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The Cross-Euler Equation Approach to Testing for the Liquidity Constraint: Evidence from Consumer Expenditure Survey*

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In this paper, we utilize Cross-Euler method in testing for the existence of liquidity constraint. We adopt standard two goods version of Life-Cycle model to study the consumption behavior of necessity goods and luxury goods. Then we construct synthetic panel data from the Consumer Expenditure Survey where households have been classified to cohorts by their ages and educational attainments. Taking the Cross-Euler equation approach in testing for the liquidity constraints, the test rejected the null of no liquidity constraint for low-education cohorts, while accepting the null for high-education cohorts. Taking an education level as a proxy for permanent income, the test results were consistent with the view that poorer agents are more likely to be liquidity constrained.

Keywords Cross-Euler Equation, Liquidity Constraint, Luxury Goods, Necessity Goods

1 Introduction

Whether there are liquidity constraints in the economy or not is an important question. It is important because fiscal and monetary policy implications from Life-Cycle model will be considerably altered in the presence of liquidity constraints. As pointed out by Altonji and Siow (1987) and Shea (1995), consumption growth may respond asymmetrically to change in transitory income when liquidity constraints are binding. This, in turn, implies the asymmetric fiscal policy effect. Also, when liquidity constraints are binding, change in real interest rate will not cause any intertemporal substitution in consumption that expansionary monetary policy may not have any effect in inducing consumers to spend more. Ironically, since consumers' net wealth are often seriously damaged during the economic downturn - making liquidity constraints

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even more compelling -, monetary policy may be ineffective during the recession when the policy stimulus is desperately needed. In the presence of liquidity constraints, monetary policy will face a serious problem during an economic downturn. In this connection, the asymmetric monetary policy effect reported by Choi (1999) and Weise (1999) may well be stemming from the presence of liquidity constraints in the economy. Thus, whether there exist liquidity constraints or not is a serious question for policy makers.

Reflecting the importance of liquidity constraints, not surprisingly, considerable amount of research have been devoted in testing for the liquidity constraints. Based on aggregate data, Flavin (1981) and Campbell and Mankiw (1989, 1990), among others, have conducted an excess sensitivity test and found that consumption growth rate to be significantly correlated with lagged or predicted income growth, which can be interpreted as evidence of liquidity constraint. Turning to the excess sensitivity test based on panel data, Hall and Mishkin (1982), Shapiro (1986) and Hayashi (1985) all found some evidence that lagged income change or real disposable income change to be significantly correlated with consumption growth. Mariger (1987), Altonji and Siow (1987) and Zeldes (1989) specifically take into account for the Kuhn-Tucker condition emerging from the liquidity constraint. Mariger (1987), based on cross-sectional surveys, reports that 19.4% of the households are liquidity constrained. Zeldes (1989), based on Panel Study of Income Dynamics (PSID), have found that less wealthy households to be more vulnerable to liquidity constraints. Runkle (1991), based on PSID, tests the over-identifying restrictions implied by Euler equation and reports little evidence of liquidity constraints. Attanasio and Webber (1993) and Meghir and Webber (1996) studied the validity of Life-Cycle model using the Consumer Expenditure Survey (CES) and report some evidence that younger households are liquidity constrained. DeJuan and Seater (1999), also based on CES, exploits asymmetric response of consumption growth to income change and reports little evidence of liquidity constraints. Gross and Souleles (2001), using unique panel data on credit card accounts, estimates the marginal propensity to consume out of liquidity and found their estimates to be higher for people whose credit limit is low, which they interpret as evidence of liquidity constraints.

In this paper, we propose a new empirical method in testing for the existence of liquidity constraint utilizing the concept of Cross-Euler equation proposed by Nihsiyama (2005). In order to explore the potential of the Cross-Euler equation approach in testing the liquidity constraints we adopt two goods version of Life-cycle model. Specifically, we study the consumption behaviors of necessity goods and luxury goods of the agents. Choice of necessity and luxury goods are, to some extent, arbitrary. However, this classification has its own motivation, especially in the context of aggregate data. In aggregate data, by construction, relatively larger share of luxury goods are consumed by “rich” agents, while relatively larger share of necessity goods are consumed by “poor” agents in the economy. Thus, by studying the behavior of standard Euler equations for both goods and also studying the behavior of the Cross-Euler equation linking both goods, there is a good possibility that we can infer which type of agents are more vulnerable to liquidity constraints even from the aggregate data. Naturally, since the poorer agents tend to be more vulnerable to the liquidity constraint, we expect that the Euler equation for the necessity goods to be misspecified, but the Euler equation for the luxury goods to be specified. Empirical evidence in this paper, though yielding mixed results, seemed to have supported this prediction.

In an attempt to overcome aggregation problem and to legitimately test for the liquidity constraints, we conduct cohort analysis proposed by Deaton (1985). Under the cohort analysis, the households are aggregated into cohorts who share the similar taste and, therefore, it has an advantage over the representative model in the sense that it is relatively free from the aggregation problem. Based on the Consumer Expenditure Survey from 1984 to 1998, we classify the households into cohorts by their age and educational attainment following Attanasio and Browning (1995). Classification by the age are necessary because the households are expected to have heterogeneous consumption patterns over the life-cycle. Classification by education attainments was adopted as a mean to classify the households by their life-time income (i.e. permanent income). Then we estimate the preference parameters for each education cohorts based on their Cross-Euler and standard Euler equations. As a mean to formally compare the parameters estimates from both Euler equations, we conduct Cooley and Ogaki’s LR type test (1996). Empirical evidence based on cohort analysis suggested that low-education cohort to be liquidity constrained, but not for the high-education cohort. Taking the education level as a proxy for lifetime income, the test results seems to support the view that poorer agents are more likely to be liquidity constrained.

The rest of paper is organized as follows. Section 2 describes the standard two goods version of the life-cycle model to study the consumption behavior of necessity goods and luxury goods. Section 3 describes the Cross-Euler equation approach in testing the liquidity constraints. In Section 4, we construct the cohort data set from Consumer Expenditure Survey and apply the Cross-Euler equation approach in testing for the liquidity constraints. Section 5 provides the concluding remark.

2 Model Description

This paper adopts the standard two-goods version of Life Cycle/ Permanent Income Model (LCPIM) as in Ogaki (1992). Representative agent is assumed to maximize his expected lifetime utility under his lifetime budget constraint. Stating mathematically,

$$\max \quad E_0 \sum_{t=0}^{\infty} \beta^t U(N_t, L_t) \tag{1}$$

$$s.t. \quad A_t = (1+r_t)A_{t-1} + Y_t - P_t^N N_t - P_t^L L_t \quad \text{for } \forall t \geq 0 \tag{2}$$

where N_t stands for necessity goods at period t, L_t stands for luxury goods, A_t stands for the asset holding of the agent, Y_t stands for the labor income of the agent, r_t stands for the real interest rate from period $t-1$ to t, P_t^N stands for the price of a necessity good, and P_t^L stands for the price of an luxury goods. Finally, we parameterize agent's subjective discount rate as constant β.

We have assumed that period-by-period utility is time separable for this agent and have implicitly assumed the additive separability between durable goods and non-durable goods. Solving above optimization problem yields the following first order conditions (FOC).

$$\frac{P_t^N}{P_t^L} = \frac{U_{N_t}}{U_{L_t}} \quad \text{for } \forall t \geq 0 \tag{3}$$

$$E_0\left[\beta \frac{U_{N_{t+1}}}{U_{N_t}}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^N} - 1\right] = 0 \quad \text{for } \forall t \geq 0 \tag{4}$$

$$E_0\left[\beta \frac{U_{L_{t+1}}}{U_{L_t}}(1+r_{t+1})\frac{P_t^L}{P_{t+1}^L} - 1\right] = 0 \quad \text{for } \forall t \geq 0 \tag{5}$$

Eq. (3) represents the contemporaneous FOC for this representative agent. These FOC's follow if the agent is maximizing his utility given the contemporaneous price ratio of necessity and luxury goods. In other words, representative agent will equalize his contemporaneous marginal rate of substitution (MRS) to current price ratio of two goods. Eq. (4) represents the intertemporal FOC, the Euler equation, of necessity goods. This FOC will follow, if the agent is maximizing his expected utility over time given the discounted expected price ratio of necessity goods at period t to period $t+1$. The Euler equation for luxury goods (eq. (5)) holds by the parallel logic.

Next, in order to make the model econometricaly estimable, we are going to parametrize the utility function. We specify the utility function as a standard addi-log function following Houthakker (1960).

$$U(N_t, L_t) = \frac{(N_t)^{1-\alpha}}{1-\alpha} + K\frac{(L_t)^{1-\gamma}}{1-\gamma} \tag{6}$$

This addi-log specification was used in Ogaki (1992). Houthakker's addi-log specification reveals the non-homothetic preference of the agent in general, but contains the homothetic preference as a special case when $\alpha=\gamma$. This non-homothetic preference is crucial in our model since we try to capture intertemporal aspects of necessity goods (which by definition requires the income elasticity to be smaller than 1) and luxury goods (which requires the income elasticity to be greater than 1). Homothetic preference, such as CES utility function, reveals the unit income elasticity that it is not an appropriate utility specification to adopt when modeling the behavior of necessity and luxury goods consumption at the same time. It should be noted that under this addi-log specification, $1/\alpha$ and $1/\gamma$ can be interpreted as the intertemporal elasticity of substitution (IES) of N_t and L_t respectively.[1)]

Under this specification, FOC will then be as follows.

$$\frac{P_t^N}{P_t^L}=\frac{1}{K}\frac{(N_t)^{-\alpha}}{(L_t)^{-\gamma}} \quad \text{for } \forall t\geq 0 \tag{7}$$

$$E_0\left[\beta\left(\frac{N_{t+1}}{N_t}\right)^{-\alpha}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^N}-1\right]=0 \quad \text{for } \forall t\geq 0 \tag{8}$$

$$E_0\left[\beta\left(\frac{L_{t+1}}{L_t}\right)^{-\gamma}(1+r_{t+1})\frac{P_t^L}{P_{t+1}^L}-1\right]=0 \quad \text{for } \forall t\geq 0 \tag{9}$$

Given these specifications, we are now ready to actually estimate and test the implication of the model.

Some remarks should follow for these FOC's. As was pointed out by Ogaki and Park (1998), the specification of the intratemporal relationship eq.(3) turns out to be robust to several kinds of nuisant conditions, such as liquidity constraint and habit formation in utility function. However, the specification of Euler equations are very sensitive to the presence of liquidity constraint or habit formation. In other words, specification of the intratemporal relationship is robust, but the specification of Euler equations are not. Conversely, if for any method we can find the evidence that Euler equation is specified, that will be a strong evidence against the presence of liquidity constraint or habit formation. This specification issue of Euler equations will be the central focus of the rest of our paper.

3 The Cross-Euler Equation Approach

3.1 An Empirical Dilemma

Let us turn back to the 3 FOC's (i.e. eq. (7), (8), and (9)) implied by the model. Since the conditional moment condition is established for eq. (8) and (9), there is no problem in applying GMM on these equations. If indeed these Euler equations are well specified, then the

GMM will yield $O_P(T^{-1/2})$ consistent estimate of α and γ. However, unfortunately, the complication will arise from contemporaneous relationship eq.(7).

A natural way[2] to estimate the parameters from intratemporal relationship is to log-linearize and rearrange the eq. (7) as follow.

$$\ln L_t + const. - \frac{1}{\gamma}\ln\frac{P_t^N}{P_t^L} - \frac{\alpha}{\gamma}\ln N_t = 0$$

If the forcing variables $\ln L_t$, $\ln N_t$, and $\ln(P_t^N/P_t^L)$ follows the I(1) process, one is tempted to introduce some I(0) disturbance terms on RHS of the above equation in order to conduct the cointegration analysis.

$$\ln L_t + const. - \frac{1}{\gamma}\ln\frac{P_t^N}{P_t^L} - \frac{\alpha}{\gamma}\ln N_t = \varepsilon_t \text{ where } \varepsilon_t \sim I(0) \text{ and } E(\varepsilon_t) = 0 \qquad (10)$$

This error term can be an optimization error, measurement error, preference shock, etc. However, in so doing, one should also include this newly introduced error term into the existing Euler equations (8) and (9). In other words, in addition to the forecast error embedded in Euler equations, one is now introducing another kind of error term which is intrinsically different type of an error. Nishiyama (2005) showed that when a new error term is introduced to Euler equations, no longer eq.(8) and eq.(9) are specified.

This is the point where one experience the dilemma. The objective is to estimate the parameters from both intratemporal relationship and Euler equations. If one introduces some arbitrary error term to the contemporaneous relationship in order to conduct the cointegration analysis, this newly introduced error term will affect the specification of Euler equation. Conducting GMM on standard Euler equations (8) and (9) will no longer yield a consistent estimates for α and γ. On the other hand, if one does not introduce any error term to contemporaneous relationship, Euler equation (8) and (9) will remain to be specified and GMM on these equations will yield consistent estimates assuming that the model is correct. But then, since the error term is not present for the contemporaneous relationship, one faces a illegitimacy in conducting the cointegration analysis.

So, is there anyway to overcome this dilemma?

3. 2 A Remedy: The Cross-Euler Equation Approach

This section propose a remedy to the above empirical dilemma following Nishiyama (2005). The idea is to first define the concept called cross intertemporal marginal rate of substitution (CIMRS) and then to derive the corresponding first order condition which we will call the Cross-Euler equation. In this subsection, we will show how the concept of Cross-Euler equation can be a remedy for the above empirical dilemma.

Step 1: Defining CIMRS and deriving the Cross-Euler equations

Definition 1 (CIMRS) *Let* $V(x_1^1, \ldots, x_1^K, \ldots, x_T^1, \ldots, x_T^K)$ *be a utility function defined upon* K *goods with* T *periods. Then we call the following expression as*

$$-\frac{\partial V(\bullet)/\partial x_{t+1}^i}{\partial V(\bullet)/\partial x_t^j}$$

the cross intertemporal marginal rate of substitution (CIMRS) between goods x_{t+1}^i *and* x_t^j *where* $i \neq j$ *and* $t=1, \ldots, T-1$.

The concept of CIMRS is just a simple extension of IMRS. It can be easily conceptualized as the IMRS defined upon different goods instead of same goods.[3] From the concept of CIMRS and from our model described in eq.(1) and (2), we can derive the "alternative" FOC. For convenience we will call the following FOC as the Cross-Euler equation.

$$E_0\left[\beta K\frac{(L_{t+1})^{-\gamma}}{(N_t)^{-\alpha}}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}-1\right]=0 \tag{11}$$

We can see the intuition of the above equation by thinking of the situation where the agent is trading N_t to L_{t+1}. Now the marginal rate of substitution between L_{t+1} and N_t (or CIMRS in our terminology) is defined as $-\beta U_{L_t,\,t+1}/U_{N_t,\,t}$ and takes the form of $-\beta K(L_{t+1})^{-\gamma}/(N_t)^{-\alpha}$ under addi-log utility function. Next, let us consider the opportunity cost of obtaining L_{t+1} in terms of N_t. By selling one unit of N_t at period t, agent can obtain P_t^N of numeraire goods. By saving all of these numeraire goods at period t, agent can obtain $(1+r_{t+1})\cdot P_t^N$ of numeraire goods at period $t+1$. By using all of these to buy L_{t+1}, agent can buy $(1+r_{t+1})\cdot P_t^N/P_{t+1}^L$ units of L_{t+1}. Thus the opportunity cost of L_{t+1} in terms of N_t is $(1+r_{t+1})\cdot P_t^N/P_{t+1}^L$. If the agent is optimally trading N_t to L_{t+1}, then the agent is equalizing the opportunity cost to CIMRS between L_{t+1} and N_t, yielding the above Cross-Euler equation.

By similar fashion, we can derive the another version of Cross-Euler equation as follow.

$$E_0\left[\frac{\beta}{K}\frac{(N_{t+1})^{-\alpha}}{(L_t)^{-\gamma}}(1+r_{t+1})\frac{P_t^L}{P_{t+1}^N}-1\right]=0 \tag{12}$$

In deriving the above Cross-Euler equation, we have equalized the CIMRS between N_{t+1} and L_t (i.e. $-(\beta/K)((N_{t+1})^{-\alpha}/(L_t)^{-\gamma})$) to the opportunity cost of N_{t+1} in terms of L_t (i.e. $(1+r_{t+1})P_t^L/P_{t+1}^N$).

Step 2: Cointegration relationship implied by Cross-Euler equation

Returning to the Cross-Euler eq. (11), it follows that

$$\beta K\frac{(L_{t+1})^{-\gamma}}{(N_t)^{-\alpha}}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}=1+e_{t+1} \tag{13}$$

where we defined e_{t+1} as

$$e_{t+1}\equiv\beta K\frac{(L_{t+1})^{-\gamma}}{(N_t)^{-\alpha}}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}-E_0\left[\beta K\frac{(L_{t+1})^{-\gamma}}{(N_t)^{-\alpha}}(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]$$

Taking the log on both side of eq.(13) will yield

$$const.+\ln\left[(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]-\gamma\ln L_{t+1}+\alpha\ln N_t=\ln(1+e_{t+1})$$

Assuming that the growth rate of both domestic and imported non-durable goods consumption (i.e. N_{t+1}/N_t and L_{t+1}/L_t), real interest rate (i.e. r_t) and the growth rate of the price level of both domestic and imported non-durable goods (i.e. P_{t+1}^N/P_t^N and P_{t+1}^L/P_t^L) are stationary, it can be shown that $\ln(1+e_{t+1})$ will also be stationary.

Exploiting the I(0) process of $\ln(1+e_{t+1})$, we can obtain the following cointegrating relationship.

$$\ln L_{t+1}+const.-\frac{1}{\gamma}\ln\left[(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]-\frac{\alpha}{\gamma}\ln N_t\sim I(0) \tag{14}$$

By similar fashion, we can derive the following cointegration relationship from eq.(12).

$$\ln L_t+const.-\frac{1}{\gamma}\ln\left[\frac{1}{1+r_{t+1}}\frac{P_{t+1}^N}{P_t^L}\right]-\frac{\alpha}{\gamma}\ln N_{t+1}\sim I(0) \tag{15}$$

Given these cointegrating relationships of log-linearized Cross-Euler equations, combined with GMM-estimable standard Euler equations (8) and (9), we now have a firm ground in comparing the estimates of α and γ. To summarize, under the weaker assumption which allows for the existence of liquidity constraint and/or certain type of habit formation, log-linearized Cross-Euler equation (14) and (15) will yield a super-consistent estimates for α and γ, while Euler equation (8) and (9) are not guaranteed to yield consistent estimates. Under the stronger assumption which does not allow for the presence of liquidity constraint or habit formation, both log-linearized Cross-Euler equations and standard Euler equations will yield super-consistent and consistent estimates of α and γ, respectively. This latter proposition, which basically states that the estimates of IES parameters from cointegration analysis and GMM to be close under the stronger assumption, is particularly important for us since we can formally test this proposition using statistical method such as Cooley and Ogaki's (1996) LR type test. The following Table 0 summarizes the main idea of this section.

Table 0: Test of Liquidity Constraint

	Log-linearized Cross-Euler Equation (Method: Cointegration)	Standard Euler Equation (Method: GMM)
No Liquidity constraint	Super-consistent estimates for α and γ	Inconsistent
Liquidity constraint present	Super-consistent estimates for α and γ	Consistent estimates for α and γ

4 Empirical Evidence from Consumer Expenditure Survey

4.1 Motivation for Cohort Analysis

When estimating the preference parameters consistently from the aggregate data, extremely stringent requirements have to be met. For instance, in order for the representative agent to exist, all the agents in the economy need to share the identical preference and also their utility function have to be homothetic (See Kirman (1992) and Stoker (1993) for more details). In reality, it is very unlikely that these conditions are met. Turning to micro data, several rich data set, such as Panel Study for Income Dynamics (PSID), Consumer Expenditure Survey (CES) and Family Expenditure Survey (FES), are available. However, these micro data set, despite its richness, contain some serious defects when testing for life-cycle model. For instance, PSID only tracks the consumption expenditure of individuals, which is not too useful especially when we are interested in the consumption pattern of non-durable goods and services as a whole. On the other hand, CES and FES, albeit its richness in the categories of consumption goods, are cross-sectional survey data that it does not allow researchers to track same individuals over time.

In reconciling this dilemma, Deaton (1985) proposed a method in tracking 'cohorts' from time series of cross-sectional survey. Cohort is a subset of households sharing the identical qualities that are unchanged over time. These qualities, for instance, can be year of birth, race, gender and so on. By classifying the cross-sectional observations into these cohorts and tracking them over time, Deaton (1985) showed that it is possible to construct synthetic panel (or pseudo panel) data that allows researchers to estimate the cohort-specific parameters consistently.[4)] Moreover, since the households are aggregated into cohorts who share the similar taste, it is relatively free from the aggregation problem compared to representative agent model. Inspired by these advantages, not surprisingly, the cohort technique has been widely used in the empirical life-cycle literatures. The predecessor in the line of empirical cohort analysis have constructed the cohorts in several ways. Browning, Deaton, and Irish (1985), Moffit (1993), Attanasio and Webber (1993, 1995), have classified the households according to their ages. Attanasio et al.

(1999) have classified the households according to their ages and education attainments.

In this paper, we adopt this cohort technique in estimating the preference parameters and testing for the liquidity constraints. In constructing the cohort data, careful attention must be exerted. As pointed out by Verbeek (1996), legitimate cohorts are constructed only if taste and demographic observations of households in each cohort are drawn from the identical probability distribution. Thus, the observational difference among each observation within the same cohort must be idiosyncratic and should be "averaged out" after taking average. To comply strictly with this requirement, households should better be classified into cohorts distinguished by the finest information available from the data, so that non-idiosyncratic effects are isolated. However, due to the limitation of sample observations from the CES - approximately 5,000 household observations each quarter -, there exist a trade-off between the construction of finer cohorts and sample observations per cohort. Some judgment must be exerted to strike the "optimal" balance between two requirements

In constructing the cohorts, we basically follow Attanasio et al. (1999) - that is to classify the households by ages and educational attainments. Specifically, we classified agents into 10 cohorts by their age and education level. This classification can be justified as follows: 1) Age classification is necessary because the agents reveal the heterogeneous consumption patterns (i.e. life-cycle in consumption) depending on their age. 2) Classification by education level is adopted as a mean to classify the agents by their life-time income (i.e. permanent income). By the construction of LCPIM, an agent will face a liquidity constraint when his net wealth decreases to some certain level. Naturally, an agent with low permanent income (i.e. poor agent) is more likely to face this bound over his course of life than an agent with high permanent income (i.e. rich agent). Thus, in order to be perfectly consistent with the theory implication, it is ideal to classify agents by their permanent income. However, since the permanent income of each agent is not directly observable from the data, we have compromised to proxy the permanent income by the education level. The cohort data for each type of agent have been constructed from the series of Consumer Expenditure Survey from 1984 to 1998.

Finally, whenever making a statistical inference in this section, we assume that number of cross-sectional cohorts is fixed in pseudo panel (i.e. H is fixed), assume that household observations within the cohort is large (i.e. $N_c \to \infty$) and assume that time series observations are large (i.e. $T \to \infty$). Under these assumption, consistency of the pooled estimates in pseudo panel are known to yield consistent estimates (See Verbeek (1996) for more discussion).

4. 2 Data Description

4. 2. 1 Construction of Cohorts

As a first step, the households are classified into 5 categories by their ages at 1984. Age intervals for each categories are 25–30, 31–36, 37–42, 43–48, and 49–54, respectively. Here, we are taking intervals of 6 years for each categories, which is slightly different from the convention previously used by Browning et al. (1985) and others. This practice has been adopted in consideration to the limitation on sample observations, but we believe that the heterogeneity biases relative to conventional intervals are minor.[5)] As a second and final step, we further classify the households into two categories according to their educational attainments. Households who dropped out from a high school or whose highest educational attainment is high school has been classified to the category called “High School.” A household who at least holds a college degree or higher has been classified to the category called “College.” It should be noted that we have intentionally omitted households who have dropped out from a college. This practice has been adopted in order to preserve the sharp contrast between the “High School” and “College” categories. Thus, as a consequence of this two-step classification, we have constructed 10 cohorts. The following table summarize the average observations per quarter for each cohort.

Table 1 Average Cohort Size per Quarter: 1984Q1 to 1999Q1

High School*				
HS1	HS2	HS3	HS4	HS5
322.43	273.21	255.77	234.61	231.34
College**				
Col1	Col2	Col3	Col4	Col5
242.02	253.41	196.43	120.41	95.82

Note: *) Highest educational attainment of a household head is less than or equivalent to high school diploma. Within this educational cohort, households were further classified by their ages. HS1 was born between ’54 to ’59, HS2 between ’48 to ’53, HS3 between ’42 to ’47, HS4 between ’36 to ’41 and HS5 between ’30 to ’35.
**) Highest educational attainment of a household head is more than or equivalent to college degree. Col 1 was born between ’54 to ’59, Col2 between ’48 to ’53, Col3 between ’42 to ’47, Col4 between ’36-to ’41 and Col5 between ’30 to ’35.

The top panel of the Table 1 reports the average cohort size for High School cohorts. HS1 stands for the High School cohort who was 25–30 years old, HS2 stands for the cohorts who was 31–36 years old, HS3 for the cohorts who was 37–42 years old, HS4 for the cohorts who was 43–48 years old, and HS5 for the cohorts who was 49–54 years old at 1984. The bottom panel of Table 1 reports the average cohort size for College cohorts. Col1 stands for the College

Table 2 Descriptive Statistics of Real Expenditure Growth: 1984Q1 to 1999Q1

	High School				
	HS1	HS2	HS3	HS4	HS5
	Luxury Goods Expenditure Growth (% per Quarter)				
Mean	0.367	0.106	-0.289	-0.739	-0.755
Std. Dev.	6.298	6.391	6.103	7.393	6.826
	Necessity Goods Expenditure Growth (% per Quarter)				
Mean	0.532	-0.004	-0.311	-0.370	-0.397
Std. Dev.	4.030	3.565	4.373	4.703	3.728
	College				
	Col1	Col2	Col3	Col4	Col5
	Luxury Goods Expenditure Growth (% per Quarter)				
Mean	0.519	0.119	-0.232	-0.553	-0.802
Std. Dev.	5.898	5.609	7.178	8.819	11.53
	Necessity Goods Expenditure Growth (% per Quarter)				
Mean	0.925	0.461	-0.155	-0.434	-0.569
Std. Dev.	4.655	5.007	6.152	6.366	7.678

Note: Real expenditures are seasonally adjusted using seasonal dummies. Expenditure growth rates not adjusted for adult equivalent scale.

cohorts who was 25–30 years old, Col2 for the cohorts who was 31–36 years old, and so on. As can be seen, the cohort size for most of the cohorts were more than or approximately 200, except for Col4 and Col5. This apparently small cohort size for Col4 and Col5 is probably due to the low college enrollment for older generations.[6)]

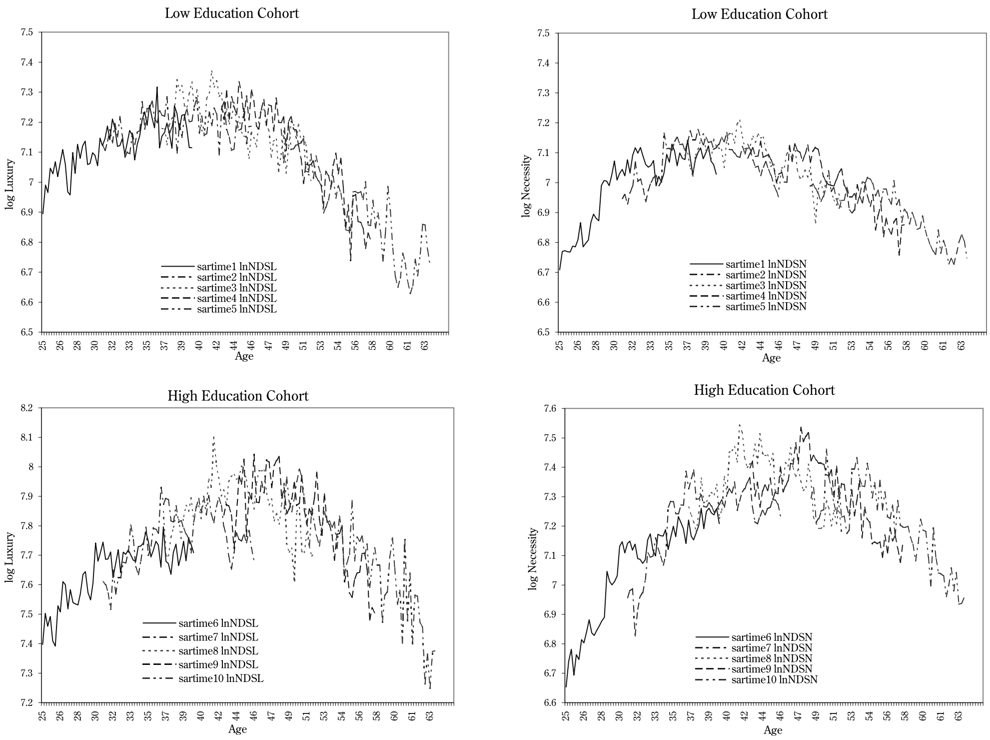
For each cohort, information regarding consumption and demographics have been extracted and were used in constructing the average cohort data.[7)] Luxury goods were composed of alcohol beverages, apparel, transportation excluding vehicle, entertainment, reading and other goods. Necessity goods were composed of food and tobacco. All cohorts are assumed to face the common opportunity cost intratemporally and intertemporally.[8)] In addition to expenditure information, we have also calculated an average number of adults and children per cohort. The descriptive statistics regarding the consumption growth is reported in Table 2.

4. 2. 2 Age Profile and Preliminary Testing

In order to visualize the consumption pattern of the cohorts, so called "Age Profile" regarding luxury goods and necessity goods expenditure have been laid out in Figure 1.

Age profile plots the life-cycle consumption pattern of same education of cohorts with different age groups on the same diagram. The left-top panel plots the log real luxury goods expen-

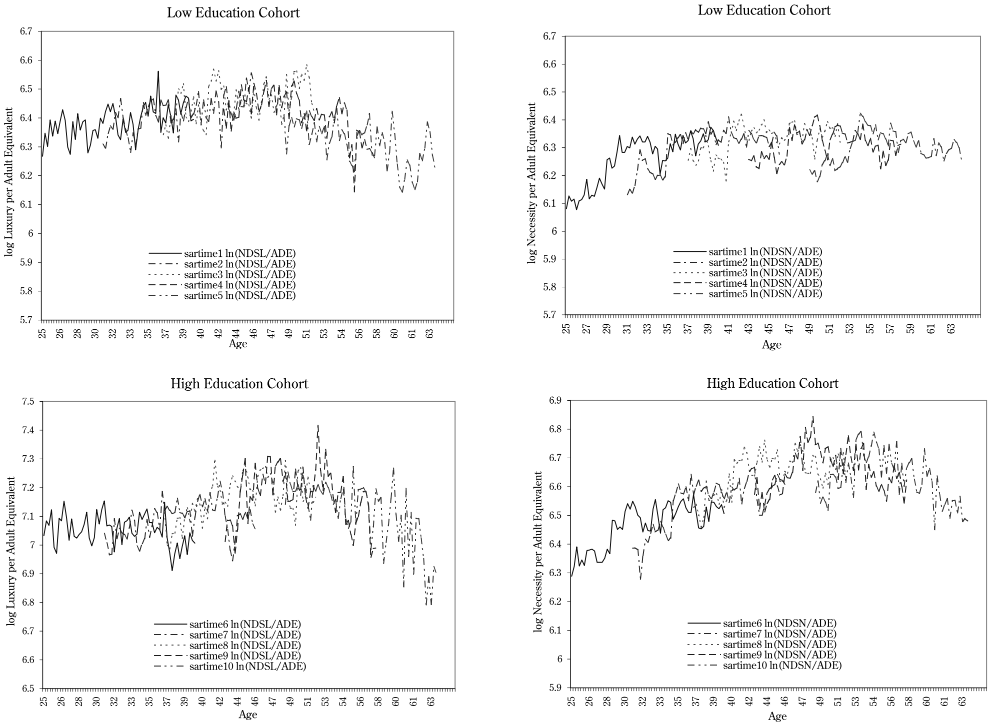
Figure 1



diture and the right-top panel plots the log real necessity goods expenditure of high school cohorts. As can be seen from these figures, consumption pattern for both goods reveals a hump over the life-cycle. For the luxury goods, consumption expenditure peaks out in the mid 40's and reveals a sharp decline towards the end of the life-cycle. In a similar fashion, necessity goods expenditure peaks out during late 30's to early 40's, although the magnitude of a hump seems to be milder than that of luxury goods. The left-bottom panel shows the age profile of the log real luxury goods expenditure and the right-bottom panel shows the age profile of the log real necessity goods expenditure of college cohorts. Again, hump shape in the consumption pattern can be clearly observed. For the college cohorts, luxury goods and necessity goods expenditure seem to peak out in the late 40's. Interestingly, necessity goods expenditure reveals a sharp increase in the beginning of the life-cycle and stays persistent toward the end of life-cycle, while increase and decrease in luxury goods seems to be fairly symmetric.

The main characteristic to be noted here is the clear violation of consumption smoothing, which is one of the main implications of life-cycle model. Is this hump shape in the consumption pattern solely induced by liquidity constraint? Not likely. Thus, before we can legitimately test

Figure 2



for the existence of liquidity constraints, the first task is to account for this obvious hump shape over the life-cycle. As pointed out by Attanasio and Webber (1993, 1995) and Attanasio et al. (1999), one of the main cause for this hump-shaped consumption pattern is due to demographic factors. As presented in their papers, the number of adults and children in the household shows similar hump-shape over the life-cycle. Mostly likely, as they argue, the hump-shape in consumption pattern can be attributed to these demographic factors. As for a quick and ad-hoc adjustment, we have adjusted consumption expenditure by the number of adult equivalent members[9] in the household. The age profiles of consumption expenditure per adult equivalent have been laid out in Figure 2.

As can be seen from Figure 2, the adjustment by adult equivalent scale have considerably dissipated a hump shape in the age profile. Now, the age profiles for both education cohorts reveal a fair magnitude of consumption smoothing over the life-cycle. For the necessity goods, both high school and college cohorts tend to increase their expenditure over the life-cycle. Interestingly, for the luxury goods, both education cohorts tend to decrease their spending toward the end of the life-cycle. Of course, the adjustment of consumption expenditure by adult equiva-

Table 3 Unit Root Test of log Luxury and Necessity Goods Expenditure

High School						
		HS1	HS2	HS3	HS4	HS5
$\ln L_t$	cst.	-2.690	-3.084*	-1.421	0.006	-1.551
	cst. & trd.	-3.184	-2.983	-3.561*	-2.717	-3.613*
$\ln N_t$	cst.	-2.215	-1.793	-0.861	-0.455	-0.696
	cst. & trd.	-0.978	-0.951	-2.698	-2.097	-2.346
$\Delta Adult_t$	cst.	-7.151**	-6.378**	-6.974**	-7.167**	-5.657**
	cst. & trd.	-7.086**	-6.319**	-7.519**	-7.185**	-5.655**
$\Delta Child_t$	cst.	-6.232**	-7.306**	-7.471**	-5.851**	-6.750**
	cst. & trd.	-7.184**	-7.527**	-7.424**	-6.245**	-7.056**
College						
		Col1	Col2	Col3	Col4	Col5
$\ln L_t$	cst.	-2.074	-2.399	-1.894	-0.574	-1.150
	cst. & trd.	-2.347	-1.913	-2.236	-2.369	-4.528**
$\ln N_t$	cst.	-1.881	-2.092	-1.580	0.012	-0.639
	cst. & trd.	-1.337	-1.597	-1.871	-1.273	-2.824
$\Delta Adult_t$	cst.	-8.450**	-5.779**	-6.460**	-6.138**	-6.701**
	cst. & trd.	-8.375**	-5.726**	-6.688**	-6.093**	-6.649**
$\Delta Child_t$	cst.	-5.540**	-4.570**	-6.867**	-6.640**	-6.676**
	cst. & trd.	-5.971**	-5.063**	-6.824**	-6.747**	-6.694**

Note: Results are based on ADF test. Lag order was fixed at 2 for all of the cases. * denotes rejection of the null of unit root non-stationarity at 5% level. ** denotes the rejection of the null at 1% level.

lent scale is rather ad-hoc. It is not our intention to claim this ad-hoc adjustment will solve the hump shape puzzle in consumption pattern, but rather wanted to illustrate that demographic adjustment is important whenever scrutinizing the consumption behavior, especially on the cohort level. In the later section, we will adopt a more sophisticated method to account for hump shape in consumption by allowing demographic taste shift in the household's utility function. The bottom line is that it is only possible to test for the existence of liquidity constraint after taking into account for the demographic factors.

Finally, as for a preliminary step for cointegration analysis in the following section, we have conducted a unit root test for consumption expenditure of each cohort. Table 3 reports the results from ADF test.[10] For the case of HS3, HS5 and Col5, the test results have indicated that log luxury goods expenditures are trend stationary. For the case of HS2, the test gave a mixed results rejecting the unit root without trend, while not rejecting the unit root with trend. For the log necessity goods expenditure, the null of unit root were not rejected for any cases. Overall, the null of unit root non-stationarity for consumption expenditures were accepted, setting the ground for the cointegration analysis in the next subsection. In addition to consumption expenditures, we have also tested the stationarity of change in demographic factors (i.e. number of adults and children in household) over the quarter. As we will see later, the stationarity in change of demographic factors are necessary when conducting Panel cointegration analysis and Panel GMM estimation. As can be clearly seen from Table 3, the null of unit root non-stationarity has been rejected for any cases, supporting the stationarity of change in demographic factors. These preliminary results set the ground for estimation and testing in the following section.

4. 3 Estimation and Test

4. 3. 1 Parametrization and Cross-Euler, Euler specification

In dealing with the cohort data, we slightly modify the shape of utility function to account for the socioeconomic factors - number of adults in the household and number of children in the household. Specifically, each cohort's period-by-period utility is specified as follows:

$$U(L_t^h, N_t^h)=\exp(\theta_h' Z_t^h)\left[\frac{(N_t^h)^{1-\alpha^h}}{1-\alpha^h}+K\frac{(L_t^h)^{1-\gamma^h}}{1-\gamma^h}\right] \text{ for } h\in\{HS1, ..., HS5, Col1, ..., Col5\}$$

where θ_h is a vector of coefficients and Z_t^h represents the socioeconomic factors. To put it another way, we have modified the Houthakker's addi-log utility function allowing for "taste shifter." When the liquidity constraints not binding, the Euler equation for luxury and necessity goods are:

$$E_t\left[\beta^h\left(\frac{L_{t+1}^h}{L_t^h}\right)^{-\gamma^h} \exp(\theta_h' \Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^L}{P_{t+1}^L}\right]=1 \tag{16}$$

$$E_t\left[\beta^h\left(\frac{N_{t+1}^h}{N_t^h}\right)^{-\alpha^h} \exp(\theta_h' \Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^N}{P_{t+1}^N}\right]=1 \tag{17}$$

and Cross-Euler equations can be derived as:

$$E_t\left[\beta K\frac{(L_{t+1}^h)^{-\gamma^h}}{(N_t^h)^{-\alpha^h}} \exp(\theta_h' \Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]=1 \tag{18}$$

$$E_t\left[\frac{\beta}{K}\frac{(N_{t+1}^h)^{-\alpha^h}}{(L_t^h)^{-\gamma^h}} \exp(\theta_h' \Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^L}{P_{t+1}^N}\right]=1. \tag{19}$$

By log-linearizing the Cross-Euler equations, we obtain the following cointegrating restrictions.

$$\ln \beta K-\gamma^h \ln L_{t+1}^h+\alpha^h \ln N_t^h+\theta_h' \Delta Z_{t+1}+\ln\left[(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right] \sim I(0) \tag{20a}$$

$$\ln \frac{\beta}{K}-\alpha^h \ln N_{t+1}^h+\gamma^h \ln L_t^h+\theta_h' \Delta Z_{t+1}+\ln\left[(1+r_{t+1})\frac{P_t^L}{P_{t+1}^N}\right] \sim I(0). \tag{20b}$$

But since constant terms and ΔZ_{t+1} are deemed stationary based on the unit root test, the above cointegration restrictions can be further transformed.

$$\ln\left[(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]-\gamma^h \ln L_{t+1}^h+\alpha^h \ln N_t^h \sim I(0) \tag{21a}$$

$$\ln\left[\frac{1}{1+r_{t+1}}\frac{P_{t+1}^N}{P_t^L}\right]-\gamma^h \ln L_t^h+\alpha^h \ln N_{t+1}^h \sim I(0). \tag{21b}$$

In principle, the estimation of the preference parameters (i.e. γ^h, α^h and θ_h') can be done allowing for the heterogeneity among all cohorts. In that case, the estimation can be implemented by single-by-single equation manner or by SUR method. However, in this paper, we are going to restrict the preference parameters to be the same among each education cohort. In other words, we restrict the preference parameters of High School cohort as $(\gamma^{HS}, \alpha^{HS}, \theta^{HS})'=(\gamma^{HS1}, \alpha^{HS1}, \theta^{HS1})'= \ldots =(\gamma^{HS5}, \alpha^{HS5}, \theta^{HS5})'$ and College cohort as $(\gamma^{Col}, \alpha^{Col}, \theta^{Col})'=(\gamma^{Col1}, \alpha^{Col1}, \theta^{Col1})'= \ldots =(\gamma^{Col5}, \alpha^{Col5}, \theta^{Col5})'$. This restriction can be motivated at least from two reasons. First, considering that time series observation per cohort is mere 61 observations, estimating preference parameters in a single equation context or even in a SUR context will be vulnerable to small sample distortion. By restricting the preference parameters to be equal among the education cohort, it will enable us to estimate the parameters in the (pseudo) panel setting offering a better small sample property. Second, among the same education cohort, the major portion of difference in the consumption pattern is probably generated by the life-cycle motives (i.e. age profile of the number of adults and children in the household). It is hard to believe that the difference in consumption pattern over time is coming from the shift in the taste parameters. Indeed, as we have already seen in Figure 2, the consumption profile adjusted by adult equivalent have revealed a considerable smoothness among the same education cohort, supporting the view that fundamental preference parameters are stable over the life-cycle.

4. 3. 2 Panel Dynamic OLS

As a preliminary step for the cointegration analysis, we test for the cointegration restriction implied in eq.(21a). We conducted Park's H(p,q) test for each cohort[11)] and the results are presented in Table 4.

As can be seen from Table 4, the null of deterministic cointegration was not rejected for most of the test, except for older college cohorts. It is likely that the rejections are due to the large sampling errors under Col4 and Col5 whose average cohort size were mere 120 and 98, respectively. For the rest of cohorts, where average cohort size are over 200, H(p,q) tests were not able rejected the null of deterministic cointegration. Based on this result, there is good reason

Table 4 Test of Cointegrating Restriction under the Null of Cointegration

	High School				
	HS1	HS2	HS3	HS4	HS5
H(0,1)	0.527	0.021	0.368	0.126	0.366
	[0.468]	[0.884]	[0.544]	[0.722]	[0.545]
H(0,2)	1.153	0.068	0.376	0.144	0.453
	[0.572]	[0.966]	[0.828]	[0.930]	[0.797]
H(0,3)	4.149	2.186	1.950	2.244	3.917
	[0.245]	[0.534]	[0.582]	[0.523]	[0.270]
	College				
	Col1	Col2	Col3	Col4	Col5
H(0,1)	1.393	0.155	0.257	4.188*	1.572
	[0.237]	[0.693]	[0.612]	[0.040]	[0.209]
H(0,2)	1.404	0.247	0.378	4.358	6.040*
	[0.495]	[0.883]	[0.827]	[0.113]	[0.046]
H(0,3)	3.282	2.375	0.947	6.040	6.270
	[0.350]	[0.498]	[0.814]	[0.109]	[0.099]

Note: Numbers in the brackets represent p-values. * denotes rejection of the null of cointegration at 5% level.

to believe that implications of deterministic cointegration by eq. (21a) are holding. We proceed to estimate the cointegrating vectors, assuming that the deterministic cointegration restriction is holding.

In estimating the preference parameters from cointegrating restrictions implied in eq. (21a), we adopt Mark and Sul's (2003) Panel Dynamic OLS (PDOLS) estimation method. PDOLS estimation method are in principle equivalent to Panel FM-OLS, but it has an advantage of computational simplicity. Obviously, by the virtue of larger degrees of freedom in estimating the parameters, PDOLS enjoys a better small sample property compared to CCR estimation in the single equation context.

The regression forms for each education group are specified as follows..

High School Pooled Regresion

$$y_t^h = const^h + \gamma^{HS} x_{1,t}^h - \alpha^{HS} x_{2,t}^h + I(0) \text{ for } h = HS1, \dots, HS5 \tag{22}$$

College Pooled Regression

$$y_t^{h'} = const^{h'} + \gamma^{Col} x_{1,t}^{h'} - \alpha^{Col} x_{2,t}^{h'} + I(0) \text{ for } h' = Col1, \dots, Col5 \tag{23}$$

where $y_t^h = \ln[(1+r_{t+1})P_t^N/P_{t+1}^L]$, $x_{1,t}^h = \ln L_{t+1}^h$ and $x_{2,t}^h = \ln N_t^h$. We pool the time series data of each cohort by education category. In order to allow for the cohort-specific fixed effect, we al-

Table 5 PDOLS Result: Cross-Euler Equation

$\ln\left[(1+r_{t+1})\frac{P_t^N}{P_{t+1}^L}\right]-\gamma^h \ln L_{t+1}^h+\alpha^h \ln N_t^h \sim I(0)$		
High School		
	γ^{HS}	α^{HS}
Pooled Estimates	0.003	0.172
S.E.	(0.015)	(0.022)
College		
	γ^{Col}	α^{Col}
Pooled Estiamtes	0.006	0.169
S.E.	(0.017)	(0.021)
$\ln\left[\frac{1}{1+r_{t+1}}\frac{P_{t+1}^N}{P_t^L}\right]-\gamma^h \ln L_t^h+\alpha^h \ln N_{t+1}^h \sim I(0)$		
High School		
	γ^{HS}	α^{HS}
Pooled Estimates	0.009	0.074
S.E.	(0.014)	(0.019)
College		
	γ^{Col}	α^{Col}
Pooled Estimates	0.013	0.073
S.E.	(0.017)	(0.020)

Note: Standard error based on Andrew's Pre-whitening method..

low the constant term to differ among each cohort. As we have seen, in eq. (20), the constant term in each cohort's cointegrating restriction depend upon a discount factor. Thus, by fixed effect approach, we are allowing for young and old cohorts to have different discount rate depending upon their stage in life-cycle.

Table 5 shows the result of the PDOLS estimation. In this subsection, we will simply report the results of the estimates and defer interpretation until the end of this section. Estimated preference parameter on luxury goods were 0.003 for high school cohorts and 0.006 for college cohorts. As can be inferred from the results, the parameter estimates on luxury goods are not significantly different from zero. Turning to the preference parameter on necessity goods, the estimates under high school cohorts was 0.172 and 0.169 for college cohorts. Both estimates for the necessity goods are significantly different from zero, showing a sharp contrast to the results in luxury goods.

4. 3. 3 Panel GMM

In this subsection, we conduct Panel GMM in estimating the preference parameters from standard Euler equations. For each of the education cohorts, standard Euler equations are specified for luxury and necessity goods. Preference parameters pertaining to each goods are estimated in the context of pooled conditional moment restrictions with fixed cross-sectional observations of 5 cohorts. Following the procedure in PDOLS estimation, we allow for the fixed effect in each cohort's discount factor. For convenience, conditional moment restrictions for each education group and goods are presented below.

High School Conditional Moment Restrictions

Luxury Goods:

$$E_t\left[\beta^h\left(\frac{L_{t+1}^h}{L_t^h}\right)^{-\gamma^{HS}}\exp(\theta'_{HS}\Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^L}{P_{t+1}^L}-1\right]=0 \text{ for } h=HS1, \ldots, HS5$$

Necessity Goods

$$E_t\left[\beta^h\left(\frac{N_{t+1}^h}{N_t^h}\right)^{-\alpha^{HS}}\exp(\theta'_{HS}\Delta Z_{t+1}^h)(1+r_{t+1})\frac{P_t^N}{P_{t+1}^N}-1\right]=0 \text{ for } h=HS1, \ldots, HS5$$

College Conditional Moment Restrictions

Luxury Goods:

$$E_t\left[\beta^{h'}\left(\frac{L_{t+1}^{h'}}{L_t^{h'}}\right)^{-\gamma^{Col}}\exp(\theta'_{Col}\Delta Z_{t+1}^{h'})(1+r_{t+1})\frac{P_t^L}{P_{t+1}^L}-1\right]=0 \text{ for } h'=Col1, \ldots, Col5$$

Necessity Goods:

$$E_t\left[\beta^{h'}\left(\frac{N_{t+1}^{h'}}{N_t^{h'}}\right)^{-\alpha^{Col}}\exp(\theta'_{Col}\Delta Z_{t+1}^{h'})(1+r_{t+1})\frac{P_t^N}{P_{t+1}^N}-1\right]=0 \text{ for } h'=Col1, \ldots, Col5$$

The choice of instrumental variables in Panel GMM were chosen according to the following principle.

- Constant term and lagged real interest rate are common for all goods and cohorts.
- For the moment restriction of goods X and cohort H, lagged growth rate of goods X of cohort H and lagged real price change in goods X are chosen as instrumental variables.

Since all cohort representative agents are forward looking and form the future expectation by exhausting all the information available at period t, life-cycle model implies that forecast errors are serially uncorrelated. Thus, when conducting panel GMM estimation, we have set the lag order of GMM disturbance terms to be zero. Although lagged instrumental variables of any order are considered to be valid since they are inside the information set at period t, we have simply adopted the lagged instrumental variables of order one.[12)] Estimation of variance-covariance matrix of GMM disturbance terms was based on Andrews and Monahan's (1992) HAC estimator with truncated kernel.

The results of Panel GMM estimation is shown in Table 6. As can be seen from the results,

Table 6 Panel GMM Results: Euler Equations for Luxury and Necessity Goods

High School						
	Luxury Goods			Necessity Goods		
	γ^{HS}	θ_1^{HS}	θ_2^{HS}	α^{HS}	θ_1^{HS}	θ_2^{HS}
Estimates	-0.0154	-0.0136	-0.0021	0.2251	0.0002	0.0002
S.E.	(0.016)	(0.022)	(0.005)	(0.108)	(0.0004)	(0.0003)
J-statistics		13.500			9.627	
P-value		[0.333]			[0.648]	
College						
	Luxury Goods			Necessity Goods		
	γ^{Col}	θ_1^{Col}	θ_2^{Col}	α^{Col}	θ_1^{Col}	θ_2^{Col}
Estiamtes	0.0047	0.0259	-0.0086	0.3094	-0.0009	0.0002
S.E.	(0.008)	(0.010)	(0.008)	(0.110)	(0.001)	(0.001)
J-statistics		20.729			6.474	
P-value		[0.054]			[0.890]	

Note: Degrees of Freedom for J-statistics was 12 for all cases. θ_1 stands for the coefficient on change in numbers of adults and θ_2 stands for the coefficient on change in number of children. * denotes rejection of the null hypothesis as 5% level.

preference parameter on luxury goods was not statistically significant for both education cohorts. Estimation from high school cohorts even showed a negative estimates. Turning to preference parameter on necessity goods, the estimates have been statistically significant for both education cohorts, though the estimated standard errors tend to be larger than those from PDOLS estimates. Probably this is partially due to the difference in the rate of convergence. Estimates of coefficient on socioeconomic factors turned out to be unrobust in general. None of the coefficients were statistically significant and were in general very close to zero. Finally, Hansen's (1982) J-statistics were not able to reject any of the over-identifying restriction of the standard Euler equations, though the call was pretty close for college cohort's luxury goods. Often, researchers have claimed non-existence of liquidity constraint solely based upon the non-rejection of the over-identifying restrictions of the standard Euler equations. There at least two arguments against this interpretation. First of all, one should bear in mind that the null hypothesis of Hansen's J-test is that conditional moment restrictions are valid, nothing less, nothing more. In other words, the null of the test is joint in nature. Thus, although it is appropriate to claim the overall validity of standard Euler equation based on the test, it is not logical to claim the non-existence of liquidity constraint directly from there. Second, in the finite sample, there is always an issue of size distortion. It may well be the case that J-test was simply lacking the power that the null was not rejected. Apprehensive of these issues, we will not hasten to give any inference regarding the existence of liquidity constraint based on the result of J-test, but rather we propose to compare the parameter estimates from Cross-Euler and standard Euler equation in making an inference regarding the existence of liquidity constraint.

4. 3. 4 Testing Liquidity Constraint

In this subsection, we report the results from Cooley and Ogaki's LR type test. Once again, the motivation of this test is to check whether the parameter estimates from cointegration restriction implied by log-linearized cross-Euler equation is close enough to the estimates from standard Euler equations. Under the null that two parameter estimates are equal, the LR type test statistics (denoted QLR in this paper) is asymptotically χ^2 distributed. Following the same procedure as in Section 4, we used same instruments were used for both restricted and unrestricted GMM. For the restricted GMM, the preference parameters were restricted based on the parameter estimates from PDOLS. Two null hypothesis were tested for each education cohorts - i.e. $H_0^1 : \hat{\gamma}_{PDOLS} = \hat{\gamma}_{GMM}$ and $H_0^2 : \hat{\alpha}_{PDOLS} = \hat{\alpha}_{GMM}$. Table 7 reports the results of LR type test.

Table 7 LR Type Test Results: Euler Equations for Luxury and Necessity Goods

	High School	
	Luxury Goods	Necessity Goods
	$H_0 : \hat{\gamma}^{HS}_{PDOLS} = \hat{\gamma}^{HS}_{GMM}$	$H_0 : \hat{\alpha}^{HS}_{PDOLS} = \hat{\alpha}^{HS}_{GMM}$
QLR statistics	3.683	3.846*
P-value	[0.054]	[0.048]
	College	
	Luxury Goods	Necessity Goods
	$H_0 : \hat{\gamma}^{Col}_{PDOLS} = \hat{\gamma}^{Col}_{GMM}$	$H_0 : \hat{\alpha}^{Col}_{PDOLS} = \hat{\alpha}^{Col}_{GMM}$
QLR statistics	1.066	3.371
P-value	[0.301]	[0.066]

Note: * denotes rejection of the null hypothesis at 5% level.

First, let us turn to the results under the null of $H_0^1 : \hat{\gamma}_{PDOLS} = \hat{\gamma}_{GMM}$. The LR type test was not able to reject the null hypothesis for both education cohorts, though the call was close for high school cohorts. QLR was 3.683 for high school cohorts and was 1.066 for college cohorts. Next, turning test the test results under the null of $H_0^2 : \hat{\alpha}_{PDOLS} = \hat{\alpha}_{GMM}$, the LR type test rejected the null hypothesis for high school cohorts at 5% level, but was not able to reject it for college cohorts. QLR was 3.846 for high school cohorts and was 3.371 for college cohorts.

4. 4 Interpretation

We observed that preference parameter estimates for both luxury and necessity goods to be extremely close to zero. Literally interpreting, the estimates implies that IES of necessity goods to be around 5 or so, and IES of luxury goods to be around 200. Comparing with the past literatures, the IES estimates of this paper are way higher than those reported in Hall (1988), Campbell and Mankiw (1989), Cooley and Ogaki (1996) and Attanasio and Webber (1995). Considering the past evidence, the IES estimates of this paper are hard to believe. One reason that may have contributed to this unaccountable estimates can be attributed to the restrictive assumption of Houthakker's addi-log utility function. Addi-log utility function assumes additive separability among goods, rendering marginal utility of one good to be independent from another. It offers a virtue of parsimony in the number of parameters when the assumption is holding, but at the same, its restrictive parametrization can mar the estimation when the assumption is not holding.[13] Thus, in the context of this paper, if luxury and necessity goods are non-separable with each other or if they are not separable from durable goods and/or leisure, IES is no longer a simple inverse of γ or α, but will be a function of luxury and necessity goods. If this is the case, parameter estimates are merely parameters that affect the intertemporal substitution and should not be directly linked to the interpretation of IES for each goods.

Apart from the abnormally low estimates of the preference parameters, we made one important observation regarding the existence of liquidity constraints. As argued in Section 3, assuming that aggregation problem is treated appropriately and each agent's preference is intertemporally additive-separable, the parameter estimates from Cross-Euler equation and standard Euler equation are expected to yield a same estimates. However, as we have seen in the LR type test results in Table 7, the null hypothesis $H_0^2 : \hat{\alpha}_{PDOLS} = \hat{\alpha}_{GMM}$ has been rejected for high school cohorts. Also, we have seen that the call for the null hypothesis $H_0^1 : \hat{\gamma}_{PDOLS} = \hat{\gamma}_{GMM}$ was pretty close for high school cohorts. Under the assumptions we have made earlier, the main culprit of the rejection is the presence of liquidity constraints. Taking education level as a proxy of life-time income, the results can be interpreted as an evidence that "poor" agents are more likely to be liquidity constrained. The test results are also consistent with the past findings by Hall and Mishkin (1982), Zeldes (1989), Meghir and Webber (1996) who report some evidence of liquidity constraint for "poor" agents. However, one should not hasten to conclude that "poor" agents are liquidity constrained, while "rich" agents are not. Turning to the test results for college cohorts (which can be thought of as a proxy of high life-time income agents), the call for the null hypothesis $H_0^2 : \hat{\alpha}_{PDOLS} = \hat{\alpha}_{GMM}$ was very close - p-value of 0.066- while the null hypothesis of

$H_0^1 : \hat{\gamma}_{PDOLS} = \hat{\gamma}_{GMM}$ was accepted, signaling the mixed evidence whether the "rich" agent are liquidity constrained or not. This observation does not exactly conform with the evidence reported, for instance, in Meghir and Webber (1996) that liquidity constraints are not binding for the "rich" agents, which is the standard view in the literature.

One factor, which should be bore in mind whenever interpreting the test result of this paper, is the power of the test based on Cross-Euler equation approach. The approach taken in this paper is structural and therefore inherently parametric. Moreover, considering that utility function has been tightly parametrized by the addi-log function, some sort of misspecification in utility function will probably contribute to the higher value of QLR statistics. Thus, unless the utility function is correctly specified, the LR type test will probably be more powerful than one desire to be. The general observation of high value of QLR statistics both for high school and college cohorts, may well be stemming from the misspecification of the utility function. That said, still the *relative* difference in QLR statistics between high school cohorts and college cohorts cannot be satisfactorily explained by the misspecification of the utility function. Under auxiliary assumptions that aggregation problem is treated appropriately and the agent's preference is time-separable, as far as we are concerned, it seems reasonable to call for the liquidity constraint factor to account for this relative difference in QLR statistics between high school and college cohorts. To summarize, we interpret the result of the LR type test in this section as an evidence, albeit weak, that agents with low life-time income is liquidity constrained.

5 Conclusion

In this paper, we adopted standard two goods version of the life-cycle model to study the consumption behavior of necessity goods and luxury goods under addi-log utility function which allows for the non-homothetic preference. We tested for the existence of liquidity constraint utilizing the concept of Cross-Euler equation proposed by Nishiyama (2005). In testing for the existence of liquidity constraints, we applied the Cross-Euler equation approach to synthetic panel data constructed from Consumer Expenditure Survey. Based on Consumer Expenditure Survey from 1984 to 1998, the households have been classified into 10 cohorts by their age and educational attainment. Age classification was necessary because the households revealed the heterogeneous consumption patterns (i.e. life-cycle in consumption) depending on their age. Classification by education attainments was adopted as a mean to classify the households by their life-time income (i.e. permanent income). In order to compare the result with the empirical evidence from aggregate data, we aggregated the consumption goods into necessity and luxury goods. Then we estimated the preference parameters for each education cohorts exploiting the cointegrating restriction implied by the Cross-Euler equations using (pseudo) Panel Dynamic OLS estimation method. Further, preference parameters has been estimated from standard Euler equations using (pseudo) Panel GMM.

The LR type test rejected the null hypothesis for high school cohorts for some cases, while the null hypothesis for college cohorts were not. Taking the educational attainment as proxy for permanent income, the test results were consistent with the view that poorer agents are more likely to be liquidity constrained. Thus, the hypothesis that the poorer agents are more liquidity constrained was supported by the evidence from disaggregated data.

Obviously, the main drawback in this paper was an adoption of tightly parametrized addi-log utility function. It is interesting to see whether the empirical results found in this paper will also be confirmed under other functional form such as trans-log utility function in Meghir and Webber (1996) or flexible functional form proposed by Attanasio and Webber (1995). The Cross-Euler equation approach to testing for the liquidity constraints under more flexible functional form will be left for future agenda.

Notes

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1) This will not be the case if a utility function is time non-separable (e.g. allowing habit formation) or goods non-separable (e.g. CES type function). This was pointed out by Constantinides (1991).

2) There will be a problem if one attempts to estimate the parameters without log-linearizing eq. (10), since the forcing variables in eq. (10) involves the I(1) processes. Suppose one attempts to estimate the parameter by GMM, which will be a non-linear estimation method in this case. Then conditional moment will be $E_t\left[\frac{1}{K}\frac{P_t^L}{P_t^N}\frac{N_t^{-\alpha}}{L_t^{-\gamma}}-1\right]=0$ which includes I(1) processes in their forcing variables. This will violate the fundamental assumption of GMM.

3) Another way of saying is that IMRS of goods i is a special case of CIMRS between x_{t+1}^i and x_t^j where $i=j$.

4) For the survey regarding the cohort technique, see Verbeek (1996).

5) We have also tried 5 years intervals. However, the average observations for some cohorts, espe-

cially for older cohorts, were smaller than 100. In order to ensure that each cohort size is over or around 100 observations, we decided to classify the households by 6 years of interval.

6) Col4 is the genration who was born between 1936-1941 and Col5 is the generation who was born between 1930-1935. Considering the effect of Great Depression and WWII, probably only the wealthy families were able to send their children to colleges. Small cohort size for Col4 and Col5 will apparently introduce a large standard error when constructing a cohort's average data. As explained in Deaton (1985) and Verbeek (1996), by rendering number of cross-sectional cohorts to infinity (i. e. $H \rightarrow \infty$) with fixed cohort size (i.e. N_c is fixed), it is possible to obtain the consistent estimator in the presence of standard error in average cohort data. But then, due to the limitations in total household observations, one face a same dillemma in claiming a large sample in terms of H. Thus, obviously there is a trade-off in choosing $H \rightarrow \infty$ or $N_c \rightarrow \infty$. In this paper, we assume $N_c \rightarrow \infty$.

7) All the average cohort data have been seasoanlly adjusted using seasonal dummies.

8) Though this assumption offers us a simplicity in calculating the real expenditure for each cohort, this assumption may be too strong. Constructing Stone Price Index for each cohort is often favored solution. See Attanasio and Webber (1995) for instance.

9) The number of adult equivalent members in the household has been calculated according to the following formula.

$$\#\ \textit{of adult equivalent} = 1 + 0.75 * \#\ \textit{of adults} + 0.4 * \#\ \textit{of children}$$

Child is defined as a household member with age below 18 years old and adult is defined as a household member with age above 18 years old. The forumula is a composition of the scale used by Attanasio and Webber (1995) and Blundell, Browning and Meghir (1994).

10) We have also conducted PP test and J(p, q) test, but the results were similar and will not be reported here.

11) Here we have applied H(p, q) test in the single-equation context. For the sake of power, it is more desirble to test the cointegrating restriction in the panel context - i.e. panel cointegration test. (Cite literature HERE.)

12) This treatment is partially due to a consideration of weak correlation between the forcing terms and instruments. Our preliminary inspection (which is not reported here) revealed that correlation between forcing terms and instruments to be weaker, as lag order of instruments increased.

13) The robust remedy for this defects is to rely on more flexible functional form such as translog utility function adopted by Meghir and Webber (1996). This remedy seems promising and will be kept for the future research.

Referrences

Altonji, J. G. and A. Siow (1987). "Testing the response of consumption to income change with (noisy) panel data," *Quarterly Journal of Economics* 102, 293-328.

Andrews, D. W. K. and J. C. Monahan (1992) "An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator," *Econometrica* 60, 953-966.

Attanasio, O. P., J. Banks, C. Meghir and G. Webber (1999) "Humps and bumps in lifetime consumption," *Journal of Business & Economic Statistics* 17, 22–35.

Attanasio, O. P. and M. Browning (1995) "Consumption over the life cycle and over the business cycle," *The American Economic Review* 85, 1118–1137.

Attanasio, O. P. and G. Webber (1993) "Consumption growth, the interest rate and aggregation," *The Review of Economic Studies* 60, 631–649.

Attanasio, O. P. and G. Webber (1995) "Is consumption growth consistent with intertemporal optimization? Evidence from the Consumer Expenditure Survey," *Journal of Political Economy* 103, 1121–1157.

Blundell, R., M. Browning and C. Meghir (1994) "Cosumer demand and the life-cycle allocation of household expenditures," *The Review of Economic Studies* 61, 57–80.

Browning, M. A., A. Deaton and M. Irish (1985) "A profitable approach to labor supply and commodity demands over the life-cycle," *Econometrica* 53, 503–543.

Campbell, J. Y. and N. G. Mankiw (1989) "Consumption, Income, and Interest Rates: Reinterpretting the Time Series Evidence," *NBER Macroeconomics Annual* 4, 185–216.

Campbell, J. Y. and N. G. Mankiw (1990) "Permanent income, current income, and consumption," *Journal of Business & Economic Statistics* 8, 265–279.

Choi, W. G. (1999) "Asymmetric Monetary Effects on Interest Rates across Monetary Policy Stances," *Journal of Money, Credit and Banking* 31, 386–416.

Constantinides, G. M. (1990) "Habit Formation: A Resolution of the Equity Premium Puzzle," *Journal of Political Economy* 98, 519–543.

Cooley, T. F. and M. Ogaki (1996) "A Time Series Analysis of Real Wages, Consumption, and Asset Returns: A Cointegration-Euler Equation Approach," *Journal of Applied Econometrics* 11, 119–134.

Deaton, A. (1985) "Panel data from time series of cross-sections," *Journal of Econometrics* 30, 109–126.

DeJuan, J. P. and J. J. Seater (1999) "The permanent income hypothesis: Evidence from the Consumer Expenditure Survey," *Journal of Monetary Economics* 43, 351–376.

Flavin, M. A. (1981) "The adjustment of consumption to changing expectations about future income," *Journal of Political Economy* 86, 974–1009.

Gross, D. B. and N. S. Souleless (2001) "Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data," NBER Working Paper No. 8314.

Hall, R. and F. Mishkin (1982) "The sensitivity of consumption to transitory income: Estimates from panel data on households," *Econometrica* 50, 461–481.

Hall, R. E. (1988) "Intertemporal Substitution in Consumption," *Journal of Political Economy* 96, 339–357.

Hansen, L. P. (1982) "Large Sample Properties of Generalized Method of Moments Estimator," *Econometrica* 50, 1029–1054.

Hayashi, F. (1985) "The permanent income hypothesis and consumption durability: Analysis based on Japanese panel data," *Quarterly Journal of Economics* 100, 1083–1113.

Houthakker, H. S. (1960) "Additive Preferences," *Econometrica* 28, 244–256.

Kirman, A. P. (1992) "Whom or What Does the Representative Individual Represent," *The Journal of*

Econometric Perspective 6, 117–136.

Mariger, R. P. (1987) "A life-cycle consumption model with liquidity constraints: Theory and empirical results," *Econometrica* 55, 533–557.

Mark, N. C. and D. Sul (2003) "Cointegration Vector Estimation by Panel DOLS and Long-run Money Demand," *Oxford Bulletin of Economics and Statistics* 65, 655–680.

Meghir, C. and G. Webber (1996) "Intertemporal nonseparability or borrowing restrictions? A disaggregated analysis using a U.S. consumption panel," *Econometrica* 64, 1151–1181.

Moffit, R. (1993) "Identification and estimation of dynamic models with a time series of repeated cross-sections," *Journal of Econometrics* 59, 99–123.

Nishiyama, S. I. (2005) "The Cross-Euler Equation Approach to Intertemporal Substitution in Import Demand," *Journal of Applied Econometrics* 20, 841–872.

Ogaki, M. (1992) "Engel's Law and Cointegration," *Journal of Political Economy* 100, 1027–1046.

Ogaki, M. and Joon Y. Park (1998) "A Cointegration Approach to Estimating Preference Parameters," *Journal of Econometrics* 82, 107–134.

Runkle, D. E. (1991) "Liquidity constraints and the permanent income hypothesis," *Journal of Monetary Economics* 27, 73–98.

Shapiro, M. (1986) "The dynamic demand for capital and labor," *Quarterly Journal of Economics* 101

Shea, J. (1995) "Union contracts and the life-cycle/permanent-income hypothesis," *American Economic Review* 85, 186–200.

Stoker, T. M. (1993) "Empirical approaches to the problem of aggregation over individuals," *Journal of Economic Literature* 31, 1827–1874.

Verbeek, M. (1996) "Pseudo Panel Data," *The Econometrics of Panel Data,* Second Revised Edition, L. Matyas and P. Sevestre eds., Dordrecht, Kluwer Academic Publishers.

Weise, C. L. (1999) "The Asymmetric Effects of Monetary Policy: A Nonlinear Vector Autore-gression Approach," *Journal of Money, Credit and Banking* 31, 85–108.

Zeldes, S. P. (1989) "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy* 97, 305–346.