The Cross-Section of Household Preferences

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Abstract

This paper estimates the cross-sectional distribution of preferences in a large administrative panel of Swedish households. We consider a life-cycle portfolio choice model, which incorporates risky financial and housing investments and risky labor income, and study middle-aged households grouped by education, industry of employment, and birth cohort. We estimate the model using the Method of Simulated Moments to match the evolution of wealth and the risky portfolio share over time. The model allows for heterogeneity in risk aversion, the elasticity of intertemporal substitution (EIS), and the rate of time preference. When all three parameters are unrestricted, they are weakly identified and we consider alternative parameter restrictions to address this problem. We obtain moderate estimates of risk aversion and values of the EIS that are always greater than the reciprocal of risk aversion, always less than one, and weakly negatively correlated with risk aversion. We find that households with higher education have higher EIS, while households in risky occupations have lower risk aversion.

1 Introduction

When households make financial decisions, are their preferences towards time and risk substantially similar, or do they vary cross-sectionally? And if preferences are heterogeneous, how do they vary with household attributes such as education and sector of employment? This paper answers these questions using a life-cycle model of saving and portfolio choice fit to high-quality household-level administrative data from Sweden.

Modern financial theory distinguishes at least three parameters that govern savings behavior and financial decisions: the rate of time preference, the coefficient of (relative) risk aversion, and the elasticity of intertemporal substitution (EIS). The canonical model of Epstein and Zin (1989, 1991) makes all three parameters constant and invariant to wealth for a given household, while breaking the reciprocal relation between relative risk aversion and the elasticity of intertemporal substitution implied by the older power utility model.

We structurally estimate these three preference parameters in the cross-section of Swedish households by embedding Epstein-Zin preferences in a life-cycle model of optimal consumption and portfolio choice decisions in the presence of uninsurable labor income risk and borrowing constraints. To mitigate the effects of idiosyncratic events not captured by the model we carry out our estimation on groups of households that share the same level of education, sector of employment, and birth cohort.[2] As standard in the life-cycle literature (Carroll and Samwick 1997, Cocco, Gomes, and Maenhout 2005), we allow households' age-income profiles to vary by education and the determinants of income risk (the variances of permanent and transitory income shocks) to also depend on the household's business sector. It is well known that these life-cycle models are much better at jointly matching portfolio allocations and wealth accumulation at mid-life than at younger ages or after retirement. Therefore we estimate the preference parameters by matching the profiles of wealth and portfolio choice between ages 40 and 60. We confine attention to the sub-sample of stockholders, to avoid the need to estimate determinants of non-participation in risky financial markets.

It is a challenging task to identify all three Epstein-Zin preference parameters. In principle, these parameters play different roles with the rate of time preference affecting only the overall slope of the household's planned consumption path, risk aversion governing the willingness to hold risky financial assets, and the EIS affecting both the overall slope of the planned consumption path and the responsiveness of this slope to changes in background risks and investment opportunities. We observe portfolio choice directly, and the slope of the planned consumption path indirectly through its relation with saving and hence wealth accumulation. However, we require variation in background risks and/or investment opportunities in order to identify the EIS separately from the rate of time preference (Kocherlakota 1990, Svensson 1989).

[2] We consider 3 education levels and 12 sectors, and our sample spans 13 cohorts, giving us a total of 468 household groups.

Background risks change over the life cycle as remaining working life diminishes with the approach of retirement. In addition, households vary their portfolio allocations over time, causing endogenous variation in the expected returns and risks of their portfolios. In practice, however, both sources of identification are quite weak. For this reason, we assume in much of our work that all households with the same level of education share the same rate of time preference, while both risk aversion and the EIS are allowed to vary freely in the cross-section. This assumption greatly improves our ability to identify the parameters of our model.

The main findings of our paper are as follows. First, we estimate moderate coefficients of risk aversion, around 4 on average, because we treat real estate as a risky investment rather than ignoring it or treating it as a safe asset. Second, our estimates of the EIS are below one for all household groups. Third, we estimate the EIS to be above the reciprocal of risk aversion for all household groups, inconsistent with the assumption that Swedish households have power utility. Fourth, however, there is a weak negative correlation in the cross-section between our estimates of the EIS and of risk aversion, consistent with the qualitative relationship between these two parameters implied by power utility. Fifth, we find that Swedish households with higher education have meaningfully higher EIS and slightly lower risk aversion than other Swedish households. Sixth, households working in sectors with high labor income risk have lower risk aversion than other households. The effect of income risk on risk aversion is primarily driven by the variance of permanent income shocks rather than transitory income shocks.

Our results shed light on a number of important issues in asset pricing and household finance.

In general equilibrium asset pricing models, Epstein-Zin preferences are popular because they are scale-independent and therefore accommodate economic growth without generating trends in interest rates or risk premia. For this reason Epstein-Zin preferences have been assumed for a representative agent in many recent asset pricing papers. In particular, the long-run risk literature following Bansal and Yaron (2004) has argued that many asset pricing patterns are explained by a moderately high coefficient of relative risk aversion (typically around ten) and an EIS around 1.5. We estimate a somewhat lower cross-sectional average risk aversion because we incorporate real estate risk, and a much lower cross-sectional average EIS well below one. Our low estimate of the EIS is consistent both with structural estimates of the Bansal-Yaron model reported in Calvet and Czellar (2015) and with Euler equation estimates in aggregate data reported by Hall (1988) and Yogo (2004) among others.

Even if individual households have constant preference parameters, cross-sectional heterogeneity in these parameters can break the relation between household preferences and the implied preferences of a representative agent. In a representative-agent economy, preferences with habit formation are needed to generate countercyclical variation in the price of risk (Constantinides 1990, Campbell and Cochrane 1999), but in heterogeneous-agent economies, countercyclical risk premia can arise from time-variation in the distribution of wealth across agents with different but constant risk preferences (Dumas 1989, Chan and Kogan 2002, Guvenen 2009). Gomes and Michaelides (2005 and 2008) illustrate the importance of preference heterogeneity for simultaneously matching the wealth accumulation and portfolio decisions of households. Our empirical evidence can be used to discipline these modeling efforts.

In household finance, there is considerable interest in estimating risk aversion at the individual level and measuring its effects on household financial decisions. This has sometimes been attempted using direct or indirect questions in surveys such as the Health and Retirement Study (Barsky et al 1997, Koijen et al 2014), the Survey of Consumer Finances (Bertaut and Starr-McCluer 2000, Vissing-Jørgensen 2002*b*, Curcuru et al 2010, Ranish 2014), and similar panels overseas (Guiso and Paiella 2006, Bonin et al 2007). One difficulty with these attempts is that even if risk aversion is correctly measured through surveys, its effects on household decisions will be mismeasured if other preference parameters or the properties of labor income covary with risk aversion. Our estimates suggest that this should indeed be a concern.

Similarly, there is interest in measuring the effects of labor income risk on households' willingness to take financial risk (Guiso, Jappelli, and Terlizzese 1996, Heaton and Lucas 2000). Models such as those of Campbell et al (2001), Viceira (2001), and Cocco, Gomes, and Maenhout (2005) show the partial effect of labor income risk for fixed preference parameters, which will be misleading if risk aversion or other parameters vary with labor income risk (Ranish 2014). Our estimates suggest that this too is a serious empirical issue.

Our findings may also contribute to an ongoing policy debate over approaches to consumer financial protection. If all households have very similar preference parameters, strict regulation of admissible financial products should do little harm to households that optimize correctly, while protecting less sophisticated households from making financial mistakes. To the extent that households are heterogeneous, however, such a stringent approach is likely to harm some households by eliminating financial products that they prefer (Campbell et al 2011, Campbell 2016).

Our model omits some features of the household decision problem that may potentially be important and deserve further research. We assume that preference parameters do not vary with wealth at the household level, contrary to evidence that relative risk aversion, in particular, declines with wealth (Carroll 2000, 2002, Wachter and Yogo 2010, Calvet and Sodini 2014). We treat labor income as exogenous and do not consider the possibility that the household can endogenously vary its labor supply (Bodie, Merton, and Samuelson 1992, Gomes, Kotlikoff and Viceira 2008). We ignore the possibility that some components of consumption involve precommitments that make them costly to adjust (Chetty and Szeidl 2007, 2010). We also do not model fixed costs of stock market participation (Haliassos and Bertaut 1995, Vissing-Jørgensen 2002*a*, Gomes and Michaelides 2005) because we restrict our sample to middle-aged stockholders, who have already decided to hold stocks and pay any one-time costs of doing so. We do not model homeownership jointly with other financial decisions as in Cocco (2005).

The organization of the paper is as follows. Section 2 presents our data and modeling methodology, section 3 estimates preference parameters, and section 4 concludes. An appendix discusses some details of the methodology.

2 Methodology

This section presents a life-cycle model of saving and portfolio choice in section 2.1, describes the dataset in section 2.2, discusses the estimation of the processes for labor income (section 2.3) and asset returns (section 2.4), and finally explains our procedure for estimating preference parameters (section 2.5).

2.1 Life-Cycle Model

In our estimation we consider a standard life-cycle model, very similar to the one in Cocco, Gomes and Maenhout (2005).

2.1.1 Preferences

Households have a finite horizon and Epstein-Zin utility over a single consumption good. The utility function U_t is specified by the coefficient of relative risk aversion γ, the elasticity of intertemporal substitution ψ, and the time preference parameter δ. It satisfies the recursion

$$U_t = \left[(1-\delta)C_t^{1-1/\psi} + \delta\left(\mathbb{E}_t p_t U_{t+1}^{1-\gamma}\right)^{(1-1/\psi)/(1-\gamma)}\right]^{1-1/\psi}, \tag{1}$$

where p_t denotes the probability that a household is alive at age $t+1$ conditional on being alive at age t. Utility, consumption, and the preference parameters γ, ψ, and δ all vary across households but we suppress the household index h in equation (1) for notational simplicity.

Capturing the wealth accumulation of young households poses several problems for life-cycle models which do not include housing purchases, transfers from relatives, investments in education, or changes in family size. In addition it is well-known that such models predict an extremely high equity share at early ages which is hard to reconcile with our data. For this reason, we focus on the stage of the life-cycle during which households are accumulating retirement saving; we initialize the model at age 40 and endow households with the same initial wealth level as the one they actually have in the data. We follow the standard notational convention in life-cycle models and let age in the model, t, start at 1 thus corresponding to effective age minus 39. Each period corresponds to one year and agents live for a maximum of $T = 61$ periods (corresponding to age 100). Matching the behavior of retirees is often hard for these models, particularly without introducing health shocks and bequest motives. For this reason in our estimation we only consider the model-implied behavior for ages 40 to 60 years.

Our model includes no bequest motive, because it would be difficult to separately identify the discount factor and the bequest motive using our sample of households in the 40 to 60 age group, and we prefer not to add one more weakly identified parameter. Our estimates of the time discount factor can be viewed as having an upward bias due to the absence of a bequest motive in the model.

2.1.2 Budget Constraint, Financial Assets and Labor Income

Before retirement households supply labor inelastically. The stochastic process for individual labor income ($L_{h,t}$) is described in Section 2.3. All households retire at age 65, as was typically the case in Sweden during our sample period, and we set retirement earnings equal to a constant replacement ratio of the last working-life permanent income.

Households can trade a one-period riskless asset (bond) and a risky asset. The household chooses the consumption level $C_{h,t}$ and risky portfolio share $\alpha_{h,t}$ every period, subject to borrowing and short-sales constraints that imply $0 \leq \alpha_{h,t} \leq 1$. Household wealth satisfies the budget constraint

$$W_{h,t+1} = (R^f + \alpha_{h,t} R^e_{t+1})(W_{h,t} + L_{h,t} - C_{h,t}), \tag{2}$$

where R^e_{t+1} is the return on the risky asset in excess of the risk-free rate R^f. This excess return has a constant mean μ and a white-noise shock η_t:

$$R^e_t = \mu + \eta_t, \tag{3}$$

where $\eta_t \sim N(0, \sigma^2_\eta)$.

Initial wealth $W_{h,1}$ is calibrated from the data, so $W_{h,1} = W^g_{40}$where W^g_{40} is the average wealth of 40-year-old households in the same group g.

2.2 Data and Sample Selection

Our empirical analysis is based on the administrative panel of all Swedish households which has been used in several earlier papers (Calvet, Campbell and Sodini 2007, 2009a, 2000b, Calvet and Sodini 2014, Betermier, Calvet and Sodini 2015). We define a household as a family living together with the same adult(s) over time. We define the head of the household as the adult with the highest average income, or, if the average income is the same, the oldest, or, if the other criteria fail, the man in the household. We exclude household-year observations in which some variables are missing, the head of the household is a student, or is less than 21 years old. In each year we consider households that hold stocks or risky funds, and have at least 3000 Swedish kronor in financial wealth or at least 1000 kronor in non-financial real disposable income.

We have 36.4 million household-year observations over the period 1984-2007 that can be used to estimate processes for labor income. To estimate income risk by business sector, we drop 7.2 million of these observations where the sector of employment is unobserved. When we estimate preference parameters, we study households with a head aged 40 to 60 during the shorter period 1999-2007 for which we observe wealth and its composition. This reduces the number of household-year observations to 4.9 million for this part of the analysis.

2.3 Modeling the Income Process

2.3.1 Life-Cycle Income Profile

We consider the labor income specification used in Cocco, Gomes, and Maenhout (2005):

$$\log(L_{h,t}) = a_h + b' x_{h,t} + \nu_{h,t} + \varepsilon_{h,t}, \tag{4}$$

where $L_{h,t}$ denotes real income for household h in year t, a_h is a household fixed effect, $x_{h,t}$ is a vector of characteristics, $\nu_{h,t}$ is a permanent random component of income, and $\varepsilon_{h,t}$ is a temporary income shock distributed as $\mathcal{N}(0, \sigma^2_{\varepsilon,h})$. The random variable $\nu_{h,t}$ follows a random walk,

$$\nu_{h,t} = \nu_{h,t-1} + \xi_{h,t}, \tag{5}$$

where $\xi_{h,t} \sim \mathcal{N}(0, \sigma^2_{\xi,h})$ is the permanent income shock in period t. The shocks $\varepsilon_{h,t}$ and $\xi_{h,t}$ are Gaussian white noise and are uncorrelated with each other at all leads and lags. The vector of characteristics $x_{h,t}$ contains age dummies and the number of children in the family.[3]

2.3.2 Correlation Between Income Shocks and Returns on the Risky Asset

We follow Campbell, Cocco, Gomes and Maenhout (2001) and decompose the permanent shock $\xi_{h,t}$ into a group-level shock $\kappa_{g,t}$, common to all households in group g, and an idiosyncratic shock $\omega_{h,t}$:

$$\xi_{h,t} = \kappa_{g,t} + \omega_{h,t}. \tag{6}$$

The idiosyncratic shock $\omega_{h,t}$ is uncorrelated across different households h and also uncorrelated with the group-level shock $\kappa_{g,t}$.

We allow for the possibility that the group-level income shock is correlated with risky asset returns. To estimate the correlation coefficient $\rho_{g\eta}$ between the group-level shock $\kappa_{g,t}$

[3] The household head and the number of adults in the household are constant over time by construction.

and risky asset returns, we define the household-level income growth innovation $u_{h,t}$ as:

$$\begin{aligned} u_{h,t} &= \log(L_{h,t}) - \log(L_{h,t-1}) - b'(x_{h,t} - x_{h,t-1}) \\ &= \kappa_{g,t} + \omega_{h,t} + \varepsilon_{h,t} - \varepsilon_{h,t-1}. \end{aligned} \tag{7}$$

The average of $u_{h,t}$ across households in group g is therefore:

$$\bar{u}_{g,t} = \kappa_{g,t}. \tag{8}$$

We estimate the correlation $\rho_{g\eta}$ using the annual time series of group-level income growth innovations, $\bar{u}_{g,t}$, and excess risky returns R^e_{t-1}. Risky returns are lagged one year, following Campbell, Cocco, Gomes, and Maenhout (2001), to capture a delayed response of income to macroeconomic shocks that move stock prices immediately.

2.3.3 Estimation of the Income Process

We estimate the income process from consecutive observations of household yearly income data between 1983 and 2007, excluding the first and last year of labor income to avoid measuring annual income earned over less than 12 months. We classify households by the head's age and education level. Specifically, since the vast majority of Swedish residents retire at 65, we consider two age groups: (i) non-retired households less than 65, and (ii) retired households that are at least 65. We consider three levels of educational attainment: (i) basic or missing education, (ii) high school education, and (iii) post-high school education.

The estimation of the parameter vector b proceeds separately for active and retired households. For active households younger than 65, we estimate b by running pooled regressions of specification (4) for each of the three education groups. As in Cocco, Gomes, and Maenhout (2005), the vector of explanatory variables $x_{h,t}$ includes age dummies. We then regress the estimated age dummies on a third-degree polynomial in age and use the fitted third-degree polynomial to quantify the impact of age on portfolio choice. For retired households that are at least 65, we estimate specification (4) for each education group, excluding age variables from the vector of explanatory variables. In Figure 1, we illustrate the estimated age dummies over the life-cycle, the replacement ratios, and the fitted polynomials of the three education groups.

When estimating permanent and transitory income risk $\sigma^2_{\xi,h}$ and $\sigma^2_{\varepsilon,h}$, we consider 12 employment sectors within each education group, so that the estimation is conducted on $12 \times 3 = 36$ sector-education groups. Within each group, we follow the procedure of Carroll and Samwick (1997) by estimating the variances of cumulative income growth innovations at the household level over non-overlapping intervals, and using the estimates to infer the variances of permanent and transitory income shocks.

In Table I, we report the standard deviations of the permanent and transitory components of income risk, $\sigma_{\xi,h}$ and $\sigma_{\varepsilon,h}$, for each sector-education group. There are intuitive differences across sectors, with relatively little income risk in the public sector and in mining and quarrying, electricity, gas, and water supply, and relatively high income risk in wholesale and retail trade, hotels and restaurants, and real estate activities. As in Low, Meghir and Pistaferri (2010) we find that in most sectors educated households face larger transitory shocks, whereas permanent shocks are more evenly distributed across education levels. These results contrast with earlier studies showing that in the United States, more educated people have lower transitory income risk and higher persistent income risk, or put slightly differently, that low-education people have "layoff risk" and high-education people have "career risk." The explanation is likely due to the fact that in Sweden, uneducated workers face lower unemployment risk and enjoy higher replacement ratios than in many other countries, while educated workers face relatively high income losses when they do become unemployed.[4]

2.4 Risky Assets, Returns and Wealth

A large fraction of household wealth is held in real estate, an asset that is not explicitly considered in our model. This forces us to make a decision about how to treat real estate when comparing the model with the data, both when measuring the size of total wealth and when defining the share of wealth that is invested in the risky asset.

2.4.1 Three Alternative Assumptions

We consider three different assumptions regarding the definitions of total wealth and of risky assets.

In the discussion below we define total financial wealth as the market value of holdings in cash, stocks, mutual funds (excluding Swedish money market funds), capital insurance products, derivatives and directly held bonds. Our data exclude durables and defined-contribution retirement accounts. We define cash as the sum of bank account holdings and the value of Swedish money market funds.

[4] The Swedish labor market has the following features. First, it is easy for companies to downsize divisions, but extremely difficult for them to lay off single individuals unless they have a high managerial position. Second, companies that need to downsize typically restructure their organizations by bargaining with unions. Third, unions are nationwide organizations that span large areas of employment and pay generous unemployment benefits. Fourth, the pay cut due to unemployment is larger for better paid jobs. After an initial grace period, an unemployed person will be required to enter a retraining program or will be assigned a low-paying job by a state agency. All these features imply that unemployment is slightly more likely and entails a more severe proportional income loss for workers with higher levels of education. See Brown, Fang, and Gomes (2010) for related research on the relation between education and income risk.

Risky Real Estate Wealth

Under our preferred specification, which we call *Risky Real Estate Wealth*, we define wealth W_t as the sum of net financial and real estate wealth, as is common in life-cycle models (Hubbard, Skinner and Zeldes 1984, Castaneda, Diaz-Gimenez and Rios-Rull 2003, De Nardi 2004, and Gomes and Michaelides 2005). Furthermore we treat housing as a risky asset, which implies that the risky-asset return in the model includes the return on net real estate wealth, and the risky portfolio share α_t is the fraction of total wealth invested in risky financial assets and housing equity. The excess return on the composite risky asset, R^e_{t+1}, is then given by

$$R^e_{t+1} = (1 - \phi_t)\, R^S_{t+1} + \phi_t R^{RE}_{t+1}, \tag{9}$$

where R^S_t is the excess return on risky financial assets (stocks), R^{RE}_{t+1} is the excess return on housing equity, and ϕ_t is the fraction of wealth held in the form of housing equity over total financial and residential real estate net wealth.[5]

No Real Estate Wealth

In the *No Real Estate Wealth* case we ignore real estate both in the calculation of total wealth and in the measurement of the risky asset share. So we define total wealth as net financial wealth, and risky asset holdings as the sum of stocks, mutual funds, and other risky financial assets. The excess return on the risky asset under this specification is simply

$$R^e_{t+1} = R^S_{t+1}. \tag{10}$$

Riskless Real Estate Wealth

Finally, in the *Riskless Real Estate Wealth* case we define wealth as the sum of net financial and real estate wealth, but treat real estate as a riskless asset. Therefore risky asset holdings are computed excluding real estate, and the excess return on the risky asset is given by equation (10).

In this version of the paper we report results for the *Risky Real Estate Wealth* case, and briefly compare them with preliminary estimates for the other two cases.

2.4.2 Financial Asset Returns

Table II Panel A reports the assumptions we make about financial asset returns. We assume that the real return on cash is constant at 1.60% (the average realized real cash return over the 1999-2007 period). We proxy the expected excess return on equity by the mean return

[5] This approach is similar to Gomes and Michaelides (2005), where housing is implicitly viewed as a weighted average of equity and the riskless asset. We explicitly state our assumptions about housing returns below.

of the MSCI World Index in kronor in excess of the one month Swedish T-bill over the period 1983-2007 (a longer sample period chosen to reduce noise in the estimated mean). We account for transaction costs by subtracting the average management fee on the equity funds held by the households in our calibration sample (1.42%), times the proportion of risky financial assets held in mutual funds (72%). This gives us a net-of-fee financial excess return of 3.70%.

We measure the volatility of financial asset returns accounting for portfolio underdiversification by Swedish households, using the method of Calvet, Campbell, and Sodini (2007). Specifically, over the 1983-2007 period, we estimate the variance-covariance matrix Σ of the excess return of all the stocks and funds held by Swedish households. We then use data on households' investments to calculate the vector of asset shares $\omega_{h,t}$ within the risky financial portfolio of each household in the calibration sample. The product $\sigma_{h,t}^2 = \omega_{h,t}' \Sigma \omega_{h,t}$ estimates the total variance of each household risky portfolio, and includes both systematic and idiosyncratic risk exposures. We estimate the standard deviation of household financial risky portfolios by the pooled cross-sectional average of $\sigma_{h,t}$ in our calibration sample, 21.68%. The implied Sharpe ratio of the financial risky portfolio is $3.70/21.68 = 0.17$, considerably lower than would be implied by costless investment in a global equity index.

We have estimated the correlations between income shocks and equity returns using the 1983-2007 time series of yearly average income growth innovations $\bar{u}_{g,t}$ of each education-sector group and the lagged yearly realized excess returns of the MSCI world index in kronor. The estimated correlations are very small, with an average across all groups of 0.09 and a maximum value of 0.18.

2.4.3 Housing Returns

Households use mortgage debt to buy housing, implying that they have a levered position in residential real estate. We compute the excess return on this position, R_{t+1}^{RE}, as

$$R_{t+1}^{RE} = \frac{R_{t+1}^{H} - \lambda_t R_{t+1}^{M}}{1 - \lambda_t}. \tag{11}$$

Here R_{t+1}^{H} is the excess return on housing, R_{t+1}^{M} is the mortgage spread (the cost of mortgage borrowing in excess of the riskless interest rate), and λ_t is the loan-to-value (LTV) ratio.

We calculate the LTV ratio λ_t at the household level as the ratio of total debt to residential real estate value, and the share in housing equity ϕ_t as the ratio of housing equity to total net wealth including both housing equity and financial assets. Since we can only observe these ratios from 1999 to 2007, we set them equal to their pooled cross-sectional averages in our data: 47.9% for the leverage ratio and 55.3% for the share in housing equity. Table II panel B shows that there is only modest cross-sectional variation in these ratios across groups, and we ignore this variation in our analysis.

Table II Panel C reports the assumptions we make about the returns that appear in equation (11). We calculate the spread R^M_{t+1} as the difference between the interest rate on newly issued Swedish mortgages and the yield on a Swedish one-month Treasury bill. The time series is available quarterly from 1996 and is based on a volume weighted average of the mortgage rates at all maturities. The average spread is 1.53%.

The measurement of R^H_{t+1} raises some tricky issues. Table II panel C reports that the average yearly excess returns on the Swedish index of one- or two-dwelling buildings from 1983-2007 was -0.54%. If we use this value for R^H_{t+1} it implies an even lower average return R^{RE}_{t+1} of -2.45% on levered real estate, and even after combining real estate with financial assets the implied overall risky excess return R^e_{t+1} is only 0.30%. It seems implausible that Swedish households expected such a low return on housing or on risky assets generally.

As an alternative, we estimate the expected excess return on housing by assuming that the Sharpe ratio on housing is equal to the Sharpe ratio of 0.17 we estimated for the stock market. We estimate the sample standard deviation of the excess return on housing, σ_H, over the period 1983-2007 as 14.73%. With a Sharpe ratio of 0.17, the implied average excess return on housing R^H_{t+1} is 2.50%, the implied average return R^{RE}_{t+1} on levered real estate is 3.40%, and the implied average excess return on all risky assets R^e_{t+1} is 3.53%.

To estimate the second moments of risky returns including real estate, we follow a similar approach documented in Table II panel D. We take the variance of (9), with ϕ_t equal to its sample mean $\overline{\phi}$, and obtain

$$Var\left(R^e_{t+1}\right) = \left(1-\overline{\phi}\right)^2 Var\left(R^S_{t+1}\right) + \overline{\phi}^2 Var\left(R^{RE}_{t+1}\right) + 2\left(1-\overline{\phi}\right)\overline{\phi} Cov\left(R^S_{t+1}, R^{RE}_{t+1}\right). \quad (12)$$

Similarly we assume that the mortgage spread R^M_{t+1} and the leverage ratio λ_t are equal to their sample means $\bar{R}_M$ and $\overline{\lambda}$, and use (11) to relate the variance of the excess return on the levered position in residential real estate R^{RE}_{t+1} to the variance of the underlying housing return:

$$Var\left(R^{RE}_{t+1}\right) = \left(\frac{1}{1-\overline{\lambda}}\right)^2 Var\left(R^H_{t+1}\right). \quad (13)$$

The covariance of R^{RE}_{t+1} with the excess return on financial equity R^S_t is related to the covariance of housing with financial equity by

$$Cov\left(R^S_{t+1}, R^{RE}_{t+1}\right) = \frac{Cov\left(R^S_{t+1}, R^H_{t+1}\right)}{1-\overline{\lambda}}. \quad (14)$$

We use the same approach to calculate the group-level correlations $\rho_{g\eta}$ between group-level labor income shocks $\kappa_{g,t+1}$ and lagged risky asset returns R^e_t. We compute

$$Cov\left(R^e_t, \kappa_{g,t+1}\right) = \left(1-\overline{\phi}\right) Cov\left(R^S_t, \kappa_{g,t+1}\right) + \frac{\overline{\phi}}{1-\overline{\lambda}} Cov\left(R^H_t, \kappa_{gt+1}\right). \quad (15)$$

Table II panel D reports the relevant second moments. The standard deviation of levered housing equity is 28.29%, about twice the standard deviation of housing returns, and the implied overall volatility of all risky assets is 18.19%. The implied Sharpe ratio for all risky assets is $3.53/18.19 = 0.19$. Swedish housing returns have a sample correlation close to zero (-5.7%) with stock returns. However, there is a much higher average correlation between housing returns and group-level labor income shocks, which implies an average overall correlation between the risky excess return and group-level income shocks of 38.2%. This correlation plays an important role in our model, because it helps to choke off household demand for risky assets even at moderate levels of risk aversion.

2.4.4 Measured Risky Shares and Wealth-Income Ratios

Table III shows the variation in average risky portfolio shares and wealth-income ratios across education-sector groups. We will ask our life-cycle model to fit these averages, as well as the evolution of risky portfolio shares and wealth-income ratios over time for households within each group. Within each sector, risky portfolio shares tend to rise slightly, and wealth-income ratios more strongly, with the level of education. Across sectors, a comparison of Table III with Table I shows a slight tendency for risky portfolio shares to be lower in sectors with risky labor income (such as wholesale and retail trade, hotels and restaurants, and real estate activities as compared with mining and quarrying, electricity, gas and water supply or public sector) and a more noticeable tendency for wealth-income ratios to be higher in risky sectors. When we estimate our model we will ask what these facts imply for the underlying distribution of preferences across households with higher or lower education working in riskier or safer sectors.

2.5 Estimation Method

2.5.1 Simulated Moments and Objective Function

Using the parameters from Tables I and II as inputs, we solve the life-cycle model for the different combinations of birth cohort, education level, and sector of employment. We consider 13 cohorts, indexed by c; 3 education levels, indexed by e; and 12 business sectors, index by s, giving us a total of 468 groups. In our most general estimation we allow preference parameters to vary freely across these 468 groups, but we also consider a variety of cross-group restrictions. To facilitate notation, we index each group by the vector $g = (c, e, s)$.

Since we focus on the accumulation stage of the life-cycle, we consider households whose head is between 40 and 60 years old from 1999 to 2007. For each group g, we compute the wealth-to-income ratio and the risky share predicted by the model for every year between 1999 and 2007. To make the output from the model comparable with the data we initialize the simulation by giving each group the same wealth-income ratio as they had in the data in 1999. Furthermore, in the simulations we assign to them the same realizations of unexpected risky asset returns that took place between 1999 and 2007.

The estimation of the preference parameters in each group proceeds by simulated method of moments (SMM, Duffie and Singleton 1993, Lee and Ingram 1991). Let N^g denote the number of households in group g, and let y_n^g the vector of observations corresponding to each household $n = 1, .., N^g$. The dataset for group g is therefore $Y^g = \{y_n^g\}_{1 \leq n \leq N^g}$. We denote by $N = \sum_{g=1}^{G} N^g$ the total number of households in the sample, by $k^g = N^g/N$ the fraction of households in group g, and by $\theta^g = (\delta^g, \gamma^g, \psi^g)'$ the vector of preference parameters of group g.

We estimate the preference parameters θ^g by comparing the theoretical value with the empirical value in the data. More formally, let $y^*(\theta^g)$ the vector of wealth-to-income ratios and risky shares predicted by the model. Importantly, this vector contains 2τ elements, where τ is the number of periods over which the model is simulated and over which households are observed in the data.

For every θ^g, we can estimate $y^*(\theta^g)$ by simulating the sample paths of $S\,N$ households between the ages of 40 and 60 and then computing their sample average, $m_{SN}(\theta^g)$. For every household n in group g, we measure the deviation $y_n^g - m_{SN}(\theta^g)$ and then average across households in group g, defining

$$q(\theta^g; Y^g) = \frac{1}{N^g} \sum_{n=1}^{N_g} y_n^g - m_{SN}(\theta^g). \tag{16}$$

We stack the group-specific parameters into the column vector $\theta = (\theta^{1\prime}, ..., \theta^{G\prime})'$. The *unconstrained SMM estimator* $\hat{\theta}_N$ minimizes

$$Q_N(\theta; \{Y^g\}_{g=1}^G) = \sum_{g=1}^{G} k_g \;\; [q(\theta^g; Y^g)]' \; W_N^g \; q(\theta^g; Y^g), \tag{17}$$

where k_g weights groups (either equally or in proportion to the number of households they contain), and where for every g the weighting matrix W_N^g is positive-semidefinite and converges to a positive-definite matrix W^g. In practice, we use diagonal weighting matrices W_N^g such that the criterion $[q(\theta^g; Y^g)]' \; W_N^g \; q(\theta^g; Y^g)$ is the sum of (i) squared relative differences in wealth-to-income ratios and (ii) squared absolute differences in the risky shares across age groups.[6]

[6]The diagonal element corresponding to the wealth-to-income ratio at a given age a is set equal to the squared inverse of the mean wealth-to-income ratio of households of age a in group g. Diagonal elements corresponding to risky share components are set equal to unity.

2.5.2 Optimization

The optimization procedure to minimize the objective function $Q_N(\theta)$ is divided into three separate stages.

In stage one we perform a grid search over the three preference parameters. The advantage of using a grid search is that we reduce the risk of incorrectly settling for a local optimum. For each group we solve the model for a grid of approximately twenty different values of the elasticity of intertemporal substitution, risk aversion and the discount factor.[7] Depending on which of the three assumptions we make about the role of real estate in wealth, these grids include coefficients of relative risk aversion ranging from 2 to 30, elasticities of intertemporal substitution ranging from 0.1 to 2, and discount factors ranging from 0.75 to 0.995. For each case we have selected these values so that no solution would hit the boundary, except for values of the EIS as low as 0.1 and values of the discount factor as high as 0.995.

After identifying the best combination of preference parameters from the original grid, $\theta_N^{(1)}$, in stage two we refine the optimization by applying the Newton-Raphson method:

$$\frac{\partial Q_N}{\partial \theta}(\theta) \approx \frac{\partial Q_N}{\partial \theta}(\theta_N^{(1)}) + \frac{\partial^2 Q_N}{\partial \theta \partial \theta'}(\theta_N^{(1)}) \left[\theta - \theta_N^{(1)}\right], \tag{18}$$

which gives rise to a new candidate minimizer[8]

$$\theta_N^{(2)} \approx \theta_N^{(1)} - \left[\frac{\partial^2 Q_N}{\partial \theta \partial \theta'}(\theta_N^{(1)})\right]^{-1} \frac{\partial Q_N}{\partial \theta}(\theta_N^{(1)}). \tag{19}$$

In stage three, we re-evaluate the objective function at the new candidate optimum, $\theta_N^{(2)}$. We compare $Q(\theta_N^{(2)})$ not only with $Q(\theta_N^{(1)})$ but with the objective function evaluated at all of the points considered for computing the derivatives since they are also available. We pick the best of all of these as our final optimum $\hat{\theta}_N$.

In principle we could continue to optimize over multiple iterations, but the computational cost would be extremely high. In addition, we have observed that for most of the 468 groups the differences between $\theta_N^{(2)}$ and $\theta_N^{(1)}$ are already very small. This presumably results from the fact that we have already considered a fine grid of parameter values in stage one of the optimization.

In the appendix, we state formulas for the asymptotic distribution of $\hat{\theta}_N$ and derive Wald test statistics for restrictions on the model parameters.

[7] This corresponds to approximately a total of 8000 solutions to the dynamic programming problem for each of the 468 groups, resulting in almost 4 million separate solutions.

[8] We obtain the derivatives by evaluating the model again, now for small perturbations of the different preference parameters around the optimum. Further details are given in the appendix.

2.5.3 The Challenge of Identification

When applying our method to Swedish household data, we have found that it is challenging to separately identify all three Epstein-Zin parameters, and particularly to estimate both the time discount factor δ and the EIS ψ without restrictions.

In principle these parameters can be separately identified because δ affects the unconditional slope of the planned consumption path, while ψ affects the response of this slope to changes in the investment opportunity set. In our model there are no changes in the expected returns or risks of individual financial assets, but the investment opportunity set alters over time as households approach retirement and the present value of their remaining labor income declines. This change in labor income prospects alters background risk and affects the optimal holding of risky assets (even when labor income shocks are uncorrelated with risky asset returns, but all the more so when income and financial risk are correlated). The change in portfolio composition alters the expected return and risk of the portfolio, which affects the slope of the optimal consumption path in a manner that is governed by the EIS.[9] In turn, the planned slope of the consumption path determines saving and hence the evolution of the wealth-income ratio. This highlights the fact that identification requires tracking a household over time, using a time-series of portfolio shares and wealth-income ratios rather than just the sample average of these quantities for the given household.

Despite this theoretical result, identification of δ and ψ is relatively weak in practice. Accordingly, in our empirical work we impose some restrictions either on δ or on ψ.

3 Empirical Results

3.1 The Cross-Sectional Distribution of Preferences

Table IV summarizes estimates of our model's three preference parameters. Throughout the table we assume that real estate is a risky asset. The first panel treats each cohort, with each level of education, in each business sector as an independent group. In this panel the only restriction across the 468 groups is that the rate of time preference, δ, is assumed to be the same across all groups with the same level of education. The second panel imposes the additional restriction that preferences are identical across cohorts with a given level of education and sector of employment. Thus there are only 36 separate estimates of risk aversion and the EIS, and 3 estimates of time preference in the second panel. The third panel imposes uniform preferences across all household groups, estimating only 3 free parameters for the whole Swedish economy.

[9] The appendix builds intuition by deriving some analytical results in a simpler case where labor income is riskless and there are no borrowing constraints, and by writing out the Epstein-Zin Euler equations under the assumption of lognormally distributed shocks.

Within each panel, the top row reports the least restrictive model described above, and the lower rows impose additional restrictions: first the power utility restriction that risk aversion is the reciprocal of the EIS; then a set of alternative restrictions fixing the EIS at 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, or 1.4 while leaving risk aversion as a free parameter.

The first two columns of Table IV report the cross-sectional mean and standard deviation of risk aversion across groups. The next two columns report the same summary statistics for the EIS, the next two for the time discount factor, and the next two for the implied rate of time preference. The last three columns report the value of the minimized objective function and its two components (the errors in fitting risky portfolio shares and wealth-income ratios).

The first row of Table IV shows that the average risk aversion coefficient is 4.15, with a standard deviation across household groups of 0.49. The average EIS is 0.67, with a cross-sectional standard deviation of 0.44, and the average discount factor is 0.993 (corresponding to a time discount rate of 0.67%), with a standard deviation across education levels of 0.002 (0.24%).

Our estimates of the time discount rate may appear to be low; however, in interpreting these estimates it is important to remember not only that our model excludes a bequest motive (so any real-world bequest motive will show up in the model as a lower time discount rate), but also that agents in our model further discount the future in proportion to their survival probability. If survival probability were incorporated in the time discount factor, as is often the case in representative-agent asset pricing models, the implied time discount rate would be 2-3% higher.

3.1.1 The Role of Real Estate

We have compared these preference parameter estimates with what we would obtain if we ignored real estate. Under that alternative specification, the average risk aversion rises to 10.90. The difference can be attributed to three factors. First, the measured risky share is higher when we consider real estate as an additional risky asset. Second, the risky asset represents a less attractive investment in the *Risky Real Estate* case than in the *No Real Estate* case. As previously explained, we assume that the housing return has the same Sharpe ratio as the stock market so the overall return on risky assets offers essentially the same conditional risk-return trade-off in both cases. However, in the *Risky Real Estate* case the correlation between the return on the risky asset and labor income averages 37.5% across the different groups, while in the *No Real Estate* case the average correlation is only about 10%. The final key factor is the difference in measured wealth. When we ignore real estate, measured wealth is significantly lower relative to labor income, and as a result optimal risky shares are higher. To offset this, the estimation must then deliver a high coefficient of relative risk aversion.

The specification that ignores real estate also implies a much lower discount factor of

0.923, corresponding to a much higher time discount rate of 7.99%. This difference is the combined result of two effects. First, measured wealth is significantly smaller when real estate is ignored, and to match this fact the estimation must make households more impatient. Second, the much higher estimated risk aversion in the *No Real Estate* case generates higher wealth accumulation in that model for any given time discount factor. The *No Real Estate* case also implies a somewhat lower average EIS of 0.46.[10]

3.1.2 Restricted Models

The remaining rows of Table IV show how our baseline estimates of preference parameters, within the *Risky Real Estate* case, vary when restrictions are imposed. The table also shows the effect of these restrictions on the sum of squared errors that is minimized by our estimation procedure, and its two components. We can use this information to formally test the restrictions, but do not yet implement such tests in this version of the paper.

Imposing constant preferences across cohorts, in the first row of panel B, or constant preferences across all households, in the first row of panel C, has little effect on the average values of the preference parameters, which remain close to 4 for risk aversion, close to 0.7 for the EIS, and about 0.5% for the time discount rate. However, these restrictions greatly increase the sum of squared errors, particularly the errors in fitting risky portfolio shares. This highlights the fact that preference heterogeneity is essential to explain the patterns of portfolio investment and wealth accumulation observed in household-level data.

Imposing power utility, in the second row of each panel, forces the EIS to be the reciprocal of risk aversion. This lowers the average estimate of the EIS but has little effect on the average estimate of risk aversion. It increases the sum of squared errors, particularly the errors in fitting wealth-income ratios.

Imposing fixed values of the EIS, in the remaining rows of each panel, has relatively little effect when those fixed values are in the neighborhood of the unrestricted estimate. However, fixed EIS values equal to or exceeding one generate enormous increases in the sum of squared errors, primarily because the model with such a high EIS cannot fit wealth-income ratios at any values of the time preference rate we consider.

[10]We have also conducted a preliminary analysis of the *Riskless Real Estate* case. The average estimate of risk aversion is even higher in this case than when real estate is ignored. The main reason is that if we treat real estate as riskless, the measured risky asset share is much lower than in the other two cases. Matching such a low risky share requires a very high value of risk aversion. The discount factor for the *Riskless Real Estate* case is intermediate between the other two cases. Although measured wealth is now as high as in the *Risky Real Estate* case, the higher estimated risk aversion induces more wealth accumulation that must be counter-balanced by a lower discount factor.

3.1.3 The Cross-Sectional Relation Between Risk Aversion and the EIS

Returning to the unrestricted preference estimates in Table IV, an interesting question is how our estimates of risk aversion and the EIS are related to one another across groups. This relationship is illustrated in Figures 2 and 3. Both these figures plot the log of estimated risk aversion on the vertical axis against the log of the EIS on the horizontal axis. Power utility would imply that log risk aversion is the negative of log EIS, a relationship shown as a black line with a slope of -1 in the figures.

Figure 2 plots preference estimates for the 36 education-sector groups from panel B of Table IV, weighting them equally and color-coding them by education. The figure also shows cross-sectional regression lines obtained by regressing log risk aversion on log EIS, or alternatively by regressing log EIS on log risk aversion. The figure illustrates several important properties of our preference estimates. First, all estimates lie above the power utility line, implying that risk aversion exceeds the reciprocal of the EIS. Second, all estimates of the log EIS are negative, implying that the EIS is less than one for all education-sector groups. These two findings are consistent with the results of Gomes and Michaelides (2005) who calibrated a similar life-cycle model for a representative US stockholder. Third, there is a weak negative cross-sectional relationship between the estimates of log risk aversion and the log EIS, as shown by the negative slopes of the two alternative cross-sectional regression lines. Finally, households that have some higher education tend to have higher EIS and slightly lower risk aversion than less educated households, and hence plot at the right and primarily at the bottom right of the figure.

Figure 3 repeats this exercise with groups weighted by their size, indicated in the figure by the sizes of circles representing each group. Results are qualitatively similar to those in Figure 2.

Table V reports regression results to elaborate on Figures 2 and 3. In the first four columns log EIS is regressed on log risk aversion, either equal-weighting groups or weighting them by their size, and either restricting preferences to be equal across cohorts as in panel B of Table IV, or allowing them to vary across cohorts as in panel A of Table IV and including cohort dummies in the regression. In the second four columns, log risk aversion is regressed on log EIS in the same four ways. The table shows that log risk aversion predicts the log EIS with a slope of -0.40 equal-weighted or -0.69 size-weighted, and these estimates only become more negative when we allow for variation across cohorts. The effect of log risk aversion on the log EIS is statistically significant in three out of four cases. The slope of the reverse regression is an order of magnitude smaller, because the log EIS has more cross-sectional variation than log risk aversion, but is statistically significant in the same three cases.

3.2 Household Characteristics and Preferences

3.2.1 Education, Risk Aversion, and the EIS

Table VI asks how preferences vary with a household's level of education. Figure 2 already showed a strong tendency for more educated households to have a higher EIS, and a weaker tendency for these households to have lower risk aversion. We see this in the regressions of Table VI, which are structured the same way as the regressions of Table V, with four alternative specifications that either either equal-weight groups or weight them by their size, and either restrict preferences to be equal across cohorts as in panel B of Table IV, or allow them to vary across cohorts as in panel A of Table IV while including cohort dummies in the regression. The first four columns of Table VI regress log EIS on education dummies for completing high school or completing higher education, and the second four columns regress log risk aversion on these dummies.

Higher education adds about 0.5 log points (65%) to the estimated EIS in the specification with fixed preferences across cohorts, and about 0.2 log points (22%) in the specification with cohort effects. These effects are strongly statistically significant when preferences are fixed across cohorts, but only marginally significant when cohort dummies are included. Higher education has a more modest effect on risk aversion, reducing it by about 0.03-0.05 log points (3-5%) in all specifications. The cohort dummies in Table VI show how estimated risk aversion declines among younger cohorts in our sample.

3.2.2 Income Risk, Risk Aversion, and the EIS

Table VII asks how preferences vary with the income risk of a household's sector of employment. The table is structured in the same way as Table VI, but the independent variable is now the total standard deviation of income risk. The table shows that income risk is associated with a modestly higher EIS, and a much lower coefficient of risk aversion. Since the total standard deviation of income risk ranges across groups from about 10% to about 20%, the estimated coefficients from the equal-weighted regressions imply that the riskiest groups have risk aversion about 0.37 log points (29%) lower than the safest groups. The size-weighted regressions imply even larger variation in risk aversion associated with income risk.

Figures 4 and 5 illustrate the results in Table VII. Both figures are formatted the same way as Figure 2 to illustrate an equal-weighted regression, with observations color-coded by education level. Figure 4 shows the relationship between the log EIS and income risk, while Figure 5 shows the relationship between log risk aversion and income risk. The strength of the latter relationship and the weakness of the former relationship are immediately apparent from these figures.

Table VIII repeats the analysis of Table VII, including the standard deviation of permanent labor income shocks and the standard deviation of transitory labor income shocks as separate explanatory variables. The inclusion of two components of income risk greatly increases the explanatory power for the log EIS, which is estimated to be negatively related to permanent income risk and positively related to transitory income risk. For risk aversion, both components of income risk contribute negatively but the coefficients are larger for permanent income risk. This makes some sense if one imagines households choosing their occupations in part by assessing the level of lifetime income risk they are comfortable with (Ranish 2014). Since permanent income risk is much more important for lifetime income risk, risk-tolerant households should disproportionately concentrate in sectors with high levels of permanent income risk.

To understand the patterns in the data that contribute to these results, Table IX regresses the average risky shares and wealth-income ratios for each education-sector group (averaging across cohorts and over time) onto education dummies, and then the total standard deviation of income risk, and finally the standard deviations of the two types of income shocks. The results of these regressions support the impressionistic discussion given earlier of Tables I and III. Risky shares and wealth-income ratios are higher for households with higher education. Risky shares are somewhat lower in risky occupations, particularly those with high levels of permanent income risk. Wealth-to-income ratios are higher in risky occupations, particularly those with high levels of temporary income risk (which may reflect the use of savings to buffer temporary income shocks). However, it appears that risky shares do not fall enough in risky occupations to be consistent with a model of homogeneous preferences; hence, in order to fit the patterns of Table IX our model estimates that households with risky occupations tend to have low risk aversion. An alternative explanation of this pattern would be that households in riskier occupations tend to underestimate the level of income risk they face, and hence underreact to it when making financial investment decisions.

4 Conclusion

In this paper we have asked whether the patterns of wealth accumulation and risky investment among Swedish households can be rationalized by a life-cycle model with homogeneous preferences, or whether households in different cohorts, with different levels of education, and working in different sectors appear to have different preferences. The maintained assumption throughout the paper is that all households have common expectations about the riskless interest rate and risky asset returns, understand the stochastic processes driving their labor income, and invest rationally given their preferences and information. Under this assumption, we find that if we treat real estate as a risky asset, our model fits the data with modest proportional cross-sectional variation around an average risk aversion coefficient around 4, and with larger proportional variation around an elasticity of intertemporal substitution (EIS) around 0.7. All households are estimated to have risk aversion that is higher than the reciprocal of the EIS, violating the restriction of power utility; however, the cross-sectional association between risk aversion and the EIS is weakly negative which matches the qualitative prediction of a power utility model. All households are estimated to have an EIS below one, contrary to the preference specifications used in the long-run risk literature in asset pricing. Households with higher education tend to have a higher EIS and slightly lower risk aversion. There is also a strong negative relation between income risk, particularly permanent income risk, and risk aversion. This is consistent with a model in which risk-tolerant households self-select into risky occupations.

In future versions of this paper we plan to extend this research in several directions. Most obviously, we will report formal test results of cross-sectionally restricted models against unrestricted models. We will show what restricted models, particularly the simplest model with homogeneous preferences, imply for cross-sectional patterns in risky shares and wealth-income ratios. We will explore variation in preferences across cohorts, restricting such preference changes to occur smoothly over birth years. We will explore in greater detail the effects of alternative assumptions about the risk and return of real estate and financial assets. We hope that this research will lead economists to a deeper understanding of heterogeneity in households' attitudes towards risk and intertemporal consumption smoothing, which in turn will enable the construction of more accurate models of financial markets and the macroeconomy.

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Appendix

A. Implementation of the Newton-Raphson Method

In the case where δ is fixed, the parameter vector consists of risk aversion and the elasticity of intertemporal substitution: $\theta = (\gamma, \psi)'$.We approximate

$$\frac{\partial Q}{\partial \theta}(\gamma, \psi) = \begin{pmatrix} \partial Q/\partial \gamma \\ \partial Q/\partial \psi \end{pmatrix}$$

by

$$\begin{pmatrix} [Q(\gamma + \Delta\gamma) - Q(\gamma - \Delta\gamma)]/(2\Delta\gamma) \\ [Q(\psi + \Delta\psi) - Q(\psi - \Delta\psi)]/(2\Delta\psi) \end{pmatrix}.$$

Similarly, we consider the Hessian matrix

$$\frac{\partial^2 Q}{\partial \theta \partial \theta'}(\gamma, \psi) = \begin{pmatrix} \partial^2 Q/\partial \gamma^2 & \partial^2 Q/\partial \gamma \partial \psi \\ \partial^2 Q/\partial \gamma \partial \psi & \partial^2 Q/\partial \psi^2 \end{pmatrix}.$$

We use the following approximations:

$$\frac{\partial^2 Q}{\partial \gamma^2} \approx \frac{Q(\gamma + \Delta\gamma, \psi) + Q(\gamma - \Delta\gamma, \psi) - 2Q(\gamma, \psi)}{(\Delta\gamma)^2}$$

$$\frac{\partial^2 Q}{\partial \psi^2} \approx \frac{Q(\gamma, \psi + \Delta\psi) + Q(\gamma, \psi - \Delta\psi) - 2Q(\gamma, \psi)}{(\Delta\psi)^2}$$

$$\frac{\partial^2 Q}{\partial \gamma \partial \psi} \approx \frac{\begin{array}{c} Q(\gamma + \Delta\gamma, \psi + \Delta\psi) - Q(\gamma + \Delta\gamma, \psi) - Q(\gamma, \psi + \Delta\psi) + 2Q(\gamma, \psi) \\ -Q(\gamma - \Delta\gamma, \psi) - Q(\gamma, \psi - \Delta\psi) + Q(\gamma - \Delta\gamma, \psi - \Delta\psi) \end{array}}{2\Delta\gamma\Delta\psi}$$

B. Asymptotic distribution and hypothesis testing.

The asymptotic distribution of $\hat{\theta}_N$ is easily derived. Let Ω^g denote the asymptotic variance matrix of $q(\theta^g; Y^g)$, that is:

$$\sqrt{N} q(\theta^g; Y^g) \xrightarrow{d} \mathcal{N}\left[0, \left(\frac{1}{k^g} + \frac{1}{S}\right)\Omega^g\right]. \tag{20}$$

As N goes to infinity, the Jacobian matrix $\partial q/\partial \theta^{g\prime}(\theta^g; Y^g)$ converges to a deterministic limit $(D^g)'$.

The unconstrained SMM estimator is asymptotically normal:

$$\sqrt{N}(\hat{\theta}_N - \theta^*) \xrightarrow{d} \mathcal{N}(0, V), \tag{21}$$

where the asymptotic variance-covariance matrix is block-diagonal:

$$V = \begin{bmatrix} (\frac{1}{k^1} + \frac{1}{S})V^1 & & \\ & \ddots & \\ & & (\frac{1}{k^g} + \frac{1}{S})V^G \end{bmatrix}, \tag{22}$$

and $V^g = [D^g W^g (D^g)']^{-1} D^g W^g \Omega^g W^g (D^g)' [D^g W^g (D^g)']^{-1}$. In practice, we estimate V_g by

$$\hat{V}_g = \left[\hat{D}^g W_N^g (\hat{D}^g)'\right]^{-1} \hat{D}^g \; W_N^g \; \hat{\Omega}^g \; W_N^g \; (\hat{D}^g)' \; \left[\hat{D}^g W_N^g (\hat{D}^g)'\right]^{-1}, \tag{23}$$

where $\hat{D}_g' = \partial q / \partial \theta^{g\prime}(\hat{\theta}_N^g; Y^g)$ and $\hat{\Omega}^g$ is the sample-variance covariance matrix of the time paths observed for households in group g.[11]

In order to obtain a parsimonious specification, we consider restrictions on the preference parameter vectors across groups. For instance, we will impose that the discount rate depends only on the education level: $\delta_{c,e,s} = \delta_{c',e,s'}$ for every c, s, c', s'. We can also impose that some parameters are linear functions of age. Constrained optimization consists of maximizing the global criterion (17) under the constraint.

We can test the validity of the restriction by implementing a Wald test. We consider the null hypothesis

$$\mathbf{H_0} : R\theta^* = b, \tag{24}$$

where R is a matrix of dimension $r \times \dim(\theta)$ and b is a column vector of dimension r. Equation (21) implies that under the null,

$$N(R\hat{\theta}_N - b)'V^{-1}(R\hat{\theta}_N - b)' \xrightarrow{d} \chi^2(r). \tag{25}$$

We test the restriction by computing the Wald statistic, $N(R\hat{\theta}_N - b)'\hat{V}^{-1}(R\hat{\theta}_N - b)$.

C. Some Analytical Properties of Epstein-Zin Preferences.

In order to obtain some intuition for the estimation results and in particular the identification of the different parameters it is useful to consider the simpler case where labor income is riskless and there are no borrowing constraints. In this case labor income is equivalent to an implicit holding of riskless assets.

Assume further that the return on the risky assets has a lognormal distribution: $\ln(R_t^e) \sim N(\mu, \sigma^2)$. Then the certainty equivalent return is given by

$$\hat{R}_p^{CE} = \left\{\mathbb{E}_t\left[(R_f + \alpha_t R_{t+1}^e)^{1-\gamma}\right]\right\}^{\frac{1}{1-\gamma}}. \tag{26}$$

[11] We set $\hat{\Omega}^g = \sum_{n=1}^{N^g}(y_n^g - \overline{y^g})(y_n^g - \overline{y^g})'/(N^g - 1)$, where $\overline{y^g} = \sum_{n=1}^{N^g} y_n^g / N^g$ is the mean sample path in group g. Note that since households are not ordered by n, the additional terms in the usual Newey and West estimator do not appear in the definition of $\hat{\Omega}^g$.

where $\alpha_t = \hat{\alpha} \equiv (\mu + \sigma^2/2)\,\gamma\sigma^2$ at the optimum, and

$$\log(\hat{R}_p^{CE}) = \log(R_f) + \frac{1}{2\gamma\sigma^2}\left(\mu + \frac{\sigma^2}{2}\right)^2. \tag{27}$$

In the presence of deterministic labor income and no borrowing constraints the risky share is given by

$$\alpha_t = \left(1 + \frac{H_t}{W_t}\right)\hat{\alpha}, \tag{28}$$

where human capital at date t is defined as $H_t = \sum_{s=t+1}^{T} L_s/\, R_f^{s-t}$.[12] Define cash on hand $W_t^* = W_{t-1}(R^f + \alpha_{t-1} R_t^e) + L_t$, the savings rate out of total wealth $s_t^{TW} = (W_t^* + H_t - C_t)/\,(W_t^* + H_t)$ in steady state satisfies:

$$\ln\left(s_\infty^{TW}\right) = \psi \ln(\delta) + (\psi - 1)\ln\left(\hat{R}_p^{CE}\right), \tag{29}$$

or

$$\ln\left(s_\infty^{TW}\right) = \psi\left[\ln\left(\hat{R}_p^{CE}\right) - \ln\left(R^{TP}\right)\right] - \ln\left(\hat{R}_p^{CE}\right) \tag{30}$$

where R^{TP} is the pure rate of time preference.

As suggested by formulas (27) and (29) it is difficult to identify separately the subjective discount factor δ and the elasticity of intertemporal substitution ψ in the context of these models. We can obtain further intuition by considering the Euler equation for the return on optimal portfolio,

$$1 = E_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{V_{t+1}}{\mu(V_{t+1})}\right)^{\frac{1}{\psi}-\gamma} R_{t+1}^P\right]$$

where $R_{t+1}^P = \alpha R_{t+1}^e + (1-\alpha)R_f$, and $\mu(V_{t+1})$ denotes the certainty equivalent of V_{t+1}.[13]

Taking logs of both sides and making the usual assumption of joint log-normality we obtain

$$\begin{aligned} 0 \;&=\; -\delta - \frac{1}{\psi}E_t g_{t+1} + \left(\frac{1}{\psi} - \gamma\right)E_t \widetilde{v}_{t+1} + E_t r_{t+1}^P \\ &\quad + \frac{1}{2\psi^2}\sigma_g^2 + \frac{1}{2}\left(\frac{1}{\psi} - \gamma\right)^2 \sigma_{\widetilde{v}}^2 + \frac{1}{2}\sigma_r^2 + \frac{1}{\psi}\left(\frac{1}{\psi} - \gamma\right)\sigma_{g\widetilde{v}} + \left(\frac{1}{\psi} - \gamma\right)\sigma_{\widetilde{v}r} + \frac{1}{\psi}\sigma_{gr}, \end{aligned}$$

where lower-case letters denote logs of upper-case letters, $\delta = -Ln(\beta)$, $g_{t+1} \equiv Ln(C_{t+1}/C_t)$ and $\widetilde{V}_{t+1} = \frac{V_{t+1}}{\mu(V_{t+1})}$.

[12] A similar formula will also hold in the more general case but the discount rate for future labor income will change in the presence of either borrowing constraints or labor income risk.

[13] With labor income risk and a utility function that satisfies $u\prime(0) = -\infty$ the agent will always keep some (precautionary) savings and therefore, even in the presence of borrowing constraints the Euler equations will still hold with equality. In our case they might not hold because of the short-selling constraints on the asset holdings but for the age groups that we are considering (40 to 60) that should not be an issue.

Solving for $E_t g_{t+1}$:

$$\begin{aligned} E_t g_{t+1} &= \psi(E_t r_{t+1}^P - \delta) + (1-\gamma\psi)\, E_t \widetilde{v}_{t+1} \\ &\quad + \frac{1}{2\psi}\sigma_g^2 + \frac{\psi}{2}\left[\left(\frac{1}{\psi}-\gamma\right)^2 \sigma_{\widetilde{v}}^2 + \sigma_r^2 + \left(\frac{1}{\psi}-\gamma\right)\sigma_{\widetilde{v}r}\right] + \left(\frac{1}{\psi}-\gamma\right)\sigma_{g\widetilde{v}} + \sigma_{gr} \quad (31) \end{aligned}$$

Naturally we could have derived an expression for expected log consumption growth using either of the original Euler equations, the ones for R_f and R_{t+1}^e, but Campbell and Viceira (1999) show that the optimal consumption-wealth ratio is, to a first-order approximation, driven by the trade-off between the endogenous expected return on invested wealth and the discount rate, exactly the first term in equation (31).[14] This result helps to explain how we can, in theory, obtain a separate identification of the EIS and the discount factor in our estimation. Even though we have no exogenous variation in expected returns, we have *endogenous* variation in expected returns driven by the changes in the optimal portfolio of the agent, which in turn are driven by changes in the present value of future human capital and by the accumulation or decumulation of wealth. This endogenous variation of the expected return with age implies that the profile of the wealth-to-income ratio as a function of age identifies the EIS separately from the discount factor. This shows why it is important to estimate the model using wealth to income ratios at different ages as separate moments, rather than just taking the average from ages 40 to 60.

[14] Their results are obtained in an infinite horizon model without labor income but Gomes and Michaelides (2005) reach the same conclusion in a life-cycle model essentially identical to the one we are considering.

Table I
Volatility of Permanent and Transitory Income Shocks

The table reports the standard deviation of the permanent and transitory components of income for households sorted by industry and education level. The calculations are based on the sample of households defined in the main text.

	No High School Degree		High School Degree		Post-High School	
	Permanent	Transitory	Permanent	Transitory	Permanent	Transitory
Mining and quarrying, electricity, gas and water supply	8.37%	7.71%	7.69%	7.35%	7.02%	8.16%
Manufacturing	8.23%	8.74%	7.86%	8.87%	7.39%	10.58%
Construction	10.61%	10.94%	9.85%	10.27%	9.66%	10.50%
Wholesale and retail trade	9.48%	12.37%	9.62%	11.25%	8.53%	12.61%
Hotels and restaurants	11.79%	15.88%	10.39%	15.91%	11.94%	15.85%
Transport, storage and communication	9.78%	11.05%	8.37%	10.46%	7.22%	11.99%
Financial intermediation	7.64%	11.29%	7.66%	10.94%	6.86%	12.33%
Real estate activities	8.87%	12.38%	8.61%	12.41%	8.08%	13.86%
Public sector	8.49%	8.62%	8.36%	8.84%	7.55%	10.12%
Education and social work	9.72%	11.02%	10.20%	9.91%	8.53%	10.69%
Health care and veterinary services	9.15%	11.56%	9.27%	10.49%	8.43%	11.31%
Other services and activities	10.25%	11.54%	9.72%	12.61%	7.89%	11.54%

Table II
Calibration Parameters

This table reports the calibration parameters used in the simulations. In Panel C, expected values of excess returns are obtained by assuming a Sharpe ratio on real estate investments of 0.17.

Panel A: Financial Portfolio		
Average equity fund management fee (active funds, 1999–2007)		1.42%
Average share of risky portfolio invested in funds (1999-2007)		28.06%
Average excess return of world index in SEK (1983-2007)		4.73%
Ex ante expected return adjusted for mutual fund fees		3.70%
Average volatility of household risky portfolios (1999-2007)		21.68%
Average real risk-free rate (1999-2007)		1.60%
Panel B: Levered Position in Residential Real Estate		
Leverage Ratio		
Average leverage ratio (1999-2007)		47.94%
Standard deviation across education and business groups (2003)		3.07%
Share in Residential Real Estate Equity		
Average share in residential real estate equity (1999-2007)		55.33%
Standard deviation across education and business groups (2003)		4.21%
Panel C: Excess Returns		
	Expected Value	Sample Mean
Average mortgage rate in excess of the risk free rate		1.53%
Volatility of excess return on housing index (1983-2007)		14.73%
Average excess return on housing (1983-2007)	2.50%	-0.54%
Average excess return on residential real estate equity (1983-2007)	3.40%	-2.45%
Average excess return on financial and residential real estate equity (1983-2007)	3.53%	0.30%
Panel D: Second Moments		
Volatility of residential real estate equity (1983-2007)		28.29%
Volatility of financial and residential real estate equity		18.19%
Volatility of labor income shocks (1983-2007)		5.18%
Covariance of aggregate labor income shock κ_t and housing index (1999-2007)		0.34%
Covariance of labor income shocks with financial and housing equity return		0.36%
Correlation of housing index and MSCI World Index (1983-2007)		-5.73%
Correlation of labor income shocks with financial and residential real estate equity return		38.18%

Table III
Risky Share and Wealth-to-Income Ratio Across Sector and Education Groups

This table reports the risky share and wealth-to-income ratio of households sorted by employment sector and education. All variables are described in Table A.

	No High School Degree		High School Degree		Post-High School	
	Risky Share	Wealth-to-Income Ratio	Risky Share	Wealth-to-Income Ratio	Risky Share	Wealth-to-Income Ratio
Mining and quarrying, electricity, gas and water supply	70.49%	3.050	72.88%	3.068	79.32%	4.044
Manufacturing	67.93%	2.862	70.86%	3.105	77.58%	4.296
Construction	74.11%	4.118	75.13%	3.912	79.08%	4.764
Wholesale and retail trade	70.93%	3.980	73.33%	4.227	78.25%	5.113
Hotels and restaurants	65.73%	4.205	66.49%	4.289	68.94%	5.239
Transport, storage and communication	68.18%	3.253	70.79%	3.334	76.31%	4.321
Financial intermediation	73.63%	3.947	76.16%	4.102	80.54%	5.019
Real estate activities	67.84%	3.777	72.28%	4.236	78.58%	5.460
Public sector	68.55%	3.351	71.80%	3.646	76.80%	4.016
Education and social work	63.78%	3.374	64.65%	3.284	72.45%	3.988
Health care and veterinary services	63.42%	3.208	66.48%	3.428	74.31%	4.105
Other services and activities	67.36%	4.080	68.43%	4.357	72.77%	4.539

Table IV
Preference Parameter Estimates

This table reports estimates of the preference parameters computed on the representative panel of households over the 1999 to 2007 period. In Panel A, we allow the EIS and risk aversion coefficients to vary across cohorts and employment sectors. In Panel B, the EIS and risk aversion coefficients are held constant within cohorts but can vary across sectors. In both panels, the discount factor is constrained to be identical for households with the same education level. In Panel C, all households are assumed to have the same EIS, risk aversion and time preference coefficients. Panel D considers alternative definitions of wealth.

	Risk Aversion γ		EIS ψ		Discount Factor δ		Discount Rate $-\log(\delta)$		Mean Sum of Squared Errors		
	Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.	Total	Risky Share	Wealth to Income
Panel A: Heterogeneous Preferences, Fixed Discount Factor within Education Groups											
Unconstrained γ and ψ	4.15	0.49	0.67	0.44	0.993	0.002	0.67%	0.24%	0.19	0.13	0.06
CRRA (γ=1/ψ)	4.19	0.50	0.24	0.03	0.995	0.000	0.50%	0.00%	0.24	0.11	0.14
Fixed EIS: ψ = 0.2	4.20	0.49	0.20	0.00	0.995	0.000	0.50%	0.00%	0.25	0.11	0.14
Fixed EIS: ψ = 0.4	4.15	0.48	0.40	0.00	0.995	0.000	0.50%	0.00%	0.22	0.12	0.11
Fixed EIS: ψ = 0.6	4.13	0.48	0.60	0.00	0.992	0.002	0.84%	0.24%	0.22	0.12	0.10
Fixed EIS: ψ = 0.8	4.10	0.47	0.80	0.00	0.992	0.002	0.84%	0.24%	0.22	0.12	0.09
Fixed EIS: ψ = 1	4.34	1.01	1.00	0.00	0.967	0.005	3.39%	0.49%	3.22	0.46	2.76
Fixed EIS: ψ = 1.2	4.74	1.09	1.20	0.00	0.973	0.005	2.70%	0.48%	1.64	0.15	1.50
Fixed EIS: ψ = 1.4	4.63	0.66	1.40	0.00	0.982	0.002	1.85%	0.24%	1.08	0.10	0.97
Panel B: Zero Trend Across Cohorts, Fixed Discount Factor within Education Groups											
Unconstrained γ and ψ	4.16	0.47	0.67	0.21	0.995	0.000	0.50%	0.00%	0.40	0.32	0.08
CRRA (γ=1/ψ)	4.20	0.41	0.24	0.03	0.995	0.000	0.50%	0.00%	0.48	0.34	0.14
Fixed EIS: ψ = 0.2	4.75	3.18	0.20	0.00	0.995	0.000	0.50%	0.00%	0.50	0.35	0.15
Fixed EIS: ψ = 0.4	4.17	0.39	0.40	0.00	0.995	0.000	0.50%	0.00%	0.46	0.34	0.12
Fixed EIS: ψ = 0.6	4.12	0.38	0.60	0.00	0.992	0.002	0.84%	0.24%	0.44	0.33	0.10
Fixed EIS: ψ = 0.8	4.10	0.39	0.80	0.00	0.992	0.002	0.84%	0.24%	0.42	0.32	0.09
Fixed EIS: ψ = 1	4.39	1.05	1.00	0.00	0.963	0.005	3.74%	0.49%	3.69	0.69	3.00
Fixed EIS: ψ = 1.2	4.69	0.69	1.20	0.00	0.973	0.005	2.70%	0.48%	1.80	0.29	1.51
Fixed EIS: ψ = 1.4	4.58	0.67	1.40	0.00	0.982	0.002	1.85%	0.24%	1.23	0.26	0.97

Table IV—*Continued*
Preference Parameter Estimates

	Risk Aversion γ		EIS ψ		Discount Factor δ		Discount Rate $-\log(\delta)$		Mean Sum of Squared Errors		
	Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.	Mean	Standard Dev.	Total	Risky Share	Wealth to Income
Panel C: Uniform Preferences											
Unconstrained	4.00	0.00	0.69	0.00	0.995	0.000	0.50%	0.00%	0.74	0.63	0.11
CRRA (γ=1/ψ)	4.25	0.00	0.24	0.00	0.995	0.000	0.50%	0.00%	0.87	0.72	0.15
Fixed EIS: ψ = 0.2	4.25	0.00	0.20	0.00	0.995	0.000	0.50%	0.00%	0.87	0.72	0.15
Fixed EIS: ψ = 0.4	4.00	0.00	0.40	0.00	0.995	0.000	0.50%	0.00%	0.78	0.67	0.12
Fixed EIS: ψ = 0.6	4.00	0.00	0.60	0.00	0.995	0.000	0.50%	0.00%	0.74	0.64	0.10
Fixed EIS: ψ = 0.8	4.00	0.00	0.80	0.00	0.995	0.000	0.50%	0.00%	0.74	0.62	0.12
Fixed EIS: ψ = 1	4.00	0.00	1.00	0.00	0.970	0.000	3.05%	0.00%	4.21	0.97	3.24
Fixed EIS: ψ = 1.2	4.50	0.00	1.20	0.00	0.970	0.000	3.05%	0.00%	2.56	0.97	1.59
Fixed EIS: ψ = 1.4	4.50	0.00	1.40	0.00	0.980	0.000	2.02%	0.00%	1.88	0.89	0.99

Table V
Cross-Sectional Relationship Between Risk Aversion and the EIS

This table reports regressions of the logarithm of the EIS on the logarithm of risk aversion (columns 1 to 4) and regressions of the logarithm of risk aversion on the log of the EIS (columns 5 to 8).

	Dependent Variable: Logarithm of EIS								Dependent Variable: Logarithm of Risk Aversion Coefficient							
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Log risk aversion	-0.400	-2.74	-0.689	-4.78	-0.489	-1.29	-1.141	-2.41								
Log EIS									-0.037	-2.72	-0.058	-3.53	-0.008	-1.29	-0.013	-2.18
Intercept	0.114	0.54	0.536	2.47	0.060	0.10	1.138	1.55	1.402	174.4	1.407	200.7	1.506	82.85	1.519	68.28
Cohort dummies:																
- Cohort 2					-0.069	-0.38	-0.113	-0.45					-0.018	-0.69	-0.018	-0.59
- Cohort 3					0.113	0.71	-0.016	-0.07					-0.027	-1.13	-0.023	-0.78
- Cohort 4					0.110	0.63	-0.039	-0.17					-0.027	-1.08	-0.024	-0.80
- Cohort 5					-0.111	-0.54	-0.156	-0.64					-0.052	-2.08	-0.050	-1.65
- Cohort 6					0.319	1.87	0.013	0.06					-0.066	-2.69	-0.074	-2.59
- Cohort 7					0.015	0.09	-0.280	-1.39					-0.092	-3.65	-0.096	-3.22
- Cohort 8					-0.095	-0.47	-0.405	-1.62					-0.101	-4.11	-0.112	-3.80
- Cohort 9					-0.200	-1.03	-0.292	-1.44					-0.131	-5.23	-0.142	-4.77
- Cohort 10					-0.102	-0.54	-0.405	-1.70					-0.151	-6.05	-0.159	-5.19
- Cohort 11					0.038	0.21	-0.160	-0.67					-0.172	-7.32	-0.180	-6.42
- Cohort 12					-0.187	-0.91	-0.451	-1.75					-0.189	-7.92	-0.198	-7.05
- Cohort 13					-0.165	-0.85	-0.468	-1.62					-0.220	-9.68	-0.233	-8.03
Weighting	Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted	
Cohort-varying parameters	No		No		Yes		Yes		No		No		Yes		Yes	
Adjusted R^2	0.013		0.040		0.000		0.037		0.013		0.040		0.305		0.454	
Number of groups	468		468		467		467		468		468		467		467	

Table VI
Preference Parameters and Education

This table reports regressions of the logarithm of the EIS on education variables (columns 1 to 4) and regressions of the logarithm of risk aversion on education (columns 5 to 8).

	Dependent Variable: Logarithm of EIS								Dependent Variable: Logarithm of Risk Aversion Coefficient							
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
High school	0.093	2.40	0.020	0.58	-0.452	-4.75	-0.528	-5.27	0.021	1.62	0.000	0.00	-0.013	-1.15	-0.021	-1.29
Post-high school	0.525	21.5	0.482	24.0	0.200	2.31	0.140	1.29	-0.037	-3.34	-0.047	-2.85	-0.031	-2.61	-0.028	-2.07
Intercept	-0.660	-27.9	-0.655	-49.0	-0.595	-4.94	-0.409	-3.03	1.424	174.8	1.452	94.8	1.526	79.9	1.549	61.2
Cohort dummies:																
- Cohort 2					-0.061	-0.38	-0.104	-0.55					-0.017	-0.67	-0.017	-0.57
- Cohort 3					0.127	0.89	-0.001	0.00					-0.028	-1.18	-0.023	-0.80
- Cohort 4					0.113	0.75	-0.047	-0.28					-0.030	-1.21	-0.030	-1.00
- Cohort 5					-0.086	-0.44	-0.119	-0.61					-0.051	-2.06	-0.049	-1.59
- Cohort 6					0.353	2.32	0.065	0.35					-0.069	-2.82	-0.076	-2.69
- Cohort 7					0.060	0.40	-0.207	-1.24					-0.092	-3.67	-0.095	-3.16
- Cohort 8					-0.046	-0.26	-0.310	-1.61					-0.100	-4.13	-0.109	-3.64
- Cohort 9					-0.136	-0.79	-0.161	-1.07					-0.130	-5.22	-0.141	-4.72
- Cohort 10					-0.028	-0.17	-0.262	-1.21					-0.151	-6.04	-0.157	-5.17
- Cohort 11					0.123	0.80	0.016	0.09					-0.173	-7.34	-0.182	-6.49
- Cohort 12					-0.095	-0.52	-0.255	-1.22					-0.189	-7.88	-0.197	-7.05
- Cohort 13					-0.058	-0.34	-0.227	-0.83					-0.219	-9.72	-0.233	-8.09
Weighting	Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted	
Cohort-varying parameters	No		No		Yes		Yes		No		No		Yes		Yes	
Adjusted R^2	0.396		0.440		0.110		0.188		0.043		0.052		0.312		0.450	
Number of groups	468		468		467		467		468		468		468		468	

Table VII
Preference Parameters and Income Risk

This table reports regressions of the logarithm of the EIS on total income risk (columns 1 to 4) and regressions of the logarithm of risk aversion on total income risk (columns 5 to 8).

	Dependent Variable: Logarithm of EIS								Dependent Variable: Logarithm of Risk Aversion Coefficient							
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Total income risk	1.212	1.19	5.612	6.03	4.598	2.41	15.483	6.28	-3.728	-28.6	-5.623	-28.6	-3.670	-32.7	-4.410	-17.0
Intercept	-0.628	-4.41	-1.230	-9.75	-1.337	-4.65	-2.755	-7.81	1.952	98.6	2.213	78.5	2.036	105.6	2.140	58.5
Cohort dummies:																
- Cohort 2					-0.061	-0.34	-0.096	-0.43					-0.017	-1.05	-0.016	-0.73
- Cohort 3					0.127	0.79	0.013	0.06					-0.028	-1.80	-0.024	-1.11
- Cohort 4					0.124	0.71	-0.003	-0.02					-0.030	-1.86	-0.030	-1.39
- Cohort 5					-0.086	-0.42	-0.100	-0.48					-0.051	-3.26	-0.049	-2.28
- Cohort 6					0.353	2.13	0.099	0.49					-0.069	-4.22	-0.075	-3.57
- Cohort 7					0.060	0.36	-0.168	-0.95					-0.092	-6.05	-0.095	-5.24
- Cohort 8					-0.046	-0.23	-0.277	-1.21					-0.100	-6.76	-0.110	-5.86
- Cohort 9					-0.136	-0.73	-0.125	-0.72					-0.130	-8.27	-0.142	-7.85
- Cohort 10					-0.028	-0.16	-0.224	-1.06					-0.151	-9.84	-0.157	-8.51
- Cohort 11					0.123	0.74	0.052	0.26					-0.173	-11.6	-0.182	-10.2
- Cohort 12					-0.095	-0.51	-0.224	-0.99					-0.189	-12.6	-0.196	-11.1
- Cohort 13					-0.058	-0.32	-0.199	-0.80					-0.219	-15.2	-0.232	-12.7
Weighting	Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted	
Cohort-varying parameters	No		No		Yes		Yes		No		No		Yes		Yes	
Adjusted R^2	0.003		0.052		0.011		0.102		0.497		0.621		0.718		0.754	
Number of groups	468		468		467		467		468		468		468		468	

Table VIII
Permanent and Temporary Income Risk

This table reports regressions of the logarithm of the EIS on the volatility of permanent and transitory income risk (columns 1 to 4) and regressions of the logarithm of risk aversion on the volatility of permanent and transitory income risk (columns 5 to 8).

	Dependent Variable: Logarithm of EIS								Dependent Variable: Logarithm of Risk Aversion Coefficient							
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Permanent income risk	-20.25	-15.7	-22.931	-15.7	-23.068	-7.12	-26.806	-6.31	-5.005	-15.4	-5.404	-17.5	-4.743	-18.8	-5.347	-18.4
Temporary income risk	11.20	16.1	14.258	18.6	16.172	8.23	25.509	13.3	-1.590	-9.64	-3.758	-22.1	-1.663	-10.8	-2.564	-10.2
Intercept	0.09	0.65	-0.014	-0.13	-0.440	-1.48	-1.066	-2.84	2.040	85.7	2.306	66.6	2.117	114.9	2.265	75.7
Cohort dummies:																
- Cohort 2					-0.061	-0.39	-0.093	-0.69					-0.017	-1.29	-0.016	-0.97
- Cohort 3					0.127	0.86	0.021	0.17					-0.028	-2.20	-0.023	-1.43
- Cohort 4					0.109	0.69	-0.049	-0.42					-0.030	-2.22	-0.030	-1.79
- Cohort 5					-0.086	-0.44	-0.093	-0.61					-0.051	-3.81	-0.048	-2.97
- Cohort 6					0.353	2.25	0.111	0.83					-0.069	-4.87	-0.074	-4.61
- Cohort 7					0.060	0.37	-0.156	-1.28					-0.092	-6.89	-0.094	-6.28
- Cohort 8					-0.046	-0.25	-0.265	-1.57					-0.100	-7.70	-0.109	-6.88
- Cohort 9					-0.136	-0.81	-0.111	-0.96					-0.130	-9.06	-0.141	-9.53
- Cohort 10					-0.028	-0.16	-0.207	-1.18					-0.151	-11.1	-0.156	-10.2
- Cohort 11					0.123	0.78	0.073	0.44					-0.173	-13.3	-0.181	-12.6
- Cohort 12					-0.095	-0.55	-0.195	-1.07					-0.189	-14.4	-0.194	-13.7
- Cohort 13					-0.058	-0.34	-0.163	-0.70					-0.219	-16.4	-0.229	-15.1
Weighting	Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted		Equal-weighted		Size-weighted	
Cohort-varying parameters	No		No		Yes		Yes		No		No		Yes		Yes	
Adjusted R^2	0.412		0.647		0.135		0.320		0.567		0.653		0.770		0.809	
Number of groups	468		468		467		467		468		468		468		468	

Table IX
Risky Share and Wealth-to-Income Ratio

This table reports regressions of the risky share on education and income risk variables (columns 1 to 4) and regressions of the wealth-to-income-ratio on the education and income risk variables (columns 5 to 8). Groups are size-weighted.

	Dependent Variable: Risky Share						Dependent Variable: Wealth-to-Income Ratio					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Education dummies:												
High school	0.023	1.60					0.148	0.76				
Post-high school	0.077	5.56					0.975	4.80				
Income Risk												
Total income volatility			-0.686	-2.75					16.234	3.88		
Volatility of permanent income shocks					-2.679	-4.37					-19.386	-2.75
Volatility of temporary income shocks					0.550	1.63					26.866	5.93
Intercept	0.685	70.25	0.817	22.07	0.894	24.74	3.601	26.73	1.653	2.79	2.694	4.57
Adjusted R^2	0.457		0.069		0.347		0.416		0.262		0.507	
Number of groups	36		36		36		36		36		36	

Figure 1
Fitted Labor Income Profiles

This figure illustrates the fitted labor income profiles for each education group (no high school, high school, post-high school), with and without age dummies.

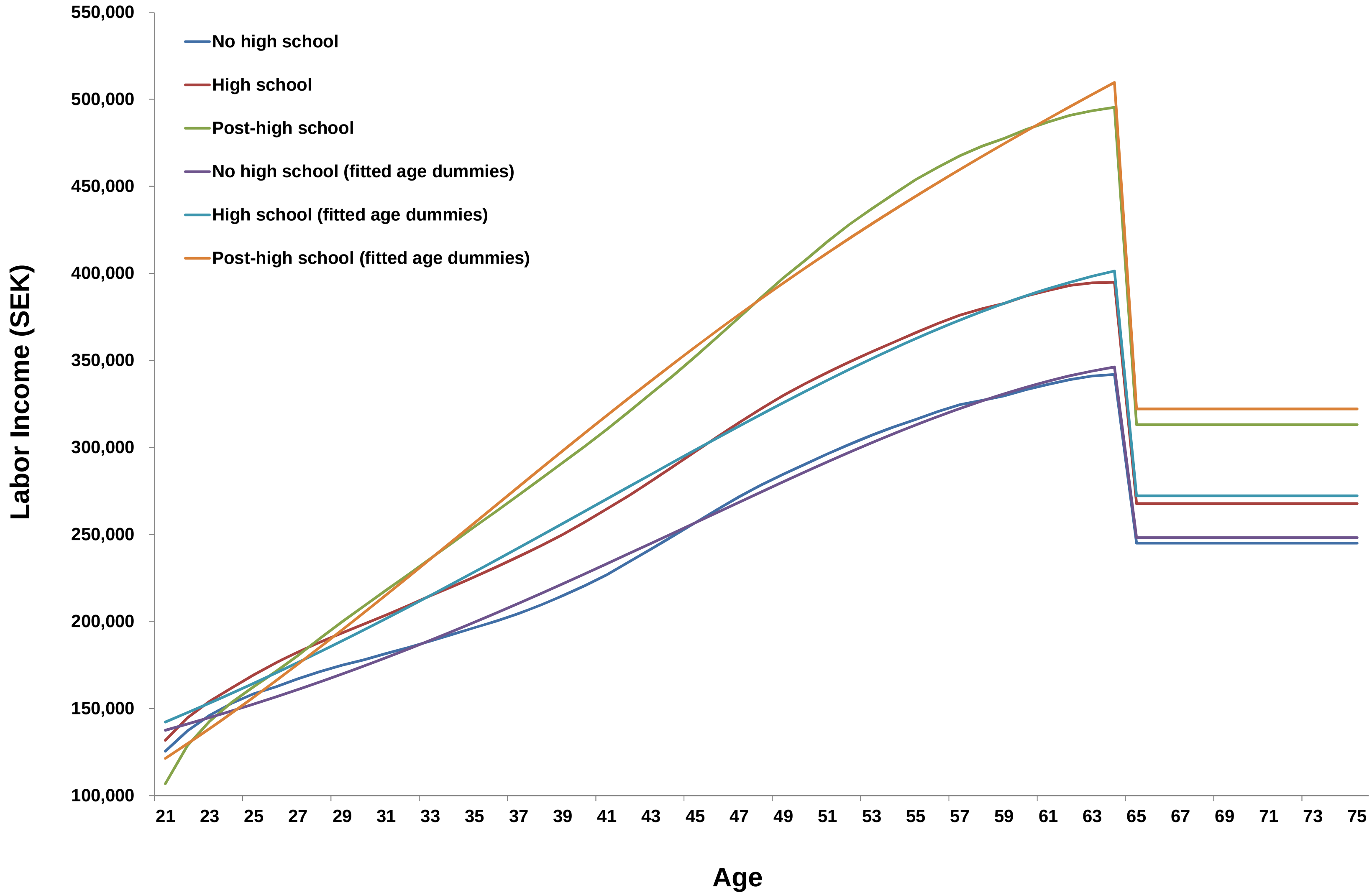

Figure 2

Cross-Sectional Relationship Between the EIS and Risk Aversion

Equal-Weighted Groups

This figure illustrates the cross-sectional relationship between the EIS and the relative risk aversion coefficient. Preferences are held constant within each cohort..

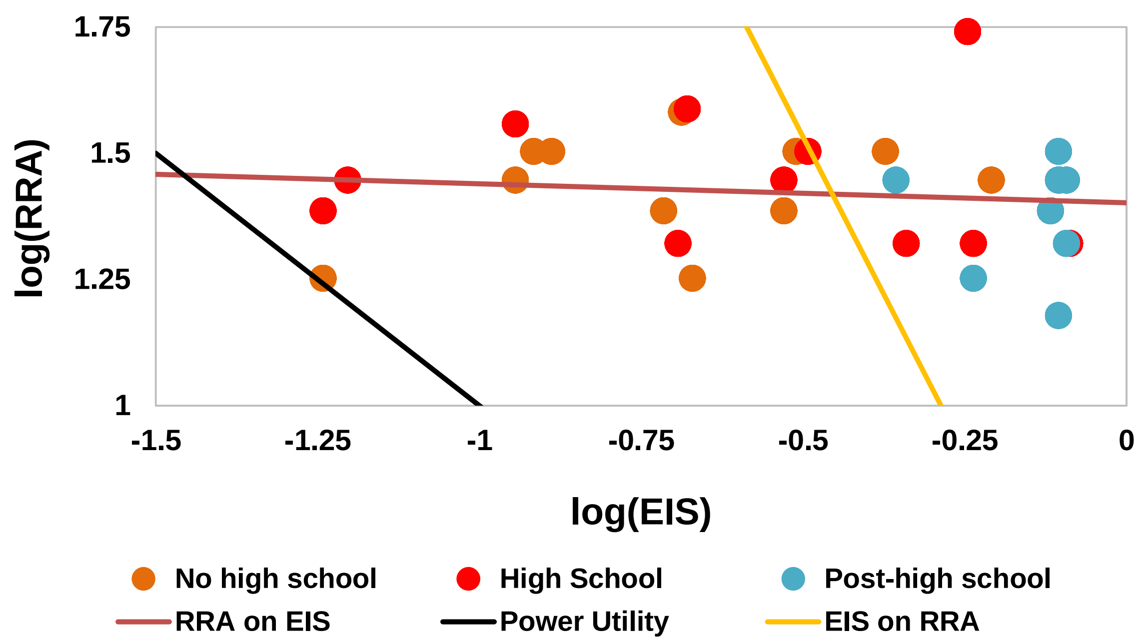

Figure 3
Cross-Sectional Relationship Between the EIS and Risk Aversion
Size-Weighted Groups

This figure illustrates the cross-sectional relationship between the EIS and the relative risk aversion coefficient. Parameters are held constant within each cohort.

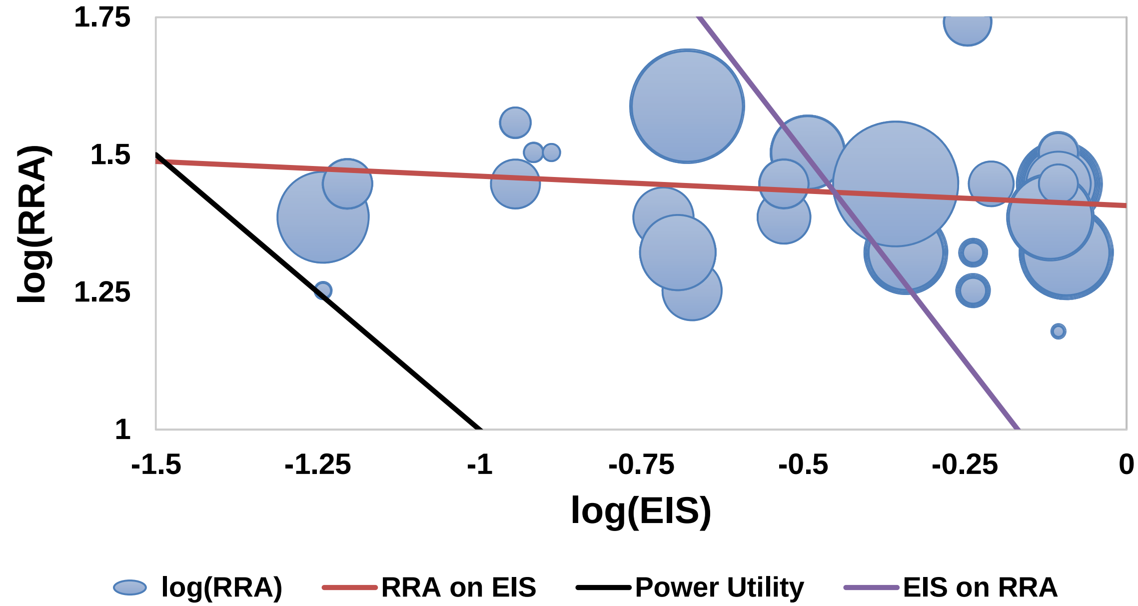

Figure 4

Cross-Sectional Relationship Between the EIS and Labor Income Risk

Equal-Weighted Groups

This figure illustrates the cross-sectional relationship between the EIS and the total volatility of labor income. Parameters are held constant within each cohort.

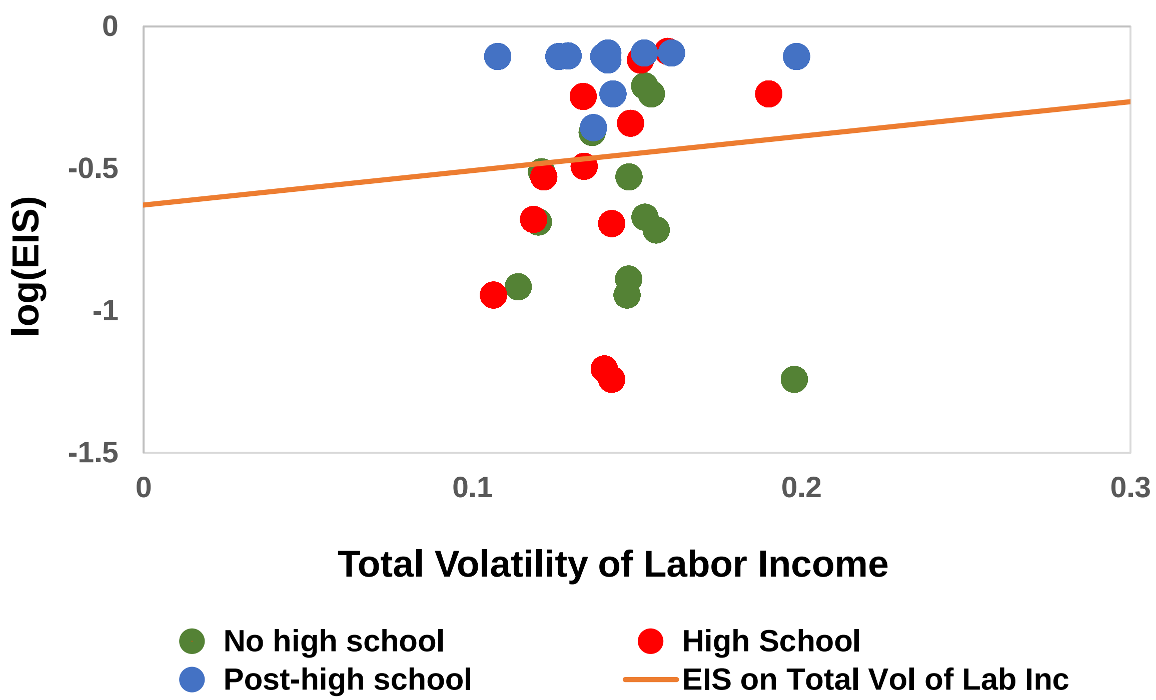

Figure 5

Cross-Sectional Relationship Between Risk Aversion and Labor Income Risk

Equal-Weighted Groups

This figure illustrates the cross-sectional relationship between the coefficient of relative risk aversion and the total volatility of labor income. Parameters are held constant within each cohort.