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Income Risk and Portfolio Choice: An Empirical Study

XIAOHONG ANGERER and POK-SANG LAM*

ABSTRACT

This paper investigates the relationship between portfolio choice and labor income risk in the National Longitudinal Survey of Youth 1979 Cohort. Permanent income risk (variability of shocks to income that have permanent effect) significantly reduces the share of risky assets in the household's portfolio, while transitory income risk (variability of shocks with no lasting effect) does not. This result provides strong evidence that households' portfolio choices respond to labor income risks in a manner consistent with economic theory.

THEORETICAL WORK HAS SHOWN that uninsurable labor income risk is likely to reduce the share of risky assets in an investor's portfolio (Pratt and Zeckhauser (1987), Kimball (1993), Bertaut and Haliassos (1997), Koo (1998, 1999), Elmendorf and Kimball (2000)). In a dynamic context, when labor income consists of components of different persistence, the magnitude of this effect should depend on the persistence associated with the risk—the risk to a persistent component should have a larger effect than the risk to a transitory component. Surprisingly, however, empirical work has not examined this interesting implication of the theory. This paper uses the rich information contained in the National Longitudinal Survey of Youth 1979 Cohort (NLSY79) to examine this implication.

We assume that labor income has two components: permanent and transitory. We then measure the risks of the components for a sample of households in the survey and estimate their effects on the risky asset share. Previous empirical research on the relationship between labor income risk and portfolio shares uses the standard deviation of labor income growth to measure risk (Guiso,

*Angerer is with the Center for Human Resource Research, Ohio State University; Lam is with the Department of Economics, Ohio State University. The authors are deeply grateful to Campbell R. Harvey, Patricia Reagan, Rene Stulz, an anonymous referee, and the Editor (Robert F. Stambaugh), whose comments and suggestions greatly strengthened the paper. The authors thank Xiaoqiang Cheng, Paul Evans, Virginia Goettl, Donald Haurin, Andrew Karolyi, Amanda McClain, Ross Miller, Randall J. Olsen, and Chana Ulm for their helpful comments, and Rosella Gardecki, Traci Mach, Steve McClaskie, Karima Nagi, and Jay Zagorsky for their valuable assistance in processing the data. The authors also acknowledge the excellent research assistance of Vipul Bhatt and the financial assistance provided by Department of Economics, Ohio State University. The paper has benefited from presentation at the 2006 Summer Econometric Society North America Meeting at Minneapolis, the 2007 Chinese Economists Society Meeting at Changsha, China, and the Institute of Economics, Academia Sinica, Taiwan. Any errors are our own.

Jappelli, and Terilizze (1996), Heaton and Lucas (2000)). Under our assumption, this standard deviation represents a mixture of the risk to the permanent component and the risk to the transitory component. The literature thus estimates the overall effect of the permanent risk component and the transitory risk component. A negative and equal effect from each risk is inconsistent with economic theory, and yet it would produce a negative relationship between the standard deviation of labor income growth and risky portfolio share. By distinguishing between the two risks, this paper confronts the theory with a more stringent empirical test.

The NLSY79 data contain detailed information about the labor income and demographic characteristics of many households. This information allows us to address a number of empirical difficulties in this literature. First, much of an individual's earnings growth is explainable by demographic factors such as schooling, experience, gender, and race (Ben-Porath (1967)). Since the effects of these factors are largely predictable, risk measures based on raw income data exaggerate the risk. In this paper, we use data from both the Current Population Survey (CPS) and NLSY79 to estimate the effect of demographic factors on household incomes. The effect is removed from the income data before we estimate the income risks. Second, human wealth is substantial for most households, and yet it has been largely ignored in empirical work. Ignoring human wealth leads to an "omitted variable" problem and inaccurate inferences about portfolio behaviors (Bodie, Merton, and Samuelson (1992)). In this paper, we apply a signal extraction technique to labor income histories and estimate human wealth as the expected present value of lifetime incomes. We include human wealth in the definition of total wealth and consider the effects of income risks on the asset allocation of total wealth.

The findings of this paper can be briefly summarized. Permanent income risk significantly shifts a household's portfolio allocation away from risky assets, while transitory income risk has little effect. The effect of permanent income risk is about six times as large as the effect of transitory income risk.

The rest of the paper is organized as follows. Section I discusses the NLSY79 data, while Section II presents the empirical model. Section III details the construction of the variables used in the estimation, particularly the risks to permanent income and transitory income. Section IV presents the empirical results. Section V concludes.

I. Data Set

The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14 to 22 years old when first interviewed in 1979. The respondents were interviewed annually through 1994, after which they were interviewed every other year. Retention rates remained near 90% after 18 rounds of interviews (Center for Human Resource Research (1999)).

Beginning in 1983, the respondents were asked about income from various sources, including military income, wages, salaries, tips, farm and business income, unemployment compensation, Aid to Families with Dependent Children

(AFDC) payments, food stamps, Supplemental Security Income (SSI), and other welfare payments. We construct total labor income by adding up these items.

In 1988, the NLSY79 began to collect information about two categories of financial assets. The first category consists of savings and checking accounts, money market funds, certificates of deposit, U.S. saving bonds, individual retirement accounts, 401(k) and pre-tax annuities, and personal loans to others. The second category consists of common stock, preferred stock, stock options, government and corporate bonds, and mutual funds. Until 1994, the survey asked only about the sum of each category; that is, the information for the individual components of each category was not available. Since 1994, the survey has asked questions about the components of the first category: (a) savings and checking accounts, money market funds, credit unions, and U. S. saving bonds; (b) certificates of deposit and personal loans to others; (c) individual retirement accounts; and (d) tax-deferred accounts. The NLSY79 also collects information on other individual components of total wealth: net value of residential property and real estate, farm and proprietary businesses, investment trusts, vehicles, and other possessions. We use the asset information to construct net wealth and risky asset share.[1]

When a respondent is married, the reported income and asset information refers to the combined values of the respondent and spouse. We therefore construct total labor income, net wealth, and risky asset share for each household (the respondent if single, the respondent and spouse if married), assuming that the decision unit is a household. The asset and income data are expressed in 1988 constant dollars using the CPI-U.[2]

We use the asset information from 1988 to 1998 and income and demographic variables from 1983 to 1998. As an income regression is used to remove the effect of demographic variables on income growth, the respondents with a missing value in total labor income or in the demographic variable between 1983 and 1998 are dropped from the sample. Furthermore, we delete outliers from the sample.[3] The net result is a sample of 1,909 households that we use to conduct the empirical analysis. The selected sample has slightly more male, African American, and educated respondents, but is otherwise representative of the entire sample.[4]

[1] Several empirical studies have used the asset data from the NLSY79 (Haurin, Hendershott, and Wachter (1996, 1997), Zagorsky (1997)). The reliability of the wealth data in the NLSY79 has been verified by comparisons with other data sets, such as the Survey of Consumer Finances (SCF), Panel Study of Income Dynamics (PSID), and Survey of Income and Program Participation (SIPP) (Haurin, Hendershott, and Wachter (1996), Zagorsky (1997)).

[2] Annual CPI-U data from 1982 to 1998 are taken from the website of the Bureau of Labor Statistics. The series is normalized so that it is equal to one in 1998.

[3] A respondent is considered an outlier if at least one of the following criteria is met for the period between 1983 and 1998: (a) total income was less than $100 in any year; (b) he or she spent more than 40 weeks out of the labor force in any year; or (c) the standard deviation of income growth exceeded three.

[4] The selection of the sample from the NLSY79 base sample, the demographic characteristics of the selected sample, and the comparability of the selected sample to the base sample are detailed in a Internet Appendix available at http://www.afajof.org/supplements.asp.

II. An Empirical Model of Labor Income and Risky Asset Share

We specify an exogenous labor income process that allows us to interpret labor income data in terms of income risks. Further, we imagine a household allocating its wealth between two assets, a risky asset and a safe asset. The risky asset share is the fraction of a household's wealth invested in the risky asset. We specify portfolio rules that relate the risky asset share to household characteristics and risk measures.

A. Labor Income Process

To model labor income, we follow the literature on wage and earning regressions in adopting a log-linear specification. Log labor income consists of two parts, one explainable by demographic characteristics and another that follows a stochastic process. The stochastic process consists of two components, namely, permanent and transitory incomes. A shock to permanent income is expected to affect the household's income over a lifetime, while a shock to transitory income is expected to affect the household's income for one period. Let Y denote labor income and the subscripts i and t denote household and time, respectively. Formally, labor income follows the process

$$\text{Log}\, Y_{i,t} = Z_{i,t}\gamma + \nu_{i,t}, \tag{1}$$

$$\nu_{i,t} = \mu_{i,t} + \eta_{i,t}, \tag{2}$$

$$\mu_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t}. \tag{3}$$

where $Z_{i,t}$ is a vector of household demographic characteristics, γ is a corresponding vector of coefficients, $\nu_{i,t}$ is stochastic labor income, $\eta_{i,t}$ is the transitory income shock, $\mu_{i,t}$ is stochastic permanent income that follows a random walk, and $\varepsilon_{i,t}$ is the shock in the random walk.[5] The two shocks, $\eta_{i,t}$ and $\varepsilon_{i,t}$, are each assumed to be independently, identically and normally distributed over time with zero mean, and are mutually independent.[6] The standard deviations of the shocks are $\sigma_{i,\eta}$ and $\sigma_{i,\varepsilon}$, which we interpret as transitory income risk and permanent income risk, respectively.

[5] Similar labor income processes have previously been employed in both theoretical and empirical work (e.g., Viceira (2001), Campbell et al. (1999), Carroll (1992, 1997)). More elaborate specifications of stochastic labor incomes have also been considered in the literature. MaCurdy (1982) and Abowd and Card (1989) suggest that stochastic labor income growth follows a second-order moving average process, and Hubbard, Skinner, and Zeldes (1994) assume that the stochastic permanent income is a highly persistent first-order autoregressive process. MaCurdy (1982) studies a sample from the PSID collected over the years 1968 to 1977. Abowd and Card (1989) employ earnings data from the PSID collected over the years 1969 to 1979, from the National Longitudinal Survey of Men collected over the years 1966 to 1975, and from the nonexperimental families in the Seattle and Denver Income Maintenance Experiment collected over the years 1970 to 1978. Hubbard, Skinner, and Zeldes (1994) use earnings data from PSID collected over the years 1983 to 1987.

[6] The income shocks $\eta_{i,t}$ and $\varepsilon_{i,t}$ are potentially correlated across households due to the business cycle. In estimating the income risks, however, we exploit exclusively the time- series income variations of a household. The cross-sectional correlations between households are thus left unspecified.

B. Risky Asset Share

Let $\mathrm{RS}^*_{i,t}$ be the desired risky asset share, and $X_{i,t}$ be a vector of household characteristics including income risk measures. The desired risky asset share is determined by the household characteristics up to a random error. The error is the sum of two mutually independent, normally distributed processes, where one is household specific and the other is pure white noise. Therefore,

$$\mathrm{RS}^*_{i,t} = X_{i,t}\beta + \tau_i + \omega_{i,t}, \tag{4}$$

$$\tau_i \sim \text{N.i.i.d.}\left(0, \sigma^2_\tau\right),$$

$$\omega_{i,t} \sim \text{N.i.i.d.}\left(0, \sigma^2_\omega\right),$$

and τ_i and $\omega_{i,t}$ are independent for all i and t.

We assume a household cannot go short on risky assets, so that the observed risky asset share is nonnegative. The risky asset share may or may not exceed one, depending on whether a household can hold a negative amount of safe assets. We thus consider two models of observed risky asset shares:

$$\mathrm{RS}_{i,t} = \begin{cases} 1 & \text{if } \mathrm{RS}^*_{i,t} \geq 1 \\ \mathrm{RS}^*_{i,t} & \text{if } 0 < \mathrm{RS}^*_{i,t} < 1 \\ 0 & \text{if } \mathrm{RS}^*_{i,t} \leq 0, \end{cases} \tag{5}$$

and

$$\mathrm{RS}_{i,t} = \begin{cases} \mathrm{RS}^*_{i,t} & \text{if } \mathrm{RS}^*_{i,t} > 0 \\ 0 & \text{if } \mathrm{RS}^*_{i,t} \leq 0. \end{cases} \tag{6}$$

III. Construction of Variables

A. Income Risks

We remove the demographic effect from income growth before estimating the income risks, as equation (1) calls for. To estimate the effect of demographic variables on labor income growth, we use the March Supplement to the CPS. Using the CPS allows us to exploit a large sample size while minimizing the potential endogeneity caused by using the NLSY79 data to estimate both income risks and portfolio behavior. For considerations of data consistency over time and comparability with the NLSY79 data set, we use CPS data from 1988 to 1998. We construct a household labor income variable that closely mimics the one in the NLSY79, and regress it on household characteristics. An important characteristic is educational attainment, which we measure by the highest grade completed (HGC). Based on this variable, we construct four dummies: $\mathrm{HGC} \leq 8$, $8 < \mathrm{HGC} < 12$, $\mathrm{HGC} = 12$, and $12 < \mathrm{HGC} < 16$. The variables included in the regression are: time trend, marital status, gender, African American, Hispanic, age (fourth-order polynomial), education dummies, age of spouse (fourth-order polynomial), education dummies of spouse, and the interaction terms of gender with all other variables except time trend. All told, 40 variables are included and 309,582 observations are used to perform the regression.[7] We then use the regression coefficients and the household characteristics in the NLSY79 to remove the effect of demographic variation from labor income growth. The result is our estimate of the stochastic labor income risk.

The stochastic labor income risks are used to estimate the permanent and transitory income risks for each household. Following Carroll (1997), Bertaut and Haliassos (1997), and Campbell et al. (1999), we pool households into groups and estimate the group-specific income processes. However, we do not assume that the income processes are identical within groups. Instead, we assume that the ratio of permanent risk to transitory risk is constant within groups, but the risks themselves may differ. Under this assumption, we classify the households into groups. For each group, we pool the data of households within the group to estimate the group-specific risk ratio. Our method of estimating the group-specific risk ratio is motivated by the following implication of equations (2) and (3):

$$k\mathrm{VR}(k)_i = \alpha_i + \beta_i k, \tag{7}$$

where

$$\mathrm{VR}(k)_i = \frac{\mathrm{Var}(\nu_{i,t} - \nu_{i,t-k})}{k\mathrm{Var}(\nu_{i,t} - \nu_{i,t-1})}, \quad \alpha_i = \frac{2}{2+\delta_i}, \quad \beta_i = \frac{\delta_i}{2+\delta_i}, \quad \text{and} \quad \delta_i = \frac{\sigma_{i,\varepsilon}^2}{\sigma_{i,\eta}^2}.$$

We call $\mathrm{VR}(k)$ the variance ratio of horizon k. Thus, we infer the group-specific risk ratio from the slope coefficient of the linear relationship between k times the variance ratio and k. For each household within a group, we use the group-specific risk ratio and the stochastic income growth of the household to estimate the permanent and transitory income risks. Specifically, equations (2) and (3) imply

$$\mathrm{Var}(\nu_{i,t} - \nu_{i,t-k}) = \sigma_{i,\eta}^2(2 + k\delta_i). \tag{8}$$

We thus infer the variance of the transitory income shock from the coefficient of the proportional relationship between $\mathrm{Var}(\nu_{i,t} - \nu_{i,t-k})$ and $(2 + k\delta_i)$. The variance of the permanent income shock is then δ_i times the variance of the transitory income shock.

A household can hedge against uninsured labor income risk by investing in risky assets if risky asset returns are negatively correlated with its labor income. Risky assets are thus potentially attractive due to their value as hedge instruments. We measure this value using the covariance of equity premium (eq_t)

[7] All income observations that are less than one dollar are considered left-censored at zero when expressed in log form, and we estimate the profile using a Tobit model. The result is reported in the Internet Appendix.

with total labor income growth, $\mathrm{Cov}(\Delta \log Y_{i,t}, \mathrm{eq}_t)$, and the covariances of equity premium with two components of total labor income growth, $\mathrm{Cov}(\Delta Z_{i,t}\gamma, \mathrm{eq}_t)$ and $\mathrm{Cov}(\Delta \nu_{i,t}, \mathrm{eq}_t)$. To evaluate these measures for each household, we take the three series $\Delta \log Y_{i,t}$, $\Delta Z_{i,t}\gamma$, and $\Delta \nu_{i,t}$ and calculate their sample covariances with the ex post equity premium.[8]

B. Risky Asset Share

Two definitions of risky asset share are considered: the ratio of risky assets to total liquid financial wealth, and the ratio of risky assets to total net wealth.

In calculating risky assets, we include common stocks, preferred stocks, stock options, government and corporate bonds, and mutual funds. In calculating safe assets, we include checking and saving accounts, money market funds, certificates of deposit, U.S. saving bonds, and personal loans. Individual retirement accounts and tax-deferred accounts (401(k), 403(b), and others) are included in risky assets starting from 1994. Before 1994, because the survey lumped these accounts with other safe assets and reported only the sum, we include them in safe assets. Total liquid financial wealth is calculated as the sum of risky assets and safe assets.

Total net wealth is the sum of financial net wealth and human wealth. To calculate financial net wealth, we add to total liquid financial wealth the net value of residential property and other real estate, farms and proprietary businesses, investment trusts, vehicles, and other possessions.[9] Existing theoretical results on portfolio behavior suggest that the effect of the safe component of lifetime labor incomes is similar to carrying a safe asset in the amount of the net expected present value of future labor incomes in the household's portfolio (Merton (1971), Bodie, Merton, and Samuelson (1992), Viceira (2001), Cocco, Gomes, and Maenhout (2005)). We thus calculate human wealth as the expected present value of future labor incomes. The signal extraction technique used to calculate human wealth is presented in the Appendix.

[8] January values of the Standard & Poor's 500 Composite Stock Index and the corresponding 12-month moving average of total dividends per share from 1982 to 1998 are taken from Shiller (1989), available online. The annual stock return during year t is calculated as $\log\{(P_{t+1} + D_t)/P_t\}$, where P_t is the stock index at the beginning of year t and D_t is total dividends in year t. Monthly returns on 3-month Treasury bills from 1982 and 1998 are taken from the FRED database of the Federal Reserve Bank of St. Louis (TB3MS series). The annual risk-free rate is calculated as a geometric average of the monthly rates from January to December. The ex post equity premium of a year is calculated as the difference between the annual stock return and annual risk-free rate of the corresponding year. The ex post equity premium series from 1982 to 1998 and a household income series over the same period are used to calculate covariance.

[9] Cocco (2005) studies a life cycle model in which housing plays a crucial role in both consumption and investment decisions. He calibrates model parameters to the PSID data. By simulation, he shows that the limited participation of the young and the poor in the equity market can be explained by the housing price risk that crowds out stockholdings. Data limitations preclude us from investigating these interesting issues here. We do attempt to account for the wealth effect of housing, however, by including the net housing value in our definition of total net wealth.

IV. Empirical Results

We construct income risks and covariance measures for each household using the procedure described in Section III.A. These variables, along with household demographic characteristics, are used as explanatory variables in estimating the empirical model of risky asset share. We also construct risky asset shares for each household, using the procedure described in Section III.B. When the risky asset share is defined relative to total liquid financial assets, we use the econometric model represented by equations (4) and (5). When the risky asset share is defined relative to total net wealth, we use the econometric model represented by equations (4) and (6). We use the maximum likelihood method to estimate the model.[10]

A. Stochastic Labor Income and Income Risks

Table I displays the cross-sectional sample covariance matrix of stochastic income growth for the years between 1983 and 1993, when the households were interviewed annually. The first-order autocovariances are all negative and significant. While some of the second-order autocovariances are significant, they are small compared to the first-order autocovariances. Also, the higher-order autocovariances are mostly insignificant. Overall, Table I suggests that our random walk-plus-noise model of labor income is a good representation of the NLSY79 data.

Table I indicates that the variance of stochastic income growth declined by two-thirds between 1983 and 1988, and remained steady afterward. This phenomenon is consistent with the job instability and transition between part-time and full-time jobs associated with most young workers. Interestingly, it is also consistent with the macroeconomic conditions around the beginning of the sample. The recent long-term decline in macroeconomic volatility—the Great Moderation—is generally believed to have begun around 1984.

Table II presents the cross-sectional mean and standard deviation of the three covariances that measure the usefulness of risky assets in hedging against labor income risks. Panel A presents the statistics for the whole sample. The covariance between the equity premium and stochastic income growth is generally positive and small, consistent with the findings in the literature (Heaton and Lucas (1997), Cocco, Gomes, and Maenhout (2005)). Panel B presents the statistics for occupational groups. We divide the households into 12 occupational groups, using the 1970 Census three-digit occupational codes reported for the households in 1998.[11] The slightly positive covariance between stochastic income growth and equity premium is driven mainly by the positive covariance in three of the groups: managers and administrators, craftsmen, and

[10] Formally, the econometric model is a one-limit random-effects Tobit for the first definition of risky asset share, and a two-limit random-effects Tobit for the second definition of risky asset share. The XTTOBITT routine in STATA is used to obtain the maximum likelihood estimates and asymptotic standard errors.

[11] If the code is missing for 1998, we use the code reported for 1996.

Table I

Covariance Matrix of Stochastic Income Growth from the NLSY79, 1983–1993

The entries are based on the sample averages over 1,909 households. $\nu_{i,t}$ is the stochastic log labor income of household i in year t, and $\Delta\nu_{i,t} = \nu_{i,t} - \nu_{i,t-1}$ is the stochastic labor income growth. Diagonal entries are the variances, while off-diagonal entries are the covariances. Since the matrix is symmetric, we omit its upper right portion. Standard errors are in parentheses.

	$\Delta\nu_{i,83}$	$\Delta\nu_{i,84}$	$\Delta\nu_{i,85}$	$\Delta\nu_{i,86}$	$\Delta\nu_{i,87}$	$\Delta\nu_{i,88}$	$\Delta\nu_{i,89}$	$\Delta\nu_{i,90}$	$\Delta\nu_{i,91}$	$\Delta\nu_{i,92}$	$\Delta\nu_{i,93}$
$\Delta\nu_{i,83}$	0.348										
	(0.016)										
$\Delta\nu_{i,84}$	−0.086	0.306									
	(0.011)	(0.016)									
$\Delta\nu_{i,85}$	−0.007	−0.068	0.247								
	(0.008)	(0.009)	(0.013)								
$\Delta\nu_{i,86}$	−0.006	−0.016	−0.069	0.243							
	(0.008)	(0.008)	(0.010)	(0.015)							
$\Delta\nu_{i,87}$	−0.014	−0.010	−0.014	−0.079	0.199						
	(0.007)	(0.007)	(0.006)	(0.010)	(0.013)						
$\Delta\nu_{i,88}$	0.002	−0.002	−0.008	−0.012	−0.034	0.123					
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)					
$\Delta\nu_{i,89}$	−0.008	−0.006	0.003	−0.005	−0.015	−0.0324	0.127				
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)				
$\Delta\nu_{i,90}$	−0.002	−0.006	−0.005	−0.001	0.002	−0.006	−0.037	0.114			
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.011)			
$\Delta\nu_{i,91}$	−0.002	−0.004	−0.001	0.002	−0.014	0.000	−0.002	−0.036	0.127		
	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.010)		
$\Delta\nu_{i,92}$	0.007	−0.006	0.003	−0.013	0.010	−0.008	−0.001	−0.004	−0.035	0.114	
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)	(0.009)	
$\Delta\nu_{i,93}$	−0.007	0.005	−0.003	0.011	−0.011	0.005	−0.005	−0.007	−0.009	−0.042	0.139
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.010)

Table II

Income Growth and Equity Premium

Educational attainment is measured by the highest grade completed (HGC) in 1998. "Degree" means HGC is at least 16. "Some College" means HGC is less than 16 but greater than 12. "High School" means HGC is less than or equal to 12. The cross-sectional standard deviations are in parentheses. We multiply the equity premium by 100 so it is expressed in percent.

		Cross-sectional Mean of Covariance Measure		
Sample	Size	$\mathrm{Cov}(\Delta \nu_{i,t}, \mathrm{eq}_t)$	$\mathrm{Cov}(\Delta Z_{i,t}\gamma, \mathrm{eq}_t)$	$\mathrm{Cov}(\Delta \log Y_{i,t}, \mathrm{eq}_t)$
A. Base sample	1,909	0.021	−0.085	−0.064
		(1.383)	(0.802)	(1.414)
B. Groups, by Occupation				
Professional and technical workers	447	−0.021	−0.100	−0.122
		(1.328)	(0.890)	(1.370)
Managers and administrators	370	0.117	−0.075	0.042
		(1.256)	(0.892)	(1.324)
Sales workers	83	−0.017	−0.147	−0.164
		(1.341)	(0.832)	(1.291)
Clerical and unskilled workers	281	−0.037	−0.080	−0.117
		(1.268)	(0.835)	(1.304)
Craftsmen	244	0.144	−0.041	0.103
		(1.387)	(0.645)	(1.420)
Operatives	217	0.083	−0.087	−0.004
		(1.620)	(0.681)	(1.610)
Non-farm laborers	66	−0.391	−0.073	−0.463
		(1.690)	(0.543)	(1.734)
Farmers and farm managers	12	−0.020	−0.310	−0.330
		(2.282)	(0.658)	(2.266)
Farm laborers and farm foremen	10	0.511	−0.262	0.249
		(1.213)	(0.521)	(1.124)
Service workers	174	−0.102	−0.084	−0.186
		(1.400)	(0.747)	(1.409)
Private household workers	3	1.186	0.175	1.361
		(3.213)	(0.388)	(3.601)
Active armed forces	2	0.468	−0.616	−0.148
		(1.028)	(0.794)	(0.234)
C. Groups, by Education				
Degree	578	−0.047	−0.104	−0.151
		(1.400)	(0.890)	(1.398)
Some college	471	0.105	−0.094	0.011
		(1.317)	(0.846)	(1.413)
High school	860	0.022	−0.068	−0.046
		(1.405)	(0.709)	(1.424)

operatives. Panel C presents the statistics by educational groupings. We divide households into three groups according to their educational attainment (HGC). The slightly positive covariance between stochastic income growth and equity premium is driven mainly by the positive covariance in the two less educated groups. Neither occupation nor education explains a lot of variation in covariance measures.

To estimate permanent and transitory income risks from stochastic income growth, we divide the sample into groups using household characteristics. We first classify the households into 12 groups according to their occupational codes. Within each occupational group, we divide the households into three subgroups based on their educational attainments. This grouping scheme, which intersperses the occupational and educational groupings, results in 36 groups. However, several of the resulting groups contain too few observations for estimation. Thus, for the occupational groups with fewer than 50 households, we divide each into two subgroups (with and without a college degree), and for the occupational groups with fewer than 10 households, we do not divide at all. The net result is 30 groups, which differ from one another in occupation, educational attainment, or both. Our methodology to identify the income risks relies on the assumption of a constant risk ratio across households within a group. By using both characteristics, our grouping scheme is less vulnerable to the risk of misidentification than a scheme based on occupation or educational attainment alone would be. Table III presents the groups and their risk measures.

B. Risky Asset Share and Income Risks

In addition to income risks, we include the following household characteristics as controls for risky asset share: Marital status, gender, family size, health, race, age (fourth-order polynomial), age of spouse (fourth-order polynomial), educational attainment, educational attainment of spouse, gross income in previous year (quadratic), net wealth in previous year (quadratic), and survey year. We also include covariance measures as controls. When the standard deviation of labor income growth (total income risk) is used as the income risk measure, we control for the covariance between the equity premium and income growth. When the components of total income risk are used instead, we control for covariances between the equity premium and the components of labor income risk—$\mathrm{Cov}(\Delta Z_{i,t}\gamma, \mathrm{eq}_t)$ and $\mathrm{Cov}(\Delta \nu_{i,t}, \mathrm{eq}_t)$.[12]

The effects of the covariance measures on risky asset share are insignificant both statistically and economically. One interpretation is that the ability of risky financial assets to hedge labor income risk is not important in households' portfolio decisions. This interpretation is consistent with the findings in Table II. It is also consistent with the findings of Davis and Willen (2000), who show that, for a typical worker sampled from many demographic groups, the covariance between aggregate equity returns and labor income is statistically insignificant. If our covariance estimates are realizations of the zero population covariance, households would be rational in not basing their portfolio decisions on those estimates. We note two caveats to this interpretation, however. First, households may invest in narrowly based portfolios and their portfolio behaviors may be influenced by the ability of such a portfolio to hedge their labor

[12] The estimated coefficients of the household characteristics are intuitive. The complete results, including the coefficients of the household characteristics and covariance measures, are available in the Internet Appendix.

Table III

Income Risk Estimates by Groups

Educational attainment is measured by the highest grade completed (HGC) in 1998. "Degree" means HGC is at least 16. "Some College" means HGC is less than 16 but greater than 12. "High School" means HGC is less than or equal to 12.

Group		Group Mean of Income Risk Measures			
Occupation	Education	Total $\sqrt{\text{Var}(\Delta \log Y_{i,t})}$	Stochastic $\sqrt{\text{Var}(\Delta \nu_{i,t})}$	Permanent $\sigma_{i,\varepsilon}$	Transitory $\sigma_{i,\eta}$
Professional and technical workers	Degree	0.419	0.391	0.106	0.323
	Some college	0.383	0.338	0.164	0.172
	High school	0.349	0.320	0.093	0.249
Managers and administrators	Degree	0.376	0.357	0.079	0.311
	Some college	0.331	0.299	0.084	0.247
	High school	0.337	0.310	0.091	0.240
Sales workers	Degree	0.433	0.388	0.095	0.355
	Some college	0.356	0.322	0.107	0.246
	High school	0.298	0.282	0.078	0.233
Clerical and unskilled workers	Degree	0.368	0.345	0.083	0.301
	Some college	0.394	0.363	0.085	0.297
	High school	0.348	0.305	0.082	0.239
Craftsmen	Degree	0.414	0.397	0.109	0.330
	Some college	0.343	0.324	0.100	0.264
	High school	0.350	0.344	0.069	0.287
Operatives	Degree	0.435	0.367	0.060	0.336
	Some college	0.433	0.417	0.113	0.297
	High school	0.381	0.367	0.120	0.270
Non-farm laborers	Degree	0.404	0.431	0.202	0.390
	Some college	0.437	0.406	0.093	0.318
	High school	0.410	0.411	0.101	0.328
Farmers and farm managers	Degree	0.219	0.187	0.041	0.172
	Non-degree	0.542	0.540	0.210	0.268
Farm laborers and farm foremen	Degree	0.189	0.241	0.098	0.157
	Non-degree	0.351	0.353	0.147	0.259
Service workers	Degree	0.391	0.361	0.117	0.268
	Some college	0.355	0.323	0.112	0.243
	High school	0.445	0.403	0.159	0.241
Private household workers	All	0.376	0.395	0.152	0.190
Active armed forces	All	0.213	0.209	0.093	0.157
Full sample (1,909 households)		0.379	0.353	0.102	0.274

income risks. Davis and Willen (2000) find much stronger evidence for a relationship between the income risk of an occupational group and its associated industry portfolio returns. Second, the effect that we estimate may be subject to simultaneity bias. A highly risk-averse household not only shies away from risky assets, but also gravitates toward jobs against which risky assets are a good hedge. If risk aversion is not properly controlled for, the estimated effect of the covariance measure will be biased upward.

We present our main results in the next two subsections. First, we present the results based on risky asset share defined relative to liquid financial wealth. Then, we present the results based on risky asset share defined relative to total net wealth.

B.1. Risky Asset Share Relative to Liquid Financial Wealth

To delineate the effects of risks, we consider three versions of the model, each with a different income risk measure. Table IV presents the results. In the first version, labor income risk is the total income risk. This is reported in Column 1. In the second version, total income risk is replaced by its two components—the demographic income variation and stochastic income risk. These results are reported in Column 2. In the third version, we replace the stochastic income risk by its two components—permanent income risk and transitory income risk. These results are reported in Column 3.

Column 1 shows that the standard deviation of income growth reduces the risky asset share in liquid financial wealth. A 1% increase in the standard deviation reduces the risky asset share by about one-third of 1%. Heaton and Lucas (2000) measure labor income risk by the standard deviations of wage income growth and proprietary income growth and find similar effects of labor income risk. The effect we estimate, however, is more statistically significant.

Table IV

Risky Asset Share Relative to Liquid Financial Assets and Income Risk

The dependent variable is risky asset share relative to liquid financial assets. The estimated coefficients and standard errors (in parentheses) are presented. The estimations include household demographic characteristics as control variables. Additionally, the estimations control for the covariance between the equity premium and labor income risk. The estimations are based on the NLSY79 asset data from 1989, 1990, 1992, 1994, 1996, and 1998. The numbers of uncensored, left-censored, and right-censored observations are 3,732, 6,922, and 190, respectively.

Explanatory Variables	Total Income Risk (1)	Demographic versus Stochastic Income Risk (2)	Permanent versus Transitory Income Risk (3)
$\sqrt{\mathrm{Var}(\Delta \log Y_{i,t})}$	−0.347		
	(0.049)		
$\sqrt{\mathrm{Var}(\Delta Z_{i,t}\gamma)}$		0.125	0.134
		(0.070)	(0.070)
$\sqrt{\mathrm{Var}(\Delta \nu_{i,t})}$		−0.377	
		(0.049)	
$\sigma_{i,\varepsilon}$			−1.084
			(0.267)
$\sigma_{i,\eta}$			−0.184
			(0.110)

Column 2 shows that a 1% increase in stochastic labor income risk reduces the risky asset share in liquid financial wealth by 0.377%. This effect is larger and more statistically significant than the effect of total income risk in Column 1. This result can be understood intuitively. Total income risk is the sum of demographic income variation and stochastic labor income risk. Because demographic income variation is largely predictable, total income risk tends to exaggerate the background income risk faced by a household. Since total income risk is a noisy indicator of the true risk, the estimated effect based on total income risk underestimates the effect of the true risk.

Column 3 shows that both permanent income risk and transitory income risk reduce the risky asset share in liquid financial wealth, but the effect of permanent income risk is much larger. A 1% increase in permanent income risk reduces the risky asset share by 1.084%, and the effect is statistically significant at the 1% level. A 1% increase in transitory income risk reduces the risky asset share by about 0.184%, and the effect is statistically insignificant at the 5% level. Stochastic labor income risk is a mixture of permanent and transitory income risks. The estimated effect of stochastic income risk in Column 2 thus represents a weighted average of the effects of the two risks—permanent and transitory. Since permanent income risk has a larger effect than transitory income risk, the effect estimated based on stochastic income risk understates the effect of the permanent income risk. The understatement is substantial, which is as expected given that Table III shows permanent income risk is significantly smaller than transitory income risk for most households and the relative importance of permanent risk varies substantially across households.

It is worth noting that the estimated effect of permanent income risk is within the range obtained in theoretical models calibrated to labor income data. Viceira (2001) shows that as the coefficient of relative risk aversion varies from three to eight, the effect of permanent income risk on the risky asset share in financial wealth varies from 1 to 2.5.[13] Koo (1999) finds that this effect varies with relative risk aversion and the ratio of financial assets to labor income because of liquidity constraints. The range of the effect implied by plausible configurations of relative risk aversion and asset-income ratios is large, and it encompasses the 1.084 estimated in this paper. The effect we estimate is also broadly consistent with the findings of Bertaut and Haliassos (1997)

[13] In Viceira (2001), log labor income follows a normally distributed random walk with drift. This specification implies that the standard deviation of log income growth is equivalent to permanent income risk. The effect of a mean-preserving increase in income uncertainty is examined by varying the standard deviation of log income growth between zero and 20%, while altering the drift value to keep the mean income growth constant at 3% per year. The optimal risky asset share in financial assets of a pre-retirement investor is numerically derived under the otherwise baseline parameter values. When the coefficient of relative risk aversion is three, a 1% mean-preserving increase in the standard deviation of income growth reduces the share by about 2.5%. When the coefficient of relative risk aversion is eight, a 1% mean-preserving increase in the standard deviation of income growth reduces the share by 1%. See Figure 2 of the article.

Table V

Risky Asset Share Relative to Total Net Wealth and Income Risk

The dependent variable is risky asset share relative to total net wealth. The estimated coefficients and standard errors (in parentheses) are presented. The estimations include household demographic characteristics as control variables. Additionally, the estimations control for the covariance between the equity premium and labor income risk. The estimations are based on the NLSY79 asset data from 1989, 1990, 1992, 1994, 1996, and 1998. The numbers of uncensored and left-censored observations are 3,915, and 6,916, respectively.

Explanatory Variables	Total Income Risk (1)	Demographic versus Stochastic Income Risk (2)	Permanent versus Transitory Income Risk (3)
$\sqrt{\mathrm{Var}(\Delta \log Y_{i,t})}$	−0.028		
	(0.005)		
$\sqrt{\mathrm{Var}(\Delta Z_{i,t}\gamma)}$		0.017	0.017
		(0.007)	(0.007)
$\sqrt{\mathrm{Var}(\Delta \nu_{i,t})}$		−0.034	
		(0.005)	
$\sigma_{i,\varepsilon}$			−0.115
			(0.026)
$\sigma_{i,\eta}$			−0.002
			(0.011)

concerning the effect of permanent income risk on risky asset holdings as a fraction of annual income.[14]

B.2. Risky Asset Share Relative to Total Net Wealth

The risky asset share estimation is also performed using the second definition of risky asset share, the ratio of risky assets to total net wealth. As in the case of the first definition of risky asset share, we consider three versions of the model, each with different income risk and covariance measures. The results are presented in Table V. Both permanent and transitory income risks reduce the risky asset share, and the effect of permanent risk is about six times as large as the

[14] Bertaut and Haliassos (1997) analyze the optimal asset holdings of three representative investors whose income processes are calibrated to the income data from three education groups: high school dropouts, high school graduates, and college graduates. Their results indicate that if the coefficient of relative risk aversion is three, and, hypothetically, a high school graduate is facing instead the persistent income process of a high school dropout, risky asset holding as a fraction of annual income would drop by about 0.012. In their calibration, the persistent income processes are close to a random walk, and the standard deviation of the persistent income shock of a high school graduate is 0.024 lower than the standard deviation for a high school dropout. Their results therefore suggest that the effect of permanent labor income risk on risky asset holding as a fraction of annual income is roughly −0.5. In our sample, average total liquid financial assets are about 48% of average annual income. Our finding that the effect of permanent income risk on risk asset share is 1.08 implies the effect on risky asset holding as a fraction of annual income should be close to −0.5.

effect of transitory income risk. Also, the effect of permanent income risk is statistically significant, while the effect of transitory income risk is not. The effect of permanent income risk is estimated to be −0.115.[15] In the sample, because human wealth is typically substantial, average total net wealth ($739,512) is about 40 times the average liquid financial wealth ($17,575). To evaluate the effect of income risks on the risky asset share relative to liquid financial wealth, we therefore scale the estimates in Table V up by 40. The result is −4.4, which is quite a bit larger than the estimate based on the risky asset share relative to liquid financial assets.

V. Conclusion

Economic theory suggests that permanent income risk has a larger effect on risky asset holding than transitory income risk. However, no existing empirical work has distinguished between these two types of income risk. This paper makes the first attempt to measure permanent and transitory income risks from household-level data and estimate their effects on risky asset holding. Using NLSY79 data, we show that permanent income risk significantly shifts a household's portfolio toward risk-free assets. We also show that, consistent with theory, transitory income risk has little effect on portfolio allocation.

An accurate understanding of portfolio choice in the presence of labor income risk is important for evaluating the impact of government policies, such as income taxation, social security, and unemployment insurance. Also, reliable evaluation of the welfare gain from international financial market integration requires an accurate determination of the extent to which the international differences in risky asset shares are caused by international differences in uninsurable labor income risk. Further research could use the findings of this paper to improve the accuracy of these evaluations.

Appendix: Estimating Household Human Wealth

Let $I_{i,t}$ represent the survival status of the respondent, so that $I_{i,t} = 1$ means respondent i is alive at time t. Similarly, let $I^S_{i,t}$ represent the survival status of the spouse. Let $W_{i,t}$, $A_{i,t}$, and $A^S_{i,t}$ be the household human wealth, respondent's age, and spouse's age, respectively, at time t. We assume the maximum life span is 90, the annual discount rate is 0.04, and the survival probabilities conditional on gender and age are otherwise the same as those in the Life Tables (National Center of Health Statistics, 1997). We use the result of the income regression based on CPS data as the demographic profile of income, $Z_{i,t+k}\gamma$.

[15] We also conducted a number of robustness checks: (a) identifying the risk ratio by both slope and intercept in the variance ratio regression; (b) controlling for risk aversion; (c) using a more coarse grouping scheme; (d) confining analysis to households with stable educational attainment; (e) excluding observations from earlier years; and (f) using higher discount rates to calculate human wealth. The results are remarkably robust, and are reported in the Internet Appendix.

A. Estimating Household Human Wealth for Single Respondents

For single respondents, household human wealth is given by

$$W_{i,t} = \sum_{k=1}^{90-A_{i,t}} \frac{1}{(1+r)^k} \Pr\left(I_{i,t+k} = 1/I_{i,t} = 1\right) e^{\{Z_{i,t+k}\gamma + E_t(\nu_{i,t+k}) + \mathrm{Var}_t(\nu_{i,t+k})/2\}},$$

where $E_t(\nu_{i,t+k}) + \mathrm{Var}_t(\nu_{i,t+k})/2$ is the result of signal extraction.

B. Estimating Household Human Wealth for Married Respondents

For married respondents, household human wealth is given by

$$W_{i,t} = \sum_{k=1}^{\mathrm{Max}[90-A_{i,t},90-A^S_{i,t}]} \frac{1}{(1+r)^k} \left\{ \sum_{j_1=0}^{1} \sum_{j_2=0}^{1} E\left[Y_{i,t+k}/I_{i,t+k} = j_1, I^S_{i,t+k} = j_2\right] \right.$$
$$\left. \Pr\left[I_{i,t+k} = j_1, I^S_{i,t+k} = j_2/I_{i,t} = 1, I^S_{i,t} = 1\right] \right\}.$$

Survivals of the spouse and respondent are assumed to be independent. The expected future household income is computed using

$$E\left[Y_{i,t+k}/I_{i,t+k} = j_1, I^S_{i,t+k} = j_2\right] = e^{\{Z_{i,t+k}\gamma + E_t(\nu_{i,t+k}) + \mathrm{Var}_t(\nu_{i,t+k})/2\}},$$

where $Z_{i,t+k}\gamma$ takes into account the survival statuses of the couple, $I_{i,t+k}$ and $I^S_{i,t+k}$, and $E_t(\nu_{i,t+k}) + \mathrm{Var}_t(\nu_{i,t+k})/2$ is the result of signal extraction.

C. Signal Extraction: Forecasting Future Stochastic Labor Incomes

At time t, the household forms a forecast of the labor income at time $t+k$, using a linear function of current and past stochastic labor incomes ($\nu_{i,j}$, $j = 1, 2, \ldots, t$):

$$E_t(\nu_{i,t+k}) = \lambda_{i,1}\nu_{i,t} + \lambda_{i,2}\nu_{i,t-1} + \lambda_{i,3}\nu_{i,3} + \cdots + \lambda_{i,t}\nu_{i,1},$$

with the weights $\lambda_{i,1}, \lambda_{i,2}, \lambda_{i,3}, \ldots, \lambda_{i,t}$ chosen to minimize the forecast variance,

$$\mathrm{Var}_t(\nu_{i,t+k}) = E(\nu_{i,t+k} - E_t(\nu_{i,t+k}))^2.$$

Under the assumption that the initial permanent stochastic income is zero ($u_{i,0} = 0$), our empirical model of labor income implies

$$\mathrm{Var}_t(\nu_{i,t+k}) = k\sigma^2_{i,\varepsilon} + \sigma^2_{i,\eta} + \sigma^2_{i,\varepsilon} \sum_{j=1}^{t} \left(1 - \sum_{g=1}^{t+1-j} \lambda_{i,g}\right)^2 + \sigma^2_{i,\eta} \sum_{j=1}^{t} \lambda^2_{i,t+1-j}.$$

The minimization problem is solved numerically for the given $\sigma^2_{i,\varepsilon}$ and $\sigma^2_{i,\eta}$ to obtain $\lambda_{i,1}, \lambda_{i,2}, \lambda_{i,3}, \ldots, \lambda_{i,t}$ (see Muth (1960) for an analysis). The method described here assumes data are available annually. However, after 1994, the NLSY79 respondents were interviewed every other year. We modify the formulas accordingly to account for this data limitation.

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