.847	0.055
24	0.165	0.835	0.084	24	0.106	0.894	0.046
36	0.153	0.847	0.098	36	0.108	0.892	0.055
48	0.144	0.856	0.106	48	0.141	0.859	0.078
60	0.137	0.863	0.111	60	0.182	0.818	0.098
	Medical Care				*Transportation*		
k	Oil	$E_t x_{t+k}$	se	k	Oil	$E_t x_{t+k}$	se
1	0.087	0.913	0.025	1	0.119	0.881	0.034
3	0.279	0.721	0.047	3	0.394	0.606	0.050
6	0.356	0.644	0.061	6	0.530	0.470	0.058
12	0.375	0.625	0.086	12	0.630	0.370	0.066
24	0.365	0.635	0.123	24	0.701	0.299	0.071
36	0.354	0.646	0.145	36	0.718	0.282	0.073
48	0.346	0.654	0.157	48	0.722	0.278	0.074
60	0.341	0.659	0.165	60	0.723	0.277	0.076

Note: Variance decomposition analysis is implemented from a bivariate vector autoregressive model with the real oil price ordered first. $E_t x_{t+k}$ is the k-period ahead forecast of the variable x at time t and k denotes the forecast horizon in months. Standard errors (se) are obtained from 2,000 nonparametric bootstrap simulations.

Table 19. Variance Decomposition Analysis: Tri-Variate Models

Apparel				*Energy*			
k	Oil	$E_t x_{t+k}$	IP	k	Oil	$E_t x_{t+k}$	IP
1	0.135	0.865	0.000	1	0.210	0.790	0.000
3	0.421	0.567	0.012	3	0.585	0.413	0.003
6	0.539	0.411	0.050	6	0.733	0.256	0.011
12	0.641	0.298	0.061	12	0.814	0.165	0.021
24	0.724	0.228	0.047	24	0.840	0.120	0.040
36	0.745	0.212	0.043	36	0.833	0.105	0.062
48	0.752	0.208	0.040	48	0.820	0.097	0.083
60	0.755	0.206	0.040	60	0.806	0.092	0.102

Food				*Housing*			
k	Oil	$E_t x_{t+k}$	IP	k	Oil	$E_t x_{t+k}$	IP
1	0.037	0.963	0.000	1	0.028	0.972	0.000
3	0.120	0.878	0.002	3	0.163	0.833	0.005
6	0.139	0.856	0.005	6	0.204	0.783	0.013
12	0.136	0.860	0.004	12	0.185	0.799	0.016
24	0.126	0.854	0.019	24	0.136	0.853	0.011
36	0.124	0.821	0.055	36	0.107	0.875	0.018
48	0.129	0.777	0.094	48	0.090	0.871	0.040
60	0.137	0.735	0.127	60	0.079	0.852	0.070

Medical Care				*Transportation*			
k	Oil	$E_t x_{t+k}$	IP	k	Oil	$E_t x_{t+k}$	IP
1	0.090	0.910	0.000	1	0.135	0.865	0.000
3	0.282	0.714	0.005	3	0.421	0.567	0.012
6	0.356	0.611	0.033	6	0.539	0.411	0.050
12	0.399	0.512	0.090	12	0.641	0.298	0.061
24	0.416	0.418	0.166	24	0.724	0.228	0.047
36	0.405	0.367	0.228	36	0.745	0.212	0.043
48	0.385	0.333	0.282	48	0.752	0.208	0.040
60	0.363	0.308	0.329	60	0.755	0.206	0.040

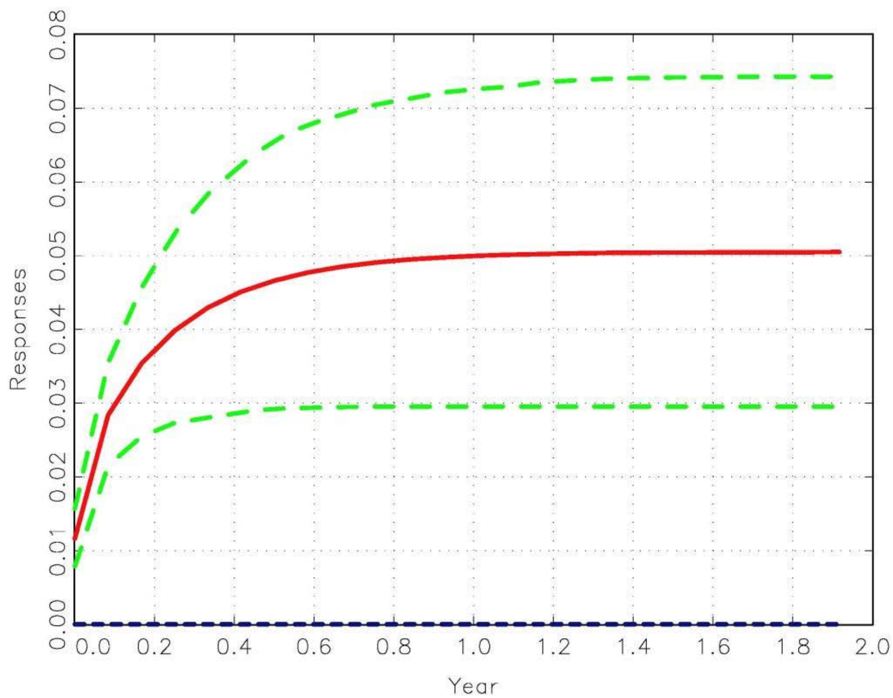
Note: Variance decomposition analysis is implemented from a trivariate vector autoregressive model with the real oil price ordered first, while the real industrial production, denoted IP, is ordered last. $E_t x_{t+k}$ is the k-period ahead forecast of the variable x at time t and k denotes the forecast horizon in months.

Table 20. Threshhold Vector Autoregressive Model Estimations

		Oil_{t-1}	Apparel_{t-1}	Consum_{t-1}
$\tau < -1.223$	Oil_t	**0.953** (0.033)	-0.458 (0.411)	0.178 (0.170)
(19.1%)	Apparel_t	-0.000 (0.002)	**1.007** (0.027)	-0.011 (0.011)
	Consum_t	**-0.010** (0.003)	-0.023 (0.038)	**0.986** (0.016)
$\tau > -1.223$	Oil_t	**0.967** (0.015)	-0.169 (0.118)	**0.172** (0.056)
(80.9%)	Apparel_t	**-0.003** (0.001)	**0.979** (0.008)	-0.003 (0.004)
	Consum_t	**-0.004** (0.001)	-0.015 (0.011)	**0.996** (0.005)
		Oil_{t-1}	Energy_{t-1}	Consum_{t-1}
$\tau < -0.214$	Oil_t	**1.141** (0.042)	**-0.431** (0.121)	0.004 (0.064)
(42.2%)	Energy_t	**0.103** (0.011)	**0.714** (0.030)	-0.025 (0.016)
	Consum_t	**-0.023** (0.004)	**0.052** (0.011)	**0.998** (0.006)
$\tau > -0.214$	Oil_t	**0.884** (0.044)	**0.288** (0.118)	**0.209** (0.072)
(57.8%)	Energy_t	**0.045** (0.011)	**0.889** (0.030)	-0.009 (0.019)
	Consum_t	-0.002 (0.004)	0.002 (0.011)	**0.993** (0.007)
		Oil_{t-1}	Food_{t-1}	Consum_{t-1}
$\tau < -1.336$	Oil_t	**0.937** (0.026)	**2.550** (0.596)	**-0.853** (0.219)
(17.7%)	Food_t	0.001 (0.001)	**0.845** (0.034)	**0.047** (0.012)
	Consum_t	**-0.008** (0.002)	**-0.124** (0.055)	**1.016** (0.020)
$\tau > -1.336$	Oil_t	**0.977** (0.010)	0.469 (0.245)	0.001 (0.083)
(82.3%)	Food_t	-0.000 (0.001)	**0.968** (0.014)	**0.012** (0.005)
	Consum_t	**-0.002** (0.001)	**-0.055** (0.023)	**1.008** (0.008)
		Oil_{t-1}	Housing_{t-1}	Consum_{t-1}
$\tau < -1.223$	Oil_t	**0.968** (0.023)	**2.633** (0.960)	**0.465** (0.186)
(19.1%)	Housing_t	0.002 (0.001)	**0.869** (0.039)	**-0.018** (0.008)
	Consum_t	**-0.008** (0.002)	-0.150 (0.089)	**0.952** (0.017)
$\tau > -1.223$	Oil_t	**0.978** (0.011)	0.372 (0.283)	**0.174** (0.058)
(80.9%)	Housing_t	-0.000 (0.000)	**0.986** (0.011)	-0.000 (0.002)
	Consum_t	**-0.003** (0.001)	0.017 (0.026)	**0.994** (0.005)
		Oil_{t-1}	Medical_{t-1}	Consum_{t-1}
$\tau < -1.223$	Oil_t	**0.964** (0.043)	-0.176 (0.410)	0.000 (0.097)
(19.1%)	Medical_t	**-0.007** (0.002)	**0.949** (0.021)	**-0.019** (0.005)
	Consum_t	**-0.016** (0.004)	**-0.087** (0.038)	**0.970** (0.009)
$\tau > -1.223$	Oil_t	**0.964** (0.018)	-0.204 (0.176)	**0.111** (0.051)
(80.9%)	Medical_t	**-0.003** (0.001)	**0.974** (0.009)	**-0.007** (0.003)
	Consum_t	**-0.004** (0.002)	-0.021 (0.016)	**0.991** (0.005)
		Oil_{t-1}	Trans_{t-1}	Consum_{t-1}
$\tau < -1.280$	Oil_t	**1.052** (0.036)	**-0.988** (0.385)	-0.171 (0.115)
(18.7%)	Trans_t	**0.019** (0.004)	**0.727** (0.043)	**-0.039** (0.013)
	Consum_t	**-0.010** (0.003)	0.020 (0.036)	**0.982** (0.011)
$\tau > -1.280$	Oil_t	**1.017** (0.020)	**-0.548** (0.268)	0.054 (0.060)
(81.3%)	Trans_t	**0.012** (0.002)	**0.856** (0.030)	**-0.014** (0.007)
	Consum_t	**-0.006** (0.002)	**0.052** (0.025)	**1.000** (0.006)

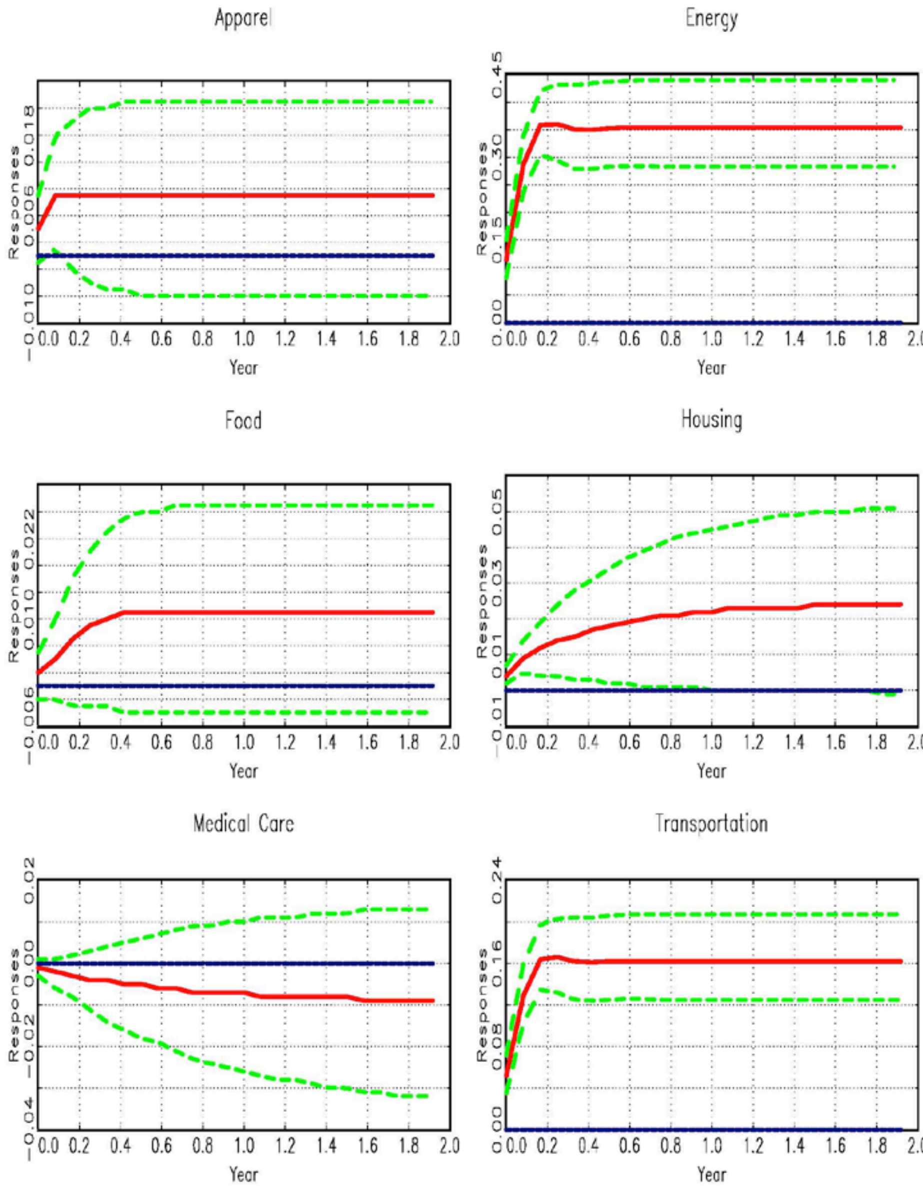
Note: Estimates that are significant at the 5% are in bold. One period lagged real consumption growth rate is used as the threshold variable. Numbers in brackets in the first column are the frequency of observations in each regime.

Figure 5. Consumer Price Index Response to an Oil Price Shock



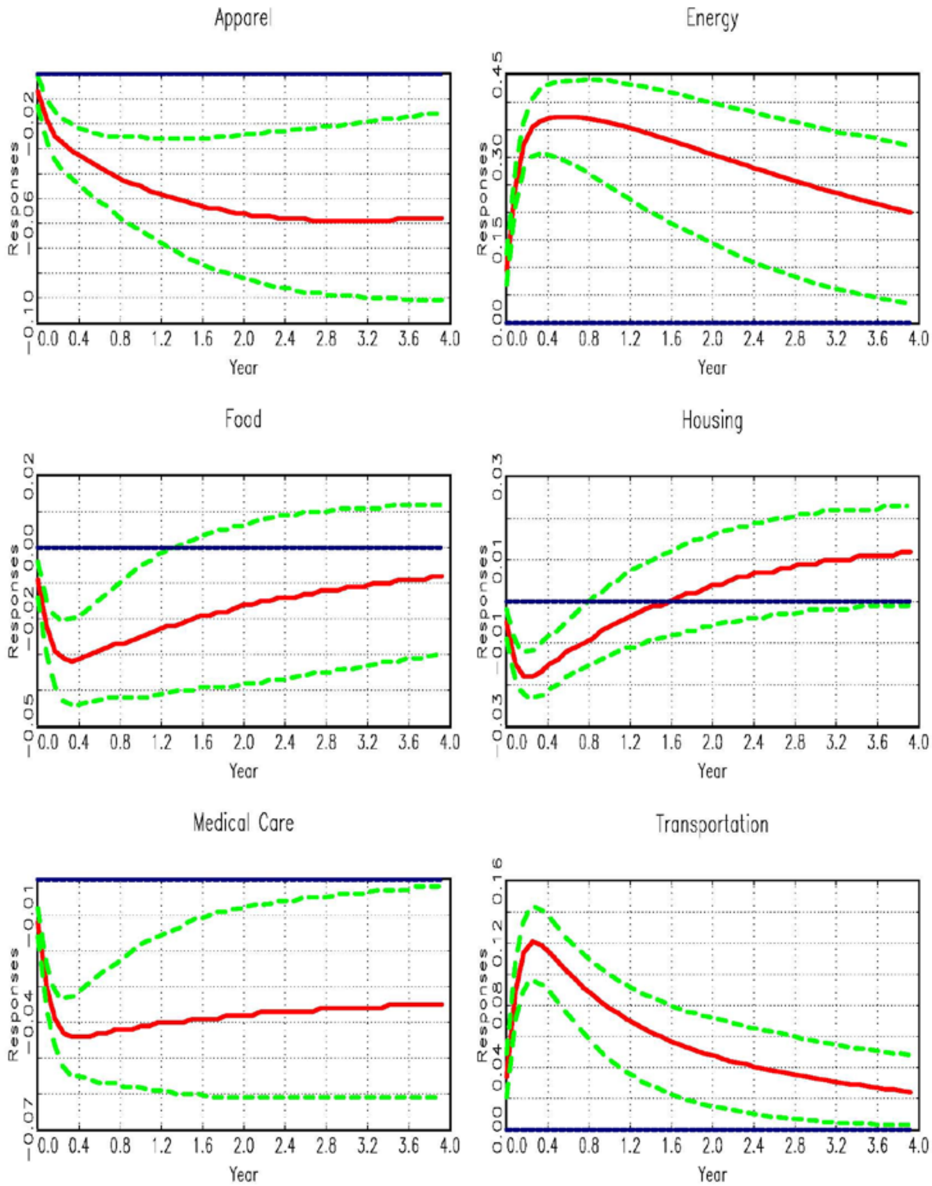
Note: Accumulative response functions are obtained from a bivariate vector autoregressive model with the oil price inflation ordered first. The 95% confidence bands (dashed lines) are obtained from 2,000 nonparametric bootstrap simulations.

Figure 6. Sectoral Responses to an Oil Price Shock



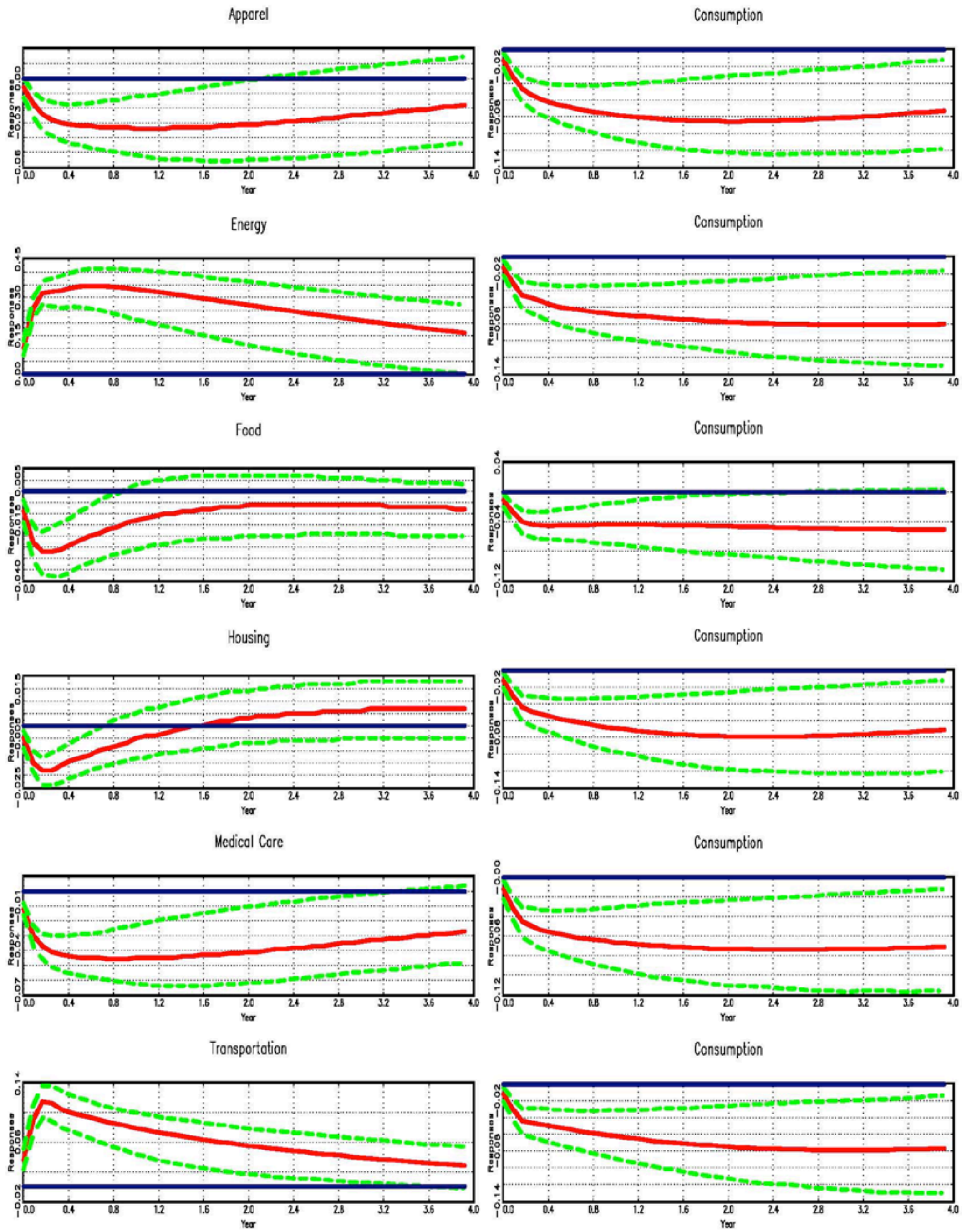
Note: Response functions are obtained from a bivariate vector autoregressive model with the real oil price is ordered first. These response functions are the same as the generalized impulse-response function by Pesaran and Shin (1998). The 95% confidence bands (dashed lines) are obtained from 2,000 nonparametric bootstrap simulations.

Figure 7. Share Response Functions to an Oil Price Shock: Bivariate Models



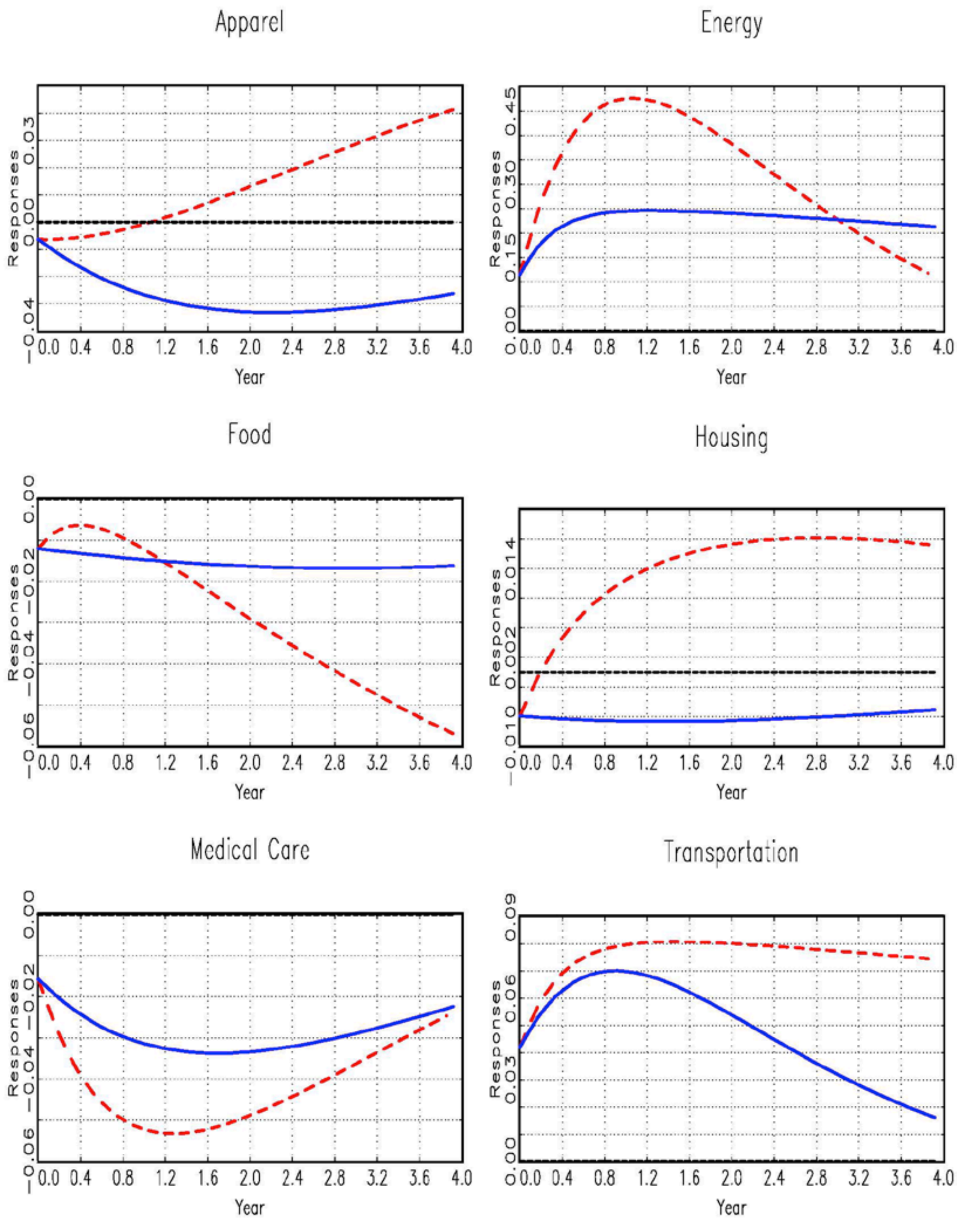
Note: Response functions are obtained from a bivariate vector autoregressive model with the real oil price is ordered first. These response functions are the same as the generalized impulse-response function by Pesaran and Shin (1998). The 95% confidence bands (dashed lines) are obtained from 2,000 nonparametric bootstrap simulations.

Figure 8. Share Response Functions to an Oil Price Shock: Tri-Variate Models



Note: Response functions are obtained from a trivariate vector autoregressive model with the real oil price is ordered first. These response functions are the same as the generalized impulse-response function by Pesaran and Shin (1998). The 95% confidence bands (dashed lines) are obtained from 2,000 nonparametric bootstrap simulations.

Figure 9. Regime Specific Impulse-Response Function Estimations



Note: Impulse-response functions are obtained from threshold trivariate vector autoregressive (VAR) models with the one-period lagged real industrial production growth rate as the threshold variable. We calculated conditional impulse-response functions from each regime, the low growth regime (dashed) and the high growth regime (solid), assuming that shocks are small enough not to result in any regime change. We used the Choleski factor from the whole threshold VAR model.

Chapter 5. Conclusions

This dissertation first revisits the empirical inconsistency of the Permanent Income Hypothesis using rural area household data in China along with the postwar US data as a benchmark. We view rural area residents as representative consumers in China since this group of consumers has been a dominant majority until recently. Further, rural China and the US make good contrasting groups of consumers. We present strong evidence against the PIH in the sense that consumption growth is highly predictable, which is in contrast to the work by Chow (1985, 2010) who reported favorable indirect evidence using conventional normal approximation based tests.

Our in-sample analysis based on Campbell and Mankiw (1990) implies a lot weaker evidence in favor of the PIH when the rural China data is used instead of the US data. The λ point estimate ranges from 0.611 to 0.879 for rural China, while much smaller values were obtained when we use the US data, which seem reasonable because λ is a fraction of consumers who are liquidity constrained. Our out-of-sample forecasting exercises directly deal with the predictability issue from the PIH. We obtain very strong results against the PIH in the sense that explanatory variables have substantial predictive contents for consumption growth, which is robust to the choice of sample split.

Our dynamic analysis with VAR framework also provides empirical results that are consistent with previous findings. Consumption responds to an income shock highly significantly in both countries, but we observed a lot stronger responses from rural China than the US. The variance decomposition analysis shows that roughly 50% of consumption changes are explained by income shocks in rural China, while income shocks explain less than 25% in the US.

This dissertation then examines potential effects of the Great Recession on household consumption for entertainment activities in the U.S. using the CES data in 2003, 2006, 2008, and 2010. We estimate consumer's decision making process by estimating consumption functions in recession years, 2008 and 2010, in comparison with 2003 and 2006 as the benchmark.

Recessionary effects were found either in intercept (F&A) or in the income coefficient (TRS and OES) during recession years. That is, we find substantial decreases in intercept for F&A activities in 2008 and 2010 compared with those in 2003 and 2006. As to TRS and OES, we note substantial decreases in the income coefficient in recession years. We note that a decrease in the income coefficient during recessions implies slow adjustment of consumption expenditure when the income growth slows down. Economic downturns tend to generate financial distress, which will negatively affect consumers' welfare. Rational consumers will re-allocate available resources to entertainment activities to improve their wellbeing. Our results may be consistent with this view.

This dissertation also empirically evaluates the role of spending adjustment when there is an oil price shock using six CPI sub-indices in the US. We find limited pass-through effects of the oil shock on apparel, food, housing, and medical care prices compared with those on the energy and transportation prices. We propose an explanation for such discrepancies from spending adjustment effects. These findings are consistent with the work of Edelstein and Kilian (2009), who point out a negative income effect caused by unexpected changes in the oil price. The regime-specific responses of CPI sub-indices to the oil price shock are also investigated, which shows that the greater responses during the low growth regime seem consistent with Edelstein and Kilian (2009).

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