Portfolio Choice with Uninsurable Labor Earnings

by

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Abstract

This thesis analyzes the households’ decision to hold risky vs. risk-free assets in the presence of uninsurable labor earnings risk.

The first Chapter, titled "A Model of Household Labor Earnings Uncertainty," introduces the earnings model to be used throughout the thesis. Models of earnings uncertainty are used often in the precautionary savings literature but little is known about how well they fit the data. This chapter considers a model that allows for large transitory shocks to the level of labor income as well as smaller permanent and transitory shocks to the growth rate of income. The model is estimated on individual data by assuming that the uncertainty process depends on demographic characteristics. Two types of specification tests are considered, and it seems that the model does an adequate job of fitting the data.

The second Chapter, titled "Stocks for the Old? Evidence from Household Portfolios," documents the facts about the decision to hold risky assets and the choice between risky vs. risk-free assets. The majority of households do not hold any stocks at all, although they generally hold some risk-free assets. Furthermore, stockholding is far more prevalent among older households. While these facts are at odds with complete-markets models of portfolio choice, they may be consistent with the buffer-stock hypothesis: most households accumulate assets late in the life-cycle, while maintaining only a small buffer stock early on, used to smooth income shocks. I test the implications of the model on micro data, by independently studying both the decision to hold stocks, and the portfolio share decision conditional on holding stocks. I present evidence that the stochastic properties of labor income have a substantial effect on both decisions, in line with the implications of buffer-stock behavior. However, I also find that the estimated effect of labor income uncertainty on total asset accumulation is quite puzzling.

The third and final Chapter, titled "Life-cycle Accumulation in the Presence of Earnings Uncertainty," examines whether standard models of intertemporal optimization are
consistent with the magnitudes of asset holdings observed in household-level data. It is documented that the average household’s total asset holdings are low early in life, increasing some after age 45. Also, the average stockholding household’s share of liquid assets in stocks is shown to be quite low early on, more than doubling by age 58, and then declining until retirement. This chapter tests the hypothesis that this behavior is consistent with optimal choice in the presence of earnings uncertainty. A structural expected-utility model is estimated by matching actual and predicted life-cycle profiles of both total asset holdings and portfolio shares. The model has little success in matching both profiles, and the estimated preference parameters suggest an implausibly high discount rate by consumers. The model’s performance is somewhat improved if the expected utility framework is abandoned and the link between relative risk aversion and intertemporal elasticity of substitution is severed.
Acknowledgments

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Professor Peter Diamond was the first member of the MIT economics faculty that I ever talked to and he has remained a major presence throughout my graduate career. My relationship with him has undoubtedly been a major part of my education, and I have enjoyed our conversations and my work for him tremendously. With a single sentence he has often shed a whole new bright light for me on various economic concepts. I know I have improved as an economist because it now only takes me an afternoon to interpret those single sentences. As I am about to leave the department, it seems unreal that over the past five years I have been associated with such a great economist.

Over the past couple of years, I have also come to know Professor Olivier Blanchard, who has gracefully accepted to be my main thesis advisor. I hope that he does not regret it. He has been a tremendous source of inspiration as well as personal support, and I have really appreciated how he has made himself available to patiently answer my myriad questions and worries. It has been an honor for me to be taught how to think about macroeconomics by one of the great macro thinkers. I will remember our exchanges for a long time, and I hope – unrealistically – to some day be able to think about macro as he does. For having taken macro from Olivier, and from having taught macro for him, I am also a much better teacher.

To both of my advisors, I owe a debt of gratitude for their support during the academic job market, and for their willingness to recommend me to their colleagues. On the job market front, I also owe thanks to Katherine Swan and to Professors Daron Acemoglu and Jiang Wang. Furthermore, I would like to thank Gary King for all his help during my time at MIT.

I would be remiss if I did not mention the influence that Daron has had on my studies.
His graduate macro sequence and his work has introduced me to issues that I have not yet tackled but that I will be working on in the future. But most importantly, I am thankful to Daron for insisting that I carefully re-examine issues which should matter theoretically and which the literature had brushed aside. He was, of course, correct and I have benefited greatly.

This incredible amount of knowledge and skill that has been transferred to me comes with a sense a responsibility. I hope to contribute to the field and to transfer some of this knowledge to future generations of students. It is also my sincere hope that I can someday use this knowledge to benefit my country, Greece. It is in this fashion that I hope to repay some of my debt to the beautiful country that raised me.

On the personal level, I have made many dear friends in the department, including (in strictly alphabetical order) Julie Berry (and her husband Brian Cullen), Daniel Dulitzky, Paul Ellickson, Robert Marquez, and Rafic Naja. Paul and I have shared many moments together and I want hefe to know that he has increased the quality of the whole experience. I am also sorry for any rumors I circulated ab ut him (no, not really). Brother Rafic was the first classmate that I talked to, and it was obvious instantly that I would have a great friend for years to come. I appreciate his humor, his uncompromising style, and his willingness to treat me like a brother. I honestly hope that I will be able to maintain these friendships for a long time to come.

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Μπαμπά, μαμά, we made it.
Στους γονείς μου με πολλή Αγάπη
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Chapter 1

A Model of Household Labor Earnings Uncertainty

1.1 Introduction

Models of household labor earnings uncertainty have been estimated at least since the work of Hall and Mishkin [1982] and MaCurdy [1982]. Recently, interest in these models has resurfaced as a result of the consumption literature studying precautionary savings, some of which is surveyed in Chapter 2. For that line of research, the estimates of earnings uncertainty are crucial because prudent consumers change their behavior radically in the face of uncertainty. This study is an attempt to supplement the available estimates in two respects.

First, the models of earnings uncertainty estimated so far have all traditionally assumed that earnings shocks affect the growth rate of income and are distributed normally. Even in the cases where the assumption is not made explicitly, the estimates of the properties of the shocks do not go beyond the second moments. Such a practice is unacceptable for any study of precautionary savings since it is known that the possibility
that bad states may occur can have a very profound effect on behavior. Marginal utility rises very fast near zero, so that the household will modify its behavior to avoid big drops in consumption even if their probability of occurrence is very low. Thus, one of the main determinants of behavior under uncertainty is the likelihood of these “catastrophic” labor income events, and any empirical exercise studying this type of behavior must account for these events. The need for a separate process for zero-income events is clear from the distribution of the change in log income, $dlnY$, presented in Figure 1A.\footnote{Source: PSID. The data are real-after tax labor income data for one- and two-earner households for the period 1977-1983} The superimposed normal distribution with matching mean and variance demonstrates that the distribution of $dlnY$ has fat tails, which seem to be the result of a separate process. Both tails are fat: the left tail is the result of sharp drops in labor income, while the right tail is the result of sharp increases. As confirmed by inspection, both tails are almost always associated with entry into or exit from unemployment. Clearly, shocks to the growth rate of labor income cannot be adequately described as normal.

Nevertheless, suppose that one is still only interested in estimating the second moment of the distribution of the smaller shocks; in fact, that is the strategy typically employed by researchers so far. A time-series of smaller shocks to labor income is created for each household by ignoring “outliers.” However, a practical problem arises in this situation: over a given period, the time-series of labor income growth rates for each individual household will have a different number of observations, depending on whether the household experienced any catastrophic events that resulted in an “outlier” for the growth rate of income. In that respect, the panel of observations will be unbalanced in the cross-section with different number of observations (i.e., households) available each period. This raises the issue of what is the correct way to construct the asymptotic variance-covariance matrix in this situation. So far, researchers have been using only balanced panels by eliminating
from the panel observations whose income fell below a certain level even once during the
period covered by the panel. This results in the loss of a significant portion of the sample.
I will show that once the process of catastrophic labor income events is modeled explicit-
ly, the above-mentioned attrition is no longer necessary. In that case, the unbalanced
panel can be thought of as resulting from a process of incidental truncation. Therefore,
the asymptotic variance-covariance matrix for the smaller shocks can be estimated on the
unbalanced panel by stacking the moment conditions for both the truncation process (i.e.,
the process of catastrophic events) and the unbalanced panel. This also yields rigorous
estimates of the catastrophic event process.

The second contribution of this chapter is to evaluate how well the model proposed in
this thesis fits the data. A common earnings uncertainty model, which allows for shocks
of different persistence, is laid out and augmented to allow for non-normal shocks. It
is then theorized that the properties of each household's earnings uncertainty process
are a function of its demographic characteristics, and the model is thus estimated. This
chapter is interested in testing the specification of the model, and evaluating what is the
best possible form of the model. For example, is there evidence of permanent shocks?
How short-lived are the transitory shocks? Is it necessary to augment the model with
non-normal shocks, or is the variance of the shocks enough to describe the uncertainty
process? Is the model misspecified, e.g., as a result of measurement error?

Questions like the ones just posed can be answered by two types of tests. The first relies
on the fact that the number of moment restrictions is typically larger that the number of
parameters to be estimated. Thus, the moment restrictions themselves can be tested. The
second type of tests relies on the observation that the model of uncertainty is by definition
a model of heteroskedasticity of the underlying earnings regression whose residuals are
used to construct the earnings shocks. Therefore, if the model of uncertainty is correctly
specified, so is the model of heteroskedasticity, and thus the appropriate weights can be
found so that the underlying earnings regression will not exhibit heteroskedasticity. A test of heteroskedasticity in the weighted model is thus a test of the specification of the model of uncertainty.

This chapter is structured as follows: Section 2 presents the augmented model of uncertainty, while Section 3 estimates it. Specification tests are presented in Section 4, and measurement error issues are considered in Section 5. Section 6 concludes.

1.2 A Model of Earnings Uncertainty

1.2.1 Setup

In period $t$ a household with a set of characteristics denoted by the subscript $i$ receives labor income $\tilde{Y}_it$, which is uncertain as of period $t - 1$. There are two possible states for labor income, a “good” state that occurs with probability $1 - \pi_i$ and a “bad” state that occurs with probability $\pi_i$. The bad state is characterized by zero labor income, $\tilde{Y}_it = 0$.

In the good state, the evolution of labor income is governed by a deterministic growth rate and two multiplicative shocks to the level of labor income, a permanent shock and a transitory shock. Suppressing the subscript $i$,

\begin{align}
\tilde{Y}_t &= \tilde{Y}_t^p \tilde{E}_t, \quad \text{and} \\
\tilde{Y}_t^p &= G Y_{t-1} \tilde{H}_t
\end{align}

where $\tilde{Y}_t^p$ is the permanent component of labor income, $G$ is the non-random component of the change in permanent income, $\tilde{H}_t$ is the permanent multiplicative shock to the level of labor income, and $\tilde{E}_t$ is the transitory multiplicative shock to the level of labor income.

The permanent and transitory shocks are assumed to be distributed independently of one another. The permanent income shock $\tilde{H}_{t+1}$ is i.i.d. strictly positive and its log
(denoted $\tilde{\eta}_t$) is assumed to be unconditionally normally distributed with mean zero and variance $\sigma^2_\eta$:

$$\ln(\tilde{\eta}_t) \equiv \tilde{\eta}_t \sim \mathcal{N}(0, \sigma^2_\eta)$$  (1.3)

Note that the evolution of permanent income is not affected by the occurrence of the bad state. While the shocks to permanent income are not observed during the bad state, permanent income still evolves as described above. For example, the bad state can be thought of as temporary involuntary unemployment, which does not affect the earnings potential of the individual.

The transitory shock is assumed to be strictly positive, but it is also assumed to follow a moving average process of order $K$. The log of the transitory shock, (denoted $\tilde{\epsilon}_t$), satisfies:

$$\ln(\tilde{\epsilon}_t) \equiv \tilde{\epsilon}_t = \sum_{j=0}^{K} \rho_j u_{t-j}, \quad \rho_0 = 1$$  (1.4)

where $u_t$ are i.i.d. shocks which are normally distributed with mean zero and variance $\sigma^2_u$. Therefore, $\tilde{\epsilon}_t$, the log of the transitory shock, is also mean zero. The evolution of the small transitory shock is also not affected by the occurrence of a zero income shock.

The above model allows us to account for the kurtosis of the distribution of the growth rate of income in a very simple fashion: the distribution is simply a mixture of normals (the smaller shocks) and of a catastrophic event which is completely concentrated on the tails of the distribution (the reason is that an isolated zero income event generates a growth rate of -100% the year it occurs and 100% the year after). The goal section is to estimate the parameters that describe this labor income process, namely $\pi$, $G$, $\sigma^2_\eta$, $\sigma^2_u$ and the MA coefficients $\rho_1, \ldots, \rho_K$.

Is such an involved model of earnings uncertainty really necessary? For example, could the labor income process for all households be accurately described as having a determin-
istic household-dependent growth rate $G_t$ and being subject to an i.i.d. multiplicative shock $\tilde{v}_{it}$ which is distributed identically across households, so that:

$$dy_{it} = g_{it} + v_{it}$$

(1.5)

$$v_{it} \sim \mathcal{N}(0, \sigma^2)$$

(1.6)

where lower case letters are simply the logs of their upper case counterparts, and where the variance of the shock $v_{it}$ is the same for all households. If that were indeed the case, then equation 1.5 can be accurately estimated on a panel by regressing the first difference in log income $dy_{it}$ on a set of household characteristics. The results from such a regression are presented in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>0.0017</td>
<td>0.0007</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0014</td>
<td>0.0001</td>
</tr>
<tr>
<td>$\mathcal{R}^2$</td>
<td>1.3%</td>
<td></td>
</tr>
</tbody>
</table>

Source: PSID 1978-83; observations 16,683.

where the standard errors are computed allowing for unknown heteroskedasticity and for autocorrelation within individuals. The data are yearly after-tax labor income data from the PSID for one- and two-earner households during the period 1977-1983 (this data set has been described in length in Chapter 2). The dependent variables (not all reported here) are year dummies, age, the education of the head of the household and dummies for eight occupational categories (Professionals; Self-Employed Managers; Non-Self-Employed Managers; Clerical-Sales Workers; Craftsmen; Operators-Laborers; Farmers; Service Workers).

All variables, including the dummies which are not reported in Table 1, were significant at the 95% critical level. Yet, the $\mathcal{R}^2$ of the regression was less than 2%! Including higher-
order terms as well as other demographic variables did not improve the $R^2$. Since only two percent of the variation in the growth rate of income can be attributed to individual characteristics, this suggests that labor earnings shocks may be quantitatively important.\footnote{Alternatively, it could suggest the presence of individual effects. While individual effects are likely to be present for the level of income (thus the first differences estimation), it is less obvious that they should matter for the growth rate.} However, it is also entirely possible that the properties of the earnings shocks do not depend on the observed household characteristics, such as occupation, education and age, so that a demographic model of earnings uncertainty is unnecessary. If that were the case, then the regression described in 1.5 would be homoskedastic, which is a testable implication. The easiest way to test for heteroskedasticity is to use the test proposed by White [1980]. Under the null hypothesis of no heteroskedasticity, the White statistic is distributed as a Chi-Square, whose 5% critical value in the case presented here is 21. For regression 1.5 the statistic is equal to 353.7, a very strong rejection of the null.

### 1.3 Estimation

#### 1.3.1 Methodology

Let us start by considering the properties of the smaller shocks first, the log permanent shock $\tilde{\eta}_t$ and the log transitory shock $\tilde{\epsilon}_t$. Their variances can be recovered by exploiting the moments of the distribution of $dy = d\log(Y)$ conditional on a good state, i.e., for the years that were not classified as zero income shocks. For example, for two consecutive non-zero-income years, the model of labor income uncertainty implies that

$$dy_t \equiv y_t - y_{t-1} = g + \tilde{\eta}_t + \tilde{\epsilon}_t - \tilde{\epsilon}_{t-1}$$

(1.7)

where lower case letters denote logs of their capital-letter counterparts and where the
individual household subscript has been suppressed. Recall from equation 1.4 that

\[ \tilde{\epsilon}_t = \sum_{j=0}^{K-1} \rho_j u_{t-j}, \quad \rho_0 = 1 \]

so that we are interested in recovering \( g, \sigma_n^2, \sigma_u^2 \) and the MA coefficients \( \rho_1 \ldots \rho_K \), a total of \( K + 3 \) parameters. Therefore, \( K + 3 \) unique moment conditions are needed to estimate the parameters of the small shocks. These will be provided by the mean, variance and \( K + 1 \) autocovariances of \( dy \). Consider, for example, the four moments of \( dy \) that will identify these parameters for the case of the transitory shock following an MA(1) process (\( K = 1 \))

\[
\begin{align*}
E[dy_t] &= g \quad (1.8) \\
E[dy_t^2] &= g^2 + \sigma_n^2 + 2(\rho_1^2 - \rho_1 + 1)\sigma_u^2 \quad (1.9) \\
E[dy_t dy_{t-1}] &= g^2 - (1 - \rho_1)^2\sigma_u^2 \quad (1.10) \\
E[dy_t dy_{t-2}] &= g^2 - \rho_1\sigma_u^2 \quad (1.11)
\end{align*}
\]

assuming that the parameters of interest stay constant at least for the period \((t-3) \ldots t\).

In principle, the above restrictions can be used to identify the underlying parameters \( g, \sigma_n, \sigma_u \) and the MA coefficients \( \rho_1 \ldots \rho_K \) at the individual level by using the corresponding sample moments for any household with \( K + 3 \) consecutive non-zero-income observations of \( Y \). While the results would be unbiased, they would also undoubtedly be very imprecise, as a result of estimating moments using so few observations. This problem, which is a direct consequence of the short-time series dimension of the sample, can be overcome by exploiting the cross-sectional dimension of the data set to estimate the parameters of interest. Another reason to exploit the cross-sectional dimension of the data set is the fact that some households will have some of the moment conditions described above but not all, as a result of having experienced zero income events. In a cross-sectional analysis,
these households could contribute to the estimation; for example, an unbiased estimator of any of the above moments (not parameters) is their sample average, and each moment can be estimated by averaging over all the households for whom that moment is observed. One case where the cross-sectional nature of the data set would be useful is if there is an underlying model of earnings uncertainty such that people with similar demographic characteristics have similar uncertainty profiles. In that case, each of the above moments can be estimated by demographic group.

Consistent estimates of the moments can then be used to derive consistent estimates of the uncertainty parameters: this is indeed the Generalized Method of Moments (GMM) estimator of Hansen [1982], Hansen and Singleton [1996], Newey [1984], Newey [1985b] and Newey [1985a]. A slight problem arises in the model presented here because not all moments have the same number of observations. While this problem does not affect the point estimates, it does affect all asymptotic test statistics including standard errors, Wald statistics, etc. The reason is that all these statistics need to be adjusted for the sample size, and it is not clear here what the relevant sample size is.

To resolve this issue, let us consider the zero income shocks. First, note that one can re-state the problem as one of incidental truncation (or of sample selection, as in Heckman [1979]). The truncation process in this case is the process for zero income events, and the moments of interest are only observed if the zero income event does not occur. Specifically, let the random variable \( z_t^* \):

\[
  z_t^* = \begin{cases} 
    0 & \text{with probability } 1 - \pi \\
    1 & \text{with probability } \pi 
  \end{cases} \tag{1.12}
\]

control the occurrence of a zero income event, so that the zero income event occurs (and the moments 1.8-1.11 are not observed) if \( z_t^* = 1 \). It is now possible to obtain the parameter estimates as well as the correct asymptotic standard errors by stacking the
moment condition for the truncation process on top of the truncated moment conditions. The correct sample size then is simply the whole sample.

In general, the shock $z_t^*$ will have a bivariate distribution with the moments that are truncated, so that the sample analog of the moments will be biased, and a correction is necessary. However, this is not the case here since the process for zero income shocks is assumed to be independent of the process for the smaller shocks. For simplicity of notation define the new dummy variable $D_t$ as the negative of $z_t^*$,

$$D_t = 1 \quad \text{if} \quad z_t^* = 0; \quad D_t = 0 \quad \text{otherwise}$$ \hspace{1cm} (1.13)

so that $D_t$ it is equal to one if $Y_t$ is observed. Continuing the MA(1) case we can now specify the following moment restrictions:

$$E[D_t - (1 - \pi)] = 0$$ \hspace{1cm} (1.14)

$$E[D_tD_{t-1}(dy_t - g)] = 0$$ \hspace{1cm} (1.15)

$$E[D_tD_{t-1}(dy_t^2 - g^2 - \sigma^2) - 2(\rho_1^2 - \rho_1 + 1)\sigma^2] = 0$$ \hspace{1cm} (1.16)

$$E[D_tD_{t-1}D_{t-2}(dy_tdy_{t-1} - g^2 + (1 - \rho_1)^2\sigma^2)] = 0$$ \hspace{1cm} (1.17)

$$E[D_tD_{t-1}D_{t-2}D_{t-3}(dy_tdy_{t-2} - g^2 + \rho_1\sigma^2)] = 0$$ \hspace{1cm} (1.18)

For the MA(1) example, equations 1.14-1.18 make up the complete dynamic system to be estimated with GMM on the entire sample. The relevant sample size is then simply that of the entire sample.

Staying with the MA(1) example, consider a sample of labor income for $N$ households for the periods 0 to 3. The estimation works as follows: let $\theta$ denote the vector of parameters to be estimated, and define $g_i(\theta)$, the moment vector for each household $i$:  

21
\[ g_t(\theta) = \begin{bmatrix}
  D_{it} - (1 - \pi), & t = 0.3 \\
  D_{it}D_{i,t-1}(dy_{it} - g), & t = 1.3 \\
  D_{it}D_{i,t-1}(dy_{it}^2 - g^2 - \sigma^2 - 2(\rho_1^2 - \rho_2 + 1)\sigma_u^2), & t = 1.3 \\
  D_{it}D_{i,t-2}D_{i,t-2}(dy_{it}dy_{i,t-1} - g^2 + (1 - \rho_1^2)\sigma_u^2), & t = 2, 3 \\
  D_{it}D_{i,t-1}D_{i,t-2}D_{i,t-3}(dy_{it}dy_{i,t-2} - g^2 + \rho_1\sigma_u^2), & t = 3
\end{bmatrix} \quad (1.19) \]

where

\[ \theta' = [g \, \sigma_\eta \, \sigma_u \, \rho_1]' \]

Therefore, \( E[g_t(\theta_0)] = 0 \), where \( \theta_0 \) is the true parameter vector.

The GMM estimate of \( \theta \) is obtained by minimizing the distance between the sample moments and zero. In that sense, GMM is a special case of a minimum distance estimator (see Newey and McFadden [1994]). For any value of \( \theta \), the sample analog of the moments \( \check{g}(\theta) \) can be constructed by averaging over each individual’s moments,

\[ \check{g}(\theta) = \sum_{i=1}^{N} \check{z}_i(\theta) \quad (1.20) \]

A consistent estimate \( \hat{\theta} \) of \( \theta \) can then be obtained as

\[ \hat{\theta} = \arg\max \left\{ \check{g}(\theta)' \check{W} \check{g}(\theta) \right\} \quad (1.21) \]

where \( \check{W} \) is a square weighting matrix whose dimension is that of the moment vector, and where \( \check{W} \rightarrow W \). The asymptotic distribution of \( \hat{\theta} \) is then given by

\[ \sqrt{N} \left( \hat{\theta} - \theta_0 \right) \rightarrow \mathcal{N}(0, \nu) \quad (1.22) \]

where \( \theta_0 \) is the true value of \( \theta \), \( N \) is the number of total observations used to derive the sample moments and \( \nu \) is estimated by
\[ \dot{\gamma} = (\hat{G}'\hat{W}\hat{G})^{-1} \hat{G}'\hat{W}\hat{\Omega}\hat{W}\hat{G} (\hat{G}'\hat{W}\hat{G})^{-1} \] (1.23)

\[ \hat{G} = \frac{1}{N} \sum_{i=1}^{N} \frac{\partial g_i(\theta)}{\partial \theta} \bigg|_{\theta=\hat{\theta}} \] (1.24)

\[ \hat{\Omega} = \frac{1}{N} \sum_{i=1}^{N} g_i(\hat{\theta})g_i(\hat{\theta})' \] (1.25)

### 1.3.2 Results

I assume that the parameters of the earnings uncertainty process are the same across similar demographic groups so that the moment restrictions of equations 1.14-1.18 can be estimated within demographic cells. These cells are defined by occupational group (Professionals; Self-Employed Managers; Non-Self-Employed Managers; Clerical-Sales Workers; Craftsmen; Operators-Laborers; Farmers; Service Workers), age group (over or under 45) and educational-attainment group (less than high-school, at least high-school but not college, at least college). Also, zero income is never observed in practice. Yet, I want differentiate the very big shocks from the small ones. So for the purposes of this exercise zero income events are defined as occurrences when the level of labor income drops to below one half of the average income for the household (calculated over the other years of the sample). Approximately six percent of the observations of labor income were classified as zero-income events, and the median drop associated with these events was to ten percent of last year's income. Overall, I traced one- and two- earner households over the period 1977-83 of my sample, and constructed for them real after-tax labor income. The estimation was conducted by demographic cells as defined above, keeping only those cells that had at least 50 households in them.

In order to allow the size of each cell to be as large as possible, I kept households that experienced changes in the family composition due to changes in the head or the spouse. However, the labor income shocks for the years affected by the changes are not
the result of exogenous earnings uncertainty, and thus those years should not be used in
deriving the uncertainty estimates. I handled this in the exact same fashion I handled the
zero income shocks: Family composition is assumed to change as a result of an exogenous
process, which is independent of the labor income shocks that are observed in the other
years (i.e., the years that the household did not experience any compositional changes).
When family change occurs, the moments of labor income for the years affected are simply
not observed. While I do not report the estimated probability of family change shocks by
cell, it was approximately 5% for most of them.

The GMM estimates of the labor income process parameters are presented in Tables
2-5. They have all been derived using the identity matrix as the GMM weighting matrix
$W$. Each row contains the results for a particular cell. The first three columns of each
row describe the demographic characteristics that have defined the cell. Not that not all
possible cells are present because only the ones with at least 50 observations were kept.
The next two columns report the standard deviation of the log permanent shock, $\sigma_n$, and
the standard deviation $\sigma_u$ of the log i.i.d. shocks that make up the transitory shock. Since
both shocks affect the growth rate of income, their scale is simply percent of the level of
earnings. Note that unless the transitory shock is MA(0), $\sigma_u$ is not the standard deviation
of the transitory shock $\sigma$. Instead, $\sigma^2 = \sigma_u^2 \sum_{j=0}^{K} \rho_j^2$. For the MA(1) and MA(2) models,
the MA coefficients $\rho_j, j = 1..2$ are reported next. Recall that by normalization $\rho_0 = 1$.

The estimate of the log growth rate of permanent income $g$ is reported next. Note
that it is not directly comparable to the growth rate of the average income paths reported
elsewhere in the literature. Specifically, for two consecutive years that are not zero income
events, the model of labor income implies that the growth rate of income is given by

$$\log(\bar{Y}_t) - \log(\bar{Y}_{t-1}) = g + \tilde{\eta}_t + \tilde{\epsilon}_t - \tilde{\epsilon}_{t-1}$$

so that the average growth rate of income is given by
\[ E \left[ \log(\bar{Y}_t) - \log(\bar{Y}_{t-1}) \right] = g \]

because the normalization was that the log shocks have zero mean. The average growth rate of income, however, is different from the growth rate of average income, which is, for example, the growth rate of the average income profiles calculated in the literature. In terms of the model presented here, the growth rate of average income is given by

\[
\log(E[\bar{Y}_t]) - \log(E[\bar{Y}_{t-1}]) = g + \log(E[\bar{H}_t])
\]

\[
= g + \frac{1}{2} \sigma^2_{\eta}
\]

where the second equality follows because the permanent multiplicative shock \( \bar{H}_t \) is assumed to be log normally distributed with mean zero and variance \( \sigma^2_{\eta} \). The final column lists the number of observations (i.e., households) that make up each cell. Asymptotic standard errors are reported in parenthesis.

Tables 2-5 suggest that most of the parameters of the dynamic uncertainty model can be estimated very accurately. The exception are the estimates of the MA coefficients \( \rho_1 \) and \( \rho_1 \) which have very large standard errors for some cells. This is especially true for the MA(2) coefficient \( \rho_2 \) which is significantly different from zero for only one demographic cell. However, the insignificance of the MA(2) coefficients may be driven by the small sample size, since they are only significant for the larger cells. The sample size seems to affect the precision of the MA coefficients more so than the other ones. It is worth noting that only the MA coefficients are identified through non-linear terms. This may be significant in small samples because the derivatives of the moments with respect to the MA coefficients (which are used to derive the asymptotic variance-covariance matrix) contain the estimated coefficients themselves.
While it is not the purpose of this chapter to discuss the qualitative implications of the findings, it is worth pointing out that the estimates of the parameters of the small shocks and of \( g \) are in the same range as those reported by others using similar models. Also, note that in the absence of an MA process for the transitory term, the variance of the permanent shock is typically overestimated. A discussion of the findings' relationship to demographic characteristics, as well as a complete set of point estimates for all the cells, regardless of size, can be found in Chapter 2.

Note that the tight estimates for most of the coefficients do not necessarily imply that the specification of the model is correct. This issue will be examined in Section 4.

1.3.3 Efficient GMM

If the weighting matrix \( W \) used in equation 1.21 is the inverse of the variance-covariance matrix \( \Omega \), i.e., \( W = \Omega^{-1} \), then the estimator is efficient in the sense that it has the smallest asymptotic variance matrix of any GMM estimator. A consistent estimate of \( \Omega \) to be used for the weighting matrix \( \hat{W} = \hat{\Omega}^{-1} \) can be obtained from first step GMM estimation using the identity weighting matrix. The asymptotic variance of the efficient GMM estimates is then equal to \( (G'\Omega^{-1}G)^{-1} \), where \( G \) and \( \Omega \) can be estimated as shown in equations 1.24 and 1.25, respectively.

Table 5 compares first-step GMM estimation (using the identity weighting matrix) with efficient GMM estimation for the MA(1) model. For each parameter the GMM estimates are reported first and the efficient GMM estimates are reported next to them in italics. The rows that have asterisks (*) for coefficients and standard errors correspond to the demographic cells for whom efficient GMM estimation was not possible. The reason was that the numerical optimization routine failed to invert the first stage \( \hat{\Omega} \) to use it as the weighting matrix. Even though \( \hat{\Omega} \) is by construction positive definite, its condition number in those cases was large, making numerical inversion impossible or extremely
imprecise. The seven cells for which such problems were incurred were the seven smallest cells, the biggest one having only 81 observations. Even if efficient GMM estimation was possible for those small cells, its results would have been unreliable since efficient GMM has very bad small sample properties Altonji and Segal [1994].

For the cells that efficient GMM was numerically possible, the estimates were very close to the ones obtained from the first-stage GMM using the identity weighting. The same is true for the MA(0) and MA(2) models which are not reported here. The only exceptions are the estimates of the MA coefficients for the cells which produced insignificant estimates in the first step. Also, note that the standard errors were substantially reduced by efficient GMM, generally by approximately one half. That efficient GMM yielded similar estimates with much tighter confidence intervals is a sign that the model is well specified. Misspecified models typically yield different coefficients when different weights are used. The validity of the model's specification is examined next.

1.4 Specification Testing

The model estimated in the last section on demographic cells, without the zero-income shocks, is one of the most commonly used in the precautionary savings literature. Yet, little is known about how well it describes the data. In this section two types of tests are used to judge the model's success in fitting the data. The first comes from the over-identifying restrictions of the moment conditions. The second comes from the realization that the model of uncertainty is essentially a model of heteroskedasticity for the underlying regression whose residuals are interpreted as the uncertainty shocks.

1.4.1 GMM Specification Tests

The moment conditions outlined in equations 1.14-1.18 for the MA(1) model
\[ E[D_t - (1 - \pi)] = 0 \]
\[ E[D_tD_{t-1}(dy_t - g)] = 0 \]
\[ E[D_tD_{t-1}(dy_t^2 - g^2 - \sigma^2_\eta - 2(\rho^2_\eta - \rho_1 + 1)\sigma^2_\eta)] = 0 \]
\[ E[D_tD_{t-1}D_{t-2}(dy_tdy_{t-1} - g^2 + (1 - \rho_1)\sigma^2_\eta)] = 0 \]
\[ E[D_tD_{t-1}D_{t-2}D_{t-3}(dy_tdy_{t-2} - g^2 + \rho_1\sigma^2_\eta)] = 0 \]

can all be used to estimate the parameters of interest \( g, \sigma_\eta, \sigma_u, \) the MA coefficient \( \rho_1, \) and the probability of zero income \( \pi. \) In fact, there are far more moments available than parameters to be estimated. For example, the labor income sample of 1977-1983 used here, yields 28 moment restrictions but there are only 5 parameters to estimate. In this case, the over-identifying restrictions can be used to test the specification of the model by constructing the statistic

\[ \chi^2_{23} = N\tilde{\gamma}(\hat{\theta})'\hat{\Omega}^{-1}\tilde{\gamma}(\hat{\theta}) \]  

(1.26)

Under the null hypothesis that the model is correctly specified, i.e., that the relevant moments are equal to zero, the \( \chi^2_{23} \) statistic is asymptotically distributed as Chi-squared with \( 28 - 5 = 23 \) degrees of freedom.

For each of the three models MA(0), MA(1) and MA(2), Table 6 presents the GMM \( \chi^2 \) statistic by demographic cell. The statistic obtained by efficient estimation is also included for comparison (in italics). Note that since both first-stage GMM Chi-Square statistic and efficient GMM estimation require that the variance-covariance matrix \( \Omega \) of the moment vector be inverted, when the numerical inversion failed, neither method's statistic was available. As was mentioned in the last section, \( \Omega \) is by definition positive-definite and thus invertible, but its eigenvalues are often such that its not possible to invert it with any accuracy. This problem has occurred for the seven smallest cells.
As the 5% critical value reported in the last row indicates, the over-identifying tests usually reject the model, although the rejection is often borderline. Also, the rejection is much weaker for the MA(2) specification than for the other ones. For example, out of the nine cells for which specification testing is possible, the efficient GMM MA(0) model is rejected eight times, but the efficient GMM MA(2) model is rejected five. Overall, there is not overwhelming evidence that the model is misspecified. Also, it seems that the MA(2) model offers a significant improvement, even though the estimated MA coefficients \( \rho_1 \) and \( \rho_2 \) often have large standard errors.

1.4.2 Are Large Shocks Important?

One of the novel features of the model is that it allows for the distribution of the shocks to the growth rate to have fat tails. This is achieved by allowing for zero income shocks. One can test whether the specification of the model is improved with the addition of such shocks by using the over-identifying restrictions for the moment conditions of the smaller shocks only. This is the subset of the moment conditions that does not include estimating the probability of zero income, as specified by equations 1.15-1.18:

\[
\begin{align*}
E[D_t D_{t-1} (dy_t - g)] &= 0 \\
E[D_t D_{t-1} (dy_t^2 - g^2 - \sigma_y^2 - 2(\rho_1^2 - \rho_1 + 1)\sigma_u^2)] &= 0 \\
E[D_t D_{t-1} D_{t-2} (dy_t dy_{t-1} - g^2 + (1 - \rho_1)^2 \sigma_u^2)] &= 0 \\
E[D_t D_{t-1} D_{t-2} D_{t-3} (dy_t dy_{t-2} - (g^2 + \rho_1 \sigma_u^2))] &= 0
\end{align*}
\]

where \( D_t \) is a dummy variable indicating whether labor income is observed in period \( t \) or not. It is possible to estimate the model without estimating the zero-income process because the zero-income shocks are assumed to be distributed independently of the smaller
shocks. For the alternative hypothesis that zero-income shocks do not matter, the growth rate of labor income is observed at all times, and the moment conditions are estimated on the entire sample ($D_t = 1$ for all households).

The results from testing the over-identifying restrictions for both cases are presented in Table 7. The first column is the test statistic for the small-shock moment conditions of the model in this paper and the second column is the statistic for the moments of a model that does not allow for big shocks. Both statistics are from the efficient GMM estimator, since omitting the first highly-nonlinear moment allows the variance-covariance matrix of the moments to be computed much more accurately, and thus efficient GMM is possible for all the cells. For the model allowing zero-income shocks (but omitting the first non-linear moment of the probability of zero income shocks) yields similar specification results as the estimation including all the moments: the model is rejected for approximately half the cells, but the rejection is not very strong at all.

The results also suggest strongly that zero-income shocks are important. The over-identifying statistic is increased dramatically for most cells when the model does not allow for zero-income shocks. For the four out of sixteen cells that the statistic is actually decreased, the magnitude of the improvement is only marginal.

1.4.3 Are Permanent Shocks Important?

The estimation of permanent shocks is very important from a theoretical perspective because the appropriately capitalized value of a permanent shock is much larger than that of a transitory shock, depending of course on the consumer's horizon. For example, in an

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3This approach is very similar to the one commonly used by researchers, where the “outliers” are simply excluded from the sample. The main difference, is that by having a theory of why some observations are missing (i.e., due to the zero-income shocks), I can estimate the system of equations using an “unbalanced” panel (as described in the introduction). This significantly increases the number of observations.
infinite horizon setting whether shocks are permanent or transitory has a dramatic effect on consumer behavior and also significant equilibrium implications (see, e.g., Constantinides and Duffie [1996]). Also, Heaton and Lucas [1996a] report that the variation of income in the PSID is mostly transitory. Therefore, I estimate a version of my model that does not allow for permanent shocks (although it does still allow for zero-income shocks). The results are presented in Table 8. Not surprisingly, the MA coefficients $\rho_1$ and $\rho_2$ are now much larger, and are also estimated much more accurately. However, they are both still considerably less than one.

To help select between the two models, I test the specification of the small-shocks moment conditions and I present the results in Table 9. Unfortunately, the results do not favor either model. The model allowing for permanent shocks appears to have a slight edge, since for most cells the over-identifying test statistic is smaller for that model. The improvement, however, is usually marginal.

1.4.4 An alternative specification test

As mentioned in Section 2, the model of earnings uncertainty is by definition a model of heteroskedasticity for the underlying “regression” of $d\log Y$ whose residuals are interpreted as labor income shocks. If the model of heteroskedasticity is correct, the underlying regression can be transformed so that the variance-covariance matrix takes the form $\sigma^2 I$ for some constant $\sigma$ (where $I$ is the identity matrix). Therefore, the specification of the model of uncertainty can be tested by performing a heteroskedasticity test on the transformed model, which is estimated by the method of Feasible Generalized Least Squares (FGLS). Here, I follow Greene [1993] in implementing the FGLS estimator.

Specifically, consider the following model for the growth rate of labor income,

$$d\log(Y_{it}) = g_{it} + \nu_{it}$$

(1.27)
\[ g_{it} = X'_{it}\beta \]  

(1.28)

\[ v_{it} \sim \mathcal{N}(0, \sigma_i^2) \]  

(1.29)

\[ \gamma_i^s \equiv \text{Cov}(v_{it}, v_{i_{t-s}}) \to 0, \text{ as } s \to \infty \]  

(1.30)

The assumption that the auto-covariance \( \gamma_i^s \) eventually dies down is necessary for OLS to produce consistent estimates of \( \beta \). If the variance of \( v_{it} \) differs among households and/or if some of the autocovariances of \( v_{it} \) are different from zero, then OLS will produce consistent estimates but it is not efficient. The reason is that the variance-covariance matrix of the shocks \( Q \) is not \( \sigma^2 I \). Instead,

\[
Q = \begin{bmatrix}
\sigma_1^2 & \gamma_1^1 & \ldots & \gamma_1^T \\
\gamma_1^1 & \sigma_1^2 & \ldots & \gamma_1^{T-1} \\
\vdots & \vdots & \ddots & \vdots \\
\gamma_1^{T-1} & \sigma_1^2 & \ldots & 0 \\
0 & 0 & \ldots & 0 \\
0 & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & 0 \\
\end{bmatrix}
\begin{bmatrix}
0 & 0 & \ldots & 0 \\
0 & 0 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & 0 \\
\sigma_2^2 & \gamma_2^1 & \ldots & \gamma_2^T \\
\gamma_2^1 & \sigma_2^2 & \ldots & \gamma_2^{T-1} \\
\vdots & \vdots & \ddots & \vdots \\
\gamma_2^{T-1} & \sigma_2^2 & \ldots & \sigma_2^2 \\
\end{bmatrix}
\]

(1.31)

The model of uncertainty estimated in the previous section used the variance \( \sigma_i^2 \) and autocovariances \( \gamma_i^s \) to identify the parameters of the earnings uncertainty model. For example, for the MA(1)-transitory model of uncertainty these moments are equal to
\[ \sigma^2 = \sigma_u^2 + 2(\rho_1^2 - \rho_1 + 1)\sigma_u^2 \]  
(1.32)

\[ \gamma^1 = -(1 - \rho_1)^2\sigma_u^2 \]  
(1.33)

\[ \gamma^2 = -\rho_1\sigma_u^2 \]  
(1.34)

for the years that zero income shocks do not occur. The individual household subscripts have been suppressed to keep the notation simple. Therefore, the earnings uncertainty parameter estimates can be used to estimate the moments \( \sigma^2 \), \( \gamma^1 \) and \( \gamma^2 \) and these can be used to construct an estimate \( \hat{Q} \) of the variance-covariance matrix for the \( dlog(Y) \) regression. If both the dependent and the independent variables are then pre-multiplied by \( \hat{Q}^{-\frac{1}{2}} \), then the resulting regression

\[ \hat{Q}^{-\frac{1}{2}}dlog(Y_{it}) = (\hat{Q}^{-\frac{1}{2}}X_{it})' \beta + \hat{Q}^{-\frac{1}{2}}u_{it} \]  
(1.35)

will have a covariance matrix of the form \( \tilde{\sigma}^2 I \) for some constant \( \tilde{\sigma} \). Therefore, under the null hypothesis that the model of uncertainty is correctly specified, a test of heteroskedasticity for equation 1.35 should reject. The estimator of \( \beta \) obtained by regressing \( \hat{Q}^{-\frac{1}{2}}dlog(Y_{it}) \) on \( \hat{Q}^{-\frac{1}{2}}X_{it} \) is the FGLS estimator.

In performing the above test, I used the uncertainty estimates derived above by demographic cell to construct \( \hat{Q} \). I then obtained the FGLS estimates using dummies for education, occupation and age as \( X_{it} \) and performed the White test for heteroskedasticity. The White test involves regressing the squared residuals on all the unique variables in the regression. Under the null hypothesis of no heteroskedasticity (spherical errors), the statistic \( N \mathcal{R}^2 \) is distributed as Chi-Square with \( P - 1 \) degrees of freedom, where \( N \) is the number of observations and \( P \) is the number of variables (not including the constant). The results of White's test for the MA(0)-MA(1) transitory shock specification are summarized in Table 10:
Table 10 Heteroskedasticity Tests for the FGLS Estimator

<table>
<thead>
<tr>
<th>Uncertainty Model</th>
<th>Statistic</th>
<th>5% Critical Value</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA(0)</td>
<td>28.10</td>
<td>33.93</td>
<td>7,026</td>
</tr>
<tr>
<td>MA(1)</td>
<td>27.40</td>
<td>33.93</td>
<td>7,026</td>
</tr>
<tr>
<td>MA(2)</td>
<td>28.10</td>
<td>33.93</td>
<td>7,026</td>
</tr>
<tr>
<td>No Model (a)</td>
<td>42.16</td>
<td>33.93</td>
<td>7,026</td>
</tr>
<tr>
<td>No Model (b)</td>
<td>353.7</td>
<td>21.03</td>
<td>16,683</td>
</tr>
</tbody>
</table>

(a) No model of uncertainty on the sample used for GMM.
(b) No model of uncertainty on the entire PSID sample.
Source: PSID 1978-83.

The first three rows report the results of the test for the model of earnings uncertainty under different MA structures for the transitory shock. All three specifications are not rejected by the model, since in neither of these cases does White's test reject. The fourth column reports the results for the same sample used in the GMM estimation when no uncertainty model is estimated. This corresponds to the assumption that all the shocks are permanent and that they have the same variance for all households. This specification is rejected, although not overwhelmingly so. The final column reports the results for the last assumption (i.e., all shocks are permanent and identically distributed across households) on the entire PSID sample, i.e. without dropping observations that experienced zero income events or family changes and also without dropping households in cells too small to use GMM on. The rejection in this case is very dramatic. These results imply that estimating the variance of the smaller shocks does improve the model of uncertainty (i.e., by allowing for heterogeneity and for temporary shocks) but that the biggest gain is realized by modeling large shocks that come from zero-income events and family compositional changes. Not surprisingly, Chapter 2 reported that it is the properties of these big shocks that have the biggest effect on household asset accumulation.
1.5 Measurement Error

When testing the specification of the model of uncertainty presented in this chapter, one has to consider the presence of measurement error. If measurement error was simply multiplicative white noise to the level of labor income, then its only effect would be to bias the estimates of transitory uncertainty upwards, but by the same amount for each household. So, any estimated slopes of the response of behavioral variables to transitory uncertainty would still be valid. In addition, the permanent uncertainty estimates would be unaffected.

Unfortunately, there is evidence that measurement error is not white noise, and is, in fact, correlated with demographic variables Duncan and Hill [1985]. If the magnitude of this effect were severe, it would prohibit use of the uncertainty estimates derived above by estimation on demographic cells. Pischke [1995] reports from the PSID that the reliability ratio, i.e., the ratio of the variance of true earnings to the ratio of the variance of reported earnings, varies from year to year from approximately 50% to 80%, and that its typically worse in boom years. He uses the PSID validation survey which is available for workers of a single plant, who were interviewed twice about their earnings in the period 1981-86. He is able to estimate a model of measurement error because the study also includes validation earnings for the entire period. He finds that a model of underreporting of the transitory component of earnings in addition to a white-noise measurement error component fits the data well. While the reliability ratio can be as low as 50%, his model suggests that the estimated transitory/permanent decomposition is roughly correct.

1.6 Conclusion

Dynamic models of earnings uncertainty are generally used in the literature without any justification for their form. This chapter set out to examine the merits of a model that al-
lowed for large transitory shocks to the level of labor income as well as smaller permanent and transitory shocks to its growth rate. The hypothesis was that the parameters of the earnings uncertainty process are determined by the household's demographic characteristics. The results obtained here suggest that the model is not overwhelmingly rejected, and often seems to fit the data quite well. The distinction between large and small shocks improves the fit substantially, while omitting permanent shocks worsens the fit but only marginally. Finally, there is some evidence that the transitory component of earnings is serially correlated over two years, even when permanent shocks are also estimated.


<table>
<thead>
<tr>
<th>Demographic Group</th>
<th>$\sigma_\eta$</th>
<th>$\sigma_\omega$</th>
<th>$g$</th>
<th>$\pi$</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Craftsmen NoHigh Age&lt;45</td>
<td>0.130</td>
<td>0.147</td>
<td>0.008</td>
<td>0.046</td>
<td>59</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.030)</td>
<td>(0.010)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>Craftsmen NoHigh Age&gt;45</td>
<td>0.101</td>
<td>0.167</td>
<td>-0.022</td>
<td>0.051</td>
<td>56</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.026)</td>
<td>(0.010)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Operators Laborers NoHigh Age&lt;45</td>
<td>0.171</td>
<td>0.142</td>
<td>0.008</td>
<td>0.061</td>
<td>129</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.016)</td>
<td>(0.008)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>Operators Laborers NoHigh Age&gt;45</td>
<td>0.134</td>
<td>0.128</td>
<td>-0.015</td>
<td>0.049</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.017)</td>
<td>(0.006)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Profes'ls High Age&lt;45</td>
<td>0.137</td>
<td>0.099</td>
<td>0.033</td>
<td>0.035</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.014)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>NotSelfEmp Managers High Age&lt;45</td>
<td>0.142</td>
<td>0.085</td>
<td>0.026</td>
<td>0.044</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.007)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Clerical High Age&lt;45</td>
<td>0.115</td>
<td>0.130</td>
<td>0.015</td>
<td>0.046</td>
<td>149</td>
</tr>
<tr>
<td>Sales Wrk</td>
<td>(0.017)</td>
<td>(0.013)</td>
<td>(0.004)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Clerical High Age&gt;45</td>
<td>0.164</td>
<td>0.096</td>
<td>-0.030</td>
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Standard errors in parentheses.
Table 3: MA(1) Model

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<td>0.044</td>
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Standard errors in parentheses.
Table 4: MA(2) Model

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<th>$\pi$</th>
<th>Obs</th>
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<td>0.046 (0.015)</td>
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<tr>
<td>Craftsman NoHigh Age≥45</td>
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<td>0.150 (0.059)</td>
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<td>-0.022 (0.010)</td>
<td>0.051 (0.013)</td>
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<td>0.176 (0.023)</td>
<td>0.261 (0.121)</td>
<td>0.157 (0.118)</td>
<td>0.008 (0.008)</td>
<td>0.061 (0.010)</td>
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<td>0.180 (0.019)</td>
<td>0.376 (0.103)</td>
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<td>-0.015 (0.006)</td>
<td>0.049 (0.011)</td>
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<td>0.035 (0.008)</td>
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<td>0.044 (0.011)</td>
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<td>0.141 (0.034)</td>
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<td>0.015 (0.004)</td>
<td>0.046 (0.008)</td>
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<td>0.038 (0.010)</td>
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<td>0.130 (0.091)</td>
<td>0.038 (0.005)</td>
<td>0.040 (0.006)</td>
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<td>0.012 (0.005)</td>
<td>0.040 (0.012)</td>
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<td>0.033 (0.006)</td>
<td>0.034 (0.009)</td>
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Standard errors in parentheses.
Table 5: MA(1) Model, First-step GMM vs. Efficient GMM

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<th>$\rho_1$</th>
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</tr>
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<td>NoHigh Age&lt;45</td>
<td>0.133 *</td>
<td>0.144 *</td>
<td>-0.019 *</td>
<td>0.008 *</td>
</tr>
<tr>
<td></td>
<td>(0.039) *</td>
<td>(0.045) *</td>
<td>(0.393) *</td>
<td>(0.010) *</td>
</tr>
<tr>
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<td>(0.068) *</td>
<td>(0.665) *</td>
<td>(0.010) *</td>
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<td><strong>Operators</strong></td>
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<td>0.008 0.001</td>
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<td>(0.026) (0.013)</td>
<td>(0.115) (0.110)</td>
<td>(0.007) (0.004)</td>
</tr>
<tr>
<td>Clerical Sales Wrk</td>
<td>0.066 0.060</td>
<td>0.158 0.142</td>
<td>0.177 0.179</td>
<td>0.015 0.015</td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>(0.035) (0.015)</td>
<td>(0.016) (0.010)</td>
<td>(0.071) (0.053)</td>
<td>(0.004) (0.003)</td>
</tr>
<tr>
<td>Clerical Sales Wrk</td>
<td>0.121 *</td>
<td>0.140 *</td>
<td>0.314 *</td>
<td>-0.030 *</td>
</tr>
<tr>
<td>High Age\geq45</td>
<td>(0.031) *</td>
<td>(0.024) *</td>
<td>(0.119) *</td>
<td>(0.009) *</td>
</tr>
<tr>
<td><strong>Craftsmen</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>0.122 0.125</td>
<td>0.153 0.126</td>
<td>0.284 0.176</td>
<td>0.010 0.011</td>
</tr>
<tr>
<td></td>
<td>(0.014) (0.011)</td>
<td>(0.012) (0.010)</td>
<td>(0.061) (0.078)</td>
<td>(0.004) (0.003)</td>
</tr>
<tr>
<td>Craftsmen High Age\geq45</td>
<td>0.090 *</td>
<td>0.169 *</td>
<td>0.371 *</td>
<td>-0.010 *</td>
</tr>
<tr>
<td></td>
<td>(0.042) *</td>
<td>(0.025) *</td>
<td>(0.083) *</td>
<td>(0.007) *</td>
</tr>
<tr>
<td><strong>Operators</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>0.103 0.102</td>
<td>0.148 0.139</td>
<td>0.160 0.112</td>
<td>0.008 0.007</td>
</tr>
<tr>
<td>Laborers</td>
<td>(0.017) (0.012)</td>
<td>(0.013) (0.010)</td>
<td>(0.071) (0.071)</td>
<td>(0.004) (0.003)</td>
</tr>
<tr>
<td>High Age\geq45</td>
<td>0.088 *</td>
<td>0.132 *</td>
<td>0.085 *</td>
<td>-0.020 *</td>
</tr>
<tr>
<td>Laborers</td>
<td>(0.052) *</td>
<td>(0.047) *</td>
<td>(0.270) *</td>
<td>(0.007) *</td>
</tr>
<tr>
<td><strong>SelfEmpl</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>0.115 0.141</td>
<td>0.168 0.106</td>
<td>0.272 0.103</td>
<td>0.010 0.021</td>
</tr>
<tr>
<td></td>
<td>(0.038) (0.016)</td>
<td>(0.026) (0.018)</td>
<td>(0.086) (0.165)</td>
<td>(0.008) (0.006)</td>
</tr>
<tr>
<td>Profes's Coll Age&lt;45</td>
<td>0.138 0.115</td>
<td>0.113 0.101</td>
<td>0.215 0.280</td>
<td>0.038 0.033</td>
</tr>
<tr>
<td></td>
<td>(0.016) (0.012)</td>
<td>(0.013) (0.011)</td>
<td>(0.105) (0.084)</td>
<td>(0.005) (0.004)</td>
</tr>
<tr>
<td>Profes's Coll Age\geq45</td>
<td>0.082 *</td>
<td>0.125 *</td>
<td>0.166 *</td>
<td>0.012 *</td>
</tr>
<tr>
<td></td>
<td>(0.046) *</td>
<td>(0.031) *</td>
<td>(0.110) *</td>
<td>(0.005) *</td>
</tr>
<tr>
<td>NotSelfEmp Managers</td>
<td>0.108 *</td>
<td>0.089 *</td>
<td>-0.141 *</td>
<td>0.033 *</td>
</tr>
<tr>
<td>Coll Age&lt;45</td>
<td>(0.017) *</td>
<td>(0.024) *</td>
<td>(0.352) *</td>
<td>(0.006) *</td>
</tr>
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</table>

Standard errors in parentheses; (*) denotes estimation was not possible; efficient estimates in italics.
Table 6: Specification Tests, GMM vs. Efficient GMM

<table>
<thead>
<tr>
<th>Demographic Group</th>
<th>MA(0)</th>
<th>MA(1)</th>
<th>MA(2)</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Craftsmen</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NoHigh Age&lt;45</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>NoHigh Age≥45</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Operators</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laborers NoHigh</td>
<td>67.54</td>
<td>57.76</td>
<td>67.85</td>
<td>55.90</td>
</tr>
<tr>
<td>Age&lt;45</td>
<td>64.82</td>
<td>53.17</td>
<td>64.82</td>
<td>53.15</td>
</tr>
<tr>
<td>Profes's</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>65.97</td>
<td>48.11</td>
<td>66.51</td>
<td>47.73</td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Managers High</td>
<td>55.60</td>
<td>35.95</td>
<td>56.82</td>
<td>36.13</td>
</tr>
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<td>Clerical Sales Wrk</td>
<td>78.95</td>
<td>55.29</td>
<td>63.92</td>
<td>49.77</td>
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<td>*</td>
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<td>*</td>
</tr>
<tr>
<td>Clerical Sales Wrk</td>
<td>High Age≥45</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Craftsmen</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>103.40</td>
<td>87.09</td>
<td>100.86</td>
<td>86.30</td>
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<tr>
<td>High Age≥45</td>
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<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Operators</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laborers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>54.73</td>
<td>43.19</td>
<td>49.49</td>
<td>41.83</td>
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<tr>
<td>High Age≥45</td>
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<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SelfEmpl</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Age&lt;45</td>
<td>58.64</td>
<td>37.08</td>
<td>64.18</td>
<td>37.64</td>
</tr>
<tr>
<td>Profes's</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coll Age&lt;45</td>
<td>103.27</td>
<td>74.32</td>
<td>99.22</td>
<td>71.31</td>
</tr>
<tr>
<td>Profes's</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coll Age≥45</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Managers Coll</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age&lt;45</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

5% Critical Value: $\chi^2_{33} = 47.12$, $\chi^2_{32} = 45.91$, $\chi^2_{31} = 44.70$

(*): denotes estimation was not possible; efficient estimates in italics.
Table 7: Specification Tests for the importance of Zero-Income Shocks

<table>
<thead>
<tr>
<th>Demographic Group</th>
<th>Zero-Income Shocks</th>
<th>No Zero-Income Shocks</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Craftsmen</td>
<td>NoHigh Age&lt;45</td>
<td>31.22</td>
<td>38.40</td>
</tr>
<tr>
<td>Craftsmen</td>
<td>NoHigh Age≥45</td>
<td>42.23</td>
<td>50.08</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>NoHigh Age&lt;45</td>
<td>31.81</td>
<td>30.01</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>NoHigh Age≥45</td>
<td>18.66</td>
<td>63.71</td>
</tr>
<tr>
<td>Profes'ls</td>
<td>High Age&lt;45</td>
<td>27.33</td>
<td>25.01</td>
</tr>
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<td>High Age&lt;45</td>
<td>21.95</td>
<td>25.67</td>
</tr>
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<td>Clerical Sales Wrk</td>
<td>High Age&lt;45</td>
<td>26.04</td>
<td>27.16</td>
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<td>65.57</td>
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<td>50.65</td>
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<tr>
<td>Craftsmen</td>
<td>High Age≥45</td>
<td>33.55</td>
<td>71.66</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>High Age&lt;45</td>
<td>12.55</td>
<td>26.00</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>H:\h Age≥45</td>
<td>33.43</td>
<td>51.40</td>
</tr>
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<td>SelfEmpl</td>
<td>High Age&lt;45</td>
<td>19.29</td>
<td>20.79</td>
</tr>
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<td>Profes'ls</td>
<td>Coll Age&lt;45</td>
<td>28.52</td>
<td>34.63</td>
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<tr>
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<td>Coll Age≥45</td>
<td>43.28</td>
<td>71.51</td>
</tr>
<tr>
<td>NotSelfEmp Managers</td>
<td>Coll Age&lt;45</td>
<td>25.23</td>
<td>22.39</td>
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</table>

5% Critical Value: $\chi^2_{19} = 30.14$  

MA(2) models estimated for both cases.
<table>
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<th>$\sigma_u$</th>
<th>$\rho_1$</th>
<th>$\rho_2$</th>
<th>$g$</th>
<th>Obs</th>
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<td></td>
<td>(0.015)</td>
<td>(0.119)</td>
<td>(0.121)</td>
<td>(0.010)</td>
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<tr>
<td></td>
<td>(0.018)</td>
<td>(0.138)</td>
<td>(0.122)</td>
<td>(0.010)</td>
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<tr>
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<td>(0.011)</td>
<td>(0.054)</td>
<td>(0.069)</td>
<td>(0.008)</td>
<td>129</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.081)</td>
<td>(0.082)</td>
<td>(0.006)</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.096)</td>
<td>(0.120)</td>
<td>(0.006)</td>
<td>95</td>
</tr>
<tr>
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<td>(0.010)</td>
<td>(0.098)</td>
<td>(0.113)</td>
<td>(0.007)</td>
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<tr>
<td></td>
<td>(0.010)</td>
<td>(0.121)</td>
<td>(0.103)</td>
<td>(0.004)</td>
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<td>(0.012)</td>
<td>(0.065)</td>
<td>(0.072)</td>
<td>(0.009)</td>
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</tr>
<tr>
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<td>(0.007)</td>
<td>(0.049)</td>
<td>(0.050)</td>
<td>(0.004)</td>
<td>268</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.075)</td>
<td>(0.108)</td>
<td>(0.007)</td>
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<td>(0.004)</td>
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<td>(0.229)</td>
<td>(0.249)</td>
<td>(0.007)</td>
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<tr>
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<td>(0.135)</td>
<td>(0.132)</td>
<td>(0.008)</td>
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<tr>
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<td>(0.009)</td>
<td>(0.054)</td>
<td>(0.052)</td>
<td>(0.005)</td>
<td>216</td>
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<tr>
<td></td>
<td>(0.018)</td>
<td>(0.329)</td>
<td>(0.295)</td>
<td>(0.005)</td>
<td>75</td>
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<tr>
<td></td>
<td>(0.008)</td>
<td>(0.103)</td>
<td>(0.080)</td>
<td>(0.006)</td>
<td>81</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.
Table 9: Specification Tests for the importance of Permanent Shocks

<table>
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<tr>
<th>Demographic Group</th>
<th>Permanent Shocks</th>
<th>No Permanent Shocks</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Craftsmen</td>
<td>NoHigh Age&lt;45</td>
<td>31.22</td>
<td>59</td>
</tr>
<tr>
<td></td>
<td>NoHigh Age≥45</td>
<td>42.23</td>
<td>56</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>NoHigh Age&lt;45</td>
<td>31.81</td>
<td>129</td>
</tr>
<tr>
<td>Operators Laborers</td>
<td>NoHigh Age≥45</td>
<td>18.66</td>
<td>85</td>
</tr>
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<td>Profes’ls</td>
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<td>95</td>
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<td>NotSelfEmp Managers</td>
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<td>87</td>
</tr>
<tr>
<td>Clrcl Sales Wrk</td>
<td>High Age&lt;45</td>
<td>26.04</td>
<td>149</td>
</tr>
<tr>
<td>Clrcl Sales Wrk</td>
<td>High Age≥45</td>
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<td>74</td>
</tr>
<tr>
<td>Craftsmen</td>
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<td>Craftsmen</td>
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</tr>
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<td>235</td>
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<td>59</td>
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<tr>
<td>SelfEmpl</td>
<td>High Age&lt;45</td>
<td>19.29</td>
<td>111</td>
</tr>
<tr>
<td>Profes’ls</td>
<td>Coll Age&lt;45</td>
<td>28.52</td>
<td>216</td>
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<tr>
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<td>Coll Age≥45</td>
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<td>75</td>
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<td>NotSelfEmp Managers</td>
<td>Coll Age&lt;45</td>
<td>25.23</td>
<td>81</td>
</tr>
</tbody>
</table>

$5\%$ Critical Value: $\chi^2_{19} = 30.14$, $\chi^2_{18} = 28.87$

MA(2) models estimated for both cases.
Figure 1A
The Whole Distribution of dlog(inc) •• Kurtosis = 145

Figure 1B
The Dist of dlog(inc) without Zero-Inc events •• Kurtosis = 6.77

45
Chapter 2

Stocks for the Old? Evidence from Household Portfolios

2.1 Introduction

Approximately three quarters of U.S. households do not directly hold any stocks at all Mankiw and Zeldes [1991]. Even if one takes into account stocks held indirectly (e.g., through pension plans), non-stockholders are still the majority Haliassos and Bertaut [1995]. However, households that do not hold stocks often have sizeable holdings of risk-free assets, as will be shown here. This empirical regularity has proven quite puzzling considering the substantial historical premium of equity over essentially risk-free assets, even if one takes into account the risk inherent in holding stocks. Since 1925, the return on the US stock market has been approximately eight percentage points higher than the return of essentially risk-free US assets.¹

¹The return on equity is taken to be the nominal simple return (including dividends) on the CRSP NYSE-AMEX value-weighted portfolio and the risk-free return to be the return on 1-month US T-Bills (monthly data). Note that the 1-month US T-Bills are not exactly risk-free since the rate of inflation may change. However, over a period of one month this risk is negligible. Also, its not clear that the
Under complete markets, standard intertemporal models of portfolio choice (such as Samuelson [1969] and Merton [1971]) suggest that households should hold a substantial share of their total wealth in equity. In this case, total wealth includes all financial assets as well as the appropriately capitalized value of the labor income stream. Given the historical distribution of returns, the share of total wealth in equity should be well over one half if relative risk aversion is under five. That the majority of households do not hold any stocks at all among their financial assets is thus a "stockholding puzzle" Haliassos and Bertaut [1995]. Furthermore, these models suggest that — absent changes in the investment opportunities set — the share of total wealth in equity should be constant. Yet, I will show that as households age and their remaining labor income stream is getting exhausted, they hold a higher share of their financial wealth in equity.

In practice, household labor income is quite risky (e.g., due to the possibility of job loss) and only partially insurable. In fact, survey data show that being prepared for emergencies is the most common reason people offer when asked why they save Carroll [1997]. If households are unable to smooth negative small (transitory) shocks by borrowing, or if shocks are big (permanent) in terms of the appropriate measure of life-time resources, labor income risk will have a major effect on asset accumulation. As long as consumers are prudent, the risk in labor income generates an additional source of demand for savings. Furthermore, the presence of this background uninsurable risk in labor income will also affect the individuals' attitudes toward other forms of risk, such as financial risk, even if the two risks are independent.²

²The definition of prudence is that marginal utility be convex; Kimball [1993] analyzes prudence in a fashion similar to risk-aversion. The effect of uninsurable labor income risk on savings and portfolio choice was first studied in a two-period model by Dreze and Modigliani [1972]. Early studies characterizing precautionary saving were Blanchard and Mankiw [1988], Skinner [1988], Kimball and Mankiw [1989], Zeldes [1989], Caballero [1991], Carroll [1991] and Deaton [1991]. Elmendorf and Kimball [1991]
The hypothesis to be tested in this paper is the following: If the typical young household's savings is mainly a small buffer stock against income shocks, then the depressed demand for highly volatile stocks until the later parts of the life-cycle may be consistent with optimal behavior, even if labor income risk is independent of stock returns. This hypothesis is an extension of the buffer-stock hypothesis introduced by Carroll [1991] and Deaton [1991] to the consumption literature. Allowing for a risk-free asset only, the buffer-stock consumption literature has claimed some success in explaining life-cycle asset accumulation patterns.

In this chapter, the above hypothesis is evaluated empirically by investigating the behavior of stockholding and total wealth accumulation at the household level. This is accomplished using micro data from Michigan University's Panel Study of Income Dynamics. Labor income processes are estimated at the individual level by assuming that the parameters of interest are determined by demographic characteristics. Subsequently, the estimates of the labor income process parameters are used as explanatory variables in regressions that allow the decision to hold stocks to be different from the share of stocks held (conditional on being a stockholder). While some demographic variables affect the stockholding decision only (indicating the presence of exogenous factors not captured by the model), age and labor income risk affect both decisions similarly, in line with the buffer-stock hypothesis advanced above. However, the response of total asset holdings to labor income risk is rather puzzling, since different forms of income risk are found to have

and Carroll and Kimball [1996] offer analytical results concerning the behavior toward other risks, and necessary restrictions on preferences to get the response of more asset accumulation and fewer risky assets in the presence of uninsurable risks.

Of course, this effect would become ever stronger if zero-income events tended to coincide with negative stock market shocks. Although an equilibrium model of the asset markets and the labor market is beyond the scope of this study, such an assumption is not unrealistic if both markets are subject to common aggregate shocks.
different effects.

This chapter is structured as follows: Section 2 estimates labor income processes by demographic groups, while Section 3 presents the empirical analysis of stock holding and total asset accumulation. Section 4 briefly surveys any related literature not yet discussed, and Section 5 concludes.

2.2 Labor Income Process Estimation

The ultimate goal of this chapter is to study portfolio choice and total asset accumulation at the household level in the presence of labor income risk. Such a task requires estimates of the individual household labor income process parameters matched with the household's asset information. This type of data is provided by the University of Michigan's Panel Study of Income Dynamics (PSID). The next section will employ asset information from the 1984 wealth supplement of the PSID, so this section will estimate the parameters of individual labor income processes from a panel household income data. The panel consists of 32,249 observations of real after-tax labor income from one- and two-earner households whose head was either employed or looking for work during the period 1977-83. For years during which the head or the spouse of the household changed, labor income was coded as missing (affecting 8,074 observations) because it reflected shocks presumably unrelated to the labor income process.

2.2.1 The Labor Income Process

The labor income model estimated in this section is the one analyzed in Chapter 1. At age $t + 1$ the household receives labor income $\hat{Y}_{t+1}$, which is uncertain as of period $t$ and uninsurable. The evolution of labor income during the working life of the household is governed by a deterministic growth rate and two multiplicative shocks to the level of labor
income, a permanent shock and a transitory shock. Specifically,

\[
\dot{Y}_{t+1} = \dot{Y}_{t+1}^p \tilde{\epsilon}_{t+1}, \quad \text{and} \\
\dot{Y}_{t+1}^p = G_{t+1} Y_t^p \tilde{\mathcal{H}}_{t+1}
\]

where \( \dot{Y}_{t+1}^p \) is the permanent component of labor income, \( G_{t+1} \) is the age-specific, non-random component of the change in permanent income between periods \( t \) and \( t+1 \), \( \tilde{\mathcal{H}}_{t+1} \) is the permanent multiplicative shock to the level of labor income, and \( \tilde{\epsilon}_{t+1} \) is the transitory multiplicative shock to the level of labor income.

The permanent and transitory shocks are assumed to be distributed independently of one another. The permanent income shock \( \tilde{\mathcal{H}}_{t+1} \) is strictly positive and its log (denoted \( \tilde{\eta}_{t+1} \)) is assumed to be unconditionally normally distributed with mean zero and variance \( \sigma_{\eta t+1}^2 \):

\[
\ln(\tilde{\mathcal{H}}_{t+1}) \equiv \tilde{\eta}_{t+1} \sim \mathcal{N}(0, \sigma_{\eta t+1}^2)
\]

On the other hand, the transitory shock is assumed to be state-dependent. There are only two possible states, a "good" state that occurs with probability \( 1 - \pi_{t+1} \) and a "bad" state that occurs with probability \( \pi_{t+1} \). In the good state, the transitory shock \( \tilde{\epsilon}_{t+1} \) is strictly positive and its log (denoted \( \tilde{\epsilon}_{t+1} \)) is normally distributed with mean zero and variance \( \sigma_{\epsilon t+1}^2 \). In the bad state the transitory shock is zero. Therefore:

\[
\begin{cases}
\ln(\tilde{\epsilon}_{t+1}) \equiv \tilde{\epsilon}_{t+1} \sim \mathcal{N}(0, \sigma_{\epsilon t+1}^2) \quad \text{with probability } 1 - \pi_{t+1} \\
\epsilon_{t+1} = 0 \quad \text{with probability } \pi_{t+1}
\end{cases}
\]

Since both shocks are multiplicative to the level of labor income, an occurrence of the bad state for the transitory shock forces labor income to zero for that period, but does not affect the evolution of the permanent component of income. For example, the bad
state can be thought of as temporary involuntary unemployment, which does not affect the earnings potential of the individual. Finally, the probability of the bad state as well as the variances of both the smaller shocks are age-dependent.

Variants of this model of earnings uncertainty have been estimated repeatedly in the consumption literature. However, the approach has almost always been to drop the low income observations. Such a practice is unacceptable for the type of exercise considered in this paper, since it is known that the possibility that bad states may occur can have a very profound effect on behavior. Even if their probability of occurrence is low, marginal utility rises very fast near zero, so that the household will modify its behavior to avoid big drops in consumption. Thus, one of the main determinants of behavior under uncertainty is the probability of occurrence of these “catastrophic” labor income events, and any empirical exercise studying this type of behavior must account for these events. So, zero income events are incorporated in the estimation of the labor income process.

The particular model used in this paper has been chosen because it fits the data well, as has been shown in Chapter 1: the above specification of the labor income process cannot be rejected. Note, however, that the model does not account for measurement error. Recent work by Pischke [1995] on measurement error in the PSID labor income data has found that 50-80% of the variability in reported earnings is due to actual signal, with measurement error being more pronounced in boom years. Fortunately, he also finds that the estimated permanent/transitory decomposition using reported earnings (rather than actual) is roughly correct. In unreported estimation, I found that measurement error corrections for labor income as proposed by Pischke [1995] did not significantly affect the results of this chapter.

The analysis is conducted in two stages. The first stage estimates the properties the zero-income events (the bad state), while the second stage estimates the properties of the permanent shock, the transitory shock and the growth rate of permanent income
conditional on a good state.

2.2.2 Zero Income Events

The need for a separate process for zero-income events is clear from the distribution of the change in log income, $dlnY$, presented in Figure 1A. The superimposed normal distribution with matching mean and variance demonstrates that the distribution of $dlnY$ has fat tails, which seem to be the result of a separate process. Both tails are fat: the left tail is the result of sharp drops in labor income, while the right tail is the result of sharp increases. As confirmed by inspection, both tails are almost always associated with entry into or exit from unemployment.⁴

Zero income events are defined here as occurrences when the level of labor income drops to below half of the average income for the household (calculated over the other years of the sample). Approximately six percent of the observations of labor income were classified as zero-income events, and the median drop associated with these events was to ten percent of last year’s income. The probability of a zero income event by demographic cell is presented in the fourth column of Tables 1A-1C. Each cell is comprised of yearly observations of households that have specific demographic characteristics as described in the tables (the age group was selected using the head’s age in 1983). The probability of a zero income event for each cell was subsequently calculated as the percentage of total observations in that cell that were classified as zero income events.

Omitting the zero-income events, the distribution of $dlnY$ (presented in Figure 1B) seems to be approximated fairly well by the normal distribution and has much slimmer tails. Therefore, it is not unreasonable to assume that the distribution in Figure 1B has been generated as the sum of two normal random variables, a permanent shock and a

⁴Note that the distribution cannot be approximated (up to a constant factor) well at all by the $t$-distribution either, since fitting the tails results in grossly over-estimating the variance of the distribution.
transitory shock, which are estimated next.

2.2.3 Smaller Shocks and the Growth Rate of Permanent Income

The normality of the log shocks, which was assumed for simplicity in the calibrations presented in the last section, is not required in order to identify the means and variances of the shocks. However, if the distribution of the shocks is not normal, then, in general, other moments of the distribution will affect optimal policies. That is exactly the reason why the shocks are separated into zero income shocks and smaller shocks: once the zero income shocks have been removed, the distribution of the change in labor income seems to be adequately described as normal.

The moments of the permanent and transitory shocks can be recovered by exploiting the moments of the distribution of $dlnY$ conditional on a good state, i.e., for the years that were not classified as zero income shocks. For example, for two consecutive non-zero-income years, the model of labor income uncertainty implies that

$$dy_{t+1} = y_{t+1} - y_t = g_{t+1} + \tilde{\eta}_{t+1} + \tilde{\epsilon}_{t+1} - \tilde{\epsilon}_t$$

where lower case letters denote logs of their capital-letter counterparts, and where the individual household subscript has been suppressed. Under the assumption that the moments of the permanent and transitory shocks are constant for each individual for certain age groups, the deterministic part of the growth rate of permanent income and the variances of the permanent and transitory shocks (all in log terms) can be recovered using the implied moment restrictions. For example, suppose that for ages $t$ through $t+5$ the set of parameters of the earnings process are constant and they are each denoted by the subscript $\alpha$. The moment restrictions would then take the following form:
\[ E[dy_\tau] = g_\alpha, \quad \tau = (t + 1)\ldots(t + 5) \tag{2.6} \]
\[ \text{Var}(dy_\tau) = \sigma^2_\eta_\alpha + 2\sigma^2_\epsilon_\alpha, \quad \tau = (t + 1)\ldots(t + 5) \tag{2.7} \]
\[ \text{Cov}(dy_{\tau+1}, dy_\tau) = -\sigma^2_\epsilon_\alpha, \quad \tau = (t + 1)\ldots(t + 4) \tag{2.8} \]

where the means of the log shocks have been normalized to zero.

In principle, the above restrictions can be used to identify the three underlying parameters \((g_\alpha, \sigma^2_\eta_\alpha \text{ and } \sigma^2_\epsilon_\alpha)\) at the individual level by using the sample moments for any household with three consecutive non-zero-income observations of \(dlnY\), i.e., six consecutive observations of \(Y\). While the results would be unbiased, they would also undoubtedly be full of measurement error, as a result of estimating moments using so few observations. This problem, which is a direct consequence of the short-time series dimension of the sample, can be overcome by exploiting the cross-sectional dimension of the data set to estimate the parameters of interest.\(^5\)

Suppose that there is an underlying model of earnings uncertainty, such that people with similar demographic characteristics have similar uncertainty profiles. In that case, the unbiased estimates of uncertainty at the individual level can be estimated by demographic group. The predicted earnings uncertainty parameters can then be used in the second stage as explanatory variables in the main regression. However, to achieve identification of the portfolio decision (i.e., the second stage), the model of uncertainty (i.e., the first stage) must include at least one variable (instrument) that is not included in the portfolio regression. Here, I use dummies for occupational categories to achieve identification.\(^6\) Note that – as pointed out by Lusardi [1997] – this choice of instruments

---

\(^5\) Even so, the standard errors of the second stage estimation would have to be corrected to reflect the fact that the uncertainty parameters have been estimated in the first stage Newey and McFadden [1994]. This issue will be discussed in the next section.

\(^6\) Skinner [1988] uses occupation as a proxy for earnings risk and does not find much evidence in favor
is problematic if people select themselves into occupations on the basis of their degree of risk aversion. Fortunately, Lusardi reports from a sample of Italian households that only 10% of workers list job security as the main reason behind their occupational choice.\footnote{On the other hand, she also notes that the percentage increases to 50% when considering all the answers which mention job security in conjunction with other factors. Lusardi then proceeds to estimate asset accumulation by instrumenting each household's perceived earnings variance on regional unemployment rates. She finds that – relative to the OLS estimates – the contribution of precautionary savings to total asset accumulation increases substantially. However, the results to be presented next suggest that large shocks (associated with unemployment) are the most important shocks for the precautionary motive. This casts doubt on whether regional unemployment rates are appropriate instruments. As always, a perfect instrument is very hard to come by...}

I use the Generalized Method of Moments (GMM) estimator of Hansen [1982], Hansen and Singleton [1996], Newey [1984], Newey [1985b] and Newey [1985a] to derive the estimates of the uncertainty parameters for the first stage. I assume that the parameters of the earnings uncertainty process are the same across similar demographic groups so that the moment restrictions of equations 2.6-2.8 can be estimated within demographic cells. These cells are defined by occupational group (Professionals; Self-Employed Managers; Non-Self-Employed Managers; Clerical-Sales Workers; Craftsmen; Operators-Laborers; Farmers; Service Workers), age group (over or under 45) and educational-attainment group (less than high-school, at least high-school but not college, at least college). The identifying assumption for the analysis of asset holding behavior that follows is that occupation affects asset holdings only through its effect on earnings uncertainty.

Columns 2 and 3 in Tables 1A-1C present the GMM estimates of the standard deviation of the log permanent and log transitory shocks, respectively, derived using the identity matrix as the weighting matrix. It is not possible to calculate standard errors for the GMM-estimated parameters directly. The reason is that the panel used for each cell is unbalanced in the sense that not all households have the same number of observations.
due to zero-income events. While the unbalanced nature of the panel does not affect the point estimates, it raises the question of what is the correct scalar that should be used to divide the variance-covariance matrix by, in order to derive the asymptotic $\chi^2$ statistics, standard errors, etc. One way around this problem is to estimate the model using as few yearly observations as possible, and only on observations were all the moments are present. In unreported estimation, I found that the coefficients estimates derived that way were very close to the ones presented in columns 2 and 3 of Tables 1A-1C, and usually significantly different from zero at the 95% level. The insignificant estimates were always associated with cells that had very few observations.

The assumption that the uncertainty parameters are constant for the period considered yields over-identifying restrictions, which unfortunately cannot be tested for the entire sample, given the unbalanced nature of the panel. In Chapter 1, a test of the unbalanced model was provided, and its specification was not rejected. Also, in unreported tests of the over-identifying restrictions for subsets of each group that were not missing any moments, I found that the asymptotic $\chi^2$ statistic is generally close to the critical 95% level. Of course, for the small cells that GMM yields negative estimates for one or both the variances, the model is clearly rejected. Allowing for an MA(1) structure for the transitory shock improved the results, leading to fewer cells rejecting the over-identifying restrictions. I also experimented with efficient GMM estimation on the subsets of each group that were not missing any moments (recall efficient GMM estimation requires a consistent estimate of the variance-covariance matrix, which is not available for the unbalanced subset). For the biggest cells, efficient GMM typically improved the fit of the model without really affecting the parameter estimates; for smaller cells, however, efficient GMM produced quite different point estimates. This is not surprising or particularly worrisome: we know from Altonji and Segal [1994] that efficient GMM has worse small sample properties than regular GMM (i.e., GMM using the identity matrix as the weighting matrix).
The estimate for $g_a$, which is the average growth rate of income $E[d\ln Y_t]$ (and also the average growth rate of permanent income), is given in Column 5. For comparison to the literature, Column 6 also reports the growth rate of average income (which corresponds to the slope of average income profiles, as estimated by Carroll and Summers [1989] and others). It is derived by correcting for the effect on the growth rate of average income due to the positive mean multiplicative transitory shock to the level of income. The correction is necessary given the initial normalization that the log of the smaller shocks were mean zero.

Finally, note that the results presented in Tables 1A-1C for the small shocks and for the growth rates are similar to those obtained by other researchers (e.g., Carroll and Samwick [1992], Pischke [1995] and Carroll and Summers [1989]).

2.3 Asset Accumulation and Portfolio Choice

The hypothesis advanced in this paper is that the typical young household's savings is mainly a buffer stock against income shocks, held as in imperfect form of insurance necessitated by the inability of the household to borrow in bad times. *Ceteris paribus*, households facing more uncertainty should save more according to this hypothesis. This is one testable implication. The focus of this study, however, is portfolio choice. As the background risk in uninsurable labor income increases, households have a lower tolerance for other independent risks (such as financial risk), and this effect tends to depress the share of risky assets in the household portfolio. On the other hand, the positive wealth effect due to the increase in savings tends to increase the share of risky assets held, because the risk now affects a smaller portion of total household resources. Which effect dominates has to be settled empirically, although it is shown in Chapter 3 that the risk tolerance effect tends to outweigh the wealth effect in simulations (unless the initial level of wealth
is extremely low). Finally, the buffer-stock model also suggests that as households age and the effect of the borrowing constraint is weakened (because financial wealth is higher and because the growth rate of income slows down), households should hold more risky assets, even as the present discounted value of expected future labor income diminishes. Armed with the estimates of earnings uncertainty derived above, the wealth information from the 1984 PSID wave can now be used to investigate portfolio choice at the household level.  

2.3.1 Household Portfolio Behavior

A major issue in the empirical investigation is that only a small fraction of households actually hold stocks (see, also, Mankiw and Zeldes [1991] and Haliassos and Bertaut [1995]). In my sample of over four thousand households, only 22% responded “yes” to the question:

Do you (or anyone in your family living there) have any shares of stock in publicly held corporations, mutual funds, or investment trusts, including stocks in IRA’s?

Using the PSID family weights, this implies that only 29% of US households held stocks in 1984. Among non-stockholders, the median holdings of “essentially” risk-free assets (such as cash or savings accounts) was slightly over $1,000, although some non-stockholding households held significant amounts. For example, the top 5% of non-stockholders held more than $40,000 in risk-free assets, while a few non-stockholding households reported holdings of risk-free assets well in excess of $100,000.

8Ideally, an estimate of each household’s ability to borrow would be included in this analysis. Unfortunately, I do not have such information in my sample. Evidence supporting the buffer-stock model’s implications of the effects of borrowing constraints can be found in Income risk and portfolio choice [1996].

9All dollar figures are in 1997 dollars.
That households have positive amounts of risk-free assets while holding no risky assets at all, is in contrast to the predictions of any expected utility model of risk averse consumers facing positive mean risks. Such models predict that even households that accumulate very little financial wealth should hold a positive amount of stocks, however small. Undoubtedly, there are reasons outside such stylized models, such as fixed costs associated with investing in risky assets, why so many households do not hold any stocks. A cursory look at the non-stockholders suggests that small costs and reasonable minimum investment requirements may well explain this behavior for the majority of households: for example, approximately 75% of non-stockholders held less than $5,000 in risk-free assets.\textsuperscript{10}

There is no evidence so far on whether the decision to enter the stock market can be described as a simple transformation of each household’s theoretically desirable holdings of risky assets. One example of such a strategy would be that households enter the stock market only if their optimal stock holdings are above a certain amount which is a function of costs associated with investing in stocks. In that case, a censored regression model such as Tobit would be appropriate. Such an approach is used by Income risk and portfolio choice [1996], who have asset holdings and subjective earnings variance information from a sample of Italian households. However, it is also possible that stock market participation is a very different decision from the decision of how many stocks to hold (conditional on being a stockholder), even if both decisions depend on the same set of variables. If that is indeed the case, then the Tobit estimates would be biased. Using the same set of variables for both decisions (to be described shortly), I tested whether the variables affect each decision in the same manner using a likelihood ratio test found in Greene [1993]. The test overwhelmingly rejects the hypothesis that the two decisions are the same. In

\textsuperscript{10}The author has found out from personal experience that until very recently, the minimum requirement for opening a stock brokerage account with most financial companies was in fact $5,000.
fact, the likelihood ratio test statistic for that test is negative! However, the small sample size of stockholders casts some doubt on the rejection.

To avoid the above problems, I use instead the Heckman [1979] two-step estimator for sample selection and allow the two decisions to differ. I estimate the following model of household stock-holding behavior:

**The Decision to Hold Stocks**

\[ z_i^* = \delta'w_i + u_i, \text{ household holds stocks if } z_i^* > 0 \]  

(2.9)

**The Share in Stocks**

\[ Share_i = \zeta'x_i + v_i, \text{ observed only if } z_i^* > 0 \]  

(2.10)

where \( w_i \) is a vector of variables that affect the decision of household \( i \) to hold stocks, \( x_i \) is a vector of variables that affect the share of stocks held by household \( i \) conditional on the household holding stocks, and where \( u_i \) and \( v_i \) are assumed to have a bivariate normal distribution with correlation coefficient \( \rho \). The two-step Heckman procedure estimates the model by performing a probit regression for the first stage, and then using the estimated coefficients to calculate and correct for the bias introduced in the second stage by the first stage truncation. An in depth discussion of the mechanics of the estimation procedure can be found in Chapter 3, Section 3.

The share in stocks for household \( i \) is defined as

\[ Share_i = \frac{Stocks_i}{Stocks_i + RiskFreeAssets_i} \]  

(2.11)

based on the wealth supplement of the 1984 PSID wave. While I had other wealth information at my disposal, such as the total of bond holdings, insurance policies, private pension claims and real estate (other than home), it is hard to classify them as risky versus risk-free since their composition is not known. Furthermore, the value of businesses and
farms was excluded from the share calculation, since it is the asset whose dividend is labor income, and in this exercise it is accounted for by the earnings profile parameters. However, the earnings of businessmen may be more correlated with the returns on the stock market. For this reason, I will also estimate both decisions for the sub-sample that does not include any self-employed workers. The effect of business risk on stockholding has been examined by Heaton and Lucas [1997].

Both decisions are allowed to be affected by age; the level of permanent income (computed as average income for the period 1977-1983 excluding the years that were classified as zero income events); the difference between current and permanent income; the presence of a spouse; the share of the spouse's income in total labor income; the number of children; whether there had been a change in the head or the spouse in the past year; and the following four parameters describing the process for labor earnings: the deterministic growth rate of permanent income, the probability of zero income, and the standard deviation of the smaller permanent and transitory shocks. I have not attempted to estimate the effect of the correlation between labor income shocks and the stock market, because I was unable to find evidence that (by demographic group) this correlation is not zero. I found some evidence of a positive correlation over lower frequencies, but I have not yet pursued this.

To achieve identification for both decisions, there has to be at least one unique variable that affects one decision but not the other. One can certainly obtain consistent parameter estimates by having the exact same set of variables affect both decisions, but it would not be possible to obtain consistent standard errors. The reason is that in addition to the parameter vectors $\delta$ and $\zeta$, one also has to estimate the correlation $\rho$ between the shocks $u_i$ and $v_i$. Assuming a value for $\rho$ is not an attractive option because $\rho$ is part of the hypothesis being tested. For example, if unobserved heterogeneity is such that if it leads to a higher probability of holding stocks, it also leads to a higher share of
stocks held, then \( \rho \) would be positive. Here I assume that the head's level of education affects the decision to hold stocks but not the share of stocks held (conditional on being a stockholder). Unfortunately, there is no way to test this hypothesis, while allowing the two decision to be different.

Total financial wealth is omitted from both decisions in the main specification because wealth accumulation is endogenous. If information were available on initial wealth, then that would be the correct independent variable to include. Nevertheless, I will also present estimates where wealth is included as an independent variable and show that it does not significantly alter the estimated effects of the other variables.

The estimates in Table 2 represent the main empirical contribution of this paper. The first column reports the estimated slopes – not the coefficient estimates since this is a Probit – of the stock-holding decision, with the associated t-statistics in the second column. Similarly, the third and fourth columns report the estimated slopes (which, in this case, are also the slopes) and t-statistics for the share decision, conditional on being a stockholder. To minimize measurement error in the estimates of the earnings profile, the sample is composed of the households which, in the previous stage of estimating the earnings profile, belonged to a demographic cell that had at least fifty observations in 1983. As a result of this restriction, no self-employed households (i.e., farmers and self-employed managers) were included in the sample, although the relative contribution of the remaining demographic groups was not affected significantly (as can be seen by the breakdown in Tables 1A-1C). Later, the restriction is relaxed to allow the self-employed to be included in the sample. Further attrition also occurred because some households did not report a dollar figure for stocks or risk-free assets held. As was found by inspecting their answer to the question of whether they held stocks, these households (not reporting dollar figures) contained more stockholders than the sample used. In unreported regressions, I found that running the first stage including these households has a very minor effect on the

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results.

A caveat is in order regarding the reported standard errors. Technically, they have to be corrected to reflect the fact that the earnings uncertainty parameters are estimated, rather than actual data Newey and McFadden [1994]. However, the earnings uncertainty estimates come from a GMM sample that is unbalanced, in the sense than there are not the same number of observations available for each moment, due to the low-income shocks. While the coefficient estimates are not affected, it is not yet known (as far as I can tell) how the asymptotic variance-covariance matrix can be estimated in this case. Consequently, I report the standard errors obtained from the Heckman estimator, which are corrected for the stockholding decision, but not for the first step estimation.

The results are very much in line with the hypothesis introduced in this paper and the magnitude of the effects is substantial. Lower uncertainty in the form of lower probability of zero income increases both the probability of holding stocks and the optimal share of stocks held. Specifically, a drop in the probability of zero income of 1.5 percentage points depresses the probability of holding stocks by 13 percentage points and the share of stocks held by 5 percentage points. With the uncorrected standard errors, these effects are significant at the 99% and 95% level, respectively.

Furthermore, households over age 55 have a much higher probability of holding stocks, while they also tend to hold higher shares, conditional on being stockholders. Similar findings have been reported by Poterba and Samwick [1997]. Such behavior is consistent with the buffer-stock behavior examined earlier. On the other hand, Poterba and Wise [1996] present evidence from pension plan data that the share of equity in these plans is higher for younger individuals. This last result is not necessarily inconsistent with the age profiles estimated above, since young households with retirement plans are probably not

\footnote{I am thankful to the macro seminar group at the New York Federal Reserve Bank and to Annette Vissing for helpful discussions on this subject.}
borrowing constrained and their behavior cannot be captured by the buffer-stock model. Furthermore, it is unknown what other risk-free assets they hold outside these pension plans.

Other significant factors include the level (very significant) and growth rate (not so significant) of permanent income which increase both the probability of holding stocks and the share of stocks held. If the buffer-stock hypothesis is correct, then a higher growth rate of (permanent) income should strengthen the effect of the borrowing constraint and reduce the demand for stocks, even though it implies higher expected future income. While the point estimate of the effect of the growth rate of income is positive for the decision to hold stocks, the t-statistic is very small. The effect is more significant for the share of stocks held, which is consistent with the view that the stockholders are less likely to be borrowing constrained, so that the coefficient is capturing the effect of higher human wealth. Furthermore, the difference between current income and permanent income affects the probability of holding stocks at the 99% confidence level but not the share of stocks held; households with current income much above permanent income have a higher probability of holding stocks, and vice versa. This response indicates that the non-stockholders are the group that cannot buffer temporary labor income shocks by borrowing at the risk-free rate and thus do not hold stocks when they are hit with negative shocks. This result also suggests that some households may actually flow in and out of the stock market, depending on their current state of labor income. If that is indeed the case, then the estimated fraction of stockholders underestimates the fraction of households that at some point have held stocks. It also seriously challenges the informational reasons offered for the non-participating households. I plan to rigorously test all these implications in the future by using other waves of the PSID that have asset information, namely 1989 and 1994.

Not surprisingly, there is significant evidence that the decision to hold stocks is affected
by factors not captured by the buffer-stock model: more years of education increase the probability of holding stocks, while a greater number of children and a recent change in the head or spouse of the household decreases it. Perhaps surprisingly, the lower the share of the spouse's earnings in total labor income, the higher the probability of holding stocks, even though the presence of a spouse does not affect the decision. This finding would be consistent with a model of endogenous labor supply, where the spouse only works during periods of negative shocks to household income.

For completeness, I also present the results of the estimation when self-employed households are included in the sample and when total wealth is included as an independent variable (Table 3). The self-employed have received special attention in this framework at least since Friedman [1957], and also by Skinner [1988] and Carroll and Samwick [1992]. They have been singled out because presumably the self-employed households are the ones facing the most labor income risk. Researchers want to make sure that these groups alone are not responsible for the estimated responses. This is certainly not the case here, since the demographic cells used to derive the uncertainty estimates of the self-employed are too small to be included in the results of Table 2. In order for them to be sufficiently represented, the minimum cell size has to fall to fifteen observations in 1983. This increases the sample size by over three hundred households, as other cells are also included. The results of Table 3 show that the estimates are qualitatively similar when the cell size is dropped to include the self-employed, although not as precise. However, the loss in precision is not entirely due to the inclusion of the self-employed, but rather to the measurement error introduced. For example, I find in unreported regressions that reducing the cell size to fifteen but excluding the self-employed yields almost identical estimates to those presented in the first two columns of Table 3.

Finally, as shown in the last two columns of Table 3, the inclusion of financial wealth as an independent variable does not really alter the estimated effect of uncertainty while
it reduces the significance of the estimated effect of age. Its hard to interpret these results given the endogeneity problem mentioned above. In any case, my measure of financial wealth is the sum of the value of risk-free assets, stocks, bonds, insurance policies, housing and other real estate minus the value of all debts.\textsuperscript{12}

The estimates suggest that higher financial wealth increases both the probability of holding stocks and the share of stocks held (with 99\% significance). The highly significant non-linear terms for the decision to hold stocks reflect the fact that the probability of holding stocks rises very quickly as financial wealth increases for very low levels of wealth, but also that at the high end of the financial wealth distribution, the percentage of stockholders actually declines. For example, while about 50\% of the households with financial wealth of $100,000-$200,000 held stocks, of the households with financial wealth above $200,000 only 42\% percent were stockholders (1984 $). These groups correspond to the second and top ten-percent of the distribution of financial wealth in my sample. This empirical regularity is somewhat puzzling, considering that (conditional on being a stockholder) the share of stocks held increases with wealth. The effect for the low levels of financial wealth (to the extent that financial wealth is capturing initial wealth and the endogeneity problem is not severe) is consistent with the qualitative implications of the standard uncertainty model. Higher initial financial wealth reduces the effect of the background risk in labor income, while it lowers the probability that the household will be borrowing constrained in the future. Thus, it leads to both a higher probability of holding stocks and a higher share of stocks held. Of course, the finding is also consistent with a lot of other theories: for example, the response of the probability of holding stocks may be due to the presence of fixed costs associated with stockholding, while the response of the share held could be indicative of decreasing relative risk aversion.

\textsuperscript{12}Below, I discuss the availability of wealth information.
2.3.2 Total Asset Accumulation

If the buffer-stock model is indeed a good explanation of household behavior, then earnings uncertainty and age should also be important factors in explaining total asset accumulation. Table 4 presents regressions similar to the ones for portfolio behavior, where the dependent variable is the ratio of financial wealth to permanent income. The measure of financial wealth is the same as the one used above and is equal to the sum of the value of risk-free assets, stocks, bonds, insurance policies, housing and other real estate minus the value of all debts. Unfortunately, the definition of wealth does not include pensions, because I did not have information on their value by household. Only about 3% of the PSID sample are actually able to estimate their assets in employer-sponsored retirement accounts. Also, the definition of wealth does not include any expected Social Security payments. Permanent income is computed as average income for the period 1977-1983 excluding the years that were classified as zero income events.

The first two columns are the estimates when the minimum cell size used to derive the earnings uncertainty estimates is fifty, and the last two columns when the minimum cell size is reduced to fifteen. The second case is considered in order to allow self-employed workers to be included in the sample (at the expense of increased measurement error for the uncertainty parameters). As was the case with the portfolio regressions, the standard errors should have been corrected to reflect that the uncertainty parameters are estimates rather than data. Unfortunately, the correction is again unknown, due to the unbalanced nature of the labor income panel.

The evidence suggests that the profile of asset holdings increases throughout the life-cycle and most dramatically right before retirement. However, the estimates for the effects of earnings uncertainty are rather puzzling. While I find that a higher variance of permanent and transitory shocks does increase total asset holdings (consistent with the findings of Carroll and Samwick [1992] and Heaton and Lucas [1997]), I also find that a
higher probability of zero income actually decreases total asset holdings! Furthermore, the
transitory shocks have a much bigger effect than the permanent shocks. The magnitude
of these effects is also substantial: increasing the variance of the permanent shocks, the
variance of the transitory shocks, and the probability of zero income from the value of
the 25th percentile of their distribution in my sample to the value of the 75th percentile,
leads to a predicted change of approximately 0.4, 0.7 and -0.7 in the ratio of permanent
income to financial wealth, respectively. This response is not consistent with the models
examined earlier. Finally, total asset accumulation increases with the expected growth
rate of permanent income indicating that the wealth effect of higher future resources
outweighs any possible effect from impatience.

I have found the above anomalies to be quite robust. For example, eliminating housing
wealth and debt from the definition of financial wealth does not alter the results, nor
does considering housing wealth and debt only. Furthermore, this result is not driven
by households that have just recently experienced a zero income event and are thus
rationally running down their buffer-stock: the results hardly change if one eliminates
from the sample households that have experienced zero income events in the past three
years.

2.4 Other Related Work

A few empirical studies have analyzed stockholding behavior from a similar perspective.
Haliassos and Bertaut [1995] study the decision to hold stocks using the 1983 Survey
of Consumer Finances and interpret their overall findings as lending support to inertia
and departures from expected utility maximization. In line with the findings presented
above, they also find qualified support that uninsurable labor income risk depresses the
probability of holding stocks; in contrast to the above findings, they present evidence that
age does not play a role in that decision.

Using a survey of Italian households, Income risk and portfolio choice [1996] present evidence that labor income risk and borrowing constraints depress the demand for risky assets. Their approach is different from the one used here in that their proxy for labor income risk is constructed using the individual households' responses to questions about their expected future income. Also, they do not separate the decision of whether to hold stocks from the decision to hold stocks conditional on being a stockholder, restricting the two decisions to be affected identically by the independent variables. Further evidence of the importance of the precautionary saving motive is presented by Vissing [1998], who works with three waves of the PSID.

Finally, Heaton and Lucas [1997] use data from individual tax returns to examine the effect of uninsurable risk on portfolio choice and total asset holdings. They argue that the uninsurable risk from proprietary business income is a more appropriate measure of the uninsurable risk relevant for the stockholding decision, and is also more correlated with returns on stocks. Heaton and Lucas present evidence from a linear model that the share of holdings in stocks is negatively related to the variability of the growth rate of proprietary income, while they cannot find an effect from the variability in the growth rate of labor income. This line of reasoning seems to capture the behavior of stockholders (for whom proprietary wealth is much larger than the capitalized value of labor income) and suggests that my analysis of the share held should include proprietary wealth as an independent variable. However, it does not necessarily contradict the evidence presented for the (non-linear) decision of whether or not to hold stocks, since the majority of non-stockholders have very little (if any) proprietary income.
2.5 Conclusion

A better understanding of the reasons for stock-market non-participation is crucial for a host of issues, ranging from the distribution of wealth to asset pricing to the development of financial markets. For example, if the widespread non-participation is the result of failure to optimize on the behalf of most households, then policies designed to encourage participation can greatly improve the welfare of non-stockholders by allowing them to enjoy the higher returns associated with investing in equity. Of course, such reasoning depends crucially on the endogenous response of asset returns to the increased participation. Given the imminent aging of the Baby Boom population, this issue has recently received theoretical and empirical attention (see, e.g., Basak and Cuoco [1997], Poterba [1997], Bergantino [1998] and Visling [1998]). Furthermore, while equilibrium consumption asset pricing models have produced some celebrated asset pricing failures (e.g., the Mehra and Prescott [1985] equity premium puzzle), it is also known from Mankiw and Zeldes [1991] that these failures are at least somewhat alleviated if the models are calibrated using the participating households only (greater support for this approach is provided by Brav and Geczy [1997]).

This paper has been an attempt to clarify the individual behavior behind stock-market non-participation. An empirical examination of portfolio behavior at the individual household level revealed responses qualitatively consistent with intertemporal optimization. Specifically, the decision to hold stocks is closely related to decision of the share of stocks held, and both decisions respond to background risks in a manner consistent with economic theory (even though there are also variables outside the standard model which affect the first decision only). Finally, the puzzling empirical picture that emerges from the study of total asset accumulation (as well as from the MSM estimation of Chapter 1) suggests that further effort should be invested in better understanding the links and
differences between the attitude of households toward risk and the attitude of households toward the intertemporal allocation of resources.
Earnings Profiles by Demographic Groups

Table 1A: Less than High-school

<table>
<thead>
<tr>
<th>Occup'l Group</th>
<th>Age Group</th>
<th>Obs in 1983</th>
<th>(2) StdDev</th>
<th>Prob Zero Income</th>
<th>(5) Exp %Δ of Perm Income</th>
<th>(6) Growth of Avg Income</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profess'n'l's</td>
<td>Young</td>
<td>3</td>
<td>0.39</td>
<td>negative</td>
<td>23.3%</td>
<td>2.3%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>6</td>
<td>0.24</td>
<td></td>
<td>3.7%</td>
<td>1.1%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>11</td>
<td>0.18</td>
<td></td>
<td>9.9%</td>
<td>1.9%</td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td>Old</td>
<td>15</td>
<td>0.16</td>
<td></td>
<td>0.0%</td>
<td>-1.5%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>9</td>
<td>negative</td>
<td>0.24</td>
<td>11.3%</td>
<td>2.6%</td>
</tr>
<tr>
<td>Self Empl</td>
<td>Old</td>
<td>18</td>
<td>negative</td>
<td>0.31</td>
<td>17.0%</td>
<td>-3.6%</td>
</tr>
<tr>
<td>Clerical-Sales</td>
<td>Young</td>
<td>45</td>
<td>0.19</td>
<td></td>
<td>10.5%</td>
<td>-1.6%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>34</td>
<td>0.15</td>
<td></td>
<td>5.8%</td>
<td>-1.0%</td>
</tr>
<tr>
<td>Craftsmen</td>
<td>Young</td>
<td>128</td>
<td>0.14</td>
<td></td>
<td>6.9%</td>
<td>0.5%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>119</td>
<td>0.06</td>
<td></td>
<td>4.1%</td>
<td>-2.2%</td>
</tr>
<tr>
<td>Operators-Laborers</td>
<td>Young</td>
<td>296</td>
<td>0.16</td>
<td></td>
<td>8.3%</td>
<td>0.4%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>192</td>
<td>0.17</td>
<td></td>
<td>5.9%</td>
<td>-1.8%</td>
</tr>
<tr>
<td>Farmers</td>
<td>Young</td>
<td>26</td>
<td>negative</td>
<td>0.12</td>
<td>9.6%</td>
<td>0.4%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>18</td>
<td>negative</td>
<td>0.36</td>
<td>8.9%</td>
<td>-7.4%</td>
</tr>
<tr>
<td>Service</td>
<td>Young</td>
<td>142</td>
<td>0.13</td>
<td></td>
<td>12.4%</td>
<td>-0.3%</td>
</tr>
<tr>
<td>Workers</td>
<td>Old</td>
<td>138</td>
<td>0.16</td>
<td></td>
<td>11.9%</td>
<td>-1.3%</td>
</tr>
</tbody>
</table>

Average of Young | N/A | 0.18 | 10.5% | 1.5% | N/A
Average of Old | N/A | 0.34 | 13.0% | -5.5% | N/A

Note:

(i) Young means Age under 45.

(ii) Based on after-tax labor income for the years 1977-1983 (PSID).

(iii) Definition of Zero Income: when income is less than half of average income in the other years of the panel (the median zero income event dropped income to 10% of last year's value).
Earnings Profiles by Demographic Groups

Table 1B: Completed High-school but not Four-Year College

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Profess'ns</td>
<td>Young</td>
<td>160</td>
<td>0.15</td>
<td>0.10</td>
<td>5.6%</td>
<td>3.2%</td>
<td>4.4%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>62</td>
<td>0.12</td>
<td>0.10</td>
<td>4.1%</td>
<td>-0.6%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>135</td>
<td>0.15</td>
<td>0.10</td>
<td>4.6%</td>
<td>2.2%</td>
<td>3.3%</td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td>Old</td>
<td>67</td>
<td>0.16</td>
<td>0.04</td>
<td>3.3%</td>
<td>-1.0%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>47</td>
<td>0.21</td>
<td>0.19</td>
<td>6.3%</td>
<td>-0.8%</td>
<td>1.4%</td>
</tr>
<tr>
<td>Self Empl</td>
<td>Old</td>
<td>30</td>
<td>0.05</td>
<td>0.20</td>
<td>9.4%</td>
<td>-1.4%</td>
<td>-1.3%</td>
</tr>
<tr>
<td>Clerical-Sales</td>
<td>Young</td>
<td>313</td>
<td>0.17</td>
<td>0.12</td>
<td>5.3%</td>
<td>0.8%</td>
<td>2.3%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>125</td>
<td>0.17</td>
<td>0.10</td>
<td>4.7%</td>
<td>-2.6%</td>
<td>-1.2%</td>
</tr>
<tr>
<td>Craftsmen</td>
<td>Young</td>
<td>427</td>
<td>0.17</td>
<td>0.11</td>
<td>4.3%</td>
<td>1.4%</td>
<td>2.8%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>125</td>
<td>0.14</td>
<td>0.13</td>
<td>4.1%</td>
<td>-1.3%</td>
<td>-0.3%</td>
</tr>
<tr>
<td>Operators-Laborers</td>
<td>Young</td>
<td>546</td>
<td>0.15</td>
<td>0.12</td>
<td>5.3%</td>
<td>0.4%</td>
<td>1.6%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>110</td>
<td>0.11</td>
<td>0.13</td>
<td>4.7%</td>
<td>-0.3%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Farmers</td>
<td>Young</td>
<td>31</td>
<td>negative</td>
<td>0.29</td>
<td>5.1%</td>
<td>0.1%</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>16</td>
<td>0.11</td>
<td>0.22</td>
<td>6.3%</td>
<td>-0.3%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Service</td>
<td>Young</td>
<td>274</td>
<td>0.17</td>
<td>0.14</td>
<td>7.9%</td>
<td>1.3%</td>
<td>2.7%</td>
</tr>
<tr>
<td>Workers</td>
<td>Old</td>
<td>100</td>
<td>0.14</td>
<td>0.16</td>
<td>7.9%</td>
<td>-0.9%</td>
<td>0.1%</td>
</tr>
<tr>
<td>Average of</td>
<td>Young</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SelfEmpl</td>
<td>Old</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average of</td>
<td>Young</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td>Old</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note:

(i) Young means Age under 45.

(ii) Based on after-tax labor income for the years 1977-1983 (PSID).

(iii) Definition of Zero Income: when income is less than half of average income in the other years of the panel (the median zero income event dropped income to 10% of last year’s value).
Earnings Profiles by Demographic Groups

Table 1C: Completed Four-Year College

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Professionals</td>
<td>Young</td>
<td>283</td>
<td>0.17</td>
<td>0.08</td>
<td>3.8%</td>
<td>3.5%</td>
<td>4.9%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>112</td>
<td>0.12</td>
<td>0.11</td>
<td>3.3%</td>
<td>2.2%</td>
<td>3.0%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>107</td>
<td>0.11</td>
<td>0.09</td>
<td>2.1%</td>
<td>3.2%</td>
<td>3.8%</td>
</tr>
<tr>
<td>NotSelfEmp</td>
<td>Old</td>
<td>71</td>
<td>0.10</td>
<td>0.08</td>
<td>3.6%</td>
<td>1.7%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Managers</td>
<td>Young</td>
<td>19</td>
<td>0.22</td>
<td>0.14</td>
<td>9.7%</td>
<td>0.4%</td>
<td>2.8%</td>
</tr>
<tr>
<td>Self Empl</td>
<td>Old</td>
<td>15</td>
<td>negative</td>
<td>0.23</td>
<td>15.3%</td>
<td>-0.7%</td>
<td>N/A</td>
</tr>
<tr>
<td>Clerical-Sales</td>
<td>Young</td>
<td>79</td>
<td>0.15</td>
<td>0.12</td>
<td>5.8%</td>
<td>2.6%</td>
<td>3.8%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>20</td>
<td>0.16</td>
<td>0.07</td>
<td>1.3%</td>
<td>5.0%</td>
<td>6.3%</td>
</tr>
<tr>
<td>Craftsmen</td>
<td>Young</td>
<td>32</td>
<td>negative</td>
<td>0.21</td>
<td>6.5%</td>
<td>1.8%</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>18</td>
<td>negative</td>
<td>0.24</td>
<td>6.3%</td>
<td>0.6%</td>
<td>N/A</td>
</tr>
<tr>
<td>Operators-Laborers</td>
<td>Young</td>
<td>20</td>
<td>0.21</td>
<td>0.08</td>
<td>3.0%</td>
<td>1.0%</td>
<td>3.1%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>6</td>
<td>0.12</td>
<td>negative</td>
<td>4.5%</td>
<td>-5.3%</td>
<td>-4.6%</td>
</tr>
<tr>
<td>Farmers</td>
<td>Young</td>
<td>11</td>
<td>0.14</td>
<td>0.14</td>
<td>3.1%</td>
<td>-5.2%</td>
<td>-4.3%</td>
</tr>
<tr>
<td></td>
<td>Old</td>
<td>6</td>
<td>0.55</td>
<td>negative</td>
<td>10.0%</td>
<td>-14.4%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Service</td>
<td>Young</td>
<td>28</td>
<td>0.28</td>
<td>0.14</td>
<td>10.6%</td>
<td>3.5%</td>
<td>7.5%</td>
</tr>
<tr>
<td>Workers</td>
<td>Old</td>
<td>12</td>
<td>0.41</td>
<td>negative</td>
<td>13.8%</td>
<td>-1.9%</td>
<td>6.4%</td>
</tr>
</tbody>
</table>

Average of Young Self Empl Old: 0.18 0.14 6.4% -2.4% -0.8% 0.55 N/A 12.6% -7.6% 1.0%

Average of Young NotSelfEmp Old: 0.18 0.12 5.3% 2.6% 4.6% 0.18 N/A 5.5% 0.4% 2.6%

Note:
(i) Young means Age under 45.
(ii) Based on after-tax labor income for the years 1977-1983 (PSID).
(iii) Definition of Zero Income: when income is less than half of average income in the other years of the panel (the median zero income event dropped income to 10% of last year’s value).
Table 2: Two Step Heckman Estimation of Household Stockholding Behavior

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Decision to Hold Stocks</th>
<th>Share of Stocks Held</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
<td>t-statistic</td>
</tr>
<tr>
<td>Age 30 to 35</td>
<td>-0.0043</td>
<td>-0.21</td>
</tr>
<tr>
<td>Age 35 to 40</td>
<td>0.0044</td>
<td>0.20</td>
</tr>
<tr>
<td>Age 40 to 45</td>
<td>0.0076</td>
<td>0.31</td>
</tr>
<tr>
<td>Age 45 to 50</td>
<td>0.0075</td>
<td>0.24</td>
</tr>
<tr>
<td>Age 50 to 55</td>
<td>0.0464</td>
<td>1.19</td>
</tr>
<tr>
<td>Age &gt; 55</td>
<td>0.1100</td>
<td>2.44</td>
</tr>
<tr>
<td>Education (Years)</td>
<td>0.0160</td>
<td>2.43</td>
</tr>
<tr>
<td>Completed High-school</td>
<td>0.0205</td>
<td>0.61</td>
</tr>
<tr>
<td>Completed College</td>
<td>0.0228</td>
<td>0.38</td>
</tr>
<tr>
<td>Number of Children</td>
<td>-0.0161</td>
<td>-2.94</td>
</tr>
<tr>
<td>Change in Head/Spouse?</td>
<td>-0.0373</td>
<td>-1.69</td>
</tr>
<tr>
<td>Spouse?</td>
<td>0.0080</td>
<td>0.46</td>
</tr>
<tr>
<td>Spouse Share of Earnings</td>
<td>-0.0944</td>
<td>-2.17</td>
</tr>
<tr>
<td>(PermInc - CurrentInc)</td>
<td>-4.9E-06</td>
<td>-8.07</td>
</tr>
<tr>
<td>Permanent Income</td>
<td>8.7E-06</td>
<td>12.45</td>
</tr>
<tr>
<td>E[Δ(PermInc)]</td>
<td>1.0037</td>
<td>1.07</td>
</tr>
<tr>
<td>Var(Permanent Shocks)</td>
<td>1.4428</td>
<td>0.85</td>
</tr>
<tr>
<td>Var(Transitory Shocks)</td>
<td>0.4515</td>
<td>0.20</td>
</tr>
<tr>
<td>Prob(Zero Income)</td>
<td>-2.4845</td>
<td>-3.15</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note:

(i) The Share in Stocks is defined as \( \text{Share} = \frac{\text{Stocks}}{\text{Stocks} + \text{RiskFreeAssets}} \).

(ii) Total number of observations is 3,187 of which 613 are stockholders.

(iii) Minimum demographic cell size for the uncertainty profiles estimates is 50 observations in 1983.

(iv) No self-employed workers are included in this regression, due to the small size of their demographic cells (used to estimate the parameters of their earnings process). The next table presents estimates when they are included, by lowering the minimum cell size.

(v) The omitted age dummy is Age<30.
Table 3: Household Stockholding Behavior – Extensions

<table>
<thead>
<tr>
<th>Indep Var’ble</th>
<th>Including Self-Employed Workers</th>
<th>Including Wealth as Indep Var’ble</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Decision to Hold Stocks</td>
<td>Share of Stocks Held</td>
</tr>
<tr>
<td></td>
<td>Slope</td>
<td>t-stat</td>
</tr>
<tr>
<td><strong>Age: 30-35</strong></td>
<td>0.0109</td>
<td>0.5</td>
</tr>
<tr>
<td><strong>Age: 35-40</strong></td>
<td>0.0182</td>
<td>0.79</td>
</tr>
<tr>
<td><strong>Age: 40-45</strong></td>
<td>0.0134</td>
<td>0.53</td>
</tr>
<tr>
<td><strong>Age: 45-50</strong></td>
<td>0.0210</td>
<td>0.73</td>
</tr>
<tr>
<td><strong>Age: 50-55</strong></td>
<td>0.0423</td>
<td>1.23</td>
</tr>
<tr>
<td><strong>Age &gt; 55</strong></td>
<td>0.1144</td>
<td>2.93</td>
</tr>
<tr>
<td><strong>Educ (Yrs)</strong></td>
<td>0.0177</td>
<td>2.72</td>
</tr>
<tr>
<td><strong>High-school</strong></td>
<td>0.0440</td>
<td>1.45</td>
</tr>
<tr>
<td><strong>College</strong></td>
<td>0.0967</td>
<td>1.62</td>
</tr>
<tr>
<td><strong>Children (#)</strong></td>
<td>-0.0186</td>
<td>-3.47</td>
</tr>
<tr>
<td><strong>Chnge Hd/Sp</strong></td>
<td>-0.0347</td>
<td>-1.56</td>
</tr>
<tr>
<td><strong>Spouse?</strong></td>
<td>0.0279</td>
<td>1.63</td>
</tr>
<tr>
<td><strong>Sp Shr of Inc</strong></td>
<td>-0.1009</td>
<td>-2.35</td>
</tr>
<tr>
<td><strong>Perm-Curr</strong></td>
<td>-6.2E-06</td>
<td>-10.7</td>
</tr>
<tr>
<td><strong>PermInc</strong></td>
<td>8.6E-06</td>
<td>13.7</td>
</tr>
<tr>
<td><strong>FinclWealth</strong></td>
<td>1.1E-19</td>
<td>4.82</td>
</tr>
<tr>
<td><strong>FinclWealth^2</strong></td>
<td>-1.1E-12</td>
<td>-5.3</td>
</tr>
<tr>
<td><strong>FinclWealth^3</strong></td>
<td>1.1E-19</td>
<td>4.82</td>
</tr>
<tr>
<td><strong>E[Δ(PermInc)]</strong></td>
<td>0.0721</td>
<td>0.09</td>
</tr>
<tr>
<td><strong>σ^2(PermShck)</strong></td>
<td>-0.2481</td>
<td>-0.28</td>
</tr>
<tr>
<td><strong>σ^2(TransShcks)</strong></td>
<td>0.6130</td>
<td>0.58</td>
</tr>
<tr>
<td><strong>Pr(y=0)</strong></td>
<td>-0.9180</td>
<td>-1.71</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.2195</td>
<td>1.797</td>
</tr>
</tbody>
</table>

**Note:**

(i) The Share in Stocks is defined as $Share = Stocks/(Stocks + RiskFreeAssets)$.

(ii) Financial wealth is defined as the sum of risk-free assets, stocks, bonds, insurance policies, housing, other real estate, and the value of private pensions minus all debts.

(iii) Total number of observations (stockholders) is 3,499 (691) for regression with Self-Employed and 2,938 (571) for regression including Wealth.

(iv) Minimum demographic cell size for the uncertainty profiles estimates is 15 observations in 1983 for the regression including the Self-Employed and 50 observations in 1983 for the regression including Wealth.

(v) The omitted age dummy is Age<30.
Table 4: Total Asset Accumulation

<table>
<thead>
<tr>
<th>Indep Var'ble</th>
<th>Minimum Cell Size: 50 (No Self-Employed Workers in Sample)</th>
<th>Minimum Cell Size: 15 (Includes Self-Employed Workers)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Financial Wealth/Permanent Income</td>
<td>Financial Wealth/Permanent Income</td>
</tr>
<tr>
<td>Coefficient</td>
<td>t-statistic</td>
<td>Coefficient</td>
</tr>
<tr>
<td>Age: 30-35</td>
<td>0.30</td>
<td>1.02</td>
</tr>
<tr>
<td>Age: 35-40</td>
<td>0.67</td>
<td>2.14</td>
</tr>
<tr>
<td>Age: 40-45</td>
<td>1.01</td>
<td>2.94</td>
</tr>
<tr>
<td>Age: 45-50</td>
<td>1.46</td>
<td>3.43</td>
</tr>
<tr>
<td>Age: 50-55</td>
<td>2.20</td>
<td>4.22</td>
</tr>
<tr>
<td>Age &gt; 55</td>
<td>4.20</td>
<td>7.69</td>
</tr>
<tr>
<td>Education (Yrs)</td>
<td>0.24</td>
<td>2.91</td>
</tr>
<tr>
<td>High-school</td>
<td>-0.20</td>
<td>-0.47</td>
</tr>
<tr>
<td>College</td>
<td>-0.82</td>
<td>-1.03</td>
</tr>
<tr>
<td>Children (#)</td>
<td>0.02</td>
<td>0.31</td>
</tr>
<tr>
<td>Change in Head/Spouse?</td>
<td>-0.77</td>
<td>-2.39</td>
</tr>
<tr>
<td>Spouse?</td>
<td>1.15</td>
<td>4.95</td>
</tr>
<tr>
<td>Spouse's Share of Inc</td>
<td>-1.48</td>
<td>-2.36</td>
</tr>
<tr>
<td>(PermInc-CurrInc)/PermInc</td>
<td>-1.39</td>
<td>-6.07</td>
</tr>
<tr>
<td>E[%Δ(PermInc)]</td>
<td>30.46</td>
<td>2.09</td>
</tr>
<tr>
<td>σ²(PermShck)</td>
<td>47.05</td>
<td>1.76</td>
</tr>
<tr>
<td>σ²(TransShcks)</td>
<td>73.47</td>
<td>2.21</td>
</tr>
<tr>
<td>Pr(y=0)</td>
<td>-30.70</td>
<td>-2.86</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.07</td>
<td>-2.44</td>
</tr>
</tbody>
</table>

Note:

(i) Financial wealth is defined as the sum of risk-free assets, stocks, bonds, insurance policies, housing, other real estate, and the value of private pensions minus all debts.

(ii) Total number of observations is 2,938 for regression without any Self-Employed Workers and 3,229 for regression including Self-Employed Workers.

(iii) Minimum demographic cell size for the uncertainty profiles estimates is 50 observations in 1983 for the regression without Self-Employed Workers and 15 observations in 1983 for the regression including Self-Employed Workers.

(iv) The omitted age dummy is Age<30.
Chapter 3

Life-cycle Asset Accumulation in the Presence of Earnings Uncertainty

3.1 Introduction

This chapter attempts to determine whether a model of consumer optimization under uninsurable labor income risk can be reconciled with the life-cycle profiles of both total asset accumulation and portfolio choice between risky and risk-free assets. It is motivated by the following two facts:

First, life-cycle profiles of household consumption have been shown to track income quite closely at young ages, at least since the work of Kotlikoff and Summers [1981]. It has been reported in the literature that consumption does not fall significantly below income until at least age 45 Carroll [1997], leading to a hump-shaped life-cycle profile. These results seem to be robust across countries and demographic groups Carroll and Summers [1989]. Furthermore, the finding that consumption tracks expected changes in income at early ages is robust to adjustments for family size, cohort, education and occupation (Attanasio [1994], Gourinchas and Parker [1995] and Lusardi [1993]).¹ As a result of the consumption-income parallel at early ages, most households do not accumulate a significant level of assets until the latter part of the life-cycle.

¹One exception is the work of Attanasio et al. [1994].
Second, this thesis documents that young stockholders hold fewer stocks than older ones, even after correcting for the bias introduced by the different rates of stock market participation at different ages.\textsuperscript{2} It is shown that before age 45 the average college-educated, white-collar, stockholding household holds less than 30\% of their liquid assets in stocks. In addition, the share of stocks in the liquid asset portfolio of these stockholding households peaks at 62\%, and the peak comes quite late in the life-cycle, around age 65.\textsuperscript{3}

Both sets of facts are at odds with the standard models of consumption and portfolio choice. Specifically, the workhorse model of the consumption literature, the life-cycle certainty-equivalent (hence LC-CEQ) model of consumption, leads to the martingale hypothesis, which is inconsistent with the first set of facts discussed above. In addition, various other implications of the LC-CEQ model have repeatedly been rejected with both micro- and macro-level data.\textsuperscript{4}

For the second set of facts, the low share of stocks for most of the stockholders' life-cycle is quite puzzling considering the substantial historical premium of risky equity over essentially risk-free assets.\textsuperscript{5} Even more puzzling is the hump-shaped age-profile of the share of stocks in the household portfolio. The standard intertemporal models of portfolio choice under complete-markets (introduced by Samuelson [1969] and Merton [1971]) suggest that households should hold a substantial share of their wealth in equity,

\textsuperscript{2}The issue of why younger households are less likely to hold stocks and the issue of why stock market participation is so low in general (the "stockholding puzzle" Haliassos and Bertaut [1995]) was discussed in the empirical investigation of the Chapter 2.

\textsuperscript{3}As it will be explained in Section 3, these portfolio findings are from the distribution of stockholders conditional on being a stockholder and on having a constant family size over the life-cycle.

\textsuperscript{4}Some other rejections of the model are offered by Souleles [1994] at the micro level and Campbell and Mankiw [1989] at the macro level. See Deaton [1992] for a survey of findings at both levels, and Browning and Lusardi [1996] for a more recent survey of micro-level evidence.

\textsuperscript{5}Taking the return on equity to be the nominal simple return (including dividends) on the CRSP NYSE-AMEX value-weighted portfolio and the risk-free return to be the return on 1-month US T-Bills, the historical equity premium from December 1925 to December 1995 (using monthly data) has been approximately eight percentage points. Note that the 1-month US T-Bills are not exactly risk-free since the rate of inflation may change. However, over a period of one month this risk is negligible. Also, its not clear that the historical equity premium is the appropriate measure of the equity premium Blanchard [1993].
well over one half if relative risk aversion is under five. In the absence of changes in the investment opportunities and with isoelastic expected utility, these models also predict that the share of total wealth in risky assets should be independent of the household's horizon and of the level of wealth.

It is worth noting that this second set of facts on household portfolios cannot be reconciled with the advice of the majority of professional financial advisors. Contrary to the implications of the standard portfolio choice models of Samuelson [1969] and Merton [1971], financial advisors typically suggest that younger households should be relatively more "aggressive" with their portfolios, holding a relatively higher share in risky assets. A popular rule of thumb is that if the households' investment attitude can be described as "playing it safe," the share of stocks in the household's portfolio should be equal to one hundred minus the age of the household Tyson [1997].

To make sense of the first set of facts, the consumption literature has recently considered the effects of uninsurable labor income risk on optimal behavior when preferences do not result in certainty-equivalent optimal rules. This modification to the complete-markets model is certainly worth considering: in practice, household labor income is quite risky (e.g., due to the possibility of job loss) and only partially insurable. As has been documented in Chapters 1 and 2, not only is the households' labor income subject to the large shocks associated with job loss, but the growth rate of labor income is also subject to smaller shocks, whose standard deviation is of the order of 20% of the level of labor earnings. These properties of household earnings undoubtedly affect household asset accumulation. In fact, survey data show that being prepared for emergencies is the most common reason people offer when asked why they save Carroll [1997].

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6Canner et al. [1997] attempt (and are unable) to reconcile financial-advisor-suggested asset allocation with economic theory.

7Early studies of multi-period consumption models in the presence of uninsurable labor income risk include Blanchard and Mankiw [1988], Skinner [1988], Kimball and Mankiw [1989], Zeldes [1989], Caballero [1991], Carroll [1991] and Deaton [1991]. The effect of uninsurable labor income risk on savings and portfolio choice was first studied in a two-period model by Dreze and Modigliani [1972].
If households are unable to smooth small negative shocks by borrowing, or if they are allowed to borrow but shocks are big in terms of the appropriate measure of lifetime resources, labor income risk will have a major effect on asset accumulation. In that case, we know from the consumption literature that the risk in labor income generates an additional source of demand for savings (i.e., other than to smooth consumption across time), as long as consumers are prudent.\(^8\) If early on in the life-cycle the household would like to borrow (because it is impatient and/or because it expects its labor income to grow), then its prudence will be at war with its impatience Deaton [1992]. If the household is either not allowed to borrow Deaton [1991] or not willing to Carroll [1991], then the optimal policy will call for a small “buffer stock” of assets to be held. To the extent that the impatience motive is stronger early in the life-cycle but diminishes later on (because, e.g., the growth rate of income slows down), the model will predict that a low level of assets is held early on (mainly a buffer stock) and that asset accumulation increases late in the life-cycle when the impatience motive is relatively weaker and when the retirement motive becomes stronger. This is the buffer stock hypothesis, and there have been recent claims in the consumption literature that (for relatively impatient consumers) the above model fits the life-cycle profiles of asset accumulation quite well (see Carroll [1997] and Gourinchas and Parker [1995]).

The hypothesis tested in this chapter is whether the buffer stock model – when augmented to allow for portfolio choice – can also be reconciled with the empirical profiles of the stockholders’ life-cycle portfolio choice. Asset accumulation and portfolio choice are part of the same intertemporal choice, and so a reasonable model should be successful in both dimensions.

The “extended” buffer stock hypothesis advanced in this chapter is that if the typical young household’s savings is mainly a buffer stock against income shocks, then the

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\(^8\)The definition of prudence is that marginal utility be convex; Kimball [1993] analyzes prudence in a fashion similar to risk-aversion.
depressed demand for highly volatile stocks early on in the life-cycle may be consistent with optimal behavior. At face value, this hypothesis is not unreasonable: the presence of the background uninsurable risk in labor income may also affect the individuals' attitudes toward other forms of risk, such as financial risk, even if the two risks are independent.\textsuperscript{9} Since the buffer stock of assets acts as an imperfect substitute for insurance against labor income shocks, it should consist of mainly risk-free assets. If early on in the life-cycle this buffer stock is the main reason why households save, then the share of stocks in the household portfolio would be quite low. Only as households age and start accumulating assets for retirement would they increase their share of stocks held.

This chapter is an attempt to test the above intuition by taking the intertemporal consumer optimization model seriously. The model is solved using a stochastic labor income process derived from household-level data, and its structural preference parameters are then estimated by fitting the models' predicted life-cycle profiles of total asset holdings and portfolio choice to those estimated from household-level data. In doing so, the chapter employs the Method of Simulated Models introduced by Fakas and Pollard [1989] and Duffie and Singleton [1993].

A similar model of portfolio choice under uninsurable labor income risk is analyzed by Viceira [1997]. Rather than estimating the model, Viceira is interested in deriving approximate analytical solutions and assumes that retirement occurs as the result of an exogenous stochastic process. In his model the households most likely to retire also have the shortest life-cycle in expected terms. For that reason, his unique analytical results – while certainly illuminating – are not directly comparable to the life-cycle calibrations reported here.

\textsuperscript{9}Of course, this effect would become ever stronger if zero-income events tended to coincide with negative stock market shocks. Although an equilibrium model of the asset markets and the labor market is beyond the scope of this study, such an assumption is not unrealistic if both markets are subject to common aggregate shocks. Elmendorf and Kimball [1991] and Carroll and Kimball [1996] offer analytical results concerning the behavior toward other risks, and necessary restrictions on preferences to get the response of more asset accumulation and fewer risky assets in the presence of uninsurable risks.

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The first part of the calibration exercise is also closely related to the work of Heaton and Lucas [1996b]. They argue that the introduction of independent and uninsurable labor income risk within the expected utility framework does not significantly improve the model's ability to generate "reasonable" optimal stockholding rules for "reasonable" preference parameters. I certainly confirm their conclusion here, and I extend the analysis to the life-cycle patterns, rigorously estimating the set of (unreasonable) preference parameters that delivers life-cycle profiles of both stock shares and total asset holdings closest to the ones observed in the data. Perhaps surprisingly, my results suggest that in order to "fit" the observed profiles, the model requires implausibly high values of impatience rather than risk-aversion. It will be argued that this finding leads naturally to an intertemporal model of consumption and portfolio choice that severs the link between risk aversion and the intertemporal elasticity of substitution. Calibrations will then show that severing that link improves the predicted life-cycle profiles, although the fit remains far from perfect.

This chapter concentrates on stockholders, because the decision of whether or not to enter the stock market is most likely affected by factors that cannot be captured by this simple stylized model. For example, the presence of fixed costs associated with holding equity may be an important factor behind the decision by the majority of households to not hold any stocks at all. While the model considered here may be valuable in obtaining the optimal share to be held by each household, this share may not be observed for some households because of the presence of the fixed costs. For this reason, the estimation will use stockholders' age profiles of portfolio shares after they have been empirically corrected for the bias introduced by the individual-specific reasons for non-participation in the stock market. The participation decision was examined empirically in Chapter 2, where it was shown that there is evidence that the underlying optimal share of stocks for both stockholders and non-stockholders is affected by earnings uncertainty in a way
consistent with the buffer stock hypothesis.

The chapter is structured as follows: Section 2 introduces the extended buffer-stock model, while Section 3 presents the life-cycle profiles of total asset holdings and portfolio shares estimated from micro data. Section 4 discusses the Method of Simulated Moments technique that will be used to estimate the model, and Section 5 presents the results of the estimation. Section 6 concludes.

3.2 A Buffer-stock Model of Consumption and Portfolio Choice

The first intertemporal maximization model examined in this chapter extends the standard expected-utility constant-relative-risk-aversion preferences to the buffer-stock setting. This formulation of preferences has some quite attractive properties, to be discussed below, and (in its infinite-horizon formulation) has become the workhorse of the consumption literature. It is adapted to the life-cycle buffer-stock setting by the introduction of impatience, borrowing constraints and uninsurable labor income risk. Impatience implies that consumers would like to borrow in order to finance higher consumption but are prohibited from doing so by the borrowing constraint. On the other hand, the presence of uninsurable labor income risk strengthens their desire to save through the precautionary motive.

Over the life-cycle, the relative strength of these two motives varies with the slope of the labor income profile and the properties of the stochastic shocks to labor income. The resulting optimal policies for consumption and portfolio choice will thus reflect the relative strength of these motives at each stage of the life-cycle.
3.2.1 Consumer Maximization

Each household works for $T$ periods (set here to 40 years) and then retires. For simplicity, there is one consumption good (which also serves as the numeraire) and only two assets, a risk-free asset and a risky stock. In each period the household must choose the optimal level of consumption and asset holdings to maximize its life-time utility. The household is assumed to have time-separable, von Neumann-Morgenstern preferences, so that life-time utility $U_0$ takes the form

$$ U_0 = E_0 \left[ \sum_{t=0}^{T-1} \beta^t U(C_t) + \beta^T V_T(W_t) \right] \quad (3.1) $$

where $U(.)$ is the expected utility function, $V_T(.)$ is the value function at retirement, $W_T$ are the total assets held at retirement, $\beta$ is the discount factor, and $C_t$ is the household level of consumption in period $t$.

Given initial household assets $W_0$, the household maximizes life-time utility $U_0$ by choosing its holdings of the risk-free asset $F_t$ and the risky stock $S_t$ in each period, so that they satisfy the intertemporal budget constraint:

$$ W_{t+1} = F_t r^f + S_t \hat{R}_{t+1} \quad (3.2) $$

$$ F_t + S_t = W_t + \tilde{Y}_t - C_t \quad (3.3) $$

where $W_t$ is the total value of all financial assets in the beginning of period $t$, $r^f$ is the constant and known gross rate of return on the risk-free asset, $\hat{R}_{t+1}$ is the stochastic (as of period $t$) gross rate of return on each unit of stock held between periods $t$ and $t + 1$, and $\tilde{Y}_t$ is the exogenous labor income received in period $t$, which is random and whose exact realization does not become known until period $t$.

The value function of wealth $W_T$ at retirement, $V_T(W_T)$, is given exogenously, and the expected utility function $U(.)$ is assumed to exhibit constant relative risk aversion.
(CRRA) equal to $\gamma$, so that it takes the form

$$U(c) = \frac{c^{1-\gamma}}{1 - \gamma}$$

(3.4)

CRRA preferences have a number of appealing properties, including the implication that under complete markets consumers will hold a constant fraction of their total wealth in the risky stock, independent of age and the level of total wealth. They are also ideally suited for the purposes of this chapter, since they satisfy the conditions which ensure that uninsurable, idiosyncratic labor income risk will increase total savings while simultaneously depressing the fraction of financial assets held in the risky stock.\(^{10}\) The intuition is that in the presence of the unavoidable risk in their labor income stream, consumers will be willing to take on less additional risk in the form of holding risky equity, even if the two forms of risk are independent.

Finally, the formulation of the problem ensures that households will never finance future consumption by becoming net borrowers, regardless of how impatient they are. This result is driven by the finite horizon and the assumption (to be introduced next) that labor income can drop to zero with positive probability in each period. If households were to become net borrowers, there would be a positive probability of entering the last period of life with negative assets and zero labor income, which would then lead to zero consumption. Since marginal utility at zero consumption is infinite, such a policy could not be optimal. In that sense, the borrowing constraint is embedded in the labor income process. It is possible to generate demand for borrowing in a model that looks almost identical to this one by requiring that the labor income cannot drop to zero two years in a row. The borrowing constraint

\[ W_t \geq 0, \quad t \in (0, T - 1) \quad (3.5) \]

would then bind, but the results would look very similar to those obtained with the model introduced above. The case of the "implicit" borrowing constraint is chosen instead simply because it is computationally cheaper.

3.2.2 Labor Income

Labor supply is assumed to be exogenous, so that in the beginning of each period \( t + 1 \) the household receives labor income \( \tilde{Y}_{t+1} \), which is uncertain as of period \( t \) and uninsurable. The evolution of labor income during the working life of the household is governed by a deterministic growth rate and two multiplicative shocks to the level of labor income, a permanent shock and a transitory shock.\(^{11}\) Specifically,

\[
\tilde{Y}_{t+1} = \tilde{Y}^p_{t+1} \tilde{E}_{t+1}, \quad \text{and} \\
\tilde{Y}^p_{t+1} = G_{t+1} Y^p_t \tilde{H}_{t+1} \quad (3.6)
\]

\[
\tilde{Y}^p_{t+1} = G_{t+1} Y^p_t \tilde{H}_{t+1} \quad (3.7)
\]

where \( \tilde{Y}^p_{t+1} \) is the permanent component of labor income, \( G_{t+1} \) is the age-specific, non-random component of the change in permanent income between periods \( t \) and \( t+1 \), \( \tilde{H}_{t+1} \) is the permanent multiplicative shock to the level of labor income, and \( \tilde{E}_{t+1} \) is the transitory multiplicative shock to the level of labor income.

The permanent and transitory shocks are assumed to be distributed independently of one another. The permanent income shock \( \tilde{H}_{t+1} \) is strictly positive and its log (denoted \( \tilde{\eta}_{t+1} \)) is assumed to be unconditionally normally distributed with mean zero and variance \( \sigma^2_{\eta_{t+1}} \):

\[
\ln(\tilde{H}_{t+1}) \equiv \tilde{\eta}_{t+1} \sim \mathcal{N}(0, \sigma^2_{\eta_{t+1}}) \quad (3.8)
\]

\(^{11}\)The properties of this particular labor income process are discussed in depth in Chapters 1 and 2.
On the other hand, the transitory shock is assumed to be state-dependent. There are only two possible states, a "good" state that occurs with probability $1 - \pi_{t+1}$ and a "bad" state that occurs with probability $\pi_{t+1}$. In the good state, the transitory shock $\tilde{\varepsilon}_{t+1}$ is strictly positive and its log (denoted $\tilde{\varepsilon}_{t+1}$) is normally distributed with mean zero and variance $\sigma^2_{t+1}$. In the bad state the transitory shock is zero. Therefore:

$$\begin{cases} 
\ln(\tilde{\varepsilon}_{t+1}) \equiv \tilde{\varepsilon}_{t+1} \sim \mathcal{N}(0, \sigma^2_{t+1}) & \text{with probability } 1 - \pi_{t+1} \\
\varepsilon_{t+1} = 0 & \text{with probability } \pi_{t+1}
\end{cases}$$

(3.9)

Since both shocks are multiplicative to the level of labor income, an occurrence of the bad state for the transitory shock forces labor income to zero for that period, but does not affect the evolution of the permanent component of income. For example, the bad state can be thought of as temporary involuntary unemployment, which does not affect the earnings potential of the individual. Finally, the probability of the bad state as well as the variances of both the smaller shocks are age-dependent.

### 3.2.3 Retirement

The retirement value function is computed as the solution to the problem presented above when the remaining life-time is certain and equal to 15 years, when terminal wealth is required to be positive, and when income during retirement is certain and equal to 70\%\ percent of the last working year's permanent income. The presence of retirement income is meant to capture the availability of retirement benefits through Social Security, and the replacement rate is chosen to approximate that of a married couple with a single-earner retiring at age 65.\textsuperscript{12} One drawback of this approach, however, is that it does not capture other forms of uncertainty that are associated with retirement, such as the uncertainty over medical expenses and the uncertainty over the real value of social security payments.

\textsuperscript{12}I am grateful to Alain Jousten for kindly providing this information.
3.2.4 Housing

A major obstacle to calibrating this type of model to asset data is the exclusion of housing (and other durable goods) from the model. The PSID data set used to estimate the life-cycle profiles of asset accumulation implies that housing accounts for 75-85% of the directly held wealth of the median pre-retirement US household. In order to avoid modeling housing explicitly, I take the housing decision of the household as given and subtract housing expenditures from the profile of income. Specifically, I construct a profile of housing expenditures for the median household from the PSID, which I then subtract from the income profile. Approximating that profile, I assume in the calibrations that housing expenditures start at 17% of permanent income in the second period of life (age 26) and drop linearly to 9% of permanent income at age 58. After age 58, I assume that the house has been completely paid for. Housing maintenance and housing taxes have not yet been included in my measure of housing expenditures.

3.2.5 Solution

One drawback of the assumption of isoelastic preferences is that it renders the problem analytically intractable, so that numerical methods must be employed to obtain the solution. It will be useful to define a new variable, cash-in-hand \((X_t)\), as the total amount of resources available to the household in the beginning of each period.

\[
X_t \equiv W_t + Y_t
\]

(3.10)

The CRRA preference specification and the labor income process used in this chapter allow the model to be expressed in terms of a single state variable, the ratio of all cash-in-hand to current permanent income. Optimal policies can then calculated numerically by discretizing the state space (which is only one dimensional), and solving the first-order
conditions recursively. Working backwards, the model can be solved as if permanent income is equal to one, yielding for each age $t$ the optimal policies for consumption and stockholdings as a function of cash-in-hand $X_t$,

$$c_t^*(X_t) \quad \text{and} \quad s_t^*(X_t)$$  \hspace{1cm} (3.11)

For different levels of permanent income, the optimal level of consumption, $C_t^*$ and $S_t^*$ and stock holdings for each age at a certain level of cash-in-hand will then simply be equal to

$$C_t^*(X_t, Y_t^P) = Y_t^P c_t^*(X_t/Y_t^P) \quad \text{and} \quad S_t^*(X_t, Y_t^P) = Y_t^P s_t^*(X_t/Y_t^P)$$  \hspace{1cm} (3.12)

A set of optimal policies for consumption and the share of stocks in total savings as a function of cash-in-hand is presented in Figures 1A and 1B, respectively. The optimal policies are given at different ages, and for permanent income set to one in each age. They are the optimal policies when risk aversion $\gamma$ is 2.9, when the discount rate is almost 20% ($\beta = 0.84$), and when the labor earnings process uses parameters estimated for college-educated white-collar workers. Also distributions of the asset returns have been discretized so that their means and variances match the corresponding moments for the real simple return (including dividends) on the CRSP NYSE-AMEX value-weighted portfolio and the real 1-month US T-Bills return from December 1925 to December 1995 (using monthly data).

At low levels of cash-in-hand relative to permanent income, consumers exhibit buffer-stock behavior: they consume most of their available resources, but also save a little to maintain the buffer. At higher levels of cash-in-hand, the households consume a smaller fraction of their total currently available resources, as their impatience is now relatively weaker. Yet, they consume enough to run down their assets rapidly, since they are still

\footnote{A discussion of the discretization method can be found in Judd [1993]. A comparison with alternative numerical methods within this framework can be found in Heaton and Lucas [1996b].}
impatient. As households age, the remaining life-time uncertainty is reduced. Therefore, the impatient household consumes a greater share of its total resources since there is less reason to save for a buffer. From one year to the next, the increase in consumption for the same total cash-in-hand varies as it also reflects the declining slope of the expected labor income profile.

The optimal share of total savings in stocks also increases with the level of cash-in-hand (relative to permanent income). The reason is that at higher levels of cash-in-hand, the household will save a greater portion of its resources. Therefore, the effect of the uninsurable labor income risk is smaller, making the household more risk-tolerant, and thus willing to take on more risk in the form of holding risky stocks. The same is true as the household ages, because the remaining life-time uncertainty is reduced, even as the life-time stream of labor income is being run down.

3.2.6 Increases in Risk

While this chapter is not concerned with the effects of different earnings processes on the optimal policy functions, it worth considering briefly the effects of increases in risk. The household profile of labor income is subject to three types of risk: permanent shocks, transitory shocks, and big (zero-income) transitory shocks. While it is unclear what the relevant measure of total increases in risk is in this framework, for all the models considered in this chapter, increases in any of the variances or increases in the probability of zero income led to higher savings and lower portfolio shares. In the intertemporal model, it is not a priori clear that such increases in risk should necessarily lead to depressed stock shares, even if the preferences satisfy the conditions necessary for an increase in risk to

---

14 The exercises mentioned here also affect the mean of expected income. For example, increasing the probability of zero income decreases expected income, while increasing the variance of the permanent and small-transitory shocks increases it. Adjusting the deterministic part of income growth so that the profile of expected income is unchanged did not affect the direction of the results. Of course, mean-preserving spreads are most likely not the theoretically correct exercises for capturing increases in risk in this framework.
lead to depressed stock share in the static model.\textsuperscript{15} Clearly, the additional background risk will increase the individual's effective risk aversion, and this tends to depress the share of stocks held. However, the effect from the endogenous increase in wealth (due to the precautionary motive) is to increase the share of stocks held, since the buffer of assets is now bigger and it enables the household to take on more financial risk. Also, the increase in wealth reduces the effect of the borrowing constraint. I have found that increases in risk can lead to higher shares of stocks when the initial level of assets held is very low, so that the percentage increase in wealth due to the additional risk is substantial. Koo [1992] reports similar findings in a comparable continuous-time expected-utility setup. However, for the level of asset holdings implied in the life-cycle simulations of this section, increases in risk (as defined above) lead to lower shares of stocks in all the calibrations considered. As will be the case in the data, the effect is much more significant for changes in the probability of zero income rather than for changes in the variances of the smaller shocks (within the variation observed in the data).

3.2.7 Life-Cycle Profiles

Given the stochastic earnings process and the policy functions for consumption and stockholding, it is possible to simulate the life-cycle profiles of asset accumulation and portfolio choice for a typical household. Some randomly drawn profiles of asset accumulation and portfolio choice for the model discussed above are shown in Figures 2A and 2B, respectively. The normalization is that permanent income is set to one in the first period. The profiles have been calculated by assuming that initial wealth is equal to zero. Profiles like the ones in Figures 2A and 2B can be averaged over a large number of households, to obtain the predicted average profiles. In Section 3, these model-predicted average profiles will be used to identify the model's structural parameters (\(\gamma\) and \(\beta\)) by comparing them

\textsuperscript{15}These conditions have been laid out by Kimball [1993] and are satisfied by the CRRA form of the expected utility function.
to the average profiles estimated next from household level data.

3.3 Life-Cycle Profiles of Asset Accumulation and Portfolio Choice from Micro Data

Suppose that for each household and at each age there is an underlying optimal level of total asset holdings $W_t$ and an optimal portfolio share in stocks $\theta_t$. However, these optimal $W_t$ and $\theta_t$ are not always observed, because some households choose not to participate in the stock market.\(^{16}\) In that case, the observed distributions of $W_t$ and $\theta_t$ are incidentally truncated, in the sense that the sample is non-randomly selected. It the truncation process (i.e., the stock market participation decision) is correlated with the distribution of $W_t$ and $\theta_t$ then the moments of the observed distribution of $W_t$ and $\theta_t$ will not be equal to the moments of the true distribution of $W_t$ and $\theta_t$. To recover the true moments of the underlying distribution one needs information on the truncation process.

Let $W_t$ and $\theta_t$ each have a bivariate normal distribution with the variable $z_{i,t}^*$, which controls whether or not $W_t$ and $\theta_t$ are observed. Specifically, for each household $i$, $W_{i,t}$ and $\theta_{i,t}$ are only observed if

$$z_{i,t}^* = \delta' w_{i,t} + u_{i,t} \geq 0$$

(3.13)

where $w_{i,t}$ is a vector of household characteristics and $\delta$ is a parameter vector. In that case, the mean of the observed distributions of $W_{i,t}$ and $\theta_{i,t}$ will be given by

$$E[ W_{i,t} | z_{i,t}^* \geq 0 ] = E[ W_{i,t} ] + \rho_{Wz} \cdot \text{Var}[ W_{i,t} ] \lambda(\delta' w_{i,t})$$

(3.14)

\(^{16}\)In reality, both $W_t$ and $\theta_t$ are always observed, except that $\theta_t$ is zero for stockholders and so $W_t$ is drawn from a different distribution (the wealth distribution of non-stockholders). Recall that we are only interested in modeling the distributions of the stockholders, since we do not have a theory of the determinants of stock-market participation. Thus, for the purposes of estimating the distribution of wealth and stockholding conditional on being a stockholder, the observations of $W_t$ and $\theta_t$ for non-stockholders can be treated as if they were missing.
\[ E \left[ \theta_{i,t} | z_{i,t}^* \geq 0 \right] = E \left[ \theta_{i,t} \right] + \rho_{\theta^*} \cdot \text{Var} \left[ \theta_{i,t} \right] \lambda (\delta' w_{i,t}) \]  \hspace{1cm} (3.15)

where \( \rho_{\theta^*} \) and \( \rho_{\omega^*} \) are the correlation coefficients of the bivariate normal distribution of each of \( W_t \) and \( \theta_t \) with the variable \( z_{i,t}^* \), respectively. \( \lambda (\delta' w_{i,t}) \) is defined as

\[ \lambda (\delta' w_{i,t}) = \frac{\phi(\delta' w_{i,t})}{\Phi(\delta' w_{i,t})} \]  \hspace{1cm} (3.16)

where \( \phi(.) \) and \( \Phi(.) \) are the pdf and cdf of the standard normal distribution, respectively.

The goal is to recover \( E [W_{i,t}] \) and \( E [\theta_{i,t}] \) and to compare them with those predicted by the theoretical model presented in the previous section. While I do not wish to model the theory behind the decision of whether or not to participate in the stock market explicitly, it is necessary to obtain empirical estimates of \( \lambda (\delta' w_{i,t}) \). This can be obtained by empirically modeling the decision of whether or not to participate in the stock market, and obtaining estimates of \( \delta \), i.e., \( \hat{\delta} \), which can then be used to estimate \( \lambda (\delta' w_{i,t}) \) as

\[ \hat{\lambda}_{i,t} = \lambda (\hat{\delta}' w_{i,t}) \]  \hspace{1cm} (3.17)

It is then possible to recover \( E [W_{i,t}] \) and \( E [\theta_{i,t}] \) by OLS regression of the observed \( W_{i,t} \) and \( \theta_{i,t} \) on a constant and \( \lambda_{i,t} \), as shown by the sample selection estimator of Heckman [1979].

### 3.3.1 The Decision To Hold Stocks

This decision was analyzed in the empirical investigation of stockholding of Chapter 2. Here, the results of the estimation will only be presented briefly, since their main purpose is to obtain the \( \lambda_{i,t} \) necessary to recover \( E [W_{i,t}] \) and \( E [\theta_{i,t}] \).

Recall that the decision of each household to hold stocks is controlled by the underlying index \( z_{i,t}^* \), which from equation 3.13 is given by

\[ z_{i,t}^* = \delta' w_{i,t} + u_{i,t} \]
Households hold stocks only if $z_{it}^* \geq 0$. Since $u_{it}$ is assumed to be distributed normally,

$$\text{Prob(} \text{HoldStocks}) = \text{Prob}(z_{it}^* \geq 0) = \Phi(\delta'w_{it})$$

and the parameter vector $\delta$ can be thus be estimated by Tobit.

The decisions to hold stocks is estimated using data from the 1984 wealth supplement of the University of Michigan's *Panel Study of Income Dynamics* (PSID). It is allowed to be affected by age; the level of permanent income (computed as average income for the period 1977-1983 excluding the years that were classified as zero income events); the difference between current and permanent income; the head's level of education; the presence of a spouse; the share of the spouse's income in total labor income; the number of children; whether there had been a change in the head or the spouse in the past year; and the following four parameters describing the process for labor earnings for the period 1977-1983: the deterministic growth rate of permanent income, the probability of zero income, and the standard deviation of the smaller permanent and transitory shocks. Financial wealth has been omitted because wealth accumulation is endogenous. If information were available on initial wealth, then that would be the correct independent variable to include. Nevertheless, I also presented estimates in Chapter 2 where wealth was included as an independent variable and showed that it did not significantly alter the estimated effects of the other variables.

The earnings process parameters have been obtained by GMM estimation of the moment restrictions of the earnings process model of Section 2 by demographic cell (defined by three levels of educational attainment, two age groups and eight occupational groups). The estimation process itself as well as the results by group were discussed in depth in the first two chapters. It was generally found that the standard deviation of both the smaller permanent and transitory shocks is in the 10-15% range, whereas the probability of a "very low income" shock (relative to permanent income) is in the 4-6% range. "Very low
income” shocks are defined as occurrences when the level of labor income drops to below half of average income for the household (calculated over the other years of the 1977-1983 sample). Approximately six percent of the sample observations were classified as such shocks, and the median drop associated with them was to ten percent of average income. In the vast majority of the time, these shocks were associated with unemployment spells.

The parameter estimates for the stockholding decision are shown in Table 1. The first column reports the estimated slopes of the decision, with the associated t-statistics in the second column.\textsuperscript{17} Note that the asymptotic t-statistics should, in theory, be adjusted to reflect the fact that the earnings process parameters are estimates obtained from a first step estimation routine rather than data Newey and McFadden [1994].\textsuperscript{18} However, the earnings uncertainty estimates come from a GMM sample that is unbalanced, in the sense than there are not the same number of observations available for each moment, due to the low-income shocks. While the coefficient estimates are not affected, it is not yet known (as far as I can tell) how the asymptotic variance-covariance matrix can be estimated in this case.

Lower uncertainty in the form of lower probability of zero income increases the probability of holding stocks at the 99% level. Furthermore, households over age 55 have a much higher probability of holding stocks, while they also tend to hold higher shares, conditional on being stockholders.\textsuperscript{19} Such behavior is consistent with the view that buffer-stock behavior examined earlier is important in the decision to hold stocks, and that the

\textsuperscript{17}Note that the slopes are not equal to the coefficient estimates since this is a probit regression.

\textsuperscript{18}I am thankful to the macro seminar group at the New York Federal Reserve Bank and to Annette Vissing for helpful discussions on this subject.

\textsuperscript{19}Poterba and Samwick [1997] also report that household investment in directly held equity increases over the working part of the life-cycle. Poterba and Wise [1996], on the other hand, present evidence from pension plan data that the share of equity in these plans is higher for younger individuals. This last result is not necessarily inconsistent with the age profiles estimated above, since young households with retirement plans are probably not borrowing constrained and their behavior cannot be captured by the buffer-stock model. Furthermore, it is unknown what other risk-free assets they hold outside these pension plans.
moments of the wealth and stock-holding distribution of stockholders cannot be estimated correctly without adjusting for the stock-market non-participation process. Other significant factors include the level (very significant) and growth rate (not so significant) of permanent income, both of which increase the probability of holding stocks. If buffer-stock considerations are important for the decision to hold stocks, then a higher growth rate of (permanent) income strengthens the effect of the borrowing constraint and thus reduce the demand for stocks. However, it also implies higher lifetime resources, thus increasing the demand for stocks. The overall effect depends on the model chosen. Here, the point estimate of the effect of the growth rate of income is positive but the t-statistic is very small. Also, the difference between current income and permanent income affects the probability of holding stocks at the 99% confidence level; households with current income much above permanent income have a higher probability of holding stocks, and vice versa. This response indicates that the non-stockholders are the group that cannot buffer temporary labor income shocks by borrowing at the risk-free rate and thus do not hold stocks when they are hit with negative shocks.

Not surprisingly, there is significant evidence that the decision to hold stocks is affected by factors not captured by the buffer-stock model: more years of education increase the probability of holding stocks, while a greater number of children and a recent change in the head or spouse of the household decreases it. Perhaps surprisingly, the lower the share of the spouse's earnings in total labor income, the higher the probability of holding stocks, even though the presence of a spouse does not affect the decision. This finding would be consistent with a model of endogenous labor supply, where the spouse only works during periods of negative shocks to household income.
3.3.2 Computing the Age Profiles

The goal is to obtain the unconditional (over all households) average age profiles of asset accumulation and portfolio shares in stocks, i.e.,

$$E[W_t] = f^W(t) \quad \text{and} \quad E[\theta_t] = f^\theta(t), \quad t \in (25, 64)$$

where the economic life of the household begins at age \( t = 25 \) and the household retires at age \( t = 65 \). Using the sample selection estimator of Heckman [1979], it is now possible to recover \( E[W_t] \) and \( E[\theta_t] \) from the 1984 cross-section of stockholders. Suppose that unconditional age profile functions \( f^W(t) \) and \( f^\theta(t) \) are fourth-order polynomials in the age of the household \( t \). Each term of the polynomials can then be estimated by regressing each stockholders’ total assets and portfolio share on a fourth-order polynomial of age and on the bias term \( \hat{\lambda}_{i,t} \), which is given from equation 3.17 by:

$$\hat{\lambda}_{i,t} = \lambda(\hat{\delta}'w_{i,t})$$

Recall also that \( w_{i,t} \) is the vector of each households' characteristics governing the stock market participation decision, and that \( \hat{\delta} \) is the vector of parameter coefficients for the stock-holding decision that was estimated above.

There are at least two potential problems with using thus estimated profiles to estimate the theoretical model described in the previous section. First, the model does not take into account life-cycle changes in the family size which undoubtedly affect both profiles. This problem can be ameliorated in part by estimating unconditional age and family-size profiles and then using the profiles that are implied had the family size been constant over the life-cycle. The second problem lies with birth-year effects. Since the data set is cross-sectional, older household have been born in earlier calendar years than younger ones, and have thus had lower total resources available over their life-cycle. However, since the wealth profiles that will be estimated will be in terms of permanent income, this
is not necessarily a problem. As long as the only difference in the income processes of households born in earlier versus later years is that the level of initial permanent income is higher for the households born later, the estimated profiles will not have to be corrected for cohort effects.\textsuperscript{20}

3.3.3 Life-Cycle Profiles for College-Educated, White-Collar Households

Given the bias correction for stock-market non-participation, the unconditional age profiles $E[W_t]$ and $E[\theta_t]$ can be obtained by different demographic groups. The model can then be estimated numerically using all the different groups. Since such an endeavor would be prohibitive using a personal computer, this chapter has opted to concentrate on only one demographic group, the college-educated, white-collar households (where the definition is based on the head of the household). This particular choice was made only because the part of the non-participation bias caused by informational effects is arguably the least important for this demographic group. These informational effects are very hard to capture empirically, and very little is known about them Haliassos and Bertaut [1995]. Hopefully, for this group they will have been captured adequately by the educational variable in the decision to hold stocks.

Another serious problem is the limited information that the PSID provides on each households' retirement accounts. While social security payments have been included in the theoretical model in a rudimentary fashion, total asset accumulation must include retirement savings from employer-sponsored retirement accounts. Since such information is available for only a tiny subset of the sample, the age profiles have been constructed only for individuals reporting that they did not hold any retirement assets in 1984. Un-

\textsuperscript{20}A more detailed discussion of these issues can be found in Attanasio and Weber [1992] and Gourinchas and Parker [1995]. If there are reasons to believe that a cohort adjustment is necessary, it can be achieved with the PSID because there are now a total of three years for which the Wealth Supplement is available: 1984, 1989 and 1994.
fortunately, this sample selection may also be correlated with the decision to hold stocks. However, it cannot be avoided given the information that is available.

The constant family-size, unconditional age profiles of total asset accumulation, $E[W]$, and portfolio share in stocks, $E[\theta]$, are thus calculated for college-educated, white-collar households without retirement accounts. Total assets are calculated as the total value of the household’s risk-free assets, stocks, bonds, insurance policies, real estate other than home minus all non-housing debts. Recall that in the model, housing expenditures are reflected in the household income profile and not in asset accumulation. The share in stocks is defined as the sum of stocks over the sum of stocks and risk-free assets. Bonds, insurance policies and other real estate are not included in the share because the theoretical model only allows for stocks and risk-free assets, and its hard to classify those assets as being one or the other. Finally, total assets are normalized by dividing them by the value of permanent income, which is obtained as the average income over the period 1977-1983, not including “very low income shocks” (as defined above).

The individual households’ ratio of total assets to permanent income and their portfolio share in stocks were regressed by OLS on a polynomial in age, a polynomial in age multiplied by family size, and the Heckman non-participation bias term. The constant family-size profiles were then obtained as the predicted values of total assets to permanent income and portfolio share in stocks keeping the family size constant at three for all ages. The profiles are shown in Figure 3, with and without the family size correction. The five years in the beginning and at the end of the working life-cycle have been omitted from the graph because of the common endpoints problems of polynomial smoothing.

Both profiles increase sharply early on, then flatten significantly until age 45 or so, and then increase later in the life-cycle. The hump after age 45-50 is more pronounced for the portfolio profile. The first wave of asset accumulation is until the late thirties and does not pick up again until the late fifties. The average household retires with only a
little over two times its permanent income in savings, which indicates that households rely mostly on social security income after retirement (recall that these households do not have any other pensions). Also, the share of liquid assets in stocks is under 30% until age 45, and then increases rapidly, peaking at 60% at age 56.

Finally, the effect of the family-size correction is to flatten out both profiles substantially. Family size has a very pronounced life-cycle pattern: it increases from a little over two and a half to almost four at age 37, decreasing after that to a little over two by age 65 Gourinchas and Parker [1995]. The profiles which are not corrected for family size simply reflect that an increase in family size increases total asset accumulation and the share of liquid assets in stocks.

### 3.4 Method of Simulated Moments

#### 3.4.1 The Estimator

Let $v_{it}^j$, $j = 1..K$, and $x_{it}$ be a set of observable variables for individual $i$ of age $t$ that obeys the following process,

$$v_{it}^j = v_{it}^j(x_{it}; \beta, \gamma) + \varepsilon_{it}^j, \quad j = 1..K$$  \hspace{1cm} (3.18)

where $\beta$ and $\gamma$ are constants; $v_{it}^j(.)$ is a function of $x_{it}$, $\beta$ and $\gamma$; and $\varepsilon_{it}^j$ are K random variables, each of which has expectation zero. In the setup examined here $[v_{i1}^t \ v_{i2}^t]'$ is the observed vector of age $t$ total-assets-to-permanent-income and of age $t$ portfolio shares for individual $i$ (i.e., $j = 1, 2$); $x_{it}$ is the ratio of cash-in-hand to permanent income; $\beta$ is the rate of time preference; $\gamma$ the constant coefficient of relative risk aversion; $[v_{i1}^t \ v_{i2}^t]'$ is the vector of optimal values of total-assets-to-permanent-income and portfolio shares (which are each functions of $x_{it}$; $\beta$; and $\gamma$); and each random variable $\varepsilon_{it}^j$ can be thought of as individual heterogeneity that is independent of the level of cash-in-hand to permanent income and/or measurement error.

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The object is to estimate the preference parameters $\beta$ and $\gamma$. Given a sample of observations on $v_{i,t}^j$ and $x_{i,t}$ and the optimal policy functions $v_t^*(\cdot)$, the General Method of Moments (GMM) estimator of Hansen [1982], Hansen and Singleton [1996], Newey [1984], Newey [1985b] and Newey [1985a] can be employed to recover the preference parameters. The model of equation 3.18 imposes the following moment restrictions:

$$E\left[v_{i,t}^j - v_t^*(x_{i,t}; \beta, \gamma) | x_{i,t}\right] = 0, \quad j = 1..K$$  \hspace{1cm} (3.19)

However, GMM estimation using equation 3.19 is not possible here because the individual realizations of cash-in-hand to permanent income $x_{i,t}$ are not observed. Nevertheless, the preference parameters could still be recovered by GMM if for each age $t$ the cdf of the distribution of $x_{i,t}$, $dF_t(x)$, were known. In that case, it would be possible to calculate

$$\tilde{v}_t^*(\beta, \gamma) = \int v_t^*(x; \beta, \gamma) dF_t(x), \quad j = 1..K$$  \hspace{1cm} (3.20)

so that the unconditional expectation

$$E\left[v_{i,t}^j - \tilde{v}_t^*(\beta, \gamma)\right] = 0, \quad j = 1..K$$  \hspace{1cm} (3.21)

would be used instead as the moment restriction for GMM.

Unfortunately, GMM estimation of equation 3.21 is also unfeasible because $dF_t(x)$ is not known explicitly. Rather, it depends on the initial level of cash-in-hand, all the cdf's of each labor income shock from age 0 to age $t - 1$ (which may be age dependent), and all the optimal policies from age 0 to age $t - 1$. Unless really restrictive assumptions are made on the model, the term $\int v_t^*(x; \beta, \gamma) dF_t(x)$ cannot even be computed with numerical methods.

Fortunately, the Method of Simulated Moments (MSM) of Pakes and Pollard [1989] and Duffie and Singleton [1993] offers a way to estimate the underlying preference parameters from the unconditional expectation 3.21,
\[
\mathbb{E}\left[u_{i,t}^j\right] - \tilde{u}_t^*(\beta, \gamma) = 0, \quad j = 1..K
\]
without calculating \(\tilde{u}_t^*(\beta, \gamma) = \int u_t^*(x; \beta, \gamma) dF^t(x)\) exactly. Instead, \(\tilde{u}_t^*(\cdot)\) is estimated by simulation.

First, \(L\) sequences of random shocks to income from age 0 to age \(t - 1\), \(\{\tilde{H}_i, \tilde{E}_i\}_{\tau=0}^{t-1}\), \(i = 1..L\), are drawn and the associated path of \(x_{i,\tau}, \tau = 0..(t - 1)\), is calculated for each sequence \(i = 1..L\). This leads to \(L\) equally likely simulated “observations” of \(x_{i,t}, i = 1..L\). These simulated “observations” for \(x_{i,t}\) can then be used to calculate the simulated sample analog of \(\tilde{u}_t^*\),

\[
\tilde{u}_t^*(\beta, \gamma) = \frac{1}{L} \sum_{i=1}^{L} u_t^*(x_{i,t}; \beta, \gamma), \quad j = 1..K
\]
(3.22)

Given \(\tilde{u}_t^*(\beta, \gamma)\), the sample analog of the unconditional expectation,

\[
\mathbb{E}\left[u_{i,t}^j\right] - \tilde{u}_t^*(\beta, \gamma), \quad j = 1..K
\]
becomes

\[
\hat{S}_t^i = \hat{v}_t^i - \tilde{u}_t^*(\beta, \gamma), \quad j = 1..K
\]
(3.23)

where \(\hat{v}_t^i = \frac{1}{N} \sum_{i=1}^{N} v_{i,t}^j\) is the sample analog of \(\mathbb{E}\left[u_{i,t}^j\right]\) obtained by the \(N\) actual observations \(v_{i,t}^j, i = 1..N\).

Pakes and Pollard [1989] and Duffie and Singleton [1993] have shown that under sufficient regularity conditions, the simulation error introduced in 3.23 by using \(\tilde{u}_t^*(\beta, \gamma)\) rather than \(\tilde{u}_t^*(\beta, \gamma)\) disappears asymptotically. Furthermore, consistent estimates of \(\beta\) and \(\gamma\) can be obtained by minimizing the distance between zero and the sample moments in 3.23 for all ages \(t = 0..(T - 1)\) and all observed variables \(v_{i,t}^j, j = 1..K\).

Let \(\psi\) denote the vector of parameters to be estimated, \(\psi' = [\beta \gamma]'\). Also, let \(\hat{g}(\psi)\) denote the vector of the \(KT\) sample moments, i.e.,

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\[ \hat{g}(\psi)' = \left[ \hat{S}_0^1 \ldots \hat{S}_{T-1}^1 \hat{S}_0^2 \ldots \hat{S}_{T-1}^2 \ldots \hat{S}_0^K \ldots \hat{S}_{T-1}^K \right]' \]  

(3.24)

Then a consistent estimate \( \hat{\psi} \) of \( \psi \) can be obtained as

\[ \hat{\psi} = \text{argmin} \{ \hat{g}(\psi)' \hat{g}(\psi) \} \]

and the asymptotic distribution of \( \hat{\psi} \) is given by

\[ \sqrt{N} \left( \hat{\psi} - \psi_0 \right) \rightarrow \mathcal{N} (0, \nu) \]  

(3.25)

where \( \psi_0 \) is the true value of \( \psi \), \( N \) is the number of total actual (i.e., not simulated) observations used to derive the sample moments and \( \nu \) is estimated by

\[ \hat{\nu} = \left( \hat{G}' \hat{G} \right)^{-1} \hat{G}' \hat{\Omega} \hat{G} \left( \hat{G}' \hat{G} \right)^{-1} \]  

(3.26)

\[ \hat{G} = \left. \frac{\partial \hat{g}(\psi)}{\partial \psi} \right|_{\psi = \hat{\psi}} \]  

(3.27)

\[ \hat{\Omega} = \hat{g}(\hat{\psi}) \hat{g}(\hat{\psi})' \]  

(3.28)

Finally, if the total number of moments \( KT \) is greater than the number of parameters to be estimated, \( M \), the over-identifying restrictions of the model can be tested by constructing the statistic

\[ x_{KT-M}^2 = N \hat{g}(\hat{\psi})' \hat{\Omega}^{-1} \hat{g}(\hat{\psi}) \]  

(3.29)

Under the null hypothesis that the model is correctly specified (i.e., that the relevant moments are equal to zero), the \( x_{KT-M}^2 \) statistic is asymptotically distributed as Chi-squared with \( KT - M \) degrees of freedom. A discussion of simulation-based estimation in general, including other simulation methods, can be found in Stern [1997].

Given a labor earnings process, the model of Section 2 can now be used to derive the predicted average level of total-assets-to-permanent-income and the predicted average
portfolio-share-in-stocks for each age. Also, household level data from the PSID can be used to derive empirical age profiles for both variables by demographic group. In fact, the profiles for college-educated, white-collar households were estimated in Section 3. Therefore, the MSM estimator presented above can be employed to recover the structural parameters $\beta$ and $\gamma$ of the model, by minimizing the distance between the actual and predicted age profiles for that demographic group.

3.4.2 Model Calibration

The model is solved for ages 25 – 64. The exogenous parameters of the model have been set as follows:

(i) *Earnings Process.* The earnings process parameters used are those for college-educated white-collar households. They have been obtained by GMM estimation of the moment restrictions of the earnings process model of Section 2, outlined in equations 3.6-3.9:

$$
\bar{Y}_{t+1} = \tilde{Y}_{t+1}^{p} \tilde{E}_{t+1}, \text{ and}
$$

$$
\bar{Y}_{t+1}^{p} = G_{t+1} Y_{t+1}^{p} \bar{H}_{t+1}
$$

$$
\ln(\bar{H}_{t+1}) \equiv \tilde{\eta}_{t+1} \sim \mathcal{N}(0, \sigma_{\eta t+1}^{2})
$$

$$
\begin{cases}
\ln(\tilde{E}_{t+1}) \equiv \tilde{\epsilon}_{t+1} \sim \mathcal{N}(0, \sigma_{\epsilon t+1}^{2}) & \text{with probability } 1 - \pi_{t+1} \\
\mathcal{E}_{t+1} = 0 & \text{with probability } \pi_{t+1}
\end{cases}
$$

Recall that $G_{t+1}$ is the non-random component of the change in permanent income, $\sigma_{\eta t+1}^{2}$ is the variance of the log permanent income shock, $\sigma_{\epsilon t+1}^{2}$ is the variance of the
log transitory income shock, and $\pi_{t+1}$ is the probability that the zero-income state will occur. In practice, the zero-income state is defined as any occurrence when the level of labor income drops to below half of average income for the household (calculated over the other years of the 1977-1983 sample). Approximately six percent of the sample observations were classified as such shocks, and the median drop associated with them was to ten percent of average income. These events were confirmed (by inspection of each one) to have been associated with unemployment.

The estimated process for college-educated white-collar households are summarized in Table 2. Standard errors, the properties of the estimates, as well as the results for other demographic groups were discussed in depth in the first two chapters. There, it was reported that the coefficients estimates were very significant. For the demographic group considered here, the variance of the permanent shock drops for older households, whereas the variance of the transitory shock increases for older households. The probability of a zero-income shock is approximately the same for both age groups, and the slope of the expected income profile declines with age. All the changes with age in the labor income process are built into the simulation. Note that the standard deviations of both shocks are lower than for most other demographic groups (which are in the range of 15%), and so is the probability of a zero-income shock (which is approximately 6% for the entire PSID sample for 1977-1983). Finally, the labor income process is assumed to be independent of asset returns.

(ii) Rates of Return. The assumed distribution of the asset returns is such that their means and variances match the corresponding moments for the real simple return (including dividends) on the CRSP NYSE-AMEX value-weighted portfolio and the real 1-month US T-Bills return from December 1925 to December 1995 (using
monthly data).

(iii) Initial Conditions. Initial permanent income is normalized to one, and initial household wealth is set to zero. The assumption on initial wealth is reasonable, since the average young household has very few if any assets. In fact, I found that a significant portion of households under thirty was in debt. Note, however, that borrowing is not allowed in this model.

(iv) Retirement and Housing. The assumptions for both retirement and housing have been discussed in Section 2. In summary, the retirement value function is calculated as that of a household with a fifteen-year horizon, and it is assumed that the household receives certain Social Security income at retirement which is equal to 70% of the permanent income in the household's last working period. Housing is assumed to be exogenous and it is excluded from the calculation of the asset profiles. However, housing expenditures by age are subtracted from income using a life-cycle profile of housing-expenses-to-permanent-income calculated for the median PSID household.

3.5 Estimation Results

The simulation of the model delivers the average level of total-assets-to-permanent-income and the average portfolio-share-in-stocks for ages 25 – 64 for college-educated, white-collar households. Similarly, the average age profiles for that demographic group have been estimated for the same ages from the PSID in Section 3. However, the first five years and the last five years of the data profiles are dropped to avoid the problems in the edges that result from polynomial fitting. Therefore, the PSID profiles are available for ages 30 – 59 yielding 30 moment restrictions for each variable, i.e. a grand total of 60 restrictions to be used to estimate the two preference parameters $\beta$ and $\gamma$. 108
In addition to using the 60 moment restrictions from the levels of the two age profiles, the parameters of interest can also be estimated from the 58 moment restrictions on the slopes of the age profiles. The advantage of this approach is that it allows the profiles to be off by a constant. In what follows, I will present results from both levels and slopes estimation.

3.5.1 The one-asset model

I first estimate the one-asset version of the model, which is similar to the models proposed by Gourinchas and Parker [1995] and Carroll [1997]. The only available asset is the risk-free asset, and the estimator matches the actual and predicted profiles of total asset accumulation. The level and slopes estimates for the preference parameters are presented in Table 3.

<table>
<thead>
<tr>
<th>Estimated Parameter</th>
<th>Levels Estimation</th>
<th>Slopes Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard Error</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.98</td>
<td>0.004</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>1.53</td>
<td>0.11</td>
</tr>
<tr>
<td>$\lambda^2$</td>
<td>533.83</td>
<td></td>
</tr>
</tbody>
</table>

(a) Data profiles derived from 148 observations.
(b) Under the null, $\lambda^2$ is distributed as Chi-Squared with 28 and 27 degrees of freedom, respectively. The 95% critical values for these distributions are 41.34 and 40.11, respectively.
(c) The estimate of $\lambda^2$ is not precise, because of numerical difficulties with inverting the moment variance-covariance matrix.

Both levels and slopes estimation yields similar, tight estimates of the preference parameters. Risk aversion is estimated to be around 1.5 and the rate of time preference is estimated at 0.98-0.99, implying a discount factor of approximately 1%, barely above the average historical risk-free rate return of 0.5%. While the risk aversion estimates are in line with those obtained by Gourinchas and Parker [1995], the estimated rate of time
preference is much higher than theirs (which was approximately 0.9). A higher rate of
time preference in this model implies that the relative strength of impatience (due to time
preference and the expected growth of permanent income) is weaker. Note that the slopes
estimates are a little tighter than the levels estimates, and imply less impatience and also
less risk aversion. For both sets of estimates, the over-identifying restrictions are strongly
rejected. However, the rejection of the model is much weaker for the slopes estimation.

The predicted life-cycle profiles of asset accumulation from levels and from slopes
estimation are presented in Figures 4A and 4B, which also graph the profile estimated
from the PSID. The estimated profiles under-predict the rate of asset accumulation early
on and under-predict in the later part. In other words, neither profile captures well the
empirical fact that asset accumulation is strong early in the life-cycle, slows down in the
middle, and picks up again late in the life-cycle. Perhaps surprisingly, the slopes profile
actually does the worse in matching that feature of the empirical profile.\textsuperscript{21} However, I
have found that this feature can be generated in the predicted profile, if at the same level
of risk aversion, the household is made to be much more impatient, in the range of $\beta = 0.9$
(which is closer to the Gourinchas and Parker [1995] estimates). Yet, those values for the
preference parameters actually lead to a greater distance of the sample moments from
zero for both the levels and the slopes estimator. Perhaps a more appropriate simulated
estimator in this case would be one that would break down the life-cycle in three parts
(early, middle and late) and would simply try to match the average slope during those
parts (strong positive, zero, not so strong positive).

3.5.2 The two-asset model

Portfolio choice is introduced in the buffer-stock model by allowing the household to also
hold a risky stock, calibrated as described above to resemble the return to the US stock

\textsuperscript{21}The upward glitch at age 58 in both profiles is due to the fact that (given the estimated profile of
household expenditures), the household has just finished paying for housing services forever.
market. In this case, both the total-asset-accumulation profile and the portfolio-share-in-stocks profile will be used to estimate the model. The level and slopes estimates for the preference parameters are presented in Table 4.

<table>
<thead>
<tr>
<th>Estimated Parameter</th>
<th>Levels Estimation</th>
<th>Slopes Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard Error</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.69</td>
<td>0.0002</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>4.23</td>
<td>0.0001</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>-26,583</td>
<td></td>
</tr>
</tbody>
</table>

(a) Data profiles derived from 148 observations.
(b) Under the null, $\chi^2$ is distributed as Chi-Squared with 58 and 57 degrees of freedom, respectively. The 95% critical values for these distributions are 41.34 and 40.11, respectively.
(c) The estimate of $\chi^2$ is not precise, because of numerical difficulties with inverting the moment variance-covariance matrix.

Forcing the model to match the life-cycle portfolio profile in addition to the life-cycle total-asset-accumulation profile results in higher estimated risk-aversion and much lower estimated time-preference. While the estimated coefficient of relative risk aversion is still in the plausible middle single-digit area, the estimated rate of time preference is clearly implausible: the levels estimate corresponds to a discount factor of over 40%, while the slopes estimate corresponds to a discount factor of almost 20%! Not surprisingly, the rejection of the over-identifying restrictions is much stronger than that for the one-asset case. Examination of the predicted savings and portfolio profiles for each set of estimates (Figures 5A-5D) reveals that the model does not really come close to matching the actual profiles. In fact, the predicted profiles do much worse than those for the one-asset only model (Figures 4A-4B).

The inability of the two-asset model to deliver reasonable looking profiles for both total asset holdings and portfolio shares undoubtedly casts doubt on the “extended” buffer-stock hypothesis laid out in the introduction. The “original” hypothesis was that
the household exhibits buffer-stock behavior early on in the life-cycle, saving only a little as insurance against labor income shocks. Extending this rationale to portfolio choice the hypothesis then stated that the buffer stock of assets – which is an imperfect form of insurance against adverse labor income shocks – should be comprised of mostly risk-free assets. Thus, the household should hold a low share of stocks early on, increasing its share only much later in the life-cycle when its impatience becomes relatively weaker to its prudence and its desire to save for retirement.

Unfortunately, the expected utility model used so far has the unattractive property that an increase in risk aversion necessarily leads to a decrease in the intertemporal elasticity of substitution (IES). Since the IES measures how willing the household is to substitute over time, and thus affects directly the strength of the impatience motive, the imposed link between the IES and risk aversion deprives the model of a crucial degree of freedom.\(^2\) The reason is that the estimated profiles are matched by varying the relative strengths of prudence and of impatience over the life-cycle. The following section addresses this concern.

3.5.3 Breaking the Link between Relative Risk Aversion and the Intertemporal Elasticity of Substitution

In the expected utility model, relative risk aversion \(\gamma\) and the IES (hence denoted by \(\phi\)) are linked by the following identity:

\[
\gamma = 1/\phi
\]  
(3.30)

\(^2\)Technically, the reason of concern is the imposed link between relative prudence and the IES. However, in the framework used here, there is a one-to-one correspondence between relative risk aversion and relative prudence. Relative prudence, first analyzed by Kimball (1993), measures the curvature of the marginal utility function in a fashion similar to how risk aversion measures the curvature of the utility function. It is relative prudence that matters for the precautionary saving motive and also for the consumer's attitude toward holding risky assets in the presence of background uninsurable labor income risk, as shown by Carroll and Kimball (1996) and Elmendorf and Kimball (1991).
The reason is simply that the expected utility framework treats states of nature and states across time identically (albeit with different weights). Higher IES implies that households desire to smooth consumption across time, so that it counters the effect of impatience. Thus, the expected utility model necessarily diminishes the effects of impatience when risk aversion is increased to strengthen the precautionary motive. This is an unattractive property for a model that relies on the relative strengths of these very two motives to deliver its life-cycle predictions.

A natural extension of the model is to abandon the expected utility framework and work instead with preferences that separate risk aversion from the IES. Such a preference specification is provided by Epstein and Zin [1989], Epstein and Zin [1991] and Weil [1989] who build on the work by Kreps and Porteus [1978]. Specifically, the value function that the consumer maximizes takes the recursive form:

$$V_t = \max_{C_t, R_t, S_t} \left\{ (1 - \beta)C_t^{1-\rho} + \beta \left( E_t \left[ V_{t+1}^\alpha \right] \right)^{\rho/\alpha} \right\}^{1/\rho} \quad (3.31)$$

subject to the same intertemporal constraint as before, where the constants $\rho$ and $\alpha$ are defined as

$$\rho = 1 - 1/\phi \quad (3.32)$$

$$\alpha = 1 - \gamma \quad (3.33)$$

When $\gamma = \phi^{-1}$ the model reduces to the expected utility model of Section 2.

As shown in Epstein and Zin [1989], Epstein and Zin [1991] and Weil [1989], the first order conditions of the consumer's problem can be derived using dynamic programming arguments. Numerical methods similar to the ones employed in the expected utility framework can then be employed to solve the problem recursively and obtain optimal policy rules for portfolio choice and consumption (and thus total asset holdings). A nice
feature of these preferences is that the model can still be solved in terms of a single state variable, the ratio of cash-in-hand to permanent income.

The MSM estimator can be applied to the Epstein-Zin-Weil model. However, numerical considerations, coupled with the curse of dimensionality, make MSM optimization over three preference parameters prohibitively costly. Thus, the Epstein-Zin-Weil model is solved by keeping the IES (φ) constant and solving, once again, for the rate of time preference β and for the coefficient of relative risk aversion γ. Still – to the extent that the link imposed by expected utility is a big part why the model has such a hard time fitting the estimated profiles – the above model is a great improvement over the expected utility model even with a fixed φ. The reason is that the relative strengths of the prudence and impatience motives can now be varied independently.

There is only one study attempting to estimate φ independently of γ on micro data that I am aware of, Attanasio and Weber [1989]. Their point estimate φ was a little less than two, and it was significantly different from zero. Also, their estimate of risk aversion was over 20, but the standard error of the estimate was extremely large.

Ideally, a value for φ would be estimated by the MSM simulator. However, for the reasons explained above, a value for φ was chosen rather than estimated. It was set at 0.8, so that it is a little below the value implied for φ by the log expected utility function. The MSM estimator and the Epstein-Zin-Weil model were then used to derive the estimates of β and γ so that the estimated age profiles of both total asset holdings and portfolio shares matched the predicted ones. The results are summarized in Table 5:
Table 5: MSM Estimates of the Epstein-Zin-Weil Model with IES=0.8

<table>
<thead>
<tr>
<th>Estimated Parameter</th>
<th>Levels Estimation</th>
<th></th>
<th>Slopes Estimation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>SE</td>
<td>Coefficient</td>
<td>SE</td>
</tr>
<tr>
<td>β</td>
<td>0.72</td>
<td>0.002</td>
<td>0.89</td>
<td>0.0004</td>
</tr>
<tr>
<td>γ</td>
<td>8.22</td>
<td>0.019</td>
<td>2.94</td>
<td>0.11</td>
</tr>
<tr>
<td>χ²</td>
<td>525.70</td>
<td></td>
<td>5,648</td>
<td></td>
</tr>
</tbody>
</table>

(a) Data profiles derived from 148 observations.
(b) Under the null, χ² is distributed as Chi-Squared with 58 and 57 degrees of freedom, respectively. The 95% critical values for these distributions are 41.34 and 40.11, respectively.
(c) The estimate of χ² is not precise, because of numerical difficulties with inverting the moment variance-covariance matrix.

Figures 6A-6D present the life-cycle profiles implied by each set of parameter estimates. Relative to the expected utility model, the Epstein-Zin-Weil specification results in higher estimated risk-aversion (yet still in the single digits), and a higher estimated rate of time preference. The estimated rate of time preference still implies unreasonably high discount rates, and the predicted profiles are still a poor match. However, there are two important reasons why breaking the link between risk aversion and the IES may be important. First, the Epstein-Zin-Weil specification, even with an arbitrarily predetermined value for the IES, delivers the weakest rejection of the over-identifying restrictions for the two asset model (achieved by the levels MSM estimator). Second, the predicted profiles recovered from the levels estimation are the only ones yet that are qualitatively roughly consistent with the observed life-cycle patterns of savings and portfolio choice.

The second point is best illustrated by looking at the predicted profiles outside the scale of the actual profiles, as presented in Figures 7A and 7C. The actual profiles are also plotted beside the predicted ones, in Figures 7B and 7D. Figure 7A shows that the average household maintains a low level of assets early on, and that this level of assets increases as the household ages. It peaks at age 53 and then declines toward retirement. Early in the life-cycle the household maintains a small buffer stock of assets. However,
between ages 30 and 53, the impatience motive gradually becomes weaker than prudence, and the household accumulates assets. Yet, the precautionary motive also declines over time, because the remaining life-time income uncertainty is diminished. Eventually (after age 53), the precautionary motive becomes weaker than impatience and the household starts to run down its assets.

On the portfolio side (Figure 7C), the share of assets held in stocks stays low and roughly constant in the early part of the life-cycle. In fact, it even slightly declines until age 45, because the effect of the increased strength of the prudence motive outweighs the wealth effect of having accumulated a higher level of assets. From age 45 on, the share in stocks rises consistently. Since the total level of asset increases until age 53, it has to be the case that the increase is driven by the wealth effect; the growth in total assets indicates that the relative strength of the precautionary motive has increased, which tends to reduce the share of stocks held. After age 53, however, the precautionary motive is weaker than impatience as evidenced by the decline in total assets. This decrease in the precautionary motive outweighs the negative wealth effect from impatience, and the overall share in stocks continues to increase.

3.6 Conclusion

This chapter set out to examine how well the expected utility model under earnings uncertainty can account for the observed patterns of asset holdings. In part, the exercise was motivated by some recent evidence that such a model can fit the observed average consumption and income profiles quite well if consumers are allowed to be impatient. This "buffer-stock" model was extended to allow for portfolio choice and asked to match not only total asset accumulation profiles, but also the life-cycle profiles of the share of assets held in stocks.

Overall, the chapter uncovered little evidence in favor of the buffer-stock model. Es-
timation of the one-asset model using the wealth profiles only yielded very low discount rates, while estimation of the two-asset model was not at all successful in matching the actual profiles of both total assets and portfolio shares. At the same time, the two asset model required implausibly high discount rates. It was then argued that the link imposed between relative risk aversion and IES by expected utility is undesirable within this framework. The link was thus severed and the Epstein-Zin-Weil preference specification was used instead. In estimating the Epstein-Zin-Weil model, the IES was arbitrarily chosen, and risk aversion and time preference were estimated from the actual profiles. Despite the restriction of the arbitrarily chosen IES (imposed for computational reasons), the model was able to fit the data better than the expected utility model, and for more reasonable discount rates.

Future research should be able to estimate the IES from the observed profiles. Also, it would be interesting to see how well the model can explain differences in the asset accumulation profiles of demographic groups with different earnings uncertainty profiles.
Table 1: Stock Market Participation

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Decision to Hold Stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Slope</td>
</tr>
<tr>
<td>Age 30 to 35</td>
<td>-0.0043</td>
</tr>
<tr>
<td>Age 35 to 40</td>
<td>0.0044</td>
</tr>
<tr>
<td>Age 40 to 45</td>
<td>0.0076</td>
</tr>
<tr>
<td>Age 45 to 50</td>
<td>0.0075</td>
</tr>
<tr>
<td>Age 50 to 55</td>
<td>0.0464</td>
</tr>
<tr>
<td>Age &gt; 55</td>
<td>0.1100</td>
</tr>
<tr>
<td>Education (Years)</td>
<td>0.0160</td>
</tr>
<tr>
<td>Completed High-school</td>
<td>0.0205</td>
</tr>
<tr>
<td>Completed College</td>
<td>0.0228</td>
</tr>
<tr>
<td>Number of Children</td>
<td>-0.0161</td>
</tr>
<tr>
<td>Change in Head/Spouse?</td>
<td>-0.0373</td>
</tr>
<tr>
<td>Spouse?</td>
<td>0.0080</td>
</tr>
<tr>
<td>Spouse Share of Earnings</td>
<td>-0.0944</td>
</tr>
<tr>
<td>(PermInc - CurrentInc)</td>
<td>-4.9E-06</td>
</tr>
<tr>
<td>Permanent Income</td>
<td>8.7E-06</td>
</tr>
<tr>
<td>E[%Δ(PermInc)]</td>
<td>1.0037</td>
</tr>
<tr>
<td>Var(Permanent Shocks)</td>
<td>1.4428</td>
</tr>
<tr>
<td>Var(Transitory Shocks)</td>
<td>0.4515</td>
</tr>
<tr>
<td>Prob(Zero Income)</td>
<td>-2.4845</td>
</tr>
</tbody>
</table>

Note:

(i) Total number of observations is 3,187 of which 613 are stockholders.

(ii) Minimum demographic cell size for the uncertainty profiles estimates is 50 observations in 1983.

(iii) No self-employed workers are included in this regression, due to the small size of their demographic cells (used to estimate the parameters of their earnings process).

(iv) The omitted age dummy is Age<30.
Table 2: The Earnings Process Parameters for College-Educated, White-Collar Households

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>18-45</td>
</tr>
<tr>
<td>Standard deviation (log permanent shock), $\sigma_{nt+1}$</td>
<td>15.5%</td>
</tr>
<tr>
<td>Standard deviation (log transitory shock), $\sigma_{ct+1}$</td>
<td>8.2%</td>
</tr>
<tr>
<td>Prob (Zero Income)</td>
<td>3.3%</td>
</tr>
<tr>
<td>Exp %Δ of Perm Inc, $G_{t+1}$</td>
<td>3.5%</td>
</tr>
<tr>
<td>... implying Growth of Avg Household Income</td>
<td>4.6%</td>
</tr>
<tr>
<td>Observations</td>
<td>390</td>
</tr>
</tbody>
</table>

Note:

(i) Source: PSID.

(ii) Based on after-tax labor income for years 1977-1983.

(iii) Definition of Zero Income: when income is less than half of average income in the other years of the panel (the median zero income event dropped income to 10% of last year's value).
Figure 1A: Optimal Consumption at Different Ages
Current Permanent Income Equal to One

Figure 1B: Optimal Share in Stocks at Different Ages
Current Permanent Income Equal to One
Bibliography


