Price Search, Consumption Inequality, and Expenditure Inequality over the Life Cycle*

Preliminary

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Abstract

In this paper, we incorporate price search decision into a life cycle model, and differentiate consumption from expenditure. The consumers with low wealth and bad income shocks search more for cheaper prices and pay less which makes their consumption higher than a model without search option. A plausibly calibrated version of our model predicts that the cross sectional variance of consumption is around 15% smaller than the cross sectional variance of expenditure through out the life cycle. Price search has an alternative productive activity role for the lower income people to increase their consumption levels.

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1 Introduction

In this paper, we investigate the effect of price search- as a partial insurance mechanism- on the life-cycle profile of consumption inequality. In general, incomplete market models ignore the role of price search as a partial insurance mechanism. However, Aguiar and Hurst (2007) show that lower income individuals search more for cheaper prices and pay lower prices to identical goods when compared to higher income individuals. Motivated by this fact, we incorporate price search into a life-cycle model.

We solve a life-cycle model with idiosyncratic income shocks, where we allow agents to search for prices in addition to the consumption/saving decision. As a result of idiosyncratic income shocks, people are ex-post heterogenous in terms of their income realizations and wealth accumulations. If agents search more they pay less but they receive less utility from leisure. Our results show that agents with low wealth and bad income shocks search more and pay less. These findings imply that the cross-sectional variance of consumption is smaller than cross-sectional variance of expenditure. A plausibly calibrated version of our model predicts that cross-sectional variance of log consumption is about 15% lower than cross-sectional variance of log expenditure. The model implies positive income, wealth and expenditure elasticities of price paid. We have a 0.15 elasticity of prices paid with respect to expenditure. People at higher expenditure levels pay higher prices. The estimated elasticity in the data changes in the range of 0.06 to 0.18 depending on the instrumental variable used.

We use A.C. Nielsen Homescan data set to document the life-cycle profile of average prices paid by shoppers. Average prices paid stay almost constant from age 25 to 45. From age 45 to 55, prices paid decreases around 3 percent and afterwards stay constant. We use the profile of average prices over the life cycle to calibrate the utility function parameter which is important in search/leisure decision. The variance of log prices at age group 25-29 is about 0.005, and it goes up to 0.01 at age group 55-59. The increase in the cross-sectional variance of prices paid over the life cycle is consistent the with our findings.

Expenditure facts have been documented and studied in several articles in the literature. Carroll and Summers (1989) document both income and expenditure patterns in the U.S. data separately for different education and different occupation groups. They show that consumption follows a hump shaped pattern and that there is co-movement in consumption and income growth rates in the similar groups of people. Cutler and Katz (1992) document income and consumption of the U.S. in 1980's and show that poverty is lower if it is measured in terms of consumption instead of income.

Pendakur and Crossley (2002) discuss the measurement of well-being and document the increasing expenditure inequality in the Canadian data.

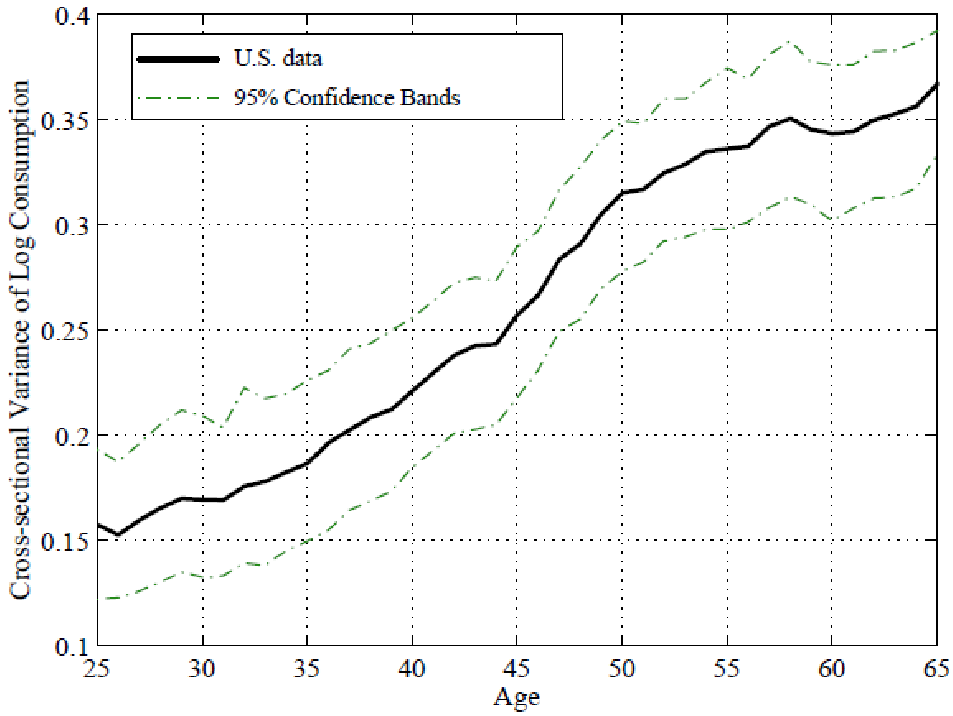
Expenditure data have also been used to test income models. Storesletten et. al. (2000) study the relationship between income processes and consumption patterns. They find that the income process needs to have persistent income shocks in order to generate realistic consumption patterns. Guvenen (2007) tests the performance of two different income models- one with persistent shocks, and the other with moderate shocks- on the U.S. expenditure data. He shows that income model with moderate shocks associated with income learning motive- as well as income model with persistent shocks- is consistent with the U.S. consumption patterns. Deaton and Paxson (1994) analyze the implications of permanent income hypothesis on cross sectional variance of consumption expenditure , and test those implications using the consumption expenditure data in Britain, Taiwan and the U.S. They document that the cross sectional variance in consumption expenditure is increasing in those countries, which is in accord with the permanent income hypothesis.

Other than a few exceptions[1], the standard life cycle models with consumption/saving decision takes the estimated labor income process as an input and solves for the optimal consumption for each age. The implications of these models are then compared to the expenditure data. This literature generally assumed that the model generated consumption decisions are represented with the expenditure data that are taken from the surveys. This paper argues that consumption and expenditure should be treated differently since expenditure is the multiplication of price paid and amount consumed. If consumers pay different prices for the same good then consumption will not be comparable to expenditure. Aguiar and Hurst (2005) bring explanation to retirement puzzle by distinguishing expenditure from consumption by home production approach. Aguiar and Hurst (2007) estimate life-cycle consumption/expenditure pattern and shows that they significantly deviate from each other during the life-cycle. Aguiar and Hurst (2009) bring explanation to movements in the subcomponents of expenditure in the life-cycle.

The paper continues as follows. In section 2 we document some important features of the data. We explain the model in section 3 and give the details of the calibration in section 4. In section 5 we report the results and in section 6 we conclude.

[1] Aguiar and Hurst (2005), (2007)

Figure 1: Age-Inequality Profile of Consumption in the US Data (CEX).



2 Empirical Motivation

In this section, first we report the existing evidence on the age-inequality profile of expenditure over the life-cycle. In figure 1 we plot the cross-sectional variance of log expenditure over the life-cycle which is reported in Guvenen (2007) obtained by using Consumer Expenditure Survey (CEX) data set.[2] As can be seen in figure 1, in the U.S. data the cross-sectional variance of log consumption increases by about 21 log points over the life-cycle, implying that expenditure inequality more than doubles during this time. CEX data set is very rich in terms of measuring expenditure. Therefore we are going to use the previous estimations on expenditure inequality over the life-cycle when we calibrate the model.

We use A.C. Nielsen Homescan data set to document facts on shopping behavior of individuals. We obtain the data set from Aguiar and Hurst (2007). In this survey, households are equipped with an electronic home scanning unit. They scan the UPC of all the purchased items after the shoppings. Therefore, the price paid for any good is available. Using this information, we are able to measure

[2] Please see Guvenen (2007) for the sample selection and details of CEX data set.

the dispersion in prices paid for identical goods. In order to document the age-inequality profile of prices in A.C. Nielsen data set, we use the constructed individual price indices in Aguiar and Hurst (2007). In particular, we run the following regression in order to estimate the life-cycle profile of prices and price variance:

$$\log(P_i) = \beta_0 + \beta_{age} AGE_i + \beta_r RACE_i + \beta_s SEX_i + \beta_h HHSIZE_i + \beta_n NEEDS_i + \epsilon_i \tag{1}$$

P_i is the individual price index paid for goods.[3] The variables AGE_i, $RACE_i$, SEX_i, and $HHSIZE_i$ represent age, race, gender, and family size of the shopper. The variable $NEEDS_i$ is a set of variables that represent shopping needs of the shopper. We calculate the variance of residuals at each age group and figure 2 depicts the life-cycle profile. Using the scanner data, we can figure out the shopping frequency of individuals. We use shopping frequency as a measurement of price search and we estimate life-cycle profile of price search using equation 1 with $\log S_i$ on the left hand side.

Although Homescan data set includes only grocery shopping, we would like to document the life-cycle profile of expenditures in this data set. We run the following regression[4] to estimate the life-cycle profile of expenditures:

$$\log(E_i) = \beta_0 + \beta_{age} AGE_i + \beta_e EDU_i + \beta_r RACE_i + \beta_s SEX_i + \beta_h HHSIZE_i + \epsilon_i \tag{2}$$

E_i denotes the expenditure of the shopper i. AGE_i is a set of five-year dummies for 8 age groups, from 25-29 to 65-74. It refers to the age of shopper. $HHSIZE_i$ is a set of ten household size dummies. EDU_i includes education dummies for the shopper's and spouse's education. And, finally $RACE_i$, and SEX_i are dummy variables for shopper's race and gender. Using the equation 2, we calculate the variance of residuals for each age group. Figure 2 depicts the variance of log expenditure at each age group. We also report the coefficients of age dummies, which gives the life-cycle profile of expenditure level, in figure 3. The life-cycle profiles of first and second moments of expenditure are qualitatively consistent with the previous results from well-known data set CEX[5].

The age-inequality profiles of expenditures obtained from CEX and AC Nielsen data sets differ significantly. But the overall shapes look similar. The difference is potentially due to the limited size of the AC Nielsen data set. AC Nielsen data set mainly focuses on the supermarket data and does not include other expenditures such as travel, education, services, etc. Because of this limitation,

[3] For detailed information about the individual price indices, please see Aguiar and Hurst (2007)

[4] For a detailed description of the data set and sample construction, please see Aguiar and Hurst (2007). We obtained the data set from the authors' website: http://troi.cc.rochester.edu/~maguiar/lifecycle/datapage.html

[5] For example: Krueger and Perri (2006), Guvenen (2007), Aguiar and Hurst (2009)

Figure 2: Age-Inequality Profiles of Expenditure, Prices and Shopping Frequency in A.C. Nielsen Data.

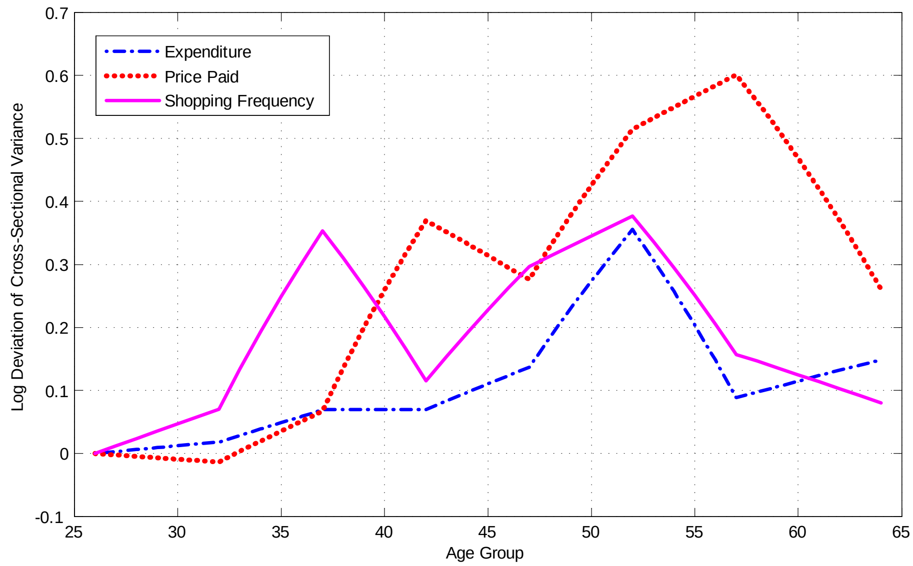
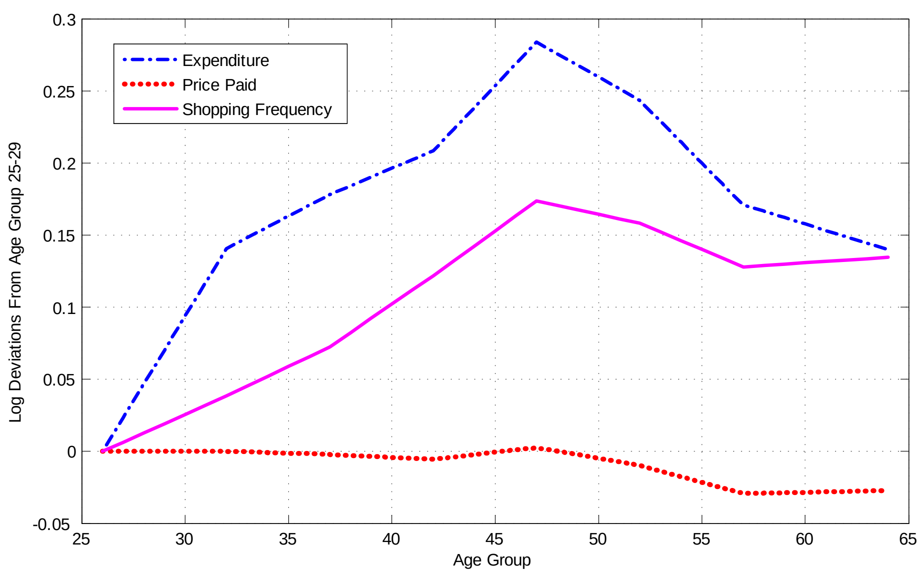


Figure 3: Life-Cycle Profiles of Expenditure, Prices and Shopping Frequency in A.C. Nielsen Data.



our results are more comparable to the CEX data. When we calibrate expenditure inequality over the life-cycle, we use CEX data set. We use the log-deviation of average prices obtained from the AC Nielsen data set to calibrate life-cycle prices in the model. Since we use two different data sets for prices and expenditures, we need to assume that search behavior is identical for different expenditure categrories.

3 Model

We consider an environment where each agent lives for T^* periods, and they work until period $T(< T^*)$. At each period, agents have two decisions: first one is consumption/saving decision, and the second one is leisure/price search decision. Consumption/saving decision at the current period affects the state of the next period. However, leisure/price search decision is static, because time is not storable. Individuals face idiosyncratic uncertainty in their income streams, which causes heterogeneity between the agents. During the working periods, each agent solves the following optimization problem:

$$
\begin{aligned}
&V_t^i(a_t^i, z_t^i, \epsilon_t^i) = \max_{c_t^i, s_t^i, a_{t+1}^i} \{u(c_t^i, l_t^i) + \delta E[V_{t+1}^i(a_{t+1}^i, z_{t+1}^i, \epsilon_{t+1}^i)|z_t^i, \epsilon_t^i]\} \\
&\text{s.t.} \\
&p(s_t^i)c_t^i + a_{t+1}^i = y_t^i + (1+r)a_t^i \\
&s_t^i + l_t^i + n = 1 \\
&a_{t+1}^i \geq \Psi_t^i \\
&\text{for } t \in \{1, 2, ..., T\}
\end{aligned}
$$

In the above problem, c_t^i is consumption, s_t^i is the time used for price search, l_t^i is leisure, a_t^i is asset level, a_{t+1}^i is saving, and y_t^i is earnings at period t. Agents can borrow up to a state dependent borrowing limit Ψ_t^i. The return on savings is denoted with r and time discount factor with β. Individuals are identified by the superscript i. We have inelastic labor supply n, and the total available time is 1. Note that the agent can enjoy the same amount of consumption with different expenditure levels. The agent can spend more time to find cheaper prices which will allow her to enjoy a certain amount of consumption with small expenditure levels. After retirement, individuals receive constant pension which depends on the earnings at the last period of working life. The problem of individual becomes deterministic due to the constant pension after retirement:

$$
\begin{aligned}
& V_t^i(a_t^i, y^i) = \max_{c_t^i, s_t^i, a_{t+1}^i} \{u(c_t^i, l_t^i) + \delta V_{t+1}^i(a_{t+1}^i, y^i)\} \\
& \text{s.t.} \\
& p(s_t^i)c_t^i + a_{t+1}^i = y^i + (1+r)a_t^i \\
& s_t^i + l_t^i = 1 \\
& a_{t+1}^i \geq \Psi_t^i \\
& y^i = \Gamma(y_T^i) \\
& \text{for } t \in \{T+1, ..., T^*\} \text{ with } V_{T^*+1}^i = 0
\end{aligned}
$$

The pension of each individual is determined by $\Gamma(.)$ function. Time endowment is larger for retired people since they do not work. We drop the inelastic labor supply n from their time endowment.

Earnings

We follow the literature in earning process. During the working ages, agent has idiosyncratic shocks to their labor earnings. At each period the agent gets a persistent and a transitory income shock. The log earnings read the following process:

$$\log(y_t^i) = \beta_0 + \beta_1 t + z_t^i + \epsilon_t^i, \quad \text{with } \epsilon_t^i \sim (0, \sigma_\epsilon^2)$$

where, β_0 is a scale parameter, β_1 is return to experience, t is the years of experience , z_t^i is persistent income shock and ϵ_t^i is the transitory income shock. The persistent income shocks follow $AR(1)$ process:

$$z_t^i = \rho z_{t-1}^i + \nu_t^i, \quad \text{with} \quad z_0 = 0 \text{ and } \quad \nu_t^i \sim N(0, \sigma_\nu^2)$$

The parameters of this income process is estimated in several studies and we pick the parameters from a recent study, Guvenen (2005)[6].

Pension System

We follow Guvenen (2007) and Storesletten et. al. (2000) in pension process which mimics the U.S. social security system. After retirement, the pension of each agent is determined by the ratio of his last working period income to the average income at the last working period, $\frac{y_T}{\bar{y}_T}$. The pension

[6] Guvenen (2005) estimates two different types of income processes, namely Restricted Income Process and Heterogeneous Income Process. We pick the first one and it gives good results in terms of the model's empirical targets.

function, $\Gamma(\frac{y_T}{\bar{y}_T})$ is as follows:

$$= \gamma \times \begin{cases} 0.9\frac{y_T}{\bar{y}_T}, & \text{if } \frac{y_T}{\bar{y}_T} < 0.3 \\ 0.27 + 0.32(\frac{y_T}{\bar{y}_T} - 0.3), & \text{if } 0.3 < \frac{y_T}{\bar{y}_T} < 2 \\ 0.81 + 0.15(\frac{y_T}{\bar{y}_T} - 2), & \text{if } 2 < \frac{y_T}{\bar{y}_T} < 4.1 \\ 1.1 & \text{if } 4.1 < \frac{y_T}{\bar{y}_T}. \end{cases}$$

Price-Search Technology

We follow Aguiar and Hurst (2007) in price function. It has a log linear form:

$$\log(p) = \theta_0 + \theta_1 \log(s)$$

where θ is the return to search on prices. In the log linear form, doubling search decreases prices by $100 * \theta$ percent. Aguiar and Hurst (2007) estimate the return to search, θ, net of how much and what type of goods purchased by the shopper. They use AC Nielsen data set to estimate the parameters.

Utility Function

Utility function is specified as CRRA in consumption and log in leisure:

$$u(c_t, l_t) = \frac{c_t^{(1-\sigma)}}{1-\sigma} + \phi_t \log(l_t).$$

The parameter ϕ_t denotes the benefit from free time. It could also be interpreted as the cost of the time the agent spends on price search.

4 Calibration

Most parts of the calibration of the model is standard. We directly use the values of the parameters which are well established in the related literature. Each individual starts working at age 20 and retires at 65.[7] Each agent starts working life with the same asset level at 0. All the population have the same earning profile with $(\beta_0, \beta_1, \beta_2)$ and they differ from each other with idiosyncratic shocks (z, ϵ). For a set of parameters we compute the policy functions, and simulate a population of $N = 10000$ individuals. We repeat this process until we match the chosen moments.

[7] We assume high school graduates start working at age 18, and college graduates at age 22. We take the average of the two ages, because we don't distinguish the education levels in the model.

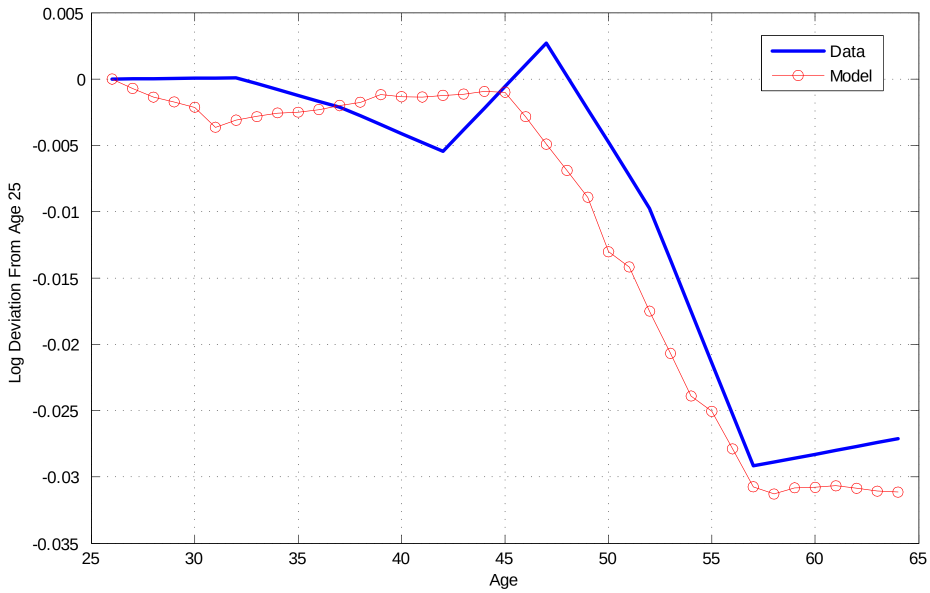
Table 1: Benchmark Model Parameters

Parameter		Value
δ	Time discount factor	0.966
r	Interest rate	0.0416
σ	Relative risk aversion	2
T	Retirement age	65
T^*	Death age	85
θ_0	Scale parameter in prices	0.76
θ_1	Return to price search	-0.1
β_1	Return to experience	0.009
ρ	Persistence of income shocks	0.988
σ^2_ε	Variance of transitory shock	0.061
σ^2_v	Variance of noise	0.015

We calibrate θ_0, ϕ_t and take the other parameters from the literature. Note that we allow ϕ to change over the life-cycle. We do that in order to match the empirical life-cycle profile of average prices paid. We target average prices and log deviation of average prices from age 25 over the life cycle. We normalize the average price paid in the whole population to 1. The benchmark parameters are reported in Table 1. Figure 4 compares the model generated log deviation of average prices to the data.

We should mention that the risk aversion coefficient σ could also be calibrated to match some other moments in the data. One reason we also take it from the literature is to quantify the importance of prices search in the earlier studies. As we increase σ, the gap between age-inequality profiles of consumption and expenditure, and also variance in prices increase. For higher levels of risk aversion the marginal return on search decreases with consumption at relatively higher rates compared to lower risk aversion case. That makes the higher wealth people to search relatively much less and lower wealth people to search much more compared to lower risk aversion case. That's why, their consumption levels get closer to each other and expenditure levels deviate from each other relatively more compared to lower risk aversion case. To quantify the effect of risk aversion we solve the model for higher risk aversion levels.

Figure 4: Life-Cycle Prices



5 Results

Age-Inequality Profiles of Consumption and Expenditure

In the earlier studies consumption is assumed to be equal to expenditure which implied exactly the same age-inequality profile of consumption and expenditure. In this paper, we differentiate consumption from expenditure by employing price search in the model. Our model predicts a higher expenditure inequality than consumption inequality throughout the life-cycle. Cross sectional variance of log expenditure starts from 0.09 at age 25 and increases up to 0.35 at age 65. However, variance of log consumption is about 0.07 at age 25 and it is about 0.27 at age 65. We draw the age-inequality profiles of consumption and expenditure in Figure 5.

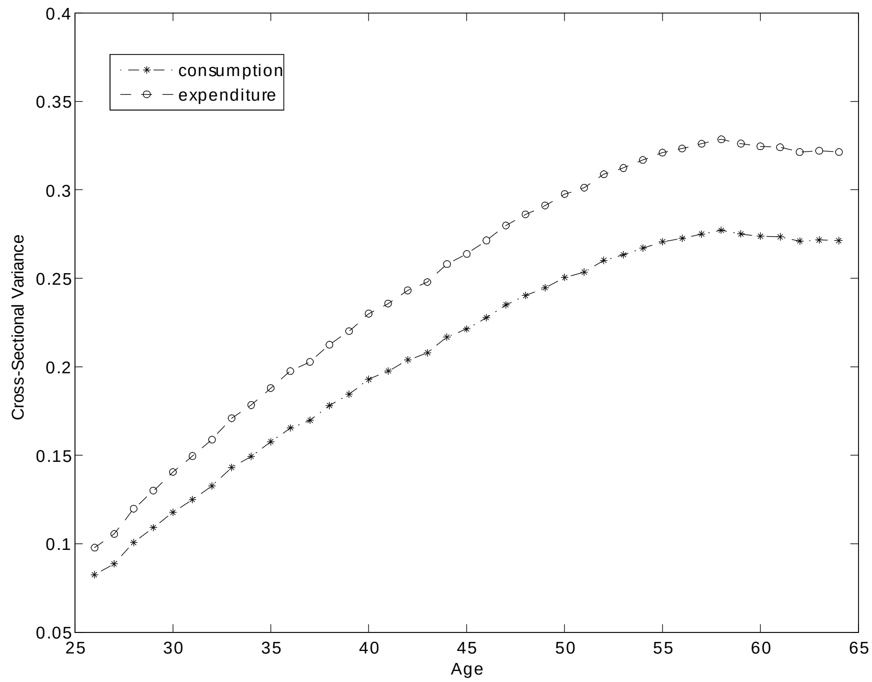
In order to understand the gap between consumption variance and expenditure variance throughout the life-cycle, we decompose expenditure variance:

$$e = p \times c \tag{3}$$

$$var(\log e) = var(\log c) + var(\log p) + 2cov(\log c, \log p) \tag{4}$$

We calculate each component of $var(\log e)$ from the model's results. Throughout the life-cycle,

Figure 5: Age-Inequality of Profile of Consumption and Expenditure.



the model predicts that around 15% of variance in log expenditure comes from covariance between consumption and prices. Around 85% of the expenditure variance comes from consumption variance. Figure 6 summarizes our findings.

We visit the optimality condition for price search to understand the positive covariance between consumption and prices.

$$-\frac{u_1(c_t, l_t)}{p(s)} p'(s_t) c_t = u_2(c_t, l_t) \tag{5}$$

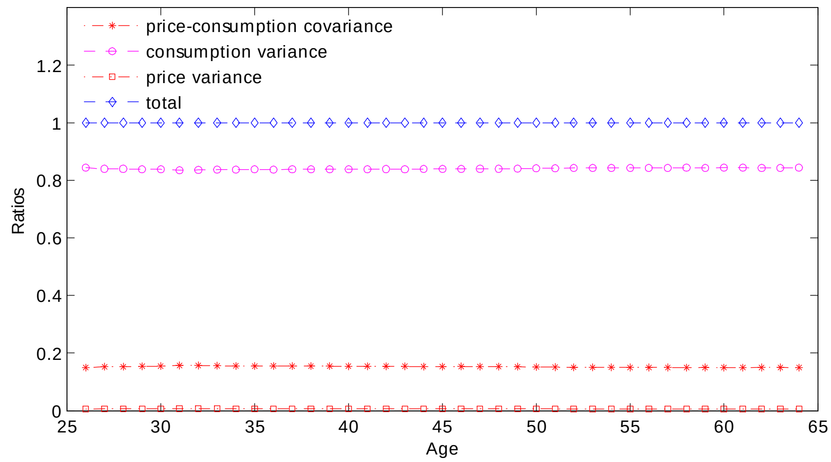
Plugging the utility and price functions into the equation 5, we get the following equation which gives the relationship between search and consumption:

$$\frac{c_t^{1-\sigma}}{s_t} \theta_1 = \frac{\phi_t}{1 - s_t}$$

The first order condition for price search implies a diminishing marginal return with consumption.[8] Wealthier people who consume at high levels have less incentive to increase their consumption by sacrificing from leisure. Note that cost of price search is utility from leisure. People with higher

[8] Note that $\sigma > 1$ in the CRRA utility is crucial here, otherwise the substitution effect disappears.

Figure 6: Decomposition of Expenditure Variance



income and wealth spend more time with non-search activities instead of searching prices to increase their consumption. People with lower income and wealth spend more time at price search to increase their consumption levels. Price search plays a productive activity role for lower income and lower wealth people to increase consumption levels.

Since we don't have a reported consumption index in the data, we use an indirect method to test the gap between age-inequality profiles of consumption and expenditure generated in the model. For this purpose, we reorganize equation 3, and we have the following equation:

$$\begin{aligned} c &= \frac{e}{p} && (6) \\ var(\log c) &= var(\log e) + var(\log p) - 2cov(\log e, \log p) && (7) \\ var(\log e) - var(\log c) &= 2cov(\log e, \log p) - var(\log p) && (8) \\ &= var(\log p)[2\frac{cov(\log e, \log p)}{var(\log p)} - 1] && (9) \end{aligned}$$

In the right hand side of equation 9, the term $\frac{cov(\log e, \log p)}{var(\log p)}$ can be estimated from the A.C. Nielsen data used in Aguiar and Hurst (2007). We run $\log(e) = \beta_0 + \beta_1 \log(p)$, where β_1 gives the term we want to estimate. Using this estimation, we compare our model with data at $var(\log e) - var(\log c)$ for whole population. The model predicts around 0.06 log points difference in log expenditure variance and log consumption variance, and we estimate it in a range between 0.01 and 0.06 log points in A.C. Nielsen data. We report the estimations in Table 2. We should mention that A.C. Nielsen data set does not represent a typical expenditure bundle in the US data since it concentrates

Table 2: Difference Between Variance of Log Expenditure and Variance of Log Consumption in A.C. Nielsen Data Set

	I	II	III	IV	V	VI	VII	VIII
IV	0.06	0.03	0.05	0.03	0.05	0.01	0.02	0.02
OLS	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Difference in the Model: 0.06

Note. We do not have a consumption index in the data, instead we only have expenditures. We estimate the difference between variance of Log expenditure and variance of Log consumption by using equation 9. We have var(Log(E))-var(Log(C))=var(Log(P))*(2*β_1-1), where E is expenditure, C is consumption, P is price, var is variance and $\beta_1$is the coefficient of Log(P) in equation $\mathrm{Log}(\mathrm{E}_i) = \beta_0 + \beta_1 \mathrm{Log}(\mathrm{P}_\mathrm{i}) + \epsilon_i$ where i represents different individuals.
Data Source: A.C. Nielsen Homescan Data Set

on supermarket data only. Nevertheless, it is the only data set that enables us to compare our results with.

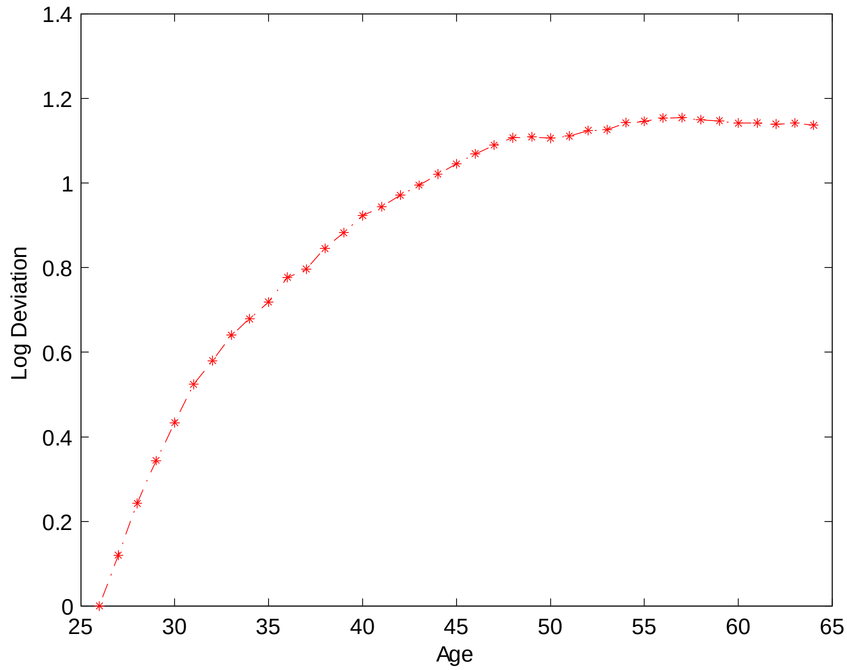
In Table 2, we predict the difference between variance of log expenditure and variance of log consumption. We do it with several specifications. The second raw estimates the equation $\mathrm{Log}(\mathrm{E}_i) = \beta_0 + \beta_1 \mathrm{Log}(\mathrm{P}_\mathrm{i}) + \epsilon_i$ with OLS. The first row shows the IV estimations for different instrumental variables in each column. The set of instrumental variables we used include income, age, and family size. In columns I-IV, we control for shopping frequency, in the rest of the columns we do not control shopping frequency. Once we estimate β_1, we use it to predict the difference between variance in log expenditure and variance in log consumption. The predicted value of this difference varies in the range of 0.01 and 0.06. The quantitative model implies a difference of 0.06.

Age-Inequality Profile of Search and Prices

Figures 7 and 8 show the age-inequality profile of search and prices over the life cycle. The model predicts an increasing inequality profile for prices which is consistent with data. For the search time model predicts an increasing profile (figure 9), however it (shopping frequency) is more like hump-shaped in data (figure 3). It could be the case that search-oriented part of the shopping frequency increases at a higher rate than the shopping frequency.

The underlying reason in the increasing profiles of shopping frequency and prices paid is the idiosyncratic income shocks over the life-cycle. As people deviate from each other in terms of

Figure 7: Age-Inequality Profile of Log Prices



income and wealth over the life-cycle, they also deviate from each other in terms of time spent for cheaper prices, and that leads to increasing dispersion in prices paid.

Elasticities

The model implies positive income, wealth, and expenditure elasticities of prices paid. We are only able to test the expenditure elasticity of prices, which is 0.15 in the model and changes in the range of 0.06 and 0.18 in the data. The wealth and income elasticities are 0.005 and 0.001 respectively.[9] The reason behind the positive elasticities is due to the optimality condition of agent with respect to price search. People with high wealth and good income consume more, and spend less time for cheaper prices. That makes their prices paid higher. We estimate elasticty with different instruments by using the A.C. Nielsen data set. The elasticity in the model is comparable to the instrumental variable estimates. We report the elasticity estimations in Table 3.

Opportunity Cost of Time

We calculate the marginal cost of time from optimality condition with respect to price search in

[9] As agents become older they become wealthier and have higher income. But, at the same time, opportunity cost of time decreases as agents become older. That is why these numbers are small.

Figure 8: Age-Inequality Profile of Log Search

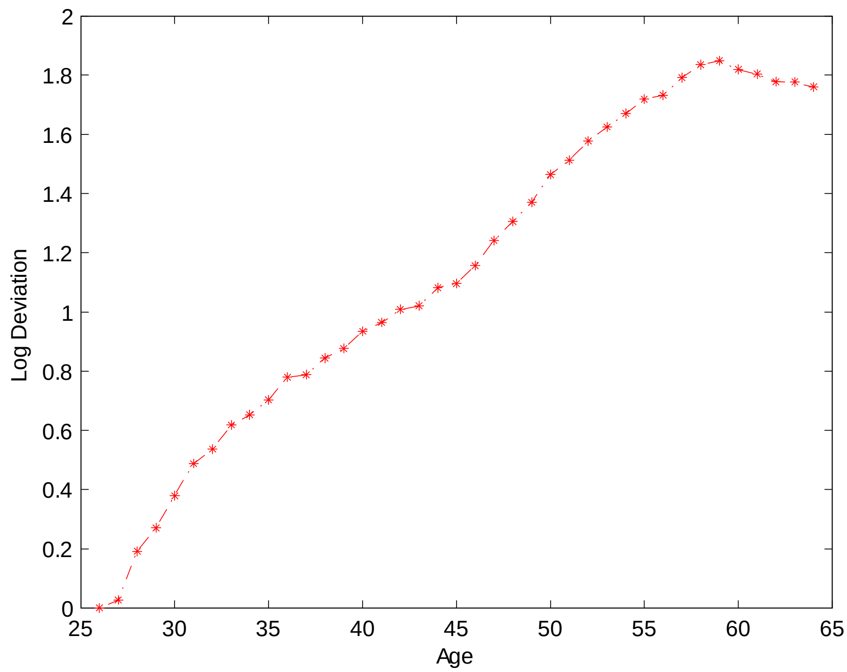


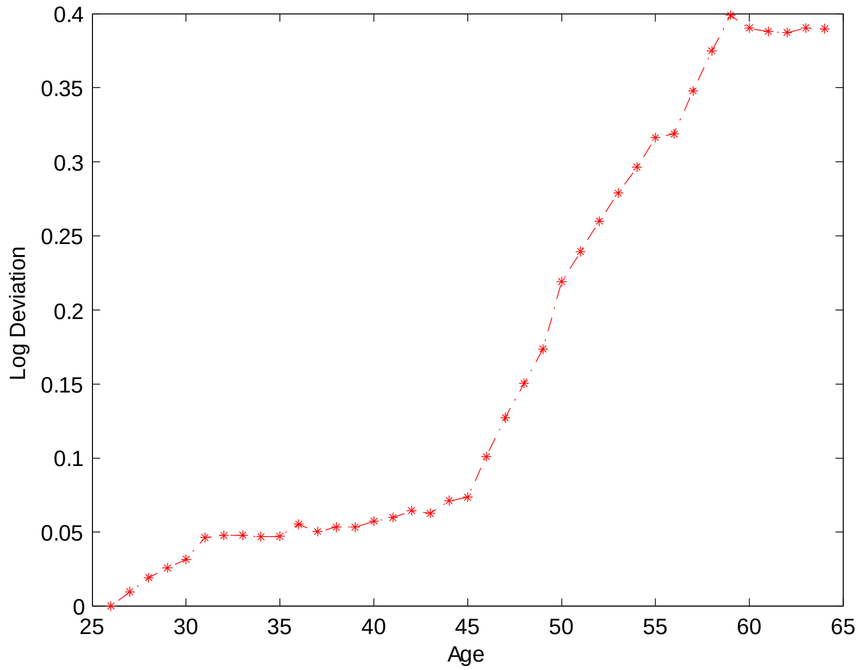
Table 3: Expenditure Elasticity of Price Paid

	I	II	III	IV	V	VI	VII	VIII
Instrumental Variable	0.15	0.06	0.11	0.08	0.1	0.07	0.18	0.11
OLS	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Elasticity in the Model: 0.15

Notes: In the first row, we run Instrumental Variable regressions. The columns are the estimates of expenditure elasticities in the data, with different regressions. In columns I to IV, shopping frequency is controlled. In columns V to VIII, shopping frequency is not controlled. In every column shopping needs are controlled. In columns I and V, we use income categories as instruments. In columns II and VI, we use household size categories. In columns III and VIII we use all three categories. as instruments. In the second row, we run OLS regressions, the estimations are based on dummy counter-parts of the first row. Data Source: A.C. Nielsen Homescan Data Set.

Figure 9: Log Deviation Average Search

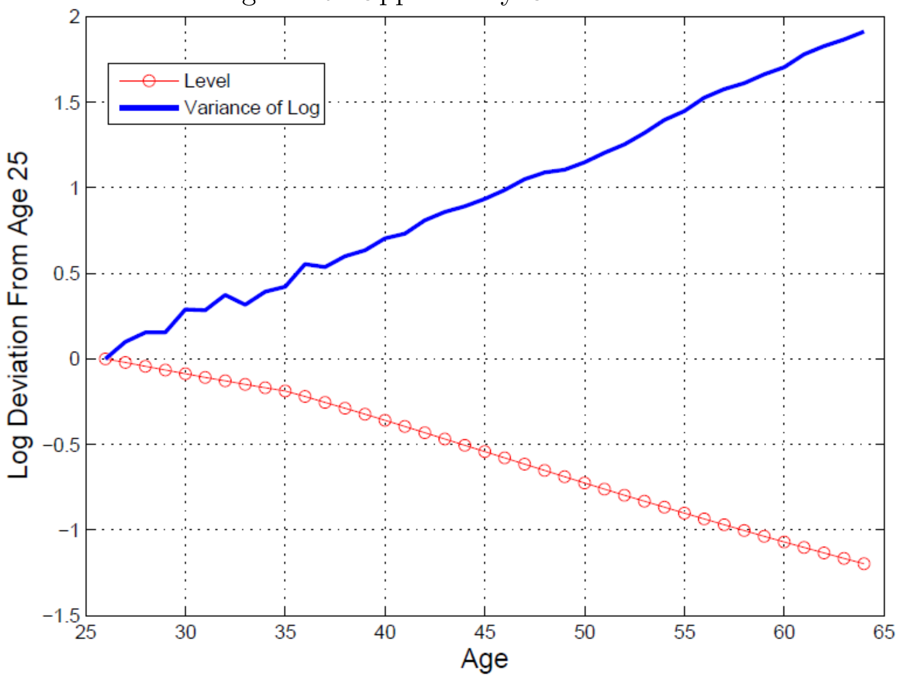


equation 10, where marginal return of search is equal to marginal cost of search. We draw the results in Figure 10, and compare to the opportunity cost of time reported in Aguiar and Hurst (2007). We get roughly the same shape in the life-cycle for levels. Opportunity cost of time is decreasing during the life-cycle. The same figure shows the variance of cost of time over the life-cycle. To our knowledge, there is no study to compare our result on the variance of cost of time over the life-cycle. In order to understand the cost of time over the life-cycle we revisit the optimality condition with respect to price search, equation (10).

$$-\frac{(y_t + (1+r)a_t - a_{t+1})^{(1-\sigma)}}{s_t}\theta_1 = \frac{\phi_t}{1-s_t} \tag{10}$$

In equation 10, left hand side is the marginal return on price search and right hand side is the marginal cost of price search, which is the marginal return on leisure time. Note that value of price search is decreasing with higher income and wealth. This is key in explaining the cost of time over the life-cycle. There are three things behind the profile of cost of time. First one is the hump-shaped income over the life-cycle. That makes value of leisure time hump-shaped, because return of price search is decreasing with higher income levels. The second one is the increasing wealth over the life

Figure 10: Opportunity Cost of Time



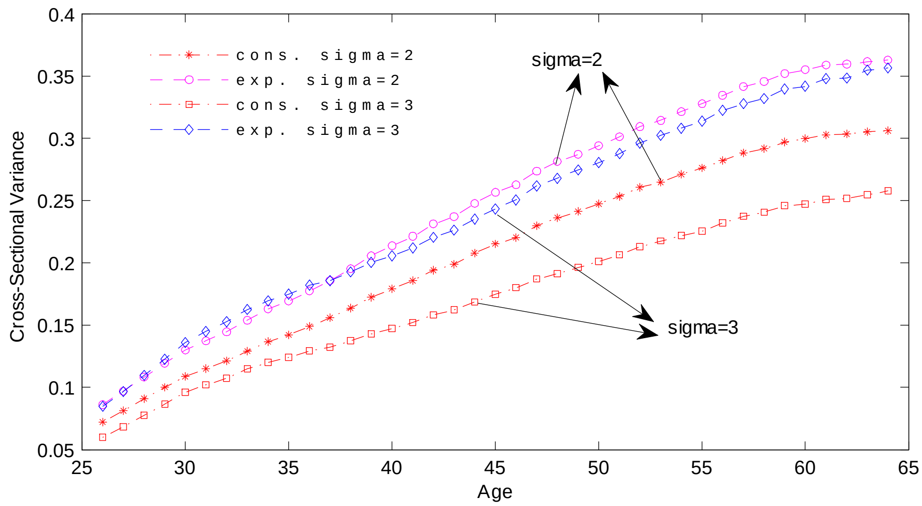
cycle. That makes the value of leisure time increasing, because return of price search is decreasing with high levels of wealth. And finally, we have ϕ_t parameter, which is decreasing over the life-cycle.[10] That makes value of leisure time decreasing over the life-cycle. So, during the young ages, effect of ϕ_t dominates income and wealth effect on the cost of time. In the middle and older ages effect of ϕ_t and income together dominates wealth effect on the cost of time. The reason behind the increasing variance of cost of time is the income process. That makes an increasing variance of income and wealth over the life-cycle. Since cost of time depends on those two variables, it has an increasing variance over the life-cycle, too.

The Effect of Risk Aversion

As we mentioned earlier the risk aversion parameter σ has potentially large effects on the search behavior. In this section we quantify this effect and examine the mechanisms which drive the results. First, we look at the expenditure and consumption inequality over the life cycle. In figure 11 we plot cross-sectional variance of consumption and expenditure for risk aversion levels 2 and 3. The figure reveals that the cross-sectional variance of expenditure does not differ much for two risk aversion levels through out the life cycle. On the other hand it appears that the level of risk aversion has

[10]Note that we calibrate ϕ_t along with other to parameters in order to match certain targets in data.

Figure 11: Age-Inequality Profiles of Consumption and Expenditure for $\sigma = 2$ and $\sigma = 3$.



quantitatively large effect on the evolution of the cross-sectional variance of consumption. The cross-sectional variance of consumption is around 15% lower if σ equals 2. The difference between expenditure inequality and consumption inequality get larger with higher risk aversion. Specifically in this exercise, the difference increases from 15% to 30% when we increase the risk aversion from 2 to 3.

To understand the reason behind the effect of risk aversion we study the effect of σ on search behavior. For that purpose we use the first order condition with respect to search behavior.

$$-\frac{c_t^{1-\sigma}}{s_t}\theta_1 = \frac{\phi_t}{1 - s_t}$$

Right hand side of the equation does not depend on σ and starts from ϕ when s is zero and goes to infinity as s approaches 1. Left hand side of the equation decreases with s for a given level of consumption. If the level of consumption is larger than 1 then higher σ will shift the left hand side to the left which will cause lower equilibrium search levels. Figure 14 (in appendix) shows the dynamics of search behavior for two risk aversion levels over the life cycle. We recalibrate the model parameters for $\sigma = 3$. As implied by the FOC average search time is larger for the low risk aversion case. As can be seen from the right panel the variance of search is lower for the high risk aversion case. This is because of the lower levels of search for the high risk aversion. Once we plot the log deviations from age 25 the evolution of the variance and the average of search look similar for different risk aversion levels.

The Effect of the Search Technology

One important parameter of the model that we use is the return to the search, θ. To calibrate it we used the estimated value from Aguiar and Hurst (2007), which is -0.1. In this section we study the implications of a change in the search technology. Particularly, we compare the results of 2 models, one with our original calibration ($\theta = -0.1$) the other with another search technology ($\theta = -0.2$). We do not recalibrate the other parameters. This exercise can also be thought of as implications of a technological innovation in the search technology, such as internet.

Figure 12 shows that as return to search increases from $\theta = -0.1$ to $\theta = -0.2$ the difference between cross-sectional variance of consumption and cross-sectional variance of expenditure increases. As can be seen from the figure, this happens because of lower cross-sectional variance of consumption for $\theta = -0.2$. As return to search increases, the increase in the search time of the poor and low income individuals are higher than the increase in the search time of the wealthy and high income individuals. As a consequence, the variance of search increases as wells as the variance of the prices with a higher return to search technology (see figure 15 in appendix , second row,).

Average price paid stays almost constant until age 45 for both of the search technologies. After the age 45 the decline in average prices paid is larger for $\theta = -0.2$ (figure 13). To match the life-cycle profile of log-deviation of prices in figure 4 we calibrated the coefficient of leisure, ϕ_t, in the utility function over the life-cycle. The life-cycle profile of ϕ_t that can fit the life-cycle profile of log-deviation of prices is decreasing over the life-cycle. If there was not decreasing ϕ_t in the model, as wealth and average income increase as people get older, average prices would increase since people would search less.

To compare the search behavior for different search technologies we plot the log deviation of average search over the life cycle (see figure 15 in appendix first row, right column). The increase in the search time over the life-cycle is larger for $\theta = -0.1$. But, that does not directly imply a higher price decline for $\theta = -0.1$ as return to search is lower for $\theta = -0.1$ (figure 13). Because of the higher return to search, average search is higher for $\theta = -0.2$ (see figure 15 in appendix first row, left column).

6 Discussion and Conclusion

In this paper, we study the life-cycle inequality profiles of consumption, expenditure, price search, and individual prices. We use A.C. Nielsen data set to document age-inequality profiles of expenditure, price search and individual prices. Then we solve a life-cycle model to analyze the joint

Figure 12: Age-Inequality Profiles of Consumption and Expenditure for $\theta = -0.1$ and $\theta = -0.2$.

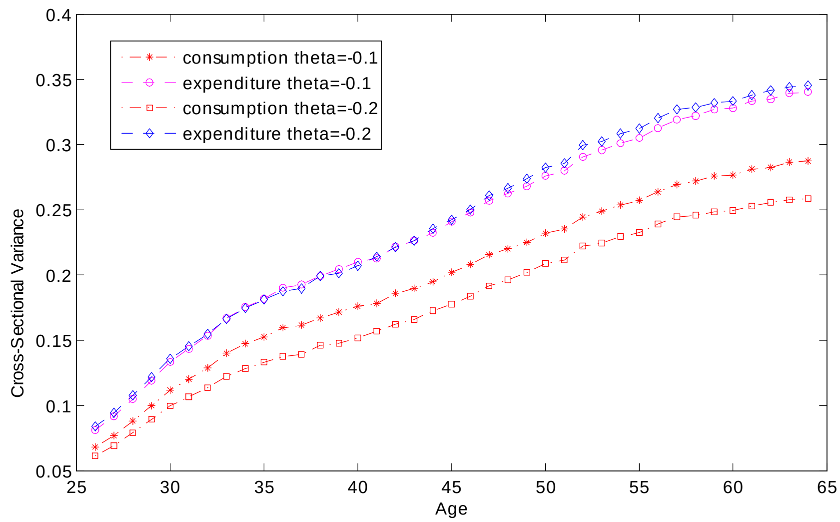
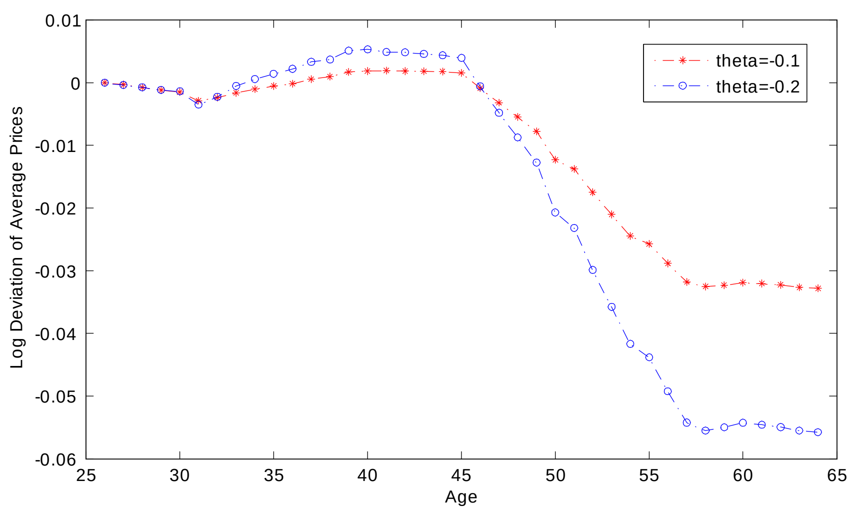


Figure 13: Log Deviations of Average Prices for $\theta = -0.1$ and $\theta = -0.2$.



behavior of shopping strategies, individual prices, and expenditures. We introduce price search decision to a life-cycle model, and differentiate consumption from expenditure. The model predicts an increasing age-inequality profile for search, prices and expenditure, consistent with data. Our quantitative study -using estimated income process and price search functions from literature- predicts that consumption inequality is not equal to expenditure inequality when agents can search for prices. A plausibly calibrated version of our model predicts that cross sectional variance of consumption is around 15% smaller than the cross sectional variance of expenditure through out the life cycle. In the earlier studies[11], consumption inequality was implicitly assumed to be the same as expenditure inequality. Also, the life-cycle profile of individual price and search levels imply a decreasing life-cycle profile for cost of time.

Aguiar and Hurst (2009) document different patterns in different expenditure categories. In their study, expenditures on some goods and services have hump-shaped profile over the life-cycle, and some others have constantly increasing profiles. Price search could be helpful in explaining the different patterns, because some categories might be more sensitive to price search. The life-cycle search profile may have different implications on the expenditure patterns of different categories due to their different sensitivities. Carroll and Summers (1989) document different expenditure patterns for different education groups. Again, price search together with income processes could be helpful to explain the expenditure patterns. Different price search technologies or time cost profiles for different education or occupation groups could be helpful in explanation to the different expenditure patterns. In this paper we used average cost of time (the coefficient of leisure in the utility function) over the life cycle. It is likely that the variance of the opportunity cost of time changes over the life-cycle with a varying degree for different education and occupation groups. Potentially it will have important implications on inequality in general.

[11] For example: Aiyagari(1994), Storesletten et al (2000), Krueger and Perri (2006), Guvenen (2007).

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Appendix A Figures

Figure 14: Behavior of Search and Prices over the Life-Cycle for σ=2 and σ=3.

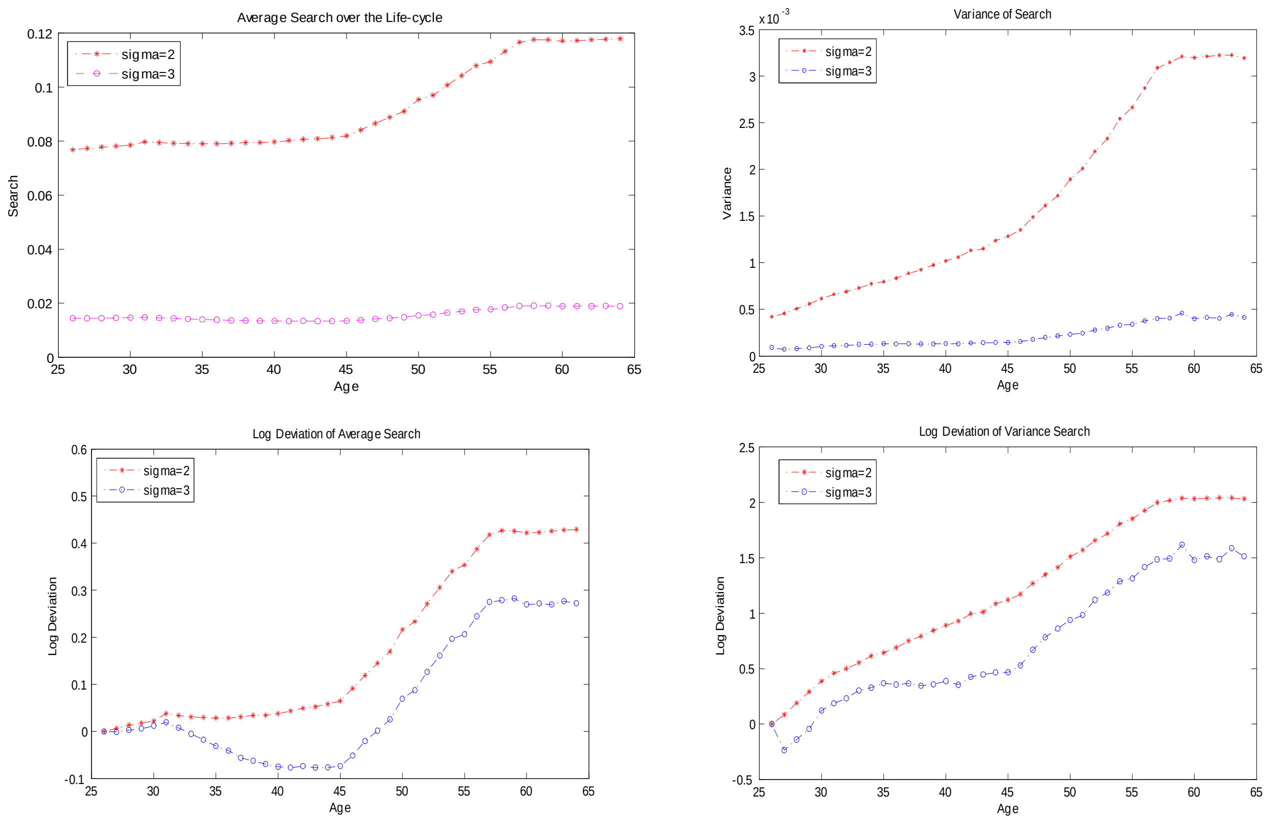

Figure 15: Behavior of Search and Prices over the Life-Cycle for θ=-0.1 and θ=-0.2.