Heterogeneous Background Risks, Portfolio Choice, and Asset Returns: Evidence from Micro-Level Data

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Abstract

This paper uses a long panel data set to investigate the empirical importance of background risks on a household's asset allocation and on asset returns. We construct a set of household-level background risk variables which capture the entire covariance structure between financial assets and three types of non-traded or illiquid assets - labor, housing, and private business. We show that all these background risks are statistically and economically important for a household's stock market participation and portfolio choice. When all background risk variables shift one standard deviation from their sample means, a household will decrease its likelihood to participate in the stock market by twelve percent and reduce the proportion of stock holdings by four percent. In addition, a stock more highly correlated with background risks is associated with a higher risk premium. Including the background risk factors significantly improves the performance of three benchmark asset pricing models, i.e., the consumption-based CAPM, CAPM, and the Fama-French three-factor model in terms of the Hansen-Jagannathan distance and the *J*-statistic of GMM estimation.

Key words: background risks, stock market participation, portfolio choice, asset returns
JEL Codes: G11, C25

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This paper uses a long panel data set to investigate the empirical importance of background risks on a household's asset allocation and on asset returns. We construct a set of household-level background risk variables which capture the entire covariance structure between financial assets and three types of non-traded or illiquid assets - labor, housing, and private business. We show that all these background risks are statistically and economically important for a household's stock market participation and portfolio choice. When all background risk variables shift one standard deviation from their sample means, a household will decrease its likelihood to participate in the stock market by twelve percent and reduce the proportion of stock holdings by four percent. In addition, a stock more highly correlated with background risks is associated with a higher risk premium. Including the background risk factors significantly improves the performance of three benchmark asset pricing models, i.e., the consumption-based CAPM, CAPM, and the Fama-French three-factor model in terms of the Hansen-Jagannathan distance and the *J*-statistic of GMM estimation.

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In his 2006 Presidential Address, Campbell (2006) states: "Household financial problems have many special features that give the field its character. Households must plan over long but finite horizons; they have important *nontraded assets*, notably their *human capital*; they hold *illiquid assets*, notably *housing*, … Of course household asset demands are important in asset pricing too. [emphasis added, pp 1553-1554]." Accordingly, this paper uses a long panel of household-level data to examine three types of nontraded/illiquid assets, namely, labor, housing and private business, on a household's investment decisions and on asset returns. Following Heaton and Lucas (2000a), we term these non-diversifiable risks sourced from labor income, housing and private business as background risks.[1]

Standard asset pricing theory predicts that in complete markets background risks should have no influence on portfolio choice or on equilibrium asset returns, because these risks can be fully insured by trading financial securities. However, when markets are incomplete such that some risky income, for instance, labor income, is not spanned by tradable assets, individuals will alter their portfolios to offset their idiosyncratic uninsurable risks (e.g., Merton, 1971; and Duffie *et al.*, 1997). Within the mean-variance framework, Cochrane (2008) shows that in an economy with incomplete markets and non-market income such as labor income, an individual's optimal portfolio deviates from the market portfolio to the extent that her individual hedging motive to non-market income is different from the market's average hedging motive to non-market income. Therefore, these idiosyncratic uninsurable background risks can generate investor heterogeneity so that individuals may choose different optimal portfolios. Our study focuses on (i) whether the *heterogeneity* of background risk exposure across households can help explain the large fraction of non-stockholders, namely, the limited stock market participation puzzle (Mankiw and Zeldes, 1991) and the substantial cross-sectional variation in a household's stock holdings, and (ii) whether these *idiosyncratic* risks have a significant impact on asset returns.

A number of calibration studies (Heaton and Lucas, 1996, 1997 and 2000a; Haliassos and Michaelides, 2003; and Cocco *et al.*, 2005) confirm that background risks have an impact on portfolio choice and asset returns as predicted by theory. In terms of economic magnitude, these studies suggest that the inclusion of background risks is in general unable to generate significant

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[1] The potential importance of background risks on asset allocation and asset returns is well established in the literature. Pratt (1964), Pratt and Zeckhauser (1987), Kimball (1993), and Gollier and Kimball (1997) suggest that under commonly used utility specifications, investors tend to be more risk averse when they face various forms of background risks. Constantinides and Duffie (1996), Heaton and Lucas (1996), and Viceira (2001) examine the importance of labor income risk; Piazzesi *et al.* (2007), Cocco (2005), Yao and Zhang (2005), and Flavin and Yamashita (2002) advocate the significance of housing risk; and Heaton and Lucas (2000b) and Polkovnichenko (1998) study entrepreneurial risk. Heaton and Lucas (2000a), Campbell (2006), and Cochrane (2006) provide excellent reviews of this literature.

cross-sectional variation in portfolio composition and especially the low level of stock market participation rate as observed in the data. Moreover, there is a debate in the literature on the properties of background risks and simulation results are sensitive to the assumptions of the underlying stochastic risk process (for a more detailed discussion of these issues, see excellent reviews by Heaton and Lucas, 2000a; and Campbell, 2006). Our paper uses data from a large sample of *heterogeneous* households with *household-specific* risk factors to directly estimate the impact of background risks on stock market participation, portfolio choice, and asset returns.

Research using micro-level data to address these issues is limited due in part to the difficulty of identifying household-specific risk factors. Several recent papers have used U.S. household-level data to examine household portfolio choice and stock market participation.[2] Using the 1983 Survey of Consumer Finance data, Haliassos and Bertaut (1995) demonstrate that the non-diversifiable income risk is a potential contributing factor to the low stock market participation. Employing the Tax Model data (1979-1990), Heaton and Lucas (2000b) find that entrepreneurial risk is important but labor income risk is relatively unimportant to household portfolio choice for a sample of households who hold stocks and own businesses.[3] They further use aggregate data from NIPA to show that entrepreneurial risk is important to asset returns. Using the Panel Study of Income Dynamics (PSID) data (1983-1994), Vissing-Jorgensen (2002a) show that the standard deviation of non-financial income has a negative impact on stock holdings and stock participation, while the correlation of non-financial income with stock returns is statistically insignificant.

This paper uses the PSID survey (1976-2003) to examine the impact of background risks on a household's stock market participation and portfolio choice and on asset returns. In research done independently, Angerer and Lam (2009) use the National Longitudinal Survey of Youth 1979 Cohort to study the impact of labor income risk on portfolio choice. By decomposing labor income risk into permanent and transitory components, they show that permanent income risk significantly reduces a household's stock investment while transitory income risk does not. We complement the analysis of Angerer and Lam (2009) by advocating the importance of additional background risks to household portfolio decisions and find consistent results. Our paper differs from Angerer and Lam (2009) in

[2] A few papers use non-U.S. household data to examine this issue. Using Italian data, Guiso *et al.* (1996) find that labor income risk has a small effect on portfolio choice. Hochguetel (2002) employs data from the Netherlands to show that households exposed to higher labor income uncertainty hold safer portfolios. Massa and Simonov (2006) use a unique Swedish data set with information broken down at investor's portfolio holding at stock level and show that households do not hedge but tend to hold stocks that are geographically and professionally close to them. Chen *et al.* (2007) and Dimmock (2006) argue that background risks also affect asset allocation of institutional investors.

[3] We use the terms entrepreneurial risk and business risk interchangeably throughout this paper.

that they emphasize the difference between permanent and transitory *labor income* risks while we focus on the joint effects of three different types of background risks. We extend Angerer and Lam's (2009) analysis of labor income risks by also examining the impact of housing and business risks on a household's stock market participation and portfolio choice. Additionally, we investigate the asset pricing implications of the three background risks.

Specifically, we use growth rates of labor income, home equity, and business income to proxy returns sourced from human capital, housing investment, and private business, respectively. Our main measures of background risks are the standard deviations of the growth rates of labor income, home equity, and business income, and the correlations of these three growth rates with stock returns and with the risk-free rate. We also include the correlations among these three growth rates. In doing so, we capture the entire covariance structure of the returns on financial and non-financial assets such as human capital, housing and private business. In order to capture the time-varying feature of background risks over life cycles, we construct the rolling-over forward looking measures of background risks (background risks are estimated using five years data) and backward measures of background risks (background risks are estimated using past eight years data).[4] Accordingly, our paper extends the empirical literature on the importance of background risks in portfolio choice and stock market participation in the following ways.

First, we jointly study three types of background risks and provide a quantitative evaluation of their relative importance. We show that all three types of background risks are statistically and economically important. If all the background risk variables shift one standard deviation from their sample means, the probability of participation decreases by 12.10 percent and the proportion of stock holdings drops by 3.98 percent. To our knowledge, this is the first paper to directly estimate the impact of housing on a household's stock participation and stock holdings. We find that the housing effect is almost as large as the labor income effect, complementing previous works emphasizing the importance of housing in portfolio choice and asset pricing (see, e.g., Cocco, 2005; Flavin and Yamashita, 2002; and Piazzesi *et al.*, 2007).

Second, we extend previous empirical studies by jointly examining the volatility of background risks and the correlations of background risks with stock returns and with the risk-free rate. We find that a household with more volatile labor income (or home equity, or business income)

[4] To further study the hedging motive hypothesis (e.g., Viceira, 2001), we also use the *covariances* between market excess returns (risky stock returns minus the risk-free rate) and returns on non-tradable assets. Following Massa and Simonov (2006), we further examine the interaction impact of the standard deviations of background risk factors and their correlations with stock returns. The results using these alternative measures of background risks are all consistent with our main results.

is less likely to participate in the stock market and invests a smaller proportion of its wealth in stocks, consistent with previous studies (e.g., Heaton and Lucas, 2000b; and Angerer and Lam, 2009). The correlation of labor income (or home equity, or business income) with stock returns has a negative impact on participation and on the proportion of stock holdings. This finding confirms the hedging motive suggested in the literature (e.g., Viceira, 2001) while previous works (Heaton and Lucas, 2000b; and Angerer and Lam, 2009) find that the hedging motive is insignificant. We further separate the correlation effects, based on whether the correlation with stock returns is positive or negative, and examine the interaction of standard deviations of background risk factors and their positive or negative correlations. We use this specification to further examine the hedging motive and find that a household with a positive (negative) correlation with stock returns is less (more) likely to participate in stock markets and invests less (more) in stocks. In contrast, the correlation of labor income (or home equity, or business income) with the risk-free rate has a positive impact on participation and on the proportion of stock holdings. Therefore, the magnitude and direction of the impact of background risks on asset allocation depends on the precise nature of the covariance structure between these risks and asset returns. Specifically, a "stock-like" income/wealth substitutes for stock holdings and reduces the demand for stocks, whereas a "bond-like" income/wealth substitutes for the risk-free asset and encourages stock holdings. These opposing effects might help us understand the conflicting results obtained in simulation-based studies, in which different assumptions on the correlation between background risks and the returns on financial assets are employed.[5]

Third, we consider the correlations among the three types of background risks and find that the correlation between labor income and home equity has a significantly negative impact on stock holdings and on participation. This finding sheds light on the importance of the interaction between labor income risk and housing risk in explaining portfolio choice and asset returns, consistent with recent studies (e.g., Lustig and Nieuwerburgh, 2005; and Davidoff, 2006).[6]

Finally, we examine the interactive effect of education and background risks on portfolio choice and participation. Mankiw and Zeldes (1991) and Vissing-Jorgensen (2002a), among others, suggest that education is a proxy for transaction costs and find that it has a significant impact on a

[5] Results from simulation studies are sensitive to the assumed underlying stochastic process of background risks. For example, Cocco *et al.* (2005) consider labor income as an implicit holding of safe assets and find that labor income *increases* stock investment. However, Benzoni *et al.* (2006) assume cointegration of labor income and stock return in the long run and find that labor income *reduces* stock holdings.

[6] Lustig and Nieuwerburgh (2005) suggest that the ratio of housing wealth to human capital wealth shifts an investor's risk perception and hence has predictive power on stock returns. Davidoff (2006) shows that the correlation between labor income and housing value has an impact on housing investment.

household's portfolio decision. We confirm their results in our sample. Further, we find an additional channel, namely, changes in background risks through which education affects a household's portfolio choice. More specifically, when all background risk variables increase one standard deviation from their sample means, a household with a college degree will reduce its likelihood to participate in the stock market by 14.49 percent and decrease its proportion of stock holdings by 4.60 percent, whereas a household without a high school education will only reduce the likelihood of participation by 9.23 percent and decrease its proportion of stock holdings by 3.32 percent. Hence, a more highly educated household responds more significantly to a given change of its background risks.

Jagannathan and Wang (1996) and Heaton and Lucas (2000b) use aggregate data to show that labor income and business income have a significant impact on asset returns. Two recent papers, Piazzesi *et al.* (2007) and Lustig and Nieuwerburgh (2005), demonstrate how housing can affect asset returns. Accordingly, we estimate household-level Euler equations using a pricing kernel augmented by the growth rates of labor income, business income, and housing value. Specifically, we add the three background risk factors to pricing kernels implied by three standard asset pricing models: the consumption-based CAPM (CCAPM), CAPM, and the Fama-French three-factor model. We find that a stock more highly correlated with a background risk is associated with a higher risk premium. Further, the background risk factors significantly improve model performance based on the Hansen and Jagannathan (1997) distance (HJD) and the *J*-statistic of GMM estimation. The above results are based on annual frequency data from PSID but are robust to using monthly frequency data from the Consumer Expenditure Survey (CES).

The remainder of the paper is organized as follows. Section I describes the data. Section II studies background risks and their impact on the cross-sectional variation of stock holdings. Section III examines the effects of background risks on asset prices and Section IV concludes.

I. Data and Descriptive Statistics

We draw data from the Panel Study of Income Dynamics (PSID), which is an annual survey maintained by the University of Michigan. The surveys are conducted every year from 1968 to 1997 and every other year after 1997.[7] The main advantage of the PSID data is that it provides a relatively

[7] The original PSID sample consisted of two independently selected samples: a cross-sectional national sample (the SRC sample) and a national sample of low-income families (the SEO sample). We exclude the SEO sample to generate a representative sample of U.S. population. The PSID was designed to capture demographic and income dynamics of U.S. households over a long period. Households which were selected in the 1968 survey have been

long panel with detailed demographic, income, and housing data, which allows us to construct various measures of income and housing risks. A limitation of the PSID data is that detailed wealth composition such as stock holdings is provided in the wealth supplement survey which was conducted only in the years 1984, 1989, 1994, 1999, 2001 and 2003. Therefore, financial asset holdings information is only available for these six years. In order to utilize the long panel feature of the PSID and to overcome the limitation of wealth data, we estimate the background risk variables using the 1976-1997 surveys, and then merge the estimated household background risk variables with the six-year wealth data to generate a six-year unbalanced panel. Since questions related to income and wealth in the PSID data are retrospective[8] (for instance, those asked in 1994 refer to the 1993 calendar year), we refer our sample years as 1983, 1988, 1993, 1998, 2000 and 2002.

A. Stock Values and Stock Participation

Stock market participation (denoted by *DumStk*) and value of stock holdings are self-reported in the surveys. Unfortunately, PSID changed the definition of stock in 1999. Up to the 1997 survey, reported stock holdings include stocks held directly or held in mutual funds, investment trusts, and pension funds. Since the 1999 survey, the value of stock holdings in pension funds is excluded. This change in definition causes inconsistencies in our stock values and stock participation variables over time. We therefore make the following adjustments using questions asked by PSID about pension accounts. The questions are "Do [you/you or anyone in your family] have any money in private annuities or Individual Retirement Accounts (IRAs)?", "Are they mostly in stocks, mostly in interest earning assets, split between the two, or what?", and "How much would they be worth?" We assume that all investments in IRAs are stocks if most money in IRAs is invested in stocks. If a household reports that the money in IRAs is split between stocks and interest sensitive assets, we assume that half of the value in the IRAs is in stocks and the other half is in savings. We then adjust the post-1999 stock variable by summing the reported stock value and the estimated stock value in pension funds.[9]

Previous studies suggest that the properties of portfolio composition relative to demographic variables are sensitive to how wealth is measured. In computing the proportion of stock value relative to wealth, we consider three definitions of wealth: (i) total family financial wealth—the sum of stock,

resurveyed thereafter. The splitoff households (households established by children of the originally selected families) have been added to the sample each year.

[8] Surveys are mostly conducted in each spring and therefore income and wealth data are for the previous year.

[9] Because the post-1999 stock holdings data may not be accurate, we conduct a robustness test using prior-1999 data and find similar results. These results are not reported but available upon request.

savings and bond values; (ii) total family wealth without home equity—the sum of values of financial assets, business, vehicles and real estates excluding owner-occupied house minus total debts owed; and (iii) total family wealth with home equity—the sum of value of financial assets, business, vehicles and real estates including home equity of owner-occupied house minus total debts owed. Home equity is the net worth of self-reported market value of house minus unpaid mortgage balance. The above three types of stock composition measures are denoted as *PflStk_1*, *PflStk_2* and *PflStk_3*, respectively.

B. Background Risk Measures

B.1 Time-invariant Background Risk Measures

To create individual background risk measures, we use the 1976-1997 PSID Family Income Files. We generate the 21-year time series of annual growth rates of labor income, housing value and business income. Since the PSID does not provide total family business income before 1993, we use the head of household business income as a proxy for total family business income. To make the labor income and business income measures comparable, we also use the head of household labor income as a proxy for total family labor income. To address the concern that the income of the head of household does not represent the total household income in the cases where a household has a second earner, we do robustness tests using a sub-sample of single-member households in which the head of household income is equivalent to total household income. In a separate robustness check, we include a dummy variable which equals to 1 if there is a second wage earner in the household and 0 otherwise in our baseline specification. We expect that the existence of the second wage earner will reduce a household's labor income risk and hence encourage stock investment. We also include a dummy variable: if the head and wife work in the same industry. We expect that this variable is negatively related to stock investment because this type of household is even more exposed to labor income risk sourced from macroeconomic shock and unemployment.

We define head of household business income as the sum of business income from assets and business income from labor.[10] We use home equity - the difference between self-reported house value and unpaid mortgage balance - as our proxy for housing value, because home equity truly reflects the household's wealth accumulation through housing investment. We also use the growth rate of self-reported market value of owner-occupied house (i.e., ignoring unpaid mortgage balance)

[10] Alternatively, we define head of household business income to be equal to business income from assets only, and include business income from labor in head of household labor income. Under this definition, none of our results change significantly. They are available upon request.

to redo our regressions.[11] Using the annual growth rates, we calculate for each household the standard deviations of labor income, home equity and business income, i.e., *Std*(*Lab*), *Std*(*Hou*) and *Std*(*Bus*), and the correlations of these growth rates with stock returns, *Corr*(R_s,.), and with the risk-free rate, *Corr*(R_f,.). We also calculate the correlations among the three growth rates, *Corr*(*Lab*,*Hou*), *Corr*(*Lab*,*Bus*) and *Corr*(*Bus*,*Hou*). The CRSP NYSE/AMEX/NASDAQ value-weighted market index return is used as a proxy for risky asset returns, and the 30-day T-bill return is used as a proxy for the risk-free rate. All monetary variables are in constant 1992 dollars using the Consumer Price Index obtained from CRSP.

To minimize errors in the data, we apply several filters to the growth rates of labor income, home equity, and business income. Our baseline analysis requires a household to have at least three years of gross growth rates ranging between 0.5 and 2 to calculate the standard deviation and correlation statistics.[12] That is, we ignore those observations with incomes dropping more than a half or more than doubling in a year because these figures seem implausible and are more likely subject to coding or other errors. This filter is denoted by *Filter2.* To check for robustness, we also require the gross growth rates to lie within the 0.3-3, 0.2-5, and 0.1-10 ranges, and denote these filters by *Filter3*, *Filter5* and *Filter10*, respectively.

B.2 Time-varying Rolling-over Background Risk Measures

The above method to calculate standard deviations and correlations assumes that background risks are time-invariant. In principle, these risks can fluctuate with general economic conditions and can change over the life cycle of a household. Our measures introduced above only capture the variation of background risks across households, but do not capture the time variation of background risks for a given household over its life cycle. To capture the time-series variation of background risks, we employ two rolling-over methods.

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[11] We find that the standard deviation of growth rate of self-reported market values of owner-occupied house has an even more significantly negative impact on household stock market participation and stock holdings than the standard deviation of growth rate of home equity, whereas the correlations of the growth rate of house value with asset returns do not have a significant impact.

[12] To check for robustness, we require a household to have at least 10 years of growth rates to calculate the standard deviation and correlation statistics. The results using this procedure are similar to our baseline analysis. We find that labor income risk and housing risk are statistically and economically significant in determining household's stock investment. While the standard deviation of business income is negatively related to stock investment, it is not statistically significant. The reason is that for a large fraction of households, the business income risk variables cannot be estimated due to insufficient data points. Although this procedure also generates more missing values in labor income and housing risk variables, it affects the business income risk measure more severely. In fact, of the 11,265 year-household observations, we only have 609 observations with non-missing business risk measures. Hence, this procedure underestimates the importance of business income risk.

First, we consider a household which makes its portfolio choice based on its current and past experience of income and housing value fluctuations, so we employ a backward rolling-over measures. These measures are calculated using prior eight-year data. For example, backward risk measures in 1983 are calculated using data from 1976 to 1983, and those in 1997 are calculated using data from 1990 to 1997.

Second, rational expectations theory suggests that a household should make its portfolio choice based on its *ex ante* expectation of background risks. We therefore estimate forward rolling-over measures using five-year posterior data. For example, forward risk measures in 1983 are calculated using data from 1983 to 1987, and those in 1993 are calculated using data from 1993 to 1997. The shortening in the number of years used in calculation increases estimation errors. Moreover, since consecutive annual growth rates are not available after 1997, statistics cannot be calculated for the sample years 1998, 2000, and 2002. Thus, our main results are based on the time-invariant measures and we provide a robustness check based on the two rolling-over measures.

C. Descriptive Statistics

Combining the estimated background risk measures with stock holdings data from the PSID wealth supplement survey, we construct a 6-year unbalanced panel dataset of 4,551 households with 16,487 year-household observations. Table I reports summary statistics of a household's stock market participation rate and the proportion of stock values relative to various measures of wealth. This table confirms the well-known fact of limited stock market participation. Overall, only 36.9 percent of households hold stocks. While the participation rates have significantly increased over the past decade, from 27.3 percent in 1983 to 42.7 percent in 2002, more than half of the U.S. households still do not hold any stocks. We report three different measures of the proportion of stock holdings by stockholders. The average proportion of stocks relative to total financial assets is 52.8 percent, indicating that stockholders allocate a large fraction of financial wealth to stocks. The standard deviation of this variable is 30.6 percent, showing the considerable cross-sectional variation in household-level stock holdings.

Table II Panel A presents some summary statistics for household-specific variables including the background risk measures. The first part of this table summarizes household demographic information. For example, 28.2 percent of head of households have college degrees, while 54.6 percent have only a high school education. The average age of the head of household is 48, and the average family income is $51,530.

In the middle part of Table II, we present the summary statistics of the background risk variables for the full sample. We observe substantial *heterogeneity* of background risks across households. For example, the standard deviation of labor income growth ranges from 0 to 0.754 with the sample mean of 0.175 and the standard deviation of 0.134. Although the sample mean of the correlation of labor income growth with stock return is only -0.003, it ranges from -0.780 to 0.804. A similar pattern appears in the housing risk and business risk variables. Figure I displays the cross-sectional variation of background risk factors. These descriptive statistics clearly demonstrate the large variation of background risk exposures across households, which may help explain the observed enormous variation of portfolio choice across households.

Given that a certain fraction of households do not have labor income or housing, and a large fraction of households do not have business, we also report the summary statistics of subsamples consisting of households which have labor income, housing, and business income, respectively. Overall, 78.3 percent households have labor income, 71.2 percent households own a house, and only 8.2 percent households have a private business. Within the group of households with business, the standard deviation of business income growth rate is 0.503 which is much higher than that for the full sample (0.041). This suggests that although business income risk is substantial, its overall effect may not be pronounced due to the fact that a large fraction of households own no business.

Table II Panel B presents the correlation matrix of the 12 background risk measures. The correlation between a background risk measure (namely, growth rate of labor income, home equity or business income) and stock returns is closely related to its correlation with the risk-free rate, suggesting some degree of multicollinearity. We therefore adjust our baseline model using the correlations between excess returns (risky stock returns minus the risk-free rate) and these background risk measures. The results using these measures are reported as a robustness check.

II. Background Risks, Stock Market Participation, and Portfolio Choice

A. Empirical Specification

To examine the explanatory power of background risk factors on a household's stock market participation and portfolio choice, we run regressions that relate stock market participation (*DumStk*) and the proportion of stock relative to various measures of wealth (*PtfStk_1*, *PtfStk_2* and *PtfStk_3*) to a set of explanatory variables. Since stock market participation is a discrete-choice variable, with 1 denoting participation, and 0 otherwise, we employ the logit model specified below:

$$
\begin{aligned}
&Prob(DumStk = 1) = F(\beta' X) \\
&Prob(DumStk = 0) = 1 - F(\beta' X) \\
&\text{where} \quad F(\beta' X) = \frac{e^{\beta' X}}{1 + e^{\beta' X}}
\end{aligned} \tag{1}
$$

Given that a large fraction of households hold no stocks, OLS regression is not suitable to study the proportion of stock holdings. Several theoretical papers (e.g., Orosel, 1998; Haliassos and Michaelides, 2003; Guo, 2004; Gomes and Michaelides 2005; and Ball, 2007) have treated stock market non-participation (i.e., zero stock holdings) as part of a household's portfolio choice. In this framework, agents maximize their life-time utility subject to a budget constraint which includes a participation cost. Consistent with this line of reasoning and following the empirical methodology utilized by Guiso *et al.* (1996), Hochoguertel (2002) and Cocco (2005), we adopt a Tobit model where the lower limit is 0 (households hold no stock).[13] The Tobit model is specified as

$$
PtfStk = \begin{cases} \beta' X + \varepsilon, & \text{if } PtfStk > 0 \\ 0, & \text{if otherwise} \end{cases} \tag{2}
$$

Our explanatory variables, *X*, include 12 background risk variables and a set of control variables, and $\beta' X$ is specified as follows:

$$
\begin{aligned}
\beta' X = a_0 &+ a_1 Years_t + a_2 Log(Famsize_{it}) + a_3 Race_{it} + a_4 HSchool_{it} + a_5 College_{it} \\
&+ a_6 Log(Age_{it}) + a_7 Log(Age_{it})^2 + a_8 Log(Wealth_{it}) + a_9 Log(Income_{it}) \\
&+ a_{10} HouseRatio_{it} + a_{11} MortgageRatio_{it} + a_{12} LaborRatio_{it} \\
&+ a_{13} Std(Lab_i) + a_{14} Corr(R_s, Lab_i) + a_{15} Corr(R_f, Lab_i) \\
&+ a_{16} Std(Hou_i) + a_{17} Corr(R_s, Hou_i) + a_{18} Corr(R_f, Hou_i) \\
&+ a_{19} Std(Bus_i) + a_{20} Corr(R_s, Bus_i) + a_{21} Corr(R_f, Bus_i) \\
&+ a_{22} Corr(Lab_i, Hou_i) + a_{23} Corr(Lab_i, Bus_i) + a_{24} Corr(Bus_i, Hou_i)
\end{aligned} \tag{3}
$$

where

i - household index;

t - year index;

$Log(X)$ - natural logarithm of variable X;

$Std(X)$ - standard deviation of X;

$Corr(X,Y)$ - correlation between X and Y;

Lab, *Hou*, *Bus* - growth rates of labor income, home equity and business income, respectively;

[13] We also use a two-sided Tobit model with the lower limit equal to 0 (households hold no stocks) and the upper limit equal to 1 (households hold only stocks). The results do not change significantly and are available upon request.

R_s, R_f - gross return rates of stock market portfolio and risk-free asset, respectively;

Years - year dummies;

Famsize - number of family members;

Race - dummy, equal to 1 if household head is white and 0 otherwise;

Age - age of head;

HSchool - dummy, equal to 1 if head has only a high school education and 0 otherwise;

College - dummy, equal to 1 if head has a college education or above and 0 otherwise;

Wealth - total family wealth including home equity;

Income - total family income before tax;

HouseRatio - ratio of home equity relative to total family wealth;

MortgageRatio - ratio of unpaid mortgage relative to total house value; and

LaborRatio - ratio of head labor income relative to total family income before tax.

Theoretical studies in the literature provide useful predictions about the signs of several parameters. Kimball (1993), among others, demonstrates that under fairly general conditions of preferences, an agent who bears one risk is less willing to bear another independent risk. Previous research also shows that the volatility of additional risky income reduces the demand for stock (Heaton and Lucas, 2000a, b; Vissing-Jorgensen, 2002a; Hochguertel, 2002; Guiso *et al.*, 1996; and Angerer and Lam, 2009). Hence, we expect $Std(Lab)$, $Std(Hou)$ and $Std(Bus)$ to have negative effects on the proportion of stock holdings and on stock market participation.

The correlation between a background risk shock and stock return is potentially important to portfolio choice (Viceira, 2001; and Benzoni *et al.*, 2006). A positive correlation between labor income and stock returns reduces the willingness to hold stock because labor income substitutes for stock. On the other hand, a negative correlation between labor income and stock returns encourages stock holdings because stock can be used as a hedge against labor income risk. We hence expect $Corr(R_s, Lab)$, $Corr(R_s, Hou)$, and $Corr(R_s, Bus)$ to carry negative coefficients. Previous empirical studies (Heaton and Lucas, 2000b; and Angerer and Lam, 2009) find the hedging motive to be insignificant.

We are aware that the impact of standard deviation of background risk, for example, labor income, may depend on the sign of the correlation between labor income growth rate and stock returns. That is, it is the covariance of labor income growth rate and stock returns that determines the optimal portfolio choice. Hence, in robustness tests, we employ the covariances of labor income, home equity, and business income growth rates with stock returns. Following Massa and Simonov (2006), we also decompose each covariance term into positive covariance (standard deviation × positive correlation) and negative covariance (standard deviation × negative correlation). This procedure further helps us test the hedging motive hypothesis. For example, a household with labor income negatively correlated with stock returns will likely increase its stock holdings because stock serves as a good hedge against labor income risk. On the other hand, a household with labor income positively correlated with stock returns will likely invest more in the risk-free asset in order to reduce the overall risk exposure.

We also include correlations between labor income (home equity, and business income) with the risk-free asset. We expect $Corr(R_f, Lab)$, $Corr(R_f, Hou)$ and $Corr(R_f, Bus)$ to have positive effects on stock market participation and the proportion of stock holdings. We are aware that theoretically the conditional correlation of the risk-free asset with any background risk should be zero and therefore should have no an impact on stock investments. The risk measures we introduced here, namely, $Corr(R_f, Lab)$, $Corr(R_f, Hou)$ and $Corr(R_f, Bus)$, effectively capture the co-movement of labor income, home equity and business income with the real interest rate which is mainly driven by unexpected inflation. This design is to test whether bond-like income reduces the pressure on precautionary savings, whereby encouraging investment in stocks (e.g., Cocco *et al.*, 2005). Intuitively, a household with stable labor income which increases with the inflation rate (for example, those working in a government or education sector) is more likely to invest in risky stocks because its labor income risk is lower. In addition, the inclusion of correlations with stock returns and risk-free rate can help us examine whether stock-like non-financial income might reduce stock investments, and bond-like non-financial income might encourage stock investments as proposed in the prior literature (e.g., Cocco *et al*., 2005; and Benzoni, 2006).

The other three correlation terms, $Corr(Lab, Hou)$, $Corr(Lab, Bus)$ and $Corr(Hou, Bus)$, are expected to have negative coefficients because the positive correlation between two background risks (e.g., labor and housing) exacerbates the overall risk exposure and hence reduces a household's willingness to bear stock risk.

Consistent with the prior literature, we add the following control variables. Numerous papers document that the race, income, wealth and education variables each have a positive impact on stock market participation (e.g., Mankiw and Zeldes, 1991; Vissing-Jorgensen, 2002a; Hong *et al.*, 2004; and Campbell, 2006). The level of education is regarded as a proxy for fixed entry and transaction costs and is found to be significantly related to stock market participation in previous studies. We use two dummy variables, *HSchool* and *College*, to control for education effects. We expect *Log(Age)* to have a positive sign and $(Log(Age))^2$ to have a negative sign to capture the hump-shaped life-cycle pattern of stock holdings (Jagannathan and Kocherlakota, 1996). Flavin and Yamashita (2002) suggest that the house to net wealth ratio influences a homeowner's portfolio composition significantly. We hence include *HouseRatio* - the ratio of home equity to total wealth to capture this effect. Cocco (2005) argues that although housing investment substitutes for stock investment, a mortgage loan serves as a leverage borrowing channel to finance investment in stocks. We include *MortgageRatio* - the ratio of unpaid mortgage balance to total house value as a control variable. Vissing-Jorgensen (2002a) documents that the level of nonfinancial income is positively related to stock market participation. We use *LaborRatio* - the ratio of labor income to total family income as a control variable.

It is well-known that the estimation of logit and Tobit models is sensitive to the distributional assumptions about the error terms. We hence calculate nonparametric *t*-statistics using bootstrapped standard errors with 100 replications. Given the large number of households (4,551 households) and only 6 time-series observations in our data, it is hard to estimate the panel regression with household-specific fixed effects. We therefore use year dummy variables to control for time-effect, and bootstrap the error terms with clustering by individuals in order to correct for serial correlations (a household that holds stocks in the previous year is more likely to hold stocks in the current year).[14] All results reported in this paper are based on bootstrapped standard errors with clustering by individuals.

In principle, some of these background risk variables can be endogenous (e.g., Bodie *et al.*, 1992; and Roussanov, 2004). Our framework above assumes that the background risk variables are predetermined. This is a reasonable assumption because adjustments in labor supply, housing and private business are much harder than adjustments in stock investment. Moreover, our specification is robust to the existence of endogeneity. A more risk-averse household may choose to invest in safer assets and select a safer occupation (with a lower standard deviation of labor income), resulting in a positive relationship between the standard deviation of labor income and stock investment. Since our testing hypothesis predicts that the standard deviation of labor income is negatively related to stock holdings, the above specification provides a conservative estimate of the true impact of these background risk factors on stock market participation and portfolio choice.

[14] Petersen (2007) shows that given a large number of firms (in our case households), and a small number of years, correct standard errors can be obtained by including time dummies and then estimating standard errors with clustering by firms (households) yields correct standard errors.

B. Empirical Results of Background Risks on Stock Market Participation

B.1 Statistical Significance

Table III presents maximum likelihood estimates of logit regressions. Five model specifications are estimated, each with a different combination of the three types of background risks: (1) no background risk; (2) with only labor income risk; (3) with both labor income and housing risks; (4) with both labor income and business risks; and (5) with all three types of background risks. The upper panel of Table III reports log likelihood values and log likelihood ratio tests for various model comparisons, while the bottom panel presents parameter estimates with the associated *t*-statistics in parentheses.

Column (1) displays our benchmark model without considering any background risk factors. All coefficients are estimated with the expected signs and are statistically significant at the 10 percent level or higher. We find strong explanatory power of education, race, income and wealth on stock market participation, confirming the results of earlier studies. The positive coefficient on $Log(Age)$ and the negative coefficient on $\left(Log(Age)\right)^2$ confirms the hump-shape pattern of stock market participation with age. Consistent with Cocco (2005) and Campbell (2006), we find that the ratio of home equity to total wealth carries a negative sign and the ratio of mortgage to house value has a positive coefficient. These results suggest that although housing investment crowds out stock investment, mortgage loans can be used as a financing channel to support stock investment. The ratio of labor income to total income has a positive impact on stock market participation, but the evidence is statistically weaker.

In Column (2), we add the three labor income risk variables to the benchmark model. The coefficients of these three variables are estimated with the expected signs and are statistically significant at the 10 percent level or higher. They imply that a household is more (less) likely to enter the stock market if its labor income is less (more) uncertain, if its labor income is less (more) highly correlated with stock return, or if its labor income is more (less) highly correlated with the risk-free rate. Both $Corr(R_s, Lab)$ and $Corr(R_f, Lab)$ are statistically significant but with opposite effects on stock investment, suggesting that labor income risk can affect a household's stock investment in different ways. This result is consistent with various simulation studies which document that labor income reduces stock holdings when it is modeled as a risky asset, whereas it encourages stock investment when it is regarded as a risk-free asset. We conduct a log likelihood ratio test to investigate whether specification (2) outperforms specification (1). Given the chi-square statistic of

48.817 with degrees of freedom of 3, we reject specification (1) in favor of specification (2) at the 1 percent significance level.

Column (3) studies housing risk after controlling for labor income risk. All four parameters associated with housing risk are estimated with the expected signs. The coefficient of *Corr*(R_s,*Hou*) is not statistically significant, while the other three variables associated with housing risk are significant at the 5 percent level or higher. The variable *Corr*(R_f,*Hou*) appears to be more significant than *Corr*(R_s,*Hou*).[15] This finding is consistent with the prior literature suggesting that real estate investment is a good hedge against inflation (e.g., Goetzmann and Valaitis, 2006). It is interesting to note that the correlation between labor income and home equity *Corr*(*Lab*,*Hou*) carries a significantly negative sign, confirming the crowding out effect. If a household allocates a large fraction of his income to housing, it would more likely reduce its stock investment. This result also suggests that the comovement of housing and labor income increases risk exposures, and thus reduces the household's willingness to participate in the stock market. Our log likelihood ratio test rejects specification (2) in favor of specification (3) at the 1 percent significance level, suggesting the importance of housing risk in the stock market participation decision.

Column (4) shows that the standard deviation of business income has a significantly negative impact on stock participation, consistent with Heaton and Lucas (2000b). Both the correlations of business income with the risk-free rate and with stock returns are insignificant. The log likelihood ratio test rejects specification (2) in favor of (4) at the 5 percent significance level, suggesting that including business risk variables improves the model performance.

In Column (5), we report the results when all three types of background risks are jointly considered. Except for the variable *Corr*(R_f,*Lab*), all background risk variables that are significant in previous regressions continue to be statistically significant. Furthermore, this model outperforms specification (4) at the 1 percent significance level and outperforms specification (3) at the 10 percent significance level. Based on the likelihood ratio tests, all three types of background risks are important to a household's decision to participate in the stock market.

B.2 Economic Significance

Given the statistical significance of the background risk factors presented above, we further study the quantitative impact of these risk factors on a household's stock market participation. For each type of risk, we estimate the change of a household's probability of participating in the stock

[15] This result is obtained in the logit regressions when studying stock participation, in the Tobit regressions when studying the proportion of stock holdings, and in various robustness tests.

market by assuming that the corresponding risk variables change one standard deviation from their sample means while holding all other variables at their sample means. Table IV reports the results. The change in the probability of stock market participation is calculated by using the logit model coefficients reported in Column (5) of Table III. For labor income risk, if *Std*(*Lab*), $Corr(R_s,Lab)$ and $Corr(R_f,Lab)$ all shift one standard deviation from their respective sample means, the household will reduce its likelihood to participate in the stock market by 5.41 percent. Similarly, for housing risk and business risk, the respective changes in probabilities are 4.11 percent and 1.99 percent. If all background risk variables change together, the probability of participation declines by 12.10 percent.[16]

In Panel B of Table IV, we estimate the marginal effects of background risks for different education groups. First, we find that a more highly educated household is more likely to enter the stock market. For example, controlling for all background risk variables at their sample means, the likelihood that a household with a college education will participate in the stock market is 42.58 percent. In contrast, the likelihood of participation for a household with (without) a high school education is only 29.99 (22.49) percent. Moreover, we find that a more highly educated household is more sensitive to a change in its background risks. When all background risks increase by one standard deviation, a household with a college education will reduce its likelihood to participate in the stock market by 14.49 percent, whereas a household without a high school education will reduce its probability by only 9.23 percent.

Figure II depicts these effects. As can be seen in all panels of Figure II, the slope of the college line is steeper than the high-school line, which in turn is steeper than that of the no high-school line, suggesting that a more highly educated household is more sensitive to a change of its background risks. Also the difference between the college line and the high-school line (the difference in participation likelihood between college and high school) is considerably larger than the difference between the high-school and the no high-school lines, indicating that the marginal improvement of college education is larger than that of high-school education. It is interesting to note that in general the impact of education shrinks as the level of background risk increases.

The above results are consistent with the notion that education level is a proxy for transaction costs (fixed entry and information costs) in previous studies (e.g., Campbell, 2006; and Vissing-

[16] The overall effect need not equal to the sum of the separate effects due to the nonlinearity of the logit model.

Jorgensen, 2002a).[17] A more highly educated household is more likely to adjust its stock investment in response to a change in its background risks because its entry costs are lower.

B.3 Alternative Measures of Background Risks on Stock Market Participation

Table V conducts more tests using alternative measures of background risks. In the first row of Table V, we report for each specification the change of probability of stock market participation assuming that all background risk variables change one standard deviation from their sample means while controlling for other variables at their sample means. In Columns (1) and (2), we redo our tests using backward rolling-over measure (the *Std*(.) and *Corr*(.) variables are calculated using eight-year prior data) and forward rolling-over measures (the *Std*(.) and *Corr*(.) variables are calculated using five-year posterior data), respectively. These tests confirm our previous findings that all background risk variables yield coefficients with the expected signs, and labor income risk is the most important, housing risk is the second most important, and business income risk is less important. Consistent with the idea that forward-looking risks affect optimal portfolio choices, we find that forward measures provide a stronger impact on stock market participation than backward measures. Specifically, if all background risks shift one standard deviation from their sample means, they will reduce stock market participation by 13.81 percent when forward measures are used and by 11.57 percent when backward measures are used. With regard to each type of background risks, we find that forward rolling-over measures of labor income and business income risks are statistically more significant than their backward rolling-over counterparts, suggesting that a household choose its optimal portfolio based on the rational expectations of its future income stream. On the other hand, the backward rolling-over measure of housing risk perform better than forward rolling-over measure, consistent with the idea that housing effect more likely reflects a household's pre-committed consumption and investment.

In Column 3, we redo the baseline regression in Table III using annual growth rate of self-reported market values of house instead of annual growth rate of home equity (market value of house minus unpaid mortgage balance) to estimate housing risk. It can be seen that the standard deviation of housing value growth rate, *Std*(*Hou*), is even more significant when the market value of house is used in Column 3 of Table V (with a coefficient of -1.494 and a *t*-statistic of -4.954) than when home

[17] Chen (2006) suggests that the impact of information cost on portfolio choice and risk premium crucially depends on the investment horizon that agents choose. Using a model with an endogenous investment horizon, he shows that the impact of information cost is relatively small because agents can choose a long investment horizon to effectively dilute the information cost.

equity is used in Column 5 of Table III (with a coefficient -0.401 and a *t*-statistic of -3.028). Correlations of housing value growth rate with stock return $Corr(R_s, Hou)$ and with the risk-free asset $Corr(R_f, Hou)$ are no longer significant when market value of house is used in Column 3 of Table V whereas $Corr(R_f, Hou)$ is significantly positively related to stock market participation when home equity is used in Column 5 of Table III. These results are consistent with our previous finding that is also documented in prior studies (e.g., Cocco, 2005; and Campbell, 2006) that mortgage loans can be used as a financing channel to support stock investment. These findings also suggest that a household may use mortgage to smooth housing market risk.

Column (4) presents the estimates using covariances rather than correlations between background risks and asset returns as explanatory variables. As shown in Panel B of Table II, the correlations between $Corr(R_s,.)$ and $Corr(R_f,.)$ are fairly high for each background risk variable, we hence employ in Column (5) the correlation of each background risk with the excess return $Corr(R_s-R_f,.)$ instead of the separate correlations with stock returns and with the risk-free rate. Results using these alternative correlation measures are similar.

In Column (6), we further study the interaction impact of standard deviations of background risk factors and their correlations with stock returns. We examine separate effects based on whether the correlation with stock returns is positive or negative. In other words, the explanatory variables are (standard deviation × positive correlation) and (standard deviation × negative correlation). We use this specification to further examine the hedging motive hypothesis. A household with labor income (home equity, business income) that is negatively correlated with stock returns is more likely to participate in the stock market and invest more in stocks because stocks are a good hedge against income and housing risk. Alternatively, a household with labor income (home equity, business income) that is positively correlated with stock returns is less likely to participate in the stock market and invest less in stocks. Results presented in Column (6) confirm this argument. All estimated coefficients have the expected signs. Moreover, these results shed some new light on the risk property of labor income. Positive covariance of labor income with stock returns ($Std(Lab)\times Corr(R_s, Lab)^+$) is significantly negatively related to stock participation while the impact of negative covariance of labor income with stock returns ($Std(Lab)\times Corr(R_s,Lab)^-$) is less significant. This finding suggests that the presence of labor income risk is more likely to reduce stock investments.

B.4 Further Robustness Checks of Background Risks on Stock Market Participation

Table VI reports several further robustness checks. Column (1) repeats our baseline regression that is reported in Column (5) of Table III. Since PSID does not provide the total business income in certain years, we use head labor income and business income to proxy the total household labor and business income. In Column (2), we redo our regressions by including two additional control variables. We include a dummy variable which is equal to 1 if there exists a second wage earner and 0 otherwise. We expect that the existence of a second wage earner will reduce a household's labor income risk and hence encourage stock investment. We also include another dummy variable which is equal to one if the husband and wife work in the same industry. We expect that this variable is negatively related to stock investment because these types of household are even more exposed to labor income risk sourced from macroeconomic shock, for example, unemployment due to recession. We find that the presence of a second wage earner is positively related to stock market participation but it is statistically not significant. However, if wife and husband work in same industry, it will significantly reduce stock market participation. This is additional evidence to support the hedging motive hypothesis, i.e., a household more exposed to labor income risk will likely reduce its financial market risk exposure.

Column (3) repeats the baseline model using a subsample of single-member families. The result presented here is consistent with our previous one. In our baseline regression, we use *Filter 2* (requiring the labor income, home equity and business income growths to be between 0.5 and 2) to estimate background risk variables. We hence use *Filter5* (requiring the labor income, home equity and business income growths to be between 0.2 and 5) to check for robustness. Results reported in Column (4) using these alternative measures are similar.

C. Empirical Results of Background Risks on the Proportion of Stock Holdings

C.1. Statistic Significance

Table VII studies the potential of background risks to explain the heterogeneity in portfolio compositions among households using Tobit regressions. The dependent variable, *PflStk_1,* is the ratio of stock to financial wealth. Compared to the results from the logit regressions in explaining market participation, we find that the variables that are used to capture the background risk factors continue to have the expected signs in explaining portfolio choice in the Tobit regressions. The log likelihood ratio tests presented in Table VII confirm our previous findings that the three types of background risks are independently important. Relatively speaking, labor income risk and housing risk appear to be more important than business risk.

C.2. Economic Significance

Table VIII and Figure III present evidence on the economic significance of background risk variables on the proportion of stock holdings. Using the estimated coefficients reported in Column (5) of Table VII, we calculate the change of the proportion of stock holdings relative to financial wealth. For labor income risk, if $Std(Lab)$, $Corr(R_s,Lab)$ and $Corr(R_f,Lab)$ all shift one standard deviation from their respective sample means, the household will reduce its proportion of stock holdings by 1.82 percent. Similarly, for housing risk and business risk, the respective changes are 1.02 percent and 0.50 percent. If all background risk variables change together, the proportion of stock holdings declines by 3.98 percent.

Panel B of Table VIII presents the impact of education on the relationship between a household's stock holdings and background risks. Consistent with the transaction costs argument, a more highly educated household is more sensitive to a change in its background risks. When the overall background risk increases by one standard deviation, a household with a college education will reduce its proportion of stock holdings by 4.60 percent, a household with only a high school education will decrease its proportion of stock holdings by 3.88 percent; and a household without a high school education will reduce its stock holdings by 3.32 percent. Consistent with the notion that education is a proxy for fixed entry costs, we find that the effect of education on stock market participation is much larger than that on the proportion of stock holdings. For example, as show in Table IV, a household with a college education is 12.59 percent (=42.58-29.99) more likely to participate in the stock market than that with only a high school education assuming that the household is exposed to the sample average background risks. Regarding the proportion of stock holdings, as shown in Table VIII, a household with a college education will invest 4.74 percent (=41.48–36.74) more in stocks than a household with only a high school education.

C.3. Alternative Measures of Background Risks and Stock Holdings

Table IX reports more results using alternative measures of background risks. Columns (1) and (2) of Table IX consider backward rolling-over and forward rolling-over measures of background risks, respectively. Consistent with the findings in the stock market participation regressions, forward rolling-over measures have a stronger impact than backward rolling-over measures. Specifically, assuming all background risk variables shift one standard deviation from their sample means, the forward rolling-over measures reduces stock holdings by 3.87 percent whereas the backward measures reduces stock holdings by 3.28 percent. Also consistent with the finding reported in the stock market participation regressions, forward measures of labor income and business income are statistically more significant than backward measures, while the backward measure of housing risk has a more significant effect than the forward measure.

In Column (3), when the market value of house is used to estimate housing risk, we find that the standard deviation of housing value (*Std*(*Hou*)) has a significantly negative impact on stock holdings while the correlation terms are statistically not significant. Column (4) employs covariances instead of correlations. Column (5) uses correlations of excess return ($Corr(R_s\text{-}R_f,.)$) with labor income, home equity, and business income. Finally, Column (6) studies separate interaction effects where (standard deviation × positive correlation) and (standard deviation × negative correlation) are used as explanatory variables. The results using these alternative measures are consistent with our baseline regression.

C.4. Further Robustness Checks of Background Risks on Stock Holdings

Table X reports several further robustness checks. Column (1) repeats the baseline regression for ease of comparison. Columns (2) and (3) report results using two broader definitions of stock holdings: *PflStk_2* and *PflStk_3*, which are respectively the ratios of stock value to total family wealth with and without home equity. These results are similar to those in our baseline model and are consistent with the previous findings on stock market participation. Regarding the economic magnitudes, the upper panel reports the change of proportion of stock holdings for each specification. The impact of background risks on the proportion of stock holdings decreases when broader wealth measures are used (3.59 percent when wealth is defined as total wealth without home equity, and 2.26 percent when wealth is defined as total wealth including home equity).

As shown in Columns (4)-(6), consistent with the finding in the stock market participation regressions, the presence a second wage earner is positively related to stock holdings but the effect is not significant; if wife and husband work in the same industry, then the household will significantly reduce its stock investment; the impact of background risks is most significant for single-member families; and results using *Filter5* are very similar to our baseline regression.

It is known that estimation of Tobit models can be sensitive to the underlying assumptions about the error terms and indeed maximum likelihood estimation can be inconsistent under heteroscedasticity or nonnormality (Amemiya, 1985, pp.378-381). We adopt three alternative specifications, which assume residual standard errors to be an exponential function of total wealth, or total income, or both, respectively. These experiments produce similar results which are not reported but are available upon request.

III. Background Risks and Asset Pricing

The results reported in the previous section suggest that background risks have an important impact on a household's investment decision. The observed enormous variation of portfolio holdings across households and the low stock market participation rates are significantly related to the heterogeneity in household background risk exposures. Motivated by these results, we next examine whether idiosyncratic background risks have an impact on asset returns. Numerous papers have suggested the importance of uninsurable idiosyncratic shock in explaining asset return (e.g., Mankiw, 1986; Constantinides and Duffie, 1996; and Cochrane, 2006 and 2008). Intuitively, the presence of an additional risk can reduce the demand for a risky asset which will then require a higher risk premium. However, the underlying mechanism by which idiosyncratic risks can affect the equilibrium risk premium is more complex. It depends on the properties of the assumed utility function and the precise natures of these risks – specifically, the size and persistence, the joint stochastic process of these risks and dividends, and the relationship between the cross-sectional dispersion of idiosyncratic risks and aggregate shocks.

Given the complexity, we do not explicitly derive an equilibrium model that would give us the exact predictions as how background risks could affect asset returns. Following Jagannathan and Wang (1996), Heaton and Lucas (2000b), and Jacobs and Wang (2004)[18], we construct a linear pricing kernel which allows us to examine the impact of background risks on asset returns by testing whether stocks that are more highly correlated with background risk measures are associated with higher returns.

A. Empirical Specification

A standard asset pricing model implies the Euler equation restriction for household i:

$$E\left[M_{i,t}R_t\right]=1 \tag{4}$$

where $M_{i,t}$ is the intertemporal marginal rate of substitution of individual i, R_t is the vector of (gross) returns of assets. In the presence of complete markets, all economic shocks can be effectively

[18] Jagannathan and Wang (1996) suggest that if aggregate wealth is the sum of stock market wealth and human capital, the stochastic discount factor is a linear combination of the return of stock market portfolio and the return of human capital. They provide evidence that labor income growth rate, a proxy for the return of human capital, is an important pricing factor in addition to the market portfolio. Heaton and Lucas (2000b) show that proprietary wealth is also a component of aggregate wealth, and so proprietary income growth rate can be another pricing factor. Jacobs and Wang (2004) examine a two-factor model of the mean and dispersion of cross-sectional consumption growth rates across households and demonstrate that idiosyncratic consumption risk matters for stock returns. Eiling (2006) argues that industry-level labor income has further explanatory power on cross-sectional stock returns.

diversified by choosing consumption and portfolios of financial assets and hence all risks are fully absorbed by consumption dynamics. Under certain assumptions on the agent's utility function and on the stochastic process of consumption and dividends, individual dynamics will coincide with aggregate dynamics. In such a case, aggregate consumption will be the only risk factor which fully captures the uncertainty of the economy. In general, an asset that is more highly correlated with consumption growth is associated with a higher risk premium (Breeden, 1979).

When markets are incomplete due to uninsurable risks, the individual optimal consumption process will reflect the hedge demand for its unique background risks, and the individual consumption dynamics no long coincide with the aggregate dynamics. The aggregate risk premium should be determined by market interactions among agents subject to idiosyncratic shocks. Deriving a closed-form solution for the risk premium in this type of economy is beyond the scope of this paper. Nevertheless, the optimal consumption of an individual should be a function of its financial and non-financial wealth, such as human capital, housing, and private business (e.g., Campbell, 1993; and Zeldes, 1989). We therefore postulate the following simple linear function that determines the individual intertemporal marginal rate of substitution:

$$M_{i,t} = \beta_0 + \beta_1 R_{Li,t} + \beta_2 R_{Hi,t} + \beta_3 R_{Bi,t} \tag{5}$$

where $R_{Li,t}$, $R_{Hi,t}$ and $R_{Bi,t}$ are respectively individual i's growth rates of labor income, home equity, and business income. To analyze how background risks affect asset returns, we aggregate individual's Euler equations across households to obtain

$$E[M_t R_t] = 1 \tag{6}$$

where the pricing kernel incorporating the potential impact of background risks on asset returns is as follows:

$$M_t = \beta_0 + \beta_1 \overline{R}_{L,t} + \beta_2 \overline{R}_{H,t} + \beta_3 \overline{R}_{B,t} \tag{7}$$

where $\overline{R}_{L,t}$, $\overline{R}_{H,t}$ and $\overline{R}_{B,t}$ are respectively cross-sectional averages of individual's growth rates of labor income, home equity, and business income at time *t*. Decomposition the cross product term in (6) using the pricing kernel (7) and after some simple algebra, we obtain:

$$E(R_t) = \frac{1}{E(M_t)} - \beta_1 \frac{Cov(\overline{R}_{L,t}, R_t)}{E(M_t)} - \beta_2 \frac{Cov(\overline{R}_{H,t}, R_t)}{E(M_t)} - \beta_3 \frac{Cov(\overline{R}_{B,t}, R_t)}{E(M_t)} \tag{8}$$

Equation (8) illustrates the relationship between background risks and asset returns. Similar to the argument that an asset that is highly correlated with consumption growth requires a higher return, we expect an asset that is highly correlated with a background risk to require a higher return because its correlation with an additional risk is undesirable. The demand for a financial asset is determined by its function to smooth out consumption. However, if an asset is highly correlated with an additional risky income such as labor income, its consumption smoothing capability is reduced and hence a higher risk premium is required. Therefore, we expect negative coefficients on the three covariance terms in equation (8). We further add these background risk factors to three benchmark pricing kernels, namely, the CCAPM, the CAPM and the Fama-French three-factor model in order to examine the relative importance of these background risk factors.

We use Hansen's (1982) generalized method of moment (GMM) to estimate model parameters. Given the large number of cross-sectional households and relatively short time series, we cannot jointly estimate the individual Euler equations. Following Jacobs (1999), we first average the error terms of the individual Euler equations, i.e., $v_t = \frac{1}{N_t}\sum_{i=1}^{N_t} e_{it}$, where $e_{i,t} = M_{i,t}R_t - 1$, and N_t is the number of households at time t. We then conduct the time-series GMM estimation based on the aggregated error term $E\left(v_t\right) = 0$.[19]

We conduct the standard two-stage GMM estimation and use the covariance matrix of returns of test assets as our first–stage weighting matrix. Using this weighting matrix, the square root of the first-step minimized value of the objective function is the Hansen and Jagannathan (1997) distance (*HJD*), which is the least-square distance between the given candidate pricing kernel and the nearest point to it in the set of correct pricing kernels. The *HJD* is also interpreted as the pricing error of the candidate pricing kernel in pricing the returns of the test assets. We use the first-stage estimated error covariance matrix as the weighted matrix to conduct the second-stage estimation, which is asymptotically efficient.

B. Estimation Results Using PSID Data

We draw consumption data from PSID 1976-1997 surveys. Because the PSID does not provide detailed categories of consumption and reports only food consumption series continuously, we follow previous studies to use food consumption in estimation. The PSID did not report food consumption in 1987 and 1988, leaving us with only 18 time-series observations. Stock information

[19] It is worth noting that this averaging does not reduce our specification to the representative agent framework. As pointed out by Balduzzi and Yao (2007), among others, the average of individual consumption growth ratios is not equal to the ratio of aggregate consumption unless the individuals' consumption growth ratios are the same across households.

is surveyed every five years from 1984-1999 and then every other year since 1999. For some early years, PSID does not provide information on the stock holdings status of households. In such a year we classify the stock holdings status using the closest available data after that year. Given 18 time-series observations with a maximum of 7 model parameters, the number of test assets must be more than 7 and less than 18 in order for the model to be identified.[20] We choose the Fama-French six size and book-to-market portfolios, the 30-day T-bill, and the 10-year government bond as our test assets. To check for robustness, in subsection III.C, we use an alternative dataset (the CES data) with 232 monthly observations, whereby we use the Fama-French 25 size and book-to-market portfolios, the 30-day T-bill and the 10-year government bond as our test assets.

Table XI presents the results. The parameter estimates as well as their *t*-statistics in parentheses are from the second-stage efficient GMM. To test model specifications, we fix the GMM weighting matrix based on the first-stage estimates of the full model. The *J*-statistic is the minimized value of the GMM objective function which asymptotically follows the chi-square distribution with the degrees of freedom equal to the number of moment conditions minus the number of parameters. To test for model restrictions, we use the difference in *J*-statistic between a restricted model and the full model, denoted by $(J_r - J_u)$, which also follows the chi-square distribution with the degrees of freedom equal to the number of parameter restrictions.

Panel A presents the results of the model with background risks only. As can be seen in Row (1), all three background risk parameters in the full model are estimated with the expected negative sign, suggesting that a stock that is more highly correlated with a background risk is associated with a higher risk premium. All three factors are statistically significant at the 5 percent or higher significance level indicating that all three types of background risks are important. In Rows (2) – (4), we in turn drop each of the three background risk factors. The likelihood ratio tests based on the $(J_r - J_u)$ statistics suggest that all three types of background risks are important.

In Panels B-D, we consider three benchmark pricing kernels – the CCAPM, the CAPM and the Fama-French three-factor model. Row (1) in each panel reports the estimate of the full model which includes the three background risk factors and the pricing factors implied by a benchmark model. In Row (2), we drop the three background risk factors and reduce the model to a benchmark model. We find a significant deterioration in both the *J*-statistic and the *HJD* measure. For example,

[20] If the number of parameters (K=7 here) is more than the number of moment conditions (i.e., the number of testing assets, N=8 here), the model is not identifiable; if the number of moment conditions (N=8) is more than the number of time-series observations (T=18), the estimated covariance matrix is not of full rank, and hence the model cannot be estimated using the two-step GMM.

in Panel B, with 3 degrees of freedom, the $(J_r - J_u)$ statistic of 14.963 rejects the CCAPM in favor of the full model at the 1 percent significance level. This result suggests that the three background risk variables are jointly important in explaining expected asset returns. The $(J_r - J_u)$ statistics reported in Rows (3)-(5) show that eliminating any one of the three background risk factors results in a significant increase in the *J*-statistic. Also, we find consistently that labor income risk and housing risk are more important than business risk.

C. Robustness Tests Using CES Data

Since we only have 18 time-series observations from PSID, the above results may be subject to small sample bias. We next use an alternative dataset, the Consumer Expenditure Survey (CES) to check for robustness. The CES is a quarterly survey produced by the Bureau of Labor Statistics (BLS), and is designed as a rotating panel to represent the U.S. population (for a detailed discussion of the CES data, see Brav *et al.*, 2002 and Vissing-Jorgensen, 2002b). Each quarter, roughly 5,000 U.S. households are surveyed, among which 80 percent of them will be re-interviewed in the next survey and the other 20 percent will be replaced by new households. A household therefore stays in the survey for at most five consecutive quarters.

Labor and business income information is gathered in the first and fifth quarter surveys and is referred to as annual income in the previous year. Hence, we can generate an annual income growth rate for each household. The market value of a household's house is only provided in the fifth quarter survey. In order to get home equity values, we backup the mortgage balance using the quarterly mortgage payment and the variable about housing mortgage status. The home equity of a household which rents a house is set to zero, while that of a household which owns a house but has no mortgage is set to the market value of the house. For the remaining households which own a house and have a mortgage (44 percent of the sample), we calculate the mortgage balance by dividing the quarterly mortgage interest payment by the mortgage interest rate. We use the 30-year mortgage interest rate reported by the Federal Reserve Bank of St. Louis. The home equity of each quarter is the market value of the house minus the outstanding mortgage at the end of that quarter. This method assumes that the market value of the house does not change over the year; the change of home equity is fully driven by mortgage payment. The annual growth rate of home equity is calculated as the ratio of home equity of the fifth quarter to home equity of the second quarter.

While the CES data for a given household is repeatedly surveyed on a quarterly basis, the interview is conducted each month for different households. Thus, we have data of annual growth rates at monthly frequency and the model's error terms will have an MA(11) component. We use the Newey-West covariance matrix estimation to correct for serially correlation of the error terms. We use the Fama-French 25 size and book-to-market portfolios, the 30-day T-bill, and the 10-year government bond as our test assets. Following Vissing-Jorgensen (2002b), we discard the observations for the years 1980 and 1981 because they are of questionable quality. We delete rural households because the BLS did not survey rural households for some years. We further restrict our sample to households with four consecutive quarterly interviews. Our final sample has 40,728 households over 232 months.

Empirical results are presented in Table XII. The first row reports the estimate of the model with three background risk factors. All three background risk coefficients are negative confirming our previous findings using the PSID data that an asset more highly correlated with background risks requires a higher return. Labor income risk and housing risk are statistically significant but business income risk is not significant. Comparing the background risk factor model with three benchmark pricing kernels, we find that the three background risk factors are jointly important and improve the model fitness significantly. For example, adding the three background risk factors to the CCAPM reduces the *J*-statistic from 90.099 to 19.687, and the $(J_r - J_u)$ statistic of 70.413 suggests that this improvement is significant at the 1 percent level.

IV. Conclusions

Using a sample of U.S. households with individual background risk measures, we examine the empirical importance of background risks on a household's investment decision and on asset returns. We document significant heterogeneity of background risk exposures across households. Our tests show that all three background risks sourced from labor income, housing and private business are important to a household's stock market participation and portfolio choice. The observed enormous variation of portfolio holdings across households and the low stock market participation rates are significantly related to the heterogeneity in household background risk exposures.

Specifically, a household is more (less) likely to enter the stock market and invests a larger (smaller) fraction of wealth in stocks if its non-financial income or wealth (i.e., labor income, home equity, and private business income) is less (more) volatile, is less (more) highly correlated with stock return, or is more (less) highly correlated with the risk-free rate. Among the three types of background risks, labor income risk is the most significant factor and housing risk is almost as important as labor income risk. The interaction between labor income and housing value is also an important factor. In addition, a more highly educated household is more sensitive to a change of its background risks.

We also show that these background risks are important to asset returns. A stock that is highly correlated with background risks is associated with a higher risk premium. Adding the background risk variables to the pricing kernel implied by the CCAPM, the CAPM or the Fama-French three-factor model significantly improves model performance.

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Table I
Characteristics of Household Stock Market Participation and Stock Holdings

This table presents summary statistics of stock market participation rate and various measures of stock holdings by stockholders. The sample contains 16,487 year-household observations covering the period 1983-2002.

Panel A: Summary Statistics of Full Sample

	Mean	Median	Std Dev
Stock market participation	0.369	0.000	0.483
Stock holdings by stockholders			
Stocks relative to financial wealth	0.528	0.508	0.306
Stocks relative to total wealth without home equity	0.366	0.318	0.298
Stocks relative to total wealth with home equity	0.231	0.164	0.221

Panel B: Summary Statistics of Each Year

	Year 1983			Year 1988			Year 1993		
	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
Stock market participation	0.273	0.000	0.446	0.339	0.000	0.474	0.363	0.000	0.481
Stock holdings by stockholders									
Stocks relative to financial wealth	0.435	0.385	0.305	0.435	0.385	0.299	0.550	0.545	0.315
Stocks relative to total wealth without home equity	0.253	0.172	0.275	0.271	0.187	0.258	0.371	0.328	0.307
Stocks relative to total wealth with home equity	0.148	0.081	0.186	0.169	0.099	0.188	0.243	0.175	0.230

	Year 1998			Year 2000			Year 2002		
	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
Stock market participation	0.387	0.000	0.487	0.422	0.000	0.494	0.427	0.000	0.495
Stock holdings by stockholders									
Stocks relative to financial wealth	0.592	0.600	0.291	0.570	0.563	0.297	0.542	0.519	0.295
Stocks relative to total wealth without home equity	0.431	0.415	0.294	0.423	0.405	0.304	0.396	0.372	0.295
Stocks relative to total wealth with home equity	0.282	0.230	0.229	0.269	0.216	0.233	0.235	0.178	0.209

Table II
Characteristics of Explanatory Variables

Panel A reports summary statistics of the explanatory variables in our regressions. *Std(X)* is standard deviation of variable X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. All nominal variables are converted to the 1992 dollar using the Consumer Price Index. Panel B reports the correlation matrix of background risk variables with associated *p*-values in parentheses. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Summary Statistics

	Minimum	Mean	Median	Maximum	Std Dev
Control variables					
Head age	18.000	48.089	46.000	101.000	15.466
Family size	1.000	2.717	2.000	10.000	1.360
Race-if white	0.000	0.918	1.000	1.000	0.275
High school education	0.000	0.546	1.000	1.000	0.498
College education	0.000	0.282	0.000	1.000	0.450
Total wealth including home equity (,000$)	-22.062	155.997	77.660	1678.640	221.880
Total family income (,000 $)	0.649	51.530	43.338	258.606	36.516
Home equity relative to total wealth	0.000	0.457	0.429	10.000	0.437
Unpaid mortgage relative to house value	0.000	0.262	0.054	1.401	0.319
Labor income relative to total income	0.000	0.543	0.600	1.000	0.357
Background risks for full sample					
Std(Lab)	0.000	0.175	0.172	0.754	0.134
Corr(R_s, Lab)	-0.780	-0.003	0.000	0.804	0.271
Corr(R_f, Lab)	-0.785	0.021	0.000	0.809	0.269
Std(House)	0.000	0.231	0.220	2.162	0.217
Corr(R_s, Hou)	-0.799	0.001	0.000	0.798	0.260
Corr(R_f, Hou)	-0.843	-0.013	0.000	0.807	0.259
Std(Bus)	0.000	0.041	0.000	1.790	0.156
Corr(R_s, Bus)	-0.797	-0.001	0.000	0.745	0.114
Corr(R_f, Bus)	-0.766	0.002	0.000	0.747	0.110
Corr(Lab, Hou)	-0.783	0.011	0.000	0.801	0.249
Corr(Lab, Bus)	-0.759	-0.001	0.000	0.811	0.074
Corr(Hou, Bus)	-0.774	0.004	0.000	0.796	0.108
Background risks for sub-samples					
Proportion of households with labor income	0.000	0.783	1.000	1.000	0.412
Std(Lab)	0.004	0.223	0.213	0.754	0.110
Corr(R_s, Lab)	-0.780	-0.003	-0.003	0.804	0.306
Corr(R_f, Lab)	-0.785	0.027	0.023	0.809	0.304
Proportion of households with house	0.000	0.712	1.000	1.000	0.453
Std(Hou)	0.004	0.325	0.290	2.162	0.189
Corr(R_s, Hou)	-0.799	0.002	-0.004	0.798	0.308
Corr(R_f, Hou)	-0.843	-0.019	-0.027	0.807	0.307
Proportion of households with business income	0.000	0.082	0.000	1.000	0.274
Std(Bus)	0.006	0.503	0.452	1.790	0.256
Corr(R_s, Bus)	-0.797	-0.010	0.002	0.745	0.399
Corr(R_f, Bus)	-0.766	0.025	0.055	0.747	0.386
Corr(Lab, Hou)	-0.783	0.023	0.028	0.801	0.336
Corr(Lab, Bus)	-0.759	-0.050	-0.060	0.811	0.449
Corr(Hou, Bus)	-0.774	0.056	0.043	0.796	0.395

Table II (continued)
Panel B: Correlation Matrix of Background Risk Factors

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	Std(Lab)	1.000	-0.030**	-0.005	-0.191***	-0.014	0.017	-0.144***	-0.020	-0.019	0.003	-0.014	-0.006
			(0.046)	(0.738)	(0.000)	(0.336)	(0.243)	(0.000)	(0.181)	(0.203)	(0.823)	(0.339)	(0.700)
(2)	Corr(R_s,Lab)		1.000	0.396***	-0.016	-0.011	-0.005	-0.020	0.007	-0.014	-0.011	0.025*	-0.018
				(0.000)	(0.278)	(0.472)	(0.741)	(0.173)	(0.642)	(0.332)	(0.438)	(0.095)	(0.234)
(3)	Corr(R_f,Lab)			1.000	0.004	-0.013	-0.010	-0.009	-0.009	-0.019	0.018	0.020	-0.015
					(0.778)	(0.371)	(0.492)	(0.557)	(0.563)	(0.193)	(0.224)	(0.169)	(0.320)
(4)	Std(Hou)				1.000	0.021	0.006	0.109***	-0.022	0.003	0.008	-0.009	0.024
						(0.158)	(0.685)	<.0001	(0.134)	(0.825)	(0.600)	(0.527)	(0.105)
(5)	Corr(R_s,Hou)					1.000	0.441***	-0.042***	0.034**	0.022	-0.033**	0.018	-0.028*
							(0.000)	(0.004)	(0.020)	(0.129)	(0.025)	(0.224)	(0.062)
(6)	Corr(R_f,Hou)						1.000	-0.027*	0.012	-0.004	0.011	0.011	-0.005
								(0.068)	(0.416)	(0.780)	(0.464)	(0.476)	(0.731)
(7)	Std(Bus)							1.000	-0.053***	0.049***	-0.002	-0.018	0.114***
									(0.000)	(0.001)	(0.872)	(0.213)	(0.000)
(8)	Corr(R_s,Bus)								1.000	0.363***	0.002	-0.130***	0.020
										(0.000)	(0.868)	(0.000)	(0.171)
(9)	Corr(R_f,Bus)									1.000	-0.007	-0.004	0.030**
											(0.628)	(0.779)	(0.047)
(10)	Corr(Lab,Hou)										1.000	-0.011	-0.005
												(0.460)	(0.719)
(11)	Corr(Lab,Bus)											1.000	-0.094
													(0.000)
(12)	Corr(Hou,Bus)												1.000

Table III
Determinants of Stock Market Participation

This table reports maximum likelihood estimation of logit regressions. The dependent variable is *DumStk*, which is a binary-choice variable equal to 1 if a household participates in stock market and 0 otherwise. The sample contains 16,487 year-household observations for the period 1983-2002. In each panel, coefficient estimates are reported with associated *t*-statistics in parentheses. *Log(X)* is natural logarithm of variable X; *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	No background risk		Labor risk		Labor & housing risks		Labor & business risks		All risks	
	(1)		(2)		(3)		(4)		(5)	
Log likelihood value	-8089.593		-8065.184		-8049.883		-8060.069		-8045.017	
Log likelihood ratio test			(2)-(1)		(3)-(2)		(4)-(2)		(5)-(3)	(5)-(4)
Chi-square (*p*-value)			48.817	(0.000)	30.602	(0.000)	10.230	(0.037)	9.732 (0.083)	30.103 (0.000)
Year dummies	Yes		Yes		Yes		Yes		Yes	
Log(Age)	3.855	(2.071)**	4.176	(2.313)**	4.600	(2.041)**	4.604	(2.222)**	4.994	(2.660)***
(Log(Age))^2	-0.523	(-2.099)**	-0.577	(-2.382)**	-0.628	(-2.083)**	-0.636	(-2.280)**	-0.682	(-2.724)***
Log(Family size)	-0.212	(-3.345)***	-0.204	(-3.748)***	-0.186	(-3.671)***	-0.205	(-3.621)***	-0.188	(-3.562)***
Race-if white	0.739	(6.232)***	0.730	(6.479)***	0.737	(7.130)***	0.736	(6.352)***	0.744	(6.918)***
High school	0.398	(4.808)***	0.394	(4.665)***	0.390	(4.518)***	0.395	(4.523)***	0.390	(5.327)***
College	0.966	(10.583)***	0.949	(9.815)***	0.937	(10.229)***	0.951	(10.227)***	0.939	(10.360)***
Log(Wealth)	1.026	(29.932)***	1.016	(30.242)***	1.038	(27.908)***	1.022	(30.673)***	1.043	(8.321)***
Log(Income)	0.380	(8.855)***	0.395	(9.086)***	0.392	(8.386)***	0.393	(9.674)***	0.390	(25.821)***
House value relative to wealth	-1.369	(-15.555)***	-1.403	(-16.812)***	-1.368	(-16.751)***	-1.417	(-16.777)***	-1.383	(-14.149)***
Mortgage relative to home equity	0.721	(8.459)***	0.704	(8.884)***	0.809	(10.292)***	0.707	(8.143)***	0.810	(9.996)***
Labor income relative to total income	0.123	(1.426)	0.249	(2.831)***	0.243	(2.598)***	0.216	(2.467)**	0.212	(2.159)**
Std(Lab)			-1.123	(-4.678)***	-1.141	(-5.05)***	-1.144	(-4.929)***	-1.160	(-4.885)***
Corr(R_s, Lab)			-0.210	(-2.163)**	-0.212	(-2.172)**	-0.206	(-2.035)**	-0.208	(-2.244)**
Corr(R_f, Lab)			0.187	(1.927)*	0.189	(1.766)*	0.186	(1.636)	0.189	(1.630)
Std(Hou)					-0.410	(-3.307)***			-0.401	(-3.028)***
Corr(R_s, Hou)					-0.148	(-1.483)			-0.153	(-1.313)
Corr(R_f, Hou)					0.273	(2.267)**			0.271	(2.275)**
Std(Bus)							-0.341	(-2.206)**	-0.322	(-2.045)**
Corr(R_s, Bus)							-0.079	(-0.309)	-0.096	(-0.434)
Corr(R_f, Bus)							0.292	(1.214)	0.290	(1.057)
Corr(Lab, Hou)					-0.187	(-2.042)**			-0.188	(-1.915)*
Corr(Lab, Bus)							-0.312	(-0.919)	-0.328	(-1.107)
Corr(Hou, Bus)									-0.084	(-0.354)

Table IV
Marginal Effects of Background Risk Factors on Stock Market Participation

Panel A reports marginal effects of various background risks and Panel B presents effects of background risks for various education groups. Using estimated coefficients from the logit regression (Table III Column 5), we assume that the corresponding risk factors change one standard deviation from their sample means while holding all other variables at their sample averages. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill.

Panel A: Marginal effects of various background risks

	Probability of participation at sample means (in percent)	Probability of participation when background risk variables increase one standard deviation (in percent)	Change in probability (in percent)
Labor income risk			
Std(Lab), Corr(R_s, Lab), Corr(R_f, Lab)	31.86	26.46	-5.41
Housing risk			
Std(Hou), Corr(R_s, Hou), Corr(R_f, Hou)	31.86	27.75	-4.11
Business income risk			
Std(Bus), Corr(R_s, Bus), Corr(R_f, Bus)	31.86	29.87	-1.99
All background risks			
12 variables	31.86	19.77	-12.10

Panel B: Marginal effects of background risks for various education groups

	Probability of participation at sample means (in percent)	Probability of participation when background risk variables increase one standard deviation (in percent)	Change in probability (in percent)
No high school	22.49	13.26	-9.23
High school	29.99	18.41	-11.58
College	42.58	28.10	-14.49

Table V Alternative Measures of Background Risks and Stock Market Participation

This table reports maximum likelihood estimation of logit regressions using alternative measures of background risks. Coefficient estimates are reported with associated *t*-statistics in parentheses. In the first row of each specification, we report the change of probability of stock market participation assuming all background risk variables change one standard deviation from their sample means. Column 1 uses the *backward rolling-over* which employs 8-year prior data to construct the background risk variables; Column 2 uses the *forward rolling-over* which employs 5-year posterior data to construct the background risk variables; Column 3 uses growth rate of market value of house rather than home equity to estimate the housing risk variables; Column 4 uses covariances instead of correlations; Column 5 uses excess return instead of stock returns; and Column 6 uses standard deviations interacted separately with positive and negative correlations with stock returns, (Std×Corr$^+$) and (Std×Corr$^-$). Control variables include yearly dummies and household characteristic variables used in Table III. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y except Column 4 where *Cov (X,Y)* replaces *Corr (X,Y)*; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity (market value of house in Column 3) and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	Backward rolling-over		Forward rolling-over		Use market value of house		Use covariances		Use excess return Corr(R_s-R_f, X)		Use separately Std×Corr$^+$ and Std×Corr$^-$	
Change in prob. of participation	(1)		(2)		(3)		(4)		(5)		(6)	
(in percent)	-11.57		-13.81		-8.96		-13.59		-9.80		-5.77	
# of observation	9,568		6,883		16,487		16,487		16,487		16,487	
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
Std(Lab)	-1.477	(-6.349)***	-1.177	(-4.013)***	-1.145	(-4.923)***	-1.158	(-4.977)***	-1.163	(-4.95)***		
Corr(R_s, Lab)	-0.076	(-0.890)	-0.229	(-2.375)**	-0.207	(-1.904)*	-5.034	(-1.915)*				
Corr(R_f, Lab)	0.126	(1.329)	0.268	(2.620)***	0.185	(1.947)*	42.329	(1.927)*				
Corr(R_s-R_f, Lab)									-0.159	(-1.875)*		
Std(Lab)×Corr(R_s, Lab)$^+$											-1.910	(-3.066)***
Std(Lab)×Corr(R_s, Lab)$^-$											0.958	(1.695)*
Std(Hou)	-0.660	(-4.557)***	-0.164	(-0.934)	-1.494	(-4.954)***	-0.411	(-3.001)***	-0.399	(-2.697)***		
Corr(R_s, Hou)	-0.110	(-1.123)	-0.155	(-1.758)*	0.105	(0.854)	-1.876	(-1.056)				
Corr(R_f, Hou)	0.168	(1.762)*	0.109	(1.228)	0.025	(0.200)	34.522	(2.245)**				
Corr(R_s-R_f, Hou)									-0.047	(-0.533)		
Std(Hou)×Corr(R_s, Hou)$^+$											-0.540	(-1.441)
Std(Hou)×Corr(R_s, Hou)$^-$											0.440	(0.950)
Std(Bus)	-0.037	(-0.123)	-0.684	(-2.073)**	-0.288	(-1.554)	-0.318	(-1.817)*	-0.304	(-1.647)		
Corr(R_s, Bus)	0.359	(0.982)	-0.489	(-1.097)	-0.093	(-0.380)	-1.780	(-0.511)				
Corr(R_f, Bus)	0.480	(1.201)	0.108	(0.266)	0.305	(1.175)	31.213	(1.276)				
Corr(R_s-R_f, Bus)									0.018	(0.084)		
Std(Bus)×Corr(R_s, Bus)$^+$											-0.230	(-0.400)
Std(Bus)×Corr(R_s, Bus)$^-$											0.612	(1.261)
Corr(Lab, Hou)					0.034	(0.384)	-2.654	(-2.504)**	-0.181	(-1.696)*		
Corr(Lab, Bus)					-0.333	(-1.121)	-3.635	(-1.326)	-0.317	(-1.070)		
Corr(Hou, Bus)					0.033	(0.153)	1.915	(1.318)	-0.079	(-0.289)		

Table VI
Further Robustness Checks of the Impact of Background Risks on Stock Market Participation

This table reports maximum likelihood estimation of logit regressions. Coefficient estimates are reported with associated *t*-statistics in parentheses. In the first row of each specification, we report the change of probability of stock market participation assuming all background risk variables change one standard deviation from their sample means. Column 1 repeats the baseline model in Column 5 of Table III; Column 2 adds two additional dummy variables to study the impact of the presence of a second wage earner on stock market participation; Column 3 uses a sample of single-member families; and Column 4 uses *Filter5* (which requires *Lab*, *Hou*, and *Bus* to be between 0.2-5) to construct background risk variables. Control variables include yearly dummies and household characteristic variables in the baseline model reported in Column 5 of Table III. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	Baseline model		Second wage earner		Single		Filter5	
Change in prob of participation	(1)		(2)		(3)		(4)	
(in percent)	-12.10		-14.21		-15.03		-12.09	
# of observation	16,487		16,487		3,220		16,669	
Year dummies & control variables	Yes		Yes		Yes		Yes	
If a second wage earner exist			0.046	(0.870)				
If husband and wife work in same industry			-0.461	(-3.671)***				
Std(Lab)	-1.160	(-4.885)***	-1.151	(-4.952)***	-1.171	(-2.139)**	-0.424	(-4.582)***
Corr(R_s, Lab)	-0.208	(-2.244)**	-0.203	(-2.133)**	-0.249	(-0.961)	-0.241	(-2.365)**
Corr(R_f, Lab)	0.189	(1.630)	0.190	(1.970)**	0.323	(1.379)	0.158	(1.571)
Std(Hou)	-0.401	(-3.028)***	-0.400	(-2.986)***	-0.877	(-1.876)*	-0.248	(-3.442)***
Corr(R_s, Hou)	-0.153	(-1.313)	-0.148	(-1.288)	0.195	(0.581)	0.019	(0.160)
Corr(R_f, Hou)	0.271	(2.275)**	0.270	(2.336)**	0.611	(2.048)**	0.217	(1.72)*
Std(Bus)	-0.322	(-2.045)**	-0.318	(-1.536)	-0.524	(-0.97)	-0.171	(-1.766)*
Corr(R_s, Bus)	-0.096	(-0.434)	-0.104	(-0.417)	-0.510	(-0.637)	0.228	(0.912)
Corr(R_f, Bus)	0.290	(1.057)	0.299	(1.044)	1.018	(0.983)	0.226	(0.926)
Corr(Lab, Hou)	-0.188	(-1.915)*	-0.183	(-2.003)**	0.161	(0.558)	-0.024	(-0.246)
Corr(Lab, Bus)	-0.328	(-1.107)	-0.341	(-1.136)	-0.133	(-0.116)	-0.801	(-2.311)**
Corr(Hou, Bus)	-0.084	(-0.354)	-0.077	(-0.280)	0.960	(1.185)	0.053	(0.209)

Table VII
Determinants of Stock Holdings

This table reports maximum likelihood estimation of Tobit regressions. The dependent variable is *PflStk_1*, which is the proportion of stock relative to total financial wealth. The sample contains 16,487 year-household observations for the period 1983-2002. In each panel, coefficient estimates are reported with associated *t*-statistics in parentheses. *Log(X)* is natural logarithm of variable X; *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	No background risk		Labor risk		Labor & housing risks		Labor & business risks		All risks			
	(1)		(2)		(3)		(4)		(5)			
Log likelihood value	-9652.706		-9633.270		-9625.374		-9627.617		-9619.835			
Log likelihood ratio test			(2)-(1)		(3)-(2)		(4)-(2)		(5)-(3)		(5)-(4)	
Chi-square (p-value)			38.870	(0.000)	15.792	(0.003)	11.307	(0.023)	11.079	(0.050)	15.565	(0.008)
Year dummies	Yes		Yes		Yes		Yes		Yes			
Log(Age)	1.318	(2.382)**	1.381	(2.296)**	1.468	(3.087)***	1.515	(2.897)***	1.594	(3.198)***		
$(\text{Log(Age)})^2$	-0.171	(-2.366)**	-0.183	(-2.292)**	-0.193	(-3.063)***	-0.201	(-2.923)***	-0.211	(-3.167)***		
Log(Family size)	-0.058	(-3.903)***	-0.055	(-3.182)***	-0.053	(-3.303)***	-0.056	(-3.429)***	-0.053	(-3.543)***		
Race-if white	0.224	(5.861)***	0.221	(5.673)***	0.222	(6.594)***	0.222	(6.705)***	0.224	(6.514)***		
High school	0.150	(6.564)***	0.149	(6.445)***	0.147	(6.268)***	0.149	(5.988)***	0.147	(6.006)***		
College	0.309	(11.386)***	0.304	(13.099)***	0.302	(11.107)***	0.305	(10.945)***	0.302	(11.744)***		
Log(Wealth)	0.281	(29.270)***	0.278	(27.016)***	0.281	(26.181)***	0.279	(28.835)***	0.282	(26.094)***		
Log(Income)	0.087	(7.111)***	0.090	(7.277)***	0.090	(6.498)***	0.089	(7.070)***	0.089	(8.540)***		
House value relative to wealth	-0.348	(-11.872)***	-0.356	(-12.790)***	-0.350	(-12.835)***	-0.359	(-13.532)***	-0.354	(-13.409)***		
Mortgage relative to home equity	0.216	(9.046)***	0.212	(8.397)***	0.228	(8.734)***	0.212	(8.940)***	0.228	(9.209)***		
Labor income relative to total income	0.053	(2.259)**	0.084	(3.180)***	0.083	(4.049)***	0.074	(2.776)***	0.073	(2.866)***		
Std(Lab)			-0.275	(-4.254)***	-0.279	(-4.774)***	-0.283	(-4.597)***	-0.286	(-4.617)***		
Corr(R_s, Lab)			-0.056	(-1.782)*	-0.056	(-1.712)*	-0.055	(-1.791)*	-0.056	(-2.082)**		
Corr(R_f, Lab)			0.042	(1.451)	0.043	(1.245)	0.042	(1.473)	0.043	(1.390)		
Std(Hou)					-0.065	(-1.664)*			-0.061	(-1.580)		
Corr(R_s, Hou)					-0.043	(-1.219)			-0.044	(-1.415)		
Corr(R_f, Hou)					0.070	(2.274)**			0.069	(1.958)*		
Std(Bus)							-0.100	(-2.470)**	-0.096	(-2.176)**		
Corr(R_s, Bus)							-0.029	(-0.455)	-0.031	(-0.506)		
Corr(R_f, Bus)							0.047	(0.700)	0.047	(0.784)		
Corr(Lab, Hou)					-0.029	(-1.093)			-0.029	(-0.996)		
Corr(Lab, Bus)							-0.109	(-1.270)	-0.026	(-1.278)		
Corr(Hou, Bus)									-0.112	(-0.409)		

Table VIII
Marginal Effects of Background Risk Factors on Stock Holdings Relative to Total Financial Wealth

Panel A reports the marginal impact of various background risks and Panel B presents effects of background risks for various education group. Using estimated coefficients in Tobit regression (Table VI Column 5), we assume that the corresponding risk factors change one standard deviation from their sample means while holding all other variables at their sample averages. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill.

Panel A: Marginal effects of various background risks

	Proportion of stock holdings at sample means (in percent)	Proportion of stock holdings when background risk variables increase one standard deviation (in percent)	Change in proportion (in percent)
Labor income risk			
Std(Lab), Corr(R_s, Lab), Corr(R_f, Lab)	37.30	35.48	-1.82
Housing risk			
Std(Hou), Corr(R_s, Hou), Corr(R_f, Hou)	37.30	36.28	-1.02
Business income risk			
Std(Bus), Corr(R_s, Bus), Corr(R_f, Bus)	37.30	36.80	-0.50
All background risks			
12 variables	37.30	33.32	-3.98

Panel B: Marginal effects of background risks for various education groups

	Proportion of stock holdings at sample means (in percent)	Proportion of stock holdings when background risk variables increase one standard deviation (in percent)	Change in proportion (in percent)
No high school	32.91	29.60	-3.32
High school	36.74	32.85	-3.88
College	41.48	36.89	-4.60

Table IX Alternative Measures of Background Risks and Stock Holdings

This table reports maximum likelihood estimation of Tobit regressions using alternative measures of background risks. Coefficient estimates are reported with associated *t*-statistics in parentheses. In the first row of each specification, we report the change of proportion of stock holdings assuming all background risk variables change one standard deviation from their sample means. Column 1 uses the *backward rolling-over* which employs 8-year prior data to construct the background risk variables; Column 2 uses the *forward rolling-over* which employs 5-year posterior data to construct the background risk variables; Column 3 uses growth rate of market value of house rather than home equity to estimate the housing risk variables; Column 4 uses covariances instead of correlations; Column 5 uses excess return instead of stock returns; and Column 6 uses standard deviations interacted separately with positive and negative correlations with stock returns, (Std×Corr$^+$) and (Std×Corr$^-$). Control variables include yearly dummies and household characteristic variables used in Table VII. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y except Column 4 where *Cov (X,Y)* replaces *Corr (X,Y)*; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity (market value of house in Column 3) and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	Backward rolling-over		Forward rolling-over		Use market value of house		Use covariances		Use excess return Corr(R_s-R_f, X)		Use separately Std×Corr$^+$ and Std×Corr$^-$	
Change of stock proportion	(1)		(2)		(3)		(4)		(5)		(6)	
(in percent)	-3.28		-3.87		-2.70		-3.71		-2.75		-0.84	
# of observation	9,568		6,970		16,487		16,487		16,487		16,487	
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
Std(Lab)	-0.372	(-5.099)***	-0.271	(-4.275)***	-0.282	(-4.324)***	-0.287	(-5.03)***	-0.286	(-4.342)***		
Corr(R_s, Lab)	-0.011	(-0.412)	-0.052	(-1.884)*	-0.056	(-2.004)**	-1.001	(-1.342)				
Corr(R_f, Lab)	0.027	(1.208)	0.066	(2.276)**	0.044	(1.614)	10.165	(1.834)*				
Corr(R_s-R_f, Lab)									-0.045	(-1.697)*		
Std(Lab)×Corr(R_s, Lab)$^+$											-0.420	(-2.486)**
Std(Lab)×Corr(R_s, Lab)$^-$											0.259	(1.515)
Std(Hou)	-0.136	(-3.352)***	-0.045	(-0.890)	-0.359	(-4.256)***	-0.065	(-1.573)	-0.061	(-1.599)		
Corr(R_s, Hou)	-0.049	(-2.110)**	-0.040	(-1.594)	0.024	(0.742)	-0.550	(-1.057)				
Corr(R_f, Hou)	0.057	(2.108)**	0.024	(0.870)	-0.010	(-0.266)	9.225	(1.998)**				
Corr(R_s-R_f, Hou)									-0.017	(-0.622)		
Std(Hou)×Corr(R_s, Hou)$^+$											-0.070	(-0.662)
Std(Hou)×Corr(R_s, Hou)$^-$											0.051	(0.428)
Std(Bus)	-0.003	(-0.052)	-0.245	(-2.644)***	-0.089	(-1.852)*	-0.095	(-2.063)**	-0.095	(-2.124)**		
Corr(R_s, Bus)	0.111	(1.098)	-0.180	(-1.592)	-0.033	(-0.507)	-0.225	(-0.265)				
Corr(R_f, Bus)	0.060	(0.664)	0.019	(0.151)	0.043	(0.626)	3.845	(0.689)				
Corr(R_s-R_f, Bus)									-0.007	(-0.113)		
Std(Bus)×Corr(R_s, Bus)$^+$											-0.050	(-0.321)
Std(Bus)×Corr(R_s, Bus)$^-$											0.109	(0.746)
Corr(Lab, Hou)					0.023	(0.880)	-0.513	(-1.738)*	-0.027	(-0.910)		
Corr(Lab, Bus)					-0.116	(-1.463)	-1.069	(-1.905)*	-0.109	(-1.314)		
Corr(Hou, Bus)					0.042	(0.647)	0.257	(0.668)	-0.024	(-0.356)		

Table X
Further Robustness Checks of the Impact of Background Risks on Stock Holdings

This table reports maximum likelihood estimation of Tobit regressions. Coefficient estimates are reported with associated *t*-statistics in parentheses. In the first row of each specification, we report the change of proportion of stock holdings assuming all background risk variables change one standard deviation from their sample means. Column 1 repeats the baseline model in Column 5 of Table VII; Columns 2 and 3 use alternative measure of stock holdings variables. The dependent variable is *PflStk_2* is the proportion of stock relative to total wealth excluding home equity. The dependent variable is *PflStk_3* is the proportion of stock relative to total wealth including home equity. Column 4 adds two additional dummy variables to study the impact of the presence of a second wage earner on stock market participation; Column 5 uses a sample of single-member families; and Column 6 uses *Filter5* (which requires *Lab, Hou,* and *Bus* to be between 0.2-5) to construct background risk variables. Control variables include yearly dummies and household characteristic variables in the baseline model reported in Column 5 of Table VII. *Std(X)* is standard deviation of X; *Corr(X,Y)* is correlation between X and Y; *Lab*, *Hou* and *Bus* are, respectively, annual growth rates of labor income, home equity and business income; R_s is annual gross return of CRSP value-weighted market index; and R_f is annual gross return of the 30-day T-bill. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	Baseline model		Portsk_2		Portsk_3		Second wage earner		Single		Filter5	
Change of stock proportion	(1)		(2)		(3)		(4)		(5)		(6)	
(in percent)	-3.98		-3.59		-2.26		-3.91		-4.02		-3.41	
# of observation	16,487		16,487		16,487		16,487		3,220		16,669	
Control variables	Yes		Yes		Yes		Yes		Yes		Yes	
If a second wage earner exist							0.001	(0.036)				
If husband and wife work in same industry							-0.110	(-3.856)***				
Std(Lab)	-0.286	(-4.656)***	-0.272	(-4.922)***	-0.169	(-5.048)***	-0.280	(-4.080)***	-0.346	(-1.822)*	-0.113	(-4.276)***
Corr(R_s, Lab)	-0.056	(-2.005)**	-0.039	(-1.58)	-0.026	(-1.582)	-0.055	(-1.721)*	-0.083	(-0.945)	-0.057	(-2.027)**
Corr(R_f, Lab)	0.043	(1.467)	0.035	(1.587)	0.029	(1.804)*	0.043	(1.451)	0.091	(1.28)	0.032	(1.043)
Std(Hou)	-0.061	(-1.652)*	-0.082	(-2.505)**	-0.052	(-2.479)**	-0.059	(-1.501)	-0.202	(-1.421)	-0.043	(-2.113)**
Corr(R_s, Hou)	-0.044	(-1.539)	-0.029	(-0.999)	-0.026	(-1.489)	-0.042	(-1.550)	0.007	(0.076)	0.001	(0.048)
Corr(R_f, Hou)	0.069	(2.327)**	0.048	(1.793)*	0.031	(1.923)*	0.068	(2.218)**	0.215	(2.166)**	0.054	(1.88)*
Std(Bus)	-0.096	(-2.309)**	-0.147	(-3.661)***	-0.090	(-3.369)***	-0.095	(-2.035)**	-0.118	(-0.749)	-0.048	(-2.128)**
Corr(R_s, Bus)	-0.031	(-0.571)	-0.066	(-1.406)	-0.030	(-0.984)	-0.034	(-0.556)	-0.086	(-0.344)	0.024	(0.371)
Corr(R_f, Bus)	0.047	(0.723)	0.044	(0.808)	0.014	(0.353)	0.050	(0.799)	0.225	(0.798)	0.085	(1.489)
Corr(Lab, Hou)	-0.029	(-1.086)	-0.020	(-0.905)	-0.005	(-0.392)	-0.028	(-1.000)	0.071	(0.773)	-0.002	(-0.08)
Corr(Lab, Bus)	-0.112	(-1.446)	-0.113	(-1.486)	-0.092	(-1.97)**	-0.115	(-1.676)*	0.155	(0.318)	-0.208	(-2.516)**
Corr(Hou, Bus)	-0.026	(-0.425)	-0.024	(-0.475)	-0.023	(-0.695)	-0.026	(-0.405)	0.284	(1.094)	0.024	(0.334)

Table XI
Background Risks and Asset Returns

This table reports estimation and tests of linear stochastic discount factor models. The test assets are the Fama-French 6 size and book-to-market portfolios, the 30-day T-bill, and the 10-year government bond. R_C, R_L, R_H, and R_B are respectively growth rates of consumption, labor income, home equity, and business income. Coefficient estimates are from the two-stage efficient GMM with the associated *t*-statistic in parentheses. *HJD* is the Hansen-Jagannathan distance. To test the statistical significance of background risk factors, we fix the weighting matrix as the first-stage estimate of the full model. *J* is the minimized value of the GMM criterion function, with the corresponding *p*-value in parenthesis. The difference in *J*-statistic between a restricted model and the unrestricted model (always the full model) is reported as J_r-J_u, with *p*-value in parenthesis and the degrees of freedom equal to the number of restrictions. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel A: Background risks only

		Constant	R_L	R_H	R_B	HJD	J	J_r-J_u
(1)	Full model	116.832***	-56.248***	-85.710***	-44.315**	0.774	3.515	
		(4.866)	(-4.746)	(-4.777)	(-1.991)		(0.476)	
(2)	Excluding labor only	11.453		-15.097*	33.444	1.247	26.309***	22.794***
		(1.441)		(-1.777)	(1.075)		(0.000)	(0.000)
(3)	Excluding housing only	4.093	-3.879		1.954	1.298	25.208***	21.693***
		(0.731)	(-0.686)		(0.057)		(0.000)	(0.000)
(4)	Excluding business only	101.066***	-47.638***	-77.175***		0.826	7.164	3.649*
		(5.399)	(-4.738)	(-5.745)			(0.209)	(0.056)

Panel B: Background risks and CCAPM

		Constant	R_L	R_H	R_B	R_C	HJD	J	J_r-J_u
(1)	Full model	131.076***	-68.459***	-109.217***	-67.911**	15.635	0.747	3.433	
		(5.604)	(-3.676)	(-3.805)	(-2.034)	(0.622)		(0.330)	
(2)	CCAPM only	19.974***				-19.203**	1.188	18.396***	14.963***
		(2.609)				(-2.515)		(0.005)	(0.002)
(3)	Excluding labor only	20.374***		0.434	55.106	-22.500***	1.147	17.433***	14.000***
		(2.684)		(0.077)	(1.419)	(-2.872)		(0.002)	(0.000)
(4)	Excluding housing only	28.832***	-7.373**		29.105	-23.383***	1.108	17.832***	14.399***
		(3.490)	(-2.014)		(0.564)	(-2.852)		(0.001)	(0.000)
(5)	Excluding business only	102.288***	-49.968***	-82.151***		4.682	0.825	7.743	4.310**
		(5.739)	(-3.570)	(-3.955)		(0.252)		(0.101)	(0.038)

Table XI (continued)

Panel C: Background risks and CAPM

		Constant	R_L	R_H	R_B	R_M	HJD	J	J_r-J_u
(1)	Full model	112.402**	-54.475**	-82.218*	-39.194	-0.122	0.774	3.486	
		(2.003)	(-2.234)	(-1.860)	(-0.911)	(-0.038)		(0.323)	
(2)	CAPM only	1.390***				-5.034***	1.150	17.778***	14.292***
		(13.828)				(-7.036)		(0.007)	(0.003)
(3)	Excluding labor only	3.428		-4.050	25.294	-4.709***	1.140	7.952*	4.466**
		(0.466)		(-0.433)	(1.327)	(-4.409)		(0.093)	(0.035)
(4)	Excluding housing only	7.851	-6.843		-17.594	-5.224***	1.122	6.514	3.028*
		(1.384)	(-1.317)		(-0.530)	(-4.893)		(0.164)	(0.082)
(5)	Excluding business only	100.952***	-47.602***	-77.069***		-0.0004	0.826	4.210	0.724
		(4.145)	(-3.937)	(-4.149)		(0.000)		(0.378)	(0.395)

Panel D: Background risks and Fama-French three factors

		Constant	R_L	R_H	R_B	R_M	SMB	HML	HJD	J	J_r-J_u
(1)	Full model	210.578	-84.823	-172.018*	-96.177	10.634	-13.153**	3.696	0.515	0.913	
		(1.625)	(-1.489)	(-1.712)	(-0.839)	(0.984)	(-2.526)	(0.607)		(0.339)	
(2)	FF3 factors only	1.965***				-6.113***	-4.181	-5.091***	0.909	12.816**	11.903***
		(7.088)				(-4.624)	(-1.129)	(-3.385)		(0.012)	(0.008)
(3)	Excluding labor only	28.489**		-32.619*	-12.633	-2.790	-14.603	-4.641	0.761	4.595	3.682*
		(2.024)		(-1.781)	(-0.305)	(-1.327)	(-1.620)	(-1.531)		(0.100)	(0.055)
(4)	Excluding housing only	-2.477	6.991		-25.283	-5.856***	-8.013	-6.250***	0.859	6.225**	5.312**
		-(0.261)	(0.703)		(-0.601)	(-4.297)	(-1.166)	(-2.805)		(0.044)	(0.021)
(5)	Excluding business only	112.662***	-40.659***	-98.357***		3.730	-14.829**	1.181	0.642	2.331	1.418
		(3.597)	(-2.683)	(-3.768)		(1.019)	(-2.404)	(0.252)		(0.312)	(0.234)

Table XII
Robustness Tests of Importance of Background Risks on Asset Returns Using CES Data

This table reports estimation using CES data and the test assets are the Fama-French 25 size and book-to-market portfolios, the 30-day T-bill, and the 10-year government bond. R_C, R_L, R_H, and R_B are respectively growth rates of consumption, labor income, home equity, and business income. *HJD* is the Hansen-Jagannathan distance. Coefficient estimates are from the two-stage efficient GMM with the associated *t*-statistic in parentheses. To test the statistical significance of background risk factors, we fix the weighting matrix as the first-stage estimate of the full model. *J* is the minimized value of the GMM criterion function, with the corresponding *p*-value in parenthesis. The difference in *J*-statistic between a restricted model and the unrestricted model (always the full model) is reported as J_r-J_u, with *p*-value in parenthesis and the degrees of freedom equal to the number of restrictions. "***", "**" and "*" denote statistical significance at the 1, 5 and 10 percent levels, respectively.

	Constant	R_L	R_H	R_B	R_C	R_M	SMB	HML	HJD	*J*	J_r-J_u
Background risks only	-46.823***	-41.202***	-16.147***	-8.149					4.570	19.702	
	(6.056)	(-5.196)	(-4.443)	(-0.816)						(0.660)	
Background risks and CCAPM	-2.794	-21.142**	-24.830***	2.518	33.619***				4.525	19.687	
	(-0.238)	(-2.200)	(-7.645)	(0.181)	(5.232)					(0.603)	
	0.481				0.422				4.650	90.099***	70.413***
	(0.065)				(0.063)					(0.000)	(0.000)
Background risks and CAPM	49.900***	-44.871***	-16.660***	3.128		-3.483***			4.534	19.622	
	(5.949)	(-5.478)	(-4.923)	(0.251)		(-3.453)				(0.607)	
	1.181***					-3.093***			4.623	74.094***	54.472***
	(12.167)					(-5.595)				(0.000)	(0.000)
Background risks and Fame-French three factors	-28.844**	-18.960	-18.973***	22.874		-5.528***	0.889	-4.693***	4.493	19.754	
	(2.356)	(-1.537)	(-5.096)	(1.069)		(-5.921)	(0.619)	(-3.253)		(0.473)	
	1.588***					-4.875***	0.181	-4.668***	4.574	47.503***	27.750***
	(10.907)					(-7.739)	(0.268)	(-5.212)		(0.002)	(0.000)

Figure I
Cross-Sectional Variation of Background Risk Factors

This figure presents the cross-section distributions of 12 background risk variables in 1993. Only households exposed to corresponding risks are included. The three panels, from left to right, in first (second, and third) row represent the standard deviation of growth rates of labor income (home equity, and business income), correlation between growth rates of labor income (home equity, and business income) and stock returns, and correlation between growth rates of labor income (home equity, and business income) and risk-free rates. The three panels in the last row stand for correlation between growth rates of labor income and growth rates of home equity, correlation between growth rates of labor income and growth rates of business income, and correlation between growth rates of home equity and growth rate of business income.

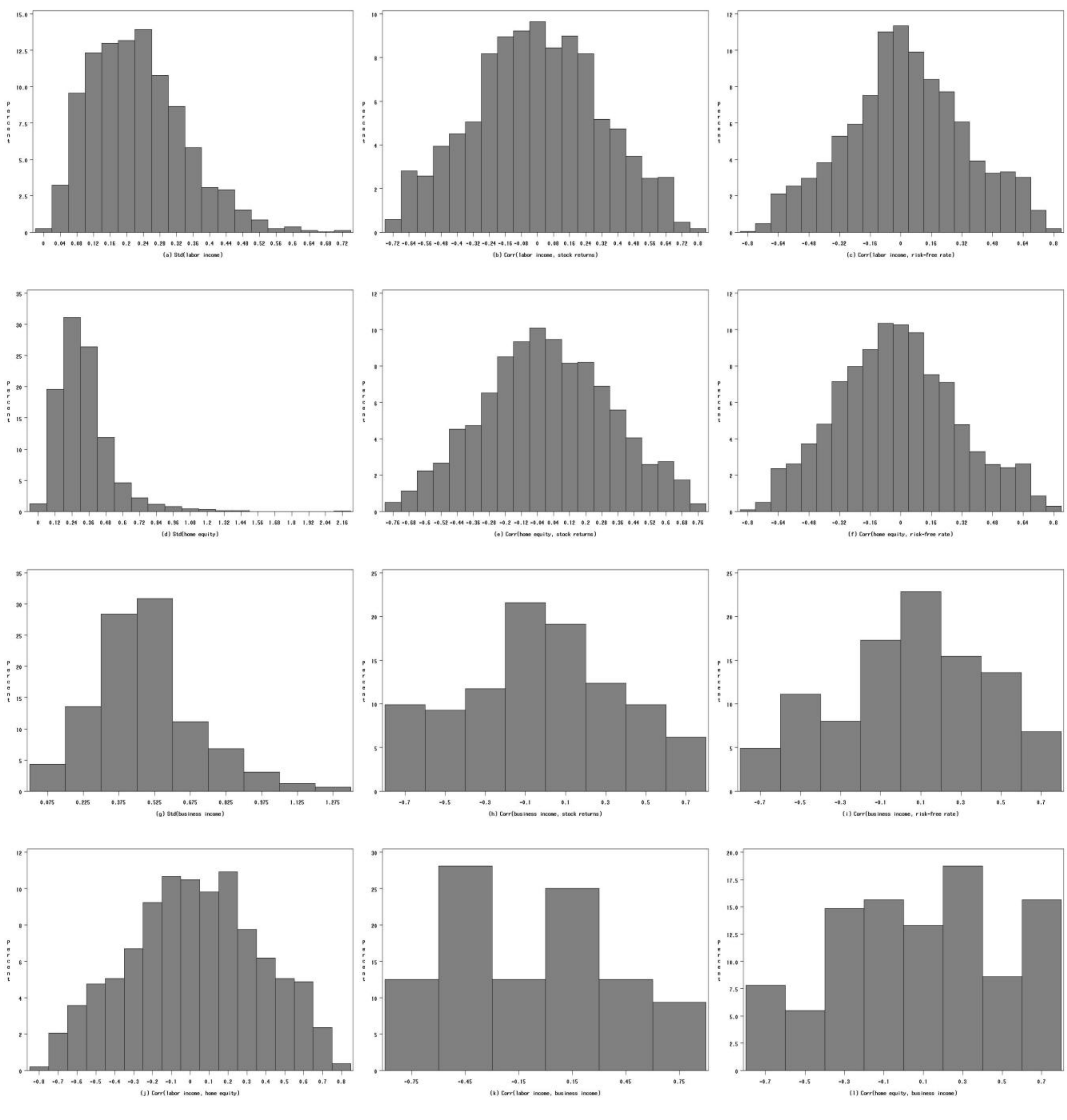

Figure II
The Impact of Education on the Relationship between Background Risks and Participation

This figure depicts the impact of education on the relationship between background risks and stock market participation. The solid vertical line represents the sample mean and the broken vertical line displays the increase of one standard deviation from the sample mean.

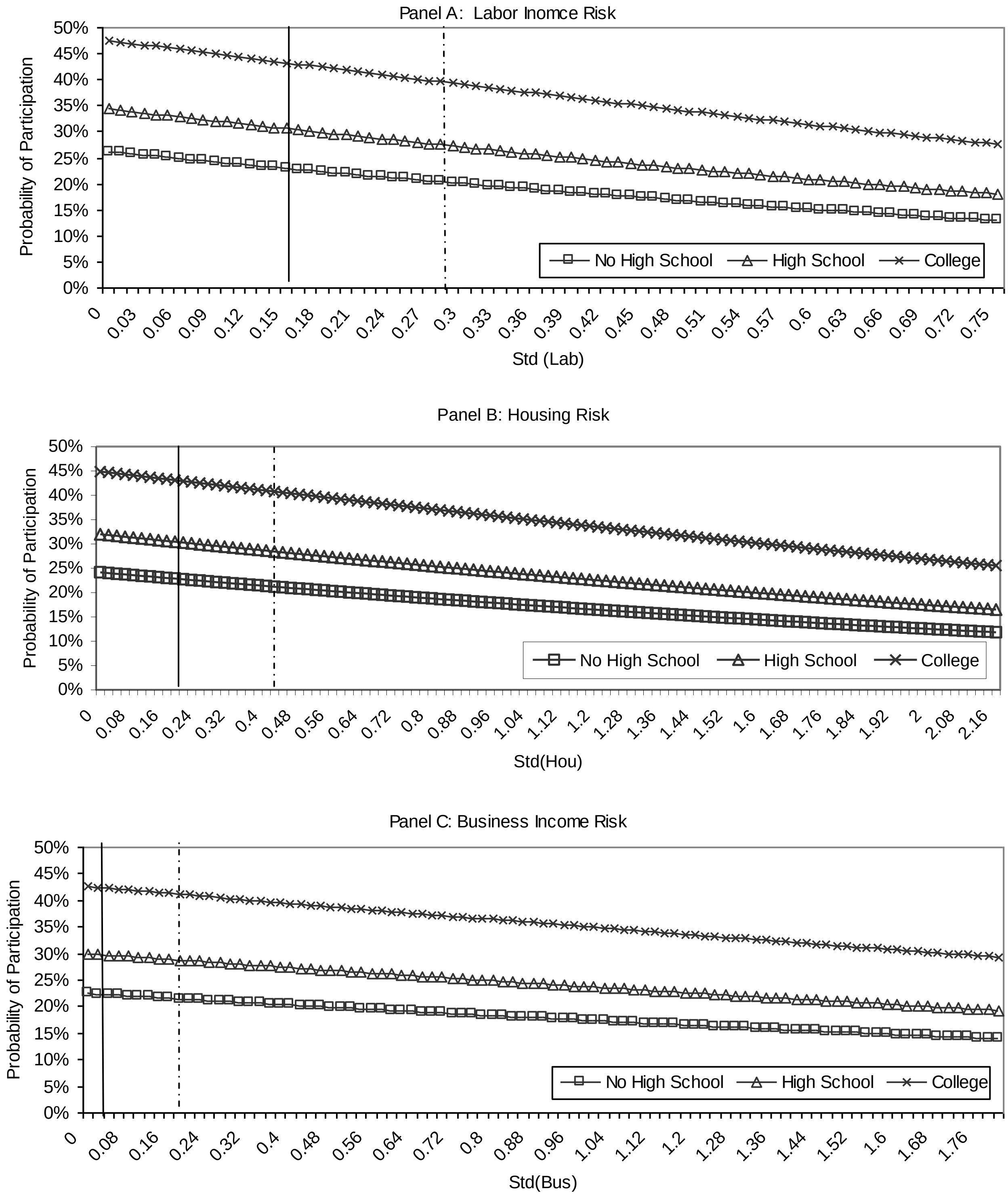

Figure III
The Impact of Education on the Relationship between Background Risks and Stock Holdings

This figure depicts the impact of education on the relationship between background risks and the proportion of stock holdings. The solid vertical line represents the sample mean and the broken vertical line displays the increase of one standard deviation from the sample mean.