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Heterogeneous Background Risks and Portfolio Choice: Evidence from Micro-level Data

We construct a set of household-level background risk variables to capture the covariance structure of three nonfinancial assets and two financial assets. These risks are in general statistically significant and economically important for a household's stock market participation and stockholdings. A one-standard-deviation increase in background risks reduces the participation probability by 11% and the stockholdings-to-wealth ratio by 4%. The volatilities of labor income, housing value, and business income reduce a household's participation and stockholdings. A household with labor income highly correlated with stock (bond) returns is less (more) likely to invest in stock.

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This paper examines how risks sourced from nontradable/illiquid assets, such as labor, housing, and private business, affect stock market participation and portfolio allocation decisions of a household. Following Heaton and Lucas (2000a), we term these nonfinancial market risks as background risks. Campbell (2006), in his AFA Presidential Address, advocates the importance of the existence of nontradable assets (human capital) and illiquid assets (owner-occupied house) in determining a household's asset allocation.[1] Standard asset pricing theory suggests that in complete markets, background risks should have no influence on an investor's portfolio choice because these risks can be fully insured by trading financial securities. However, when markets are incomplete such that these risks are not entirely spanned by financial assets, a household will alter its portfolio to offset its idiosyncratic background risks (e.g., Constantinides and Duffie 1996, Heaton and Lucas 1996, 2000b, Duffie et al. 1997, Viceira 2001, Cochrane 2008). Consequently, a household's optimal portfolio is determined by its exposure to background risks. This paper aims to provide some insight on whether and how the *heterogeneity* of background risks across households can help explain the large fraction of nonstockholders, that is, the limited stock market participation puzzle (Mankiw and Zeldes 1991) and the enormous cross-sectional variation in households' stockholdings.

The importance of background risks on asset allocation has received considerable attention in the financial economics literature. While numerous papers have studied this topic, there is still much disagreement on whether the existence of heterogeneous background risks can help to explain the observed variation of stock investments among households. Theoretical models and numerical simulation studies are sensitive to the assumptions on the properties of nonfinancial income/assets (Heaton and Lucas 1996, 1997, 2000a, Haliassos and Michaelides 2003, Storesletten, Telmer, and Yaron 2004, Cocco, Gomes, and Maenhout 2005, Benzoni, Collin-Dufresne, and Goldstein 2007, Krueger and Lustig 2010). Research using microlevel data is in paucity, partly due to the difficulty of estimating background risks at the household level. Prior studies yield mixed results, probably due to the difference of selected samples (Haliassos and Bertaut 1995, Heaton and Lucas 2000b, Vissing-Jorgensen 2002, Massa and Simonov 2006, Angerer and Lam 2009). This paper uses a long panel of a large sample of U.S. households to study the impact of three nontradable/illiquid assets, namely, labor, housing, and private business, on a household's stock investment decisions. To the best of our knowledge, our paper is the first to comprehensively examine these three backgrounds risks, which are advocated and studied separately in the prior literature.

Motivated by the mean-variance analysis (e.g., Davis and Willen 2002, Flavin and Yamashita 2002, Cochrane 2008), we characterize the *variance–covariance structure*

1. Heaton and Lucas (2000a), Campbell (2006), and Cochrane (2006) provide excellent reviews of this literature.

generated by the three nonfinancial assets and two financial assets. Specifically, we use the annual growth rates of labor income, home equity, and business income to proxy returns from human capital, housing, and private business, respectively. For each household, we estimate the standard deviations of these growth rates. We further calculate the correlations of these growth rates with stock returns and with the risk-free rate. We then use a Logit regression to examine how these background risk variables impact a household's stock market participation, and a Tobit regression to study their effects on a household's stockholdings.[2] We extend the empirical literature on the importance of background risks in a household's portfolio decision in the following ways:

First, by jointly studying the three types of background risks, we are able to quantitatively evaluate their relative importance. We show that all three types of background risks are in general statistically significant and economically important. The existence of labor income or owner-occupied house encourages stock investment whereas the existence of private business reduces stock investment. If all the background risk variables shift one standard deviation from their sample means, the probability of stock participation decreases by 10.82% and the stock holding proportion to financial wealth drops by 3.69%.[3] Given that the sample average of stock participation is 38.8% and the average stock holding proportion to financial wealth is 20.7%, we argue that the economic impact of background risks on the cross-sectional variation of portfolio choice is substantial. In terms of relative importance, labor income is the most important, followed by housing, while the impact of business income is limited.[4]

Second, we find strong evidence in support of the hedging motive (e.g., Viceira 2001), suggesting that investors alter their portfolios to hedge their labor income risk. The volatility of labor income growth significantly reduces stock market participation and the proportion of wealth invested in stocks, consistent with the notion that risky labor income reduces investment in risky assets. Moreover, a household with stock-like labor income (i.e., labor income is highly correlated with stock returns) is less likely to participate in stock market and allocates a smaller portion of wealth to stocks. In contrast, a household with risk-free-like labor income (i.e., labor income is highly correlated with the risk-free asset) is more likely to participate in stock market and invests more wealth in stocks. These findings help to reconcile the contradicting results provided by prior numerical simulations. For example, Heaton and Lucas

2. As a robustness check, we also employ the Heckman selection model, and OLS regression for a subsample consisting of stockholders.

3. This finding seems to suggest that background risks are more important for stock market participation than for stockholdings. Further results using the Heckman selection model and OLS regressions of stockholders confirm this finding.

4. This finding is different from Heaton and Lucas (2000b), who show that business income risk is more important than labor income risk. The discrepancy could be due to the fact that we use a sample of ordinary households, most of whom do not have a private business while they use the sample of wealthy households with a private business.

(1996) argue that the inclusion of labor income risks is in general unable to explain the observed low stock investment by households. Their model assumes a low correlation between labor income and stock returns and therefore labor income works like a safe asset that stimulates stock investment. Benzoni, Collin-Dufresne, and Goldstein (2007) assume that labor income and stock dividends are cointegrated, and thus labor income and stock returns are highly correlated in the long run. Consequently, the stock-like labor income reduces stock investment. In addition, our findings are different from Massa and Simonov (2006), who find that households tend to hold stocks that are geographically and professionally close to them. Their finding is against the hedging motive but is in favor of the familiarity and home bias hypothesis. Our findings support the hedging motive and are robust after controlling for industry and state fixed effects.

Third, we examine the impact of owner-occupied housing on stock investment. We find that the volatility of home equity growth significantly reduces stock market participation and stockholdings. Owner-occupied housing functions more like "bond-like" asset. The correlation of home equity growth with the risk-free rate has a positive impact on participation and stockholdings, while the correlation of home equity with stock returns has no significant impact. This finding echoes the notion that housing investment is a good hedge of inflation risk (Goetzmann and Valaitis 2006). To our knowledge, this is the first paper that uses household-level data to directly estimate the impact of correlation between housing value and financial assets on stock investment. Our finding compliments the studies advocating the importance of owner-occupied housing on stock investment (Flavin and Yamashita 2002, Cocco 2005, Yao and Zhang 2005).

Fourth, we examine the interactive effect of education and background risks on stock participation and stockholdings. Mankiw and Zeldes (1991) and Vissing-Jorgensen (2002), among others, suggest that education is a proxy for transaction costs and find that education has a significant impact on a household's portfolio decision. We extend this research by finding that the change of background risks has a more pronounced effect on more highly educated households. Specifically, when all background risk variables increase by one standard deviation from their sample means, a household whose head has a college degree will decrease its likelihood to participate in the stock market by 12.53% and reduce its proportion of stockholdings by 4.24%, whereas a household whose head has no high school education will decrease its likelihood of participation by only 8.43% and reduce its stockholdings by 3.07%.

Overall, we empirically demonstrate the importance of background risks in determining a household's portfolio choice. We document the enormous variation of background risks across households, and argue that this heterogeneity helps to explain the limited stock market participation puzzle and the observed cross-sectional variation in stockholdings.

The remainder of this paper is organized as follows. Section 1 reviews the literature and describes our empirical design. Section 2 details the data with summary statistics. Section 3 presents the empirical results and Section 4 concludes.

1. RELATED LITERATURE AND EMPIRICAL MODEL

In this section, we first discuss the construction of background risk factors. Based on theoretical studies in the prior literature, we generate testing hypotheses about the predicted impacts of background risk factors on portfolio choice. We then specify our empirical model and discuss econometric issues and measurement errors. The definition of our background risk variables and their predicted (expected) impacts on stock investment are summarized in Table 1.

1.1 Background Risks Measures

We aim to develop an empirical model that allows us to examine how the heterogeneity of background risk exposures among households affects the cross-sectional variation of stock investment. More importantly, we want to jointly consider three types of nonfinancial assets—labor, housing, and private business. While each of these background risks has been separately investigated in the literature, to the best of our knowledge, no study has jointly considered all three types of risks in an optimizing model. Developing a theoretical model of optimal portfolio choice in the presence of the three types of background risks is beyond the scope of this paper. We therefore borrow the insights from the prior literature to build a reduced-form empirical model to test the predicted impacts of these risks on household stock investment. We aim to examine whether these background risks are quantitatively important to a household's stock investment. Specifically, we investigate whether the cross-household variation of background risks can help to explain the large fraction of nonstock investment, and the observed enormous cross-sectional variation in households' stockholdings.

We consider an economy with three types of nonfinancial assets: labor, housing, and private business, and two financial assets: risky stock and risk-free bond. Motivated by the standard mean-variance framework, we argue that the optimal portfolio is determined by the variance–covariance structure of returns of these assets. Assuming that the investor cannot trade nonfinancial assets, optimal portfolio choice involves selecting a combination of stock and risk-free asset to minimize the overall risk exposure to all risky assets. A household would choose a less risky portfolio if it is exposed to more unfavorable background risks. Assuming that short sale is prohibited, zero stockholding (i.e., nonstock market participation) can yield as an optimal choice if a household is highly exposed to background risks. Therefore, a household exposed to more unfavorable background risks is expected to allocate less wealth to stocks or is less likely to participate in the stock market.

This hypothesis is motivated by a large body of literature, which provides theoretical predictions on how background risk affects portfolio choice. For example, Constantinides and Duffie (1996) and Viceira (2001) suggest that investors alter stock investment to hedge labor income risk. Cocco (2005), Yao and Zhang (2005), and Flavin and Yamashita (2002) show that the existence of risky housing reduces stock investment. Empirical studies based on numerical calibration show that the existence of background risks cannot fully explain the enormous variation of stockholdings

TABLE 1

Definition and Expected Impact of Background Risk Varaibles

Variable	Definition	Predicted sign
Labor income risk		
D_Lab	Dummy variable equal to 1 if a household has labor income in a given year	+
$Std(Lab)$	Standard deviation of annual growth rate of labor income	−
$Corr(R_s, Lab)$	Correlation between the annual growth rate of labor income and stock return	−
$Corr(R_f, Lab)$	Correlation between the annual growth rate of labor income and risk-free rate	+
Housing risk		
D_Hou	Dummy variable equal to 1 if a household owns house in a given year	+
$Std(Hou)$	Standard deviation of annual growth rate of home equity	−
$Corr(R_s, Hou)$	Correlation between the annual growth rate of home equity and stock return	−
$Corr(R_f, Hou)$	Correlation between the annual growth rate of home equity and risk-free rate	+
Business income risk		
D_Bus	Dummy variable equal to 1 if a household has business income in a given year	−
$Std(Bus)$	Standard deviation of annual growth rate of business income	−
$Corr(R_s, Bus)$	Correlation between the annual growth rate of business income and stock return	−
$Corr(R_f, Bus)$	Correlation between the annual growth rate of business income and the risk-free rate	+
Correlations among three types of background risks		
$Corr(Lab, Hou)$	Correlation between the annual growth rates of labor income and home equity	−
$Corr(Lab, Bus)$	Correlation between the annual growth rates of labor and business income	−
$Corr(Hou, Bus)$	Correlation between the annual growth rates of home equity and business income	−

Note: This table presents the definition of background risk variables and their expected impact on stock market participation and stockholdings.

across households, especially the large fraction of nonstockholding (e.g., Heaton and Lucas 1996, 1997, 2000a, Haliassos and Michaelides 2003, Cocco, Gomes, and Maenhout 2005). Research using microlevel data in general confirms the importance of background risks but yields mixed results regarding how background risks affect portfolio choice. Haliassos and Bertaut (1995) demonstrate that investors in high-risk occupations hold less stock. Vissing-Jorgensen (2002) finds that a larger standard deviation of nonfinancial income reduces stock investment, but the covariance of income and stock returns has no impact. Heaton and Lucas (2000b) show that investors invest less in stocks when they face more volatile business income, but labor income risk does not significantly affect stock investment. Angerer and Lam (2009) report that a permanent income shock reduces stock investment but a transitory income shock does not. Guiso, Jappell, and Terlizzese (1996) and Hochguetel (2002), respectively, use data from Italy and the Netherlands to show that households exposed to higher labor income risk hold safer portfolios. Chen, Yao, and Yu (2007) and Dimmock (2012) argue that background risks also affect asset allocation of institutional investors. Eiling (2013) uses the industry-level labor income to show that human capital affects the cross-sectional stock returns.

Our approach is to construct a set of factors that capture the "*unfavorable*" background risk exposures. Motivated by the mean-variance framework, we consider the covariance of returns between financial and nonfinancial assets. One big challenge in this literature is that returns of these nonfinancial assets are not observable. Following Jagannathan and Wang (1996), Flavin and Yamashita (2002), and Heaton and Lucas (2000b), we use annual growth rates of labor income, home equity, and business income to proxy their respective returns.[5] We then estimate the covariance between these annual growth rates and returns of financial assets. Our baseline model consists of 12 background risk factors, which can be grouped into four categories.

First, we consider the standard deviations of growth rates of labor income, home equity, and business income, denoted by $Std(Lab)$, $Std(Hou)$, and $Std(Bus)$, respectively. Previous research shows that the volatility of additional risky income reduces the demand for stock (Guiso, Jappell, and Terlizzese 1996, Heaton and Lucas 2000a, 2000b, Hochguertel 2002, Vissing-Jorgensen 2002, Angerer and Lam 2009). Hence, we expect each of these variables to have a negative effect on the proportion of stockholdings and on stock market participation.

Second, we calculate the correlations between the three growth rates and stock returns, denoted by $Corr(R_s, Lab)$, $Corr(R_s, Hou)$, and $Corr(R_s, Bus)$, respectively. The correlation between a background risk shock and stock returns is potentially important to a household's portfolio choice (Viceira 2001, Benzoni, Collin-Dufresne, and Goldstein 2007). For example, a positive correlation between labor income and stock returns reduces a household's willingness to hold stock because labor income substitutes for stock. On the other hand, a negative correlation between labor income and stock returns encourages stockholdings 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.

Third, we include correlations between the three growth rates and the risk-free rate, denoted by $Corr(R_f, Lab)$, $Corr(R_f, Hou)$, and $Corr(R_f, Bus)$, respectively. We expect each of these variables to have a positive effect on stock market participation and stockholdings. The measure introduced here captures the

5. We consider labor income as dividends of the unobserved human capital, growth of home equity as returns on housing investment, and business income as dividends of business investment.

comovement of a background risk variable and the real interest rate, which is primarily driven by unexpected inflation. This design is to test whether bond-like income reduces the pressure on precautionary savings, thereby encouraging investment in stocks (e.g., Cocco, Gomes, and Maenhout 2005). Intuitively, a household with stable labor income which increases with inflation (e.g., those working in the public sector) is more likely to invest in risky stocks because its labor income risk is lower.

Fourth, we include the correlations of the returns among the three nonfinancial assets, denoted by *Corr*(*Lab*, *Hou*), *Corr*(*Lab*, *Bus*), and *Corr*(*Hou*, *Bus*). We expect these variables 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.

Overall, our background risk measures consist of 12 variables. We consider a linear regression of stock investment on these variables. We further include three dummy variables, denoted by *D_Lab*, *D_Hou*, and *D_Bus* that, respectively, indicate if a household has labor income, housing, and business income in a given year to capture the change of background risks over the life cycle. The empirical model is specified as follows:

$$\begin{aligned} StockInvt_{i,t} = {} & a_0 + a_1 Std(Lab_{it}) + a_2 Corr(R_{st}, Lab_{it}) \\ & + a_3 Corr(R_f, Lab_{it}) \\ & + a_4 Std(Hou_{it}) + a_5 Corr(R_{st}, Hou_{it}) + a_6 Corr(R_{ft}, Hou_{it}) \\ & + a_7 Std(Bus_{it}) + a_8 Corr(R_{st}, Bus_{it}) + a_9 Corr(R_f, Bus_{it}) \\ & + a_{10} Corr(Lab_{it}, Hou_{it}) + a_{11} Corr(Lab_{it}, Bus_{it}) \\ & + a_{12} Corr(Bus_{it}, Hou_{it}) \\ & + a_{13} D\_Lab_{it} + a_{14} D\_Hou_{it} + a_{15} D\_Bus_{it} + \delta Controls_{it} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where subscripts i and t denote household and year, respectively; *StockInvt* is either a binary variable of stock market participation or a ratio of stock to wealth; *Lab*, *Hou*, and *Bus* are growth rates of labor income, home equity, and business income, respectively; R_s and R_f are gross return rates of a stock market portfolio and the risk-free asset, respectively; and *Controls* is a vector of control variables.

1.2 Control Variables

We follow the prior literature to add control variables. Numerous papers document that race, income, wealth, and education each has a positive impact on stock market participation (e.g., Mankiw and Zeldes 1991, Vissing-Jorgensen 2002, Hong, Kubik, and Stein 2004, Campbell 2006). The level of education is regarded as a proxy for fixed entry and transaction costs and is found to be positively significantly related to stock market participation in previous studies. We use two dummy variables, *HSchool* (equal to 1 if the head of household has a high school education) and *College* (equal to 1 if the head of household has a college education), to control for education effects. We expect *Log*(*Age*), the log transformation of the age of the household head, to have a positive sign and $(Log(Age))^2$ to have a negative sign to capture the hump-shaped life-cycle pattern of stockholdings (Jagannathan and Kocherlakota 1996).

Flavin and Yamashita (2002) suggest that the house-to-net wealth ratio influences a homeowner's portfolio composition. We hence include *Log*(*HsValue*)—the log transformation of market value of owner-occupied house. 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 *Log*(*Mortgage*)—the log transformation of unpaid mortgage balance as a control variable. Vissing-Jorgensen (2002) documents that the level of nonfinancial income is positively related to stock market participation. We use *Log*(*LabIncome*)—the log transformation of labor income as a control variable. To capture the dynamics of labor income risk, we control for unemployment shock by adding a dummy variable *Unemployment*, which equals 1 if the head of household lost its job in a given year, and 0 otherwise. We further add a dummy variable that equals 1 if husband and wife work in the same industry, and 0 otherwise.

1.3 Econometric Issues and Measurement Errors

We run regressions that relate stock market participation (*DumStk*) and the proportion of stock relative to wealth (*PtfStk*) to a set of explanatory variables. Since *DumStk* is a discrete-choice variable that equals 1 if a household participates in the stock market, and 0 otherwise, we employ the Logit model specified below:

$$\begin{aligned} Prob(DumStk = 1) &= F(\beta' X) \\ Prob(DumStk = 0) &= 1 - F(\beta' X) \\ \text{where } F(\beta' X) = \frac{e^{\beta' X}}{1+e^{\beta' X}}. \end{aligned} \tag{2}$$

Given that a large fraction of households hold no stocks, ordinary least squares (OLS) regression is not suitable to study the proportion of stockholdings. Several theoretical papers (e.g., Orosel 1998, Haliassos and Michaelides 2003, Guo 2004, Gomes and Michaelides 2005, Ball 2008) have treated stock market nonparticipation (i.e., zero stockholding) as part of a household's portfolio choice. In this framework, agents maximize their lifetime utility subject to a budget constraint that includes a participation cost. Consistent with this line of reasoning and following the empirical methodology employed by Guiso, Jappell, and Terlizzese (1996), Hochoguertel

(2002), and Cocco (2005), we adopt a Tobit model where the lower limit is 0 (a household holds no stock).[6] The Tobit model is specified as follows:

$$PtfStk = \begin{cases} \beta' X + \varepsilon, & \text{if } PtfStk > 0 \\ 0, & \text{if otherwise.} \end{cases} \tag{3}$$

An alternative method of estimating the determinants of stockholdings is the Heckman selection model. The selection model suggests that households first make a decision on whether to participate in the stock market and then, conditional on participation, choose the optimal stockholdings related to wealth.[7] Vissing-Jorgensen (2002) employs a Heckman model with a fixed participation cost. Therefore, for a robustness check, we consider the Heckman model, as specified below:

$$\begin{aligned} &\text{Participation equation: } S^* = \beta' X + \upsilon, DumStk = \begin{cases} 1, \text{if } S* > 0 \\ 0, \text{otherwise} \end{cases} \\ &\text{Stockholding equation: PtfStk } = \beta' X + \varepsilon, \text{ observed if } DumStk = 1, \end{aligned} \tag{4}$$

where S^* is a latent variable about stock market participation. We only observe a binary variable of *DumStk* and *PtfStk* when a household chooses participation in the stock market. In estimation, we include the lagged stock participation decision and lagged stockholdings as additional explanatory variables in the participation and stockholding equations, respectively.

We further consider an OLS regression using a truncated sample consisting of only stockholders. We include households that hold stock in the current year or ever held stocks in previous years. We then run the OLS regression for this subsample to shed light on how background risks affect stockholdings conditional on participation.

Given a large number of households and a limited number of years 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 estimate the standard errors with clustering by households 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).[8] Massa and Simonov (2006) argue that households tend to hold

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

7. One challenge of the Heckman selection model is to find valid instrumental variables that are related to stock market participation but not to stockholdings conditional on participation. However, in the empirical tests, we find that total wealth is significantly related to portfolio shares. Furthermore, education, which is regarded as a proxy for fixed cost for stock market participation is also significantly related to stockholdings. Hence, it is hard to identify good instrumental variables. Therefore, we report Tobit as the baseline model, and provide the Heckman and OLS models for robustness checks.

8. Petersen (2009) shows that given a large number of firms (households in our case) 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).

stocks that are geographically and professionally close to them. We hence control for industry and state fixed effects. The industry dummies are based on the major industry in which the head of household works.[9]

In our baseline model, we assume that background risks are *time invariant*. In reality, a household's background risks may change over the life cycle. As a robustness check, we consider *time-varying* background risk factors using rolling-over windows (see estimation details in Section 2). Using a rolling-over window increases measurement errors because it uses a shorter period rather than the full sample to estimate the standard deviations and correlations.

We further consider a cross-sectional regression. In particular, we regress the time average of stockholdings relative to wealth on the time-invariant background risk factors and the time averages of other control variables. As for stock market participation, we sum the stock participation dummy variable over years and divide this variable by the number of years when the household appears in the sample. We classify a household as a stock market participant if it holds stocks in more than half of the time in the sample period.

We assume that the background risk variables are predetermined because adjustments in labor supply, housing and private business are much harder than adjustments in stock investment. In principle, background risk variables can be endogenously determined (e.g., Bodie, Merton, and Samuleson 1992, Roussanov 2004) by risk attitude and investment into human capital. We do not control for risk attitude in our baseline model.[10] However, we believe that our specification is robust to the existence of endogeneity as endogeneity would bias our results toward not finding the expected relationship between the background risk variables and the investment choice. For example, a more risk-averse household would 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 stockholdings, our regressions provide a conservative estimate of the impacts of these background risk factors on stock market participation and stockholdings.

2. DATA AND DESCRIPTIVE STATISTICS

Our data are drawn from the Panel Study of Income Dynamics (PSID), which is an annual survey maintained by the University of Michigan. The surveys are conducted

9. The estimation of Logit and Tobit models is sensitive to the distributional assumptions about the error terms. In unreported robustness check, we also calculate nonparametric t-statistics using bootstrapped standard errors.

10. The PSID provides data on risk tolerance in the 1996 survey. Adding the risk tolerance variable in our regressions does not change our basic results. This test is not reported but is available upon request.

every year from 1968 to 1997 and every other year after 1997.[11] We utilize the PSID surveys from 1975 to 2009. The long panel with detailed demographic, income, and housing data allows us to construct various measures of income and housing risks. A limitation of the PSID data is that detailed wealth composition such as stockholdings is provided in the Wealth Supplement Survey, which was conducted once every 5 years from 1984 to 1999 and then every other year after 1999. Therefore, the financial asset holdings information is available for these 9 years (1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007, and 2009). Since questions related to income and wealth in the PSID data are retrospective[12] (e.g., those asked in 1994 refer to the 1993 calendar year), we refer our sample years as 1983, 1988, 1993, 1998, 2000, 2002, 2004, 2006, and 2008. We use the CRSP NYSE/AMEX/NASDAQ value-weighted market index return as a proxy for risky stock return, and the 30-day T-bill return as a proxy for the risk-free rate. All monetary variables are in constant 1992 dollars using the Consumer Price Index obtained from CRSP.

2.1 Stock Values and Stock Participation

In PSID, stock market participation (denoted by *DumStk*) and the value of stockholdings are self-reported in the surveys. Unfortunately, PSID changed the definition of stock in 1999. Up to the 1997 survey, reported stockholdings include stocks held directly and held in mutual funds, investment trusts, and pension funds. Since the 1999 survey, the value of stockholdings in pension funds is excluded. This change in definition causes an inconsistency 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.[13]

Previous studies suggest that the properties of portfolio composition relative to demographic variables are sensitive to the way wealth is measured (see, e.g., Heaton and Lucas 2000a). In computing the proportion of stock value relative to wealth,

11. 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 the U.S. population. The PSID is designed to capture demographic and income dynamics of U.S. households over a long period. Households that were selected in the 1968 survey have been resurveyed thereafter. The split-off households (households established by children of the originally selected families) have been added to the sample each year.

12. Most surveys are conducted in the springs and therefore income and wealth data are for the previous years.

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

we consider three definitions of wealth: (i) total family financial wealth—the sum of stock, savings, and bond values; (ii) total family wealth without home equity—the sum of values of financial assets, business, vehicles, and real estate 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 estate 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. These three measures are denoted as *PflStk_1*, *PflStk_2*, and *PflStk_3*, respectively. Our main measure is the stockholding relative to financial wealth (*PflStk_1*). In robustness checks, we also consider *PflStk_2* and *PflStk_3* and obtain similar results.

2.2 *Background Risk Measures*

Time-invariant background risk measures. To create individual background risk measures, we use the 1976–2009 PSID Family Income Files. We generate the 21-year consecutive time series (1976–97) of annual growth rates of labor income, housing value, and business income. Unlike the financial assets that are reported only in the PSID Wealth Supplement Survey, the market value of house and unpaid mortgage are provided in the PSID Family Income Survey. For the period 1997–2009, PSID provides data every other year. We estimate the annual growth rates by dividing the 2-year growth rates by two. Overall, we obtain annual growth rates of income and housing value for 27 years.[14] Since 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. We define the head of household business income as the sum of business income from assets and business income from labor.[15] 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 a 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) to redo our regressions.[16] Using the annual growth rates, we calculate for each household the standard deviations of labor income, home equity, and business income, that is, *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*).

14. In unreported robustness tests, we construct the background risk variables using data before 1997 when we have consecutive annual observations and we obtain similar results.

15. Alternatively, we define the head of household business income as business income from assets only, and include business income from labor in the head of household labor income. Under this definition, none of our results change significantly. The results are available upon request.

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

To minimize measurement 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 3 years of gross growth rates ranging between 0.5 and 2 to calculate the standard deviation and correlation statistics.[17] 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 and 0.2–5 ranges, and denote these filters by *Filter3*, and *Filter5*, respectively.

Note that these filters do not delete households with extraordinary changes of background risks, but they only require a household to have reasonable annual growth rates for at least 3 years to be included in our sample. For example, a household may continuously provide labor income but suddenly reports a 0 labor income in year t due to unemployment. This will yield a 0 gross growth rate of labor income in year t, and an infinite growth rate in year $t + 1$. We will exclude the observations in years t and $t + 1$ and use the observations for the rest of the years to estimate its labor income risk. We then set the labor income risk variable to 0 for years t and $t + 1$. We use a dummy variable "if head has a job" to control for households without labor income risk. These households could be students, retirees, or self-employed people. We use a dummy variable "if head is unemployed" to control for unemployment shock. For households that do not have a house or private business, we set the housing risk or business risk to 0. We include dummy variables "if owns a house" and "if owns a business" in our regressions.

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 not 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.

First, we consider a household that makes its portfolio choice based on its current and past experience of income and housing value fluctuations, so we employ a backward rolling-over measure. These measures are calculated using prior 8-year data. For example, 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 5-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

17. 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 and we obtain similar results.

of years used in calculation increases estimation errors. Thus, our main results are based on the time-invariant measures and we provide a robustness check based on the two rolling-over measures.

2.3 Descriptive Statistics

Combining the estimated background risk measures with stockholding data from the PSID Wealth Supplement Survey, we construct a 9-year unbalanced panel of 4,756 households with 22,610 year-household observations. We confirm the well-known fact of limited stock market participation. The participation rates have significantly increased over the past two decades from 28% in 1983 to 44% in 2008. However, more than half of the U.S. households still do not hold any stocks. The average ratio of stocks to financial wealth generally increases from 43% in 1983 to 51% in 2008, with two dips during 2000–02 and in 2008 that reflect, respectively, the Internet bubble crash and the subprime mortgage crisis.[18]

In Figure 1, we present the cross-sectional variation of our 12 background risk variables. In each panel, we display the estimated density using the sample of households who are exposed to the corresponding risks and the normal density curve for ease of comparison. There is a large dispersion for each of these risk factors. The distribution of the standard deviation of labor income growth is skewed to the right, indicating that most households are exposed to moderate labor income risk while a small fraction is subject to large labor risk. A similar pattern is observed for the standard deviation of housing growth. We see a spike around zero in the empirical density for the correlations of income growth with stock returns and with the risk-free rate, indicating that there are a substantial number of households whose income growth is unrelated with stocks returns and with the risk-free rate. We find a similar pattern for the correlations of housing growth with financial asset returns. The distributions of both correlations of housing income with labor income and with business income are well dispersed with a spike in zero. On the other hand, for most households, the correlation between labor and business incomes is close to zero. This result is expected as households owning a private business are mostly self-employed and have no labor income.

Panel A of Table 2 reports the summary statistics of the variables used in our regressions. The top part of this table summarizes stock investment. For example, overall 38.8% of households participate in stock market. The middle part in Panel A presents the summary statistics of the background risk variables. We observe substantial *heterogeneity* of background risks across households. Overall, 83.6% of households have labor income, 78.7% of households own a house, but only 16% have a private business.[19] Within the group of households that have labor income, the

18. These results are not tabulated, but are available upon request.

19. In the PSID survey, many households that claim owning a private business do not report their business income. Overall, although 16% of households indicate owning a private business, only 7.54% provide business income information.

TABLE 2

CHARACTERISTICS OF EXPLANATORY VARIABLES

	Obs.	Mean	Median	Std. dev.	Min	Max
Panel A. Summary statistics						
Stock investment						
Stock participation	22,610	0.388	0	0.487	0	1
Stock to financial wealth	22,610	0.207	0	0.320	0	1
Stock to wealth without home equity	22,610	0.145	0	0.261	0	1
Stock to wealth with home equity	22,610	0.091	0	0.178	0	1
Background risks						
If head of household works	22,610	0.836	1	0.370	0	1
Std(*Lab*)	18,907	0.206	0.195	0.106	0	0.718
$Corr(R_s,Lab)$	18,907	0.030	0.026	0.277	−0.791	0.801
$Corr(R_f,Lab)$	18,907	0.046	0.04	0.274	−0.789	0.861
If household owns a house	22,610	0.787	1	0.410	0	1
Std(*Hou*)	17,787	0.337	0.314	0.184	0	1.887
$Corr(R_s,Hou)$	17,787	0.029	0.013	0.272	−0.792	0.826
$Corr(R_f,Hou)$	17,787	−0.005	0	0.274	−0.812	0.814
If household owns a business	22,610	0.160	0	0.367	0	1
Std(*Bus*)	3,611	0.291	0.216	0.313	0	1.544
$Corr(R_s,Bus)$	3,611	0.034	0	0.248	−0.737	0.808
$Corr(R_f,Bus)$	3,611	0.038	0	0.264	−0.764	0.787
$Corr(Lab,Hou)$	14,090	0.014	0	0.312	−0.783	0.796
$Corr(Lab,Bus)$	3,469	−0.004	0	0.183	−0.748	0.748
$Corr(Hou,Bus)$	3,121	0.009	0	0.258	−0.808	0.816
Control variables						
Head age	22,610	48.196	46	15.691	18	101
Family size	22,610	2.682	2	1.337	1	12
Race	22,610	0.919	1	0.273	0	1
High school education	22,610	0.527	1	0.499	0	1

(*Continued*)

TABLE 2

CONTINUED

	Obs.	Mean	Median	Std. dev.	Min	Max
Panel A. Summary statistics						
Stock investment						
College education	22,610	0.309	0	0.462	0	1
Total wealth including home equity	22,610	173,428	82,674	254,124	−36,302	2,093,793
Total before-tax family income	22,610	52,644	44,558	37,882	39	258,391
Total head labor income	22,610	29,785	25,304	29,153	0	253,671
House value	22,610	107,544	81,552	116,948	0	1,731,544
Unpaid mortgage value	22,610	33,724	8,896	46,456	0	263,478
If head and wife in same industry	22,610	0.063	0	0.244	0	1
If head is in unemployment	22,610	0.061	0	0.24	0	1

	1	2	3	4	5	6	7	8	9	10	11	12
Panel B. Correlation matrix of background risk factors												
1. *Std*(*Lab*)	1.000	0034**	0.027**	−0.073**	−0.045**	−0.032**	0.094**	−0.001	0.001	0.014*	−0.025**	0.009
2. *Corr*(R_s,*Lab*)		1000	0.434**	−0.014*	0.020**	0.010	−0.025**	−0.003	−0.003	0.020**	0.014*	−0.006
3. *Corr*(R_f,*Lab*)			1.000	0.007	0.014*	−0.002	−0.038**	−0.018**	−0.017*	0.027**	0.015*	0.003
4. *Std*(*Hou*)				1.000	−0.015*	−0.054**	0.072**	0.017*	0.028**	0.002	0.003	0.021**
5. *Corr*(R_s,*Hou*)					1.000	0.492**	−0.009	−0.013	−0.013	0.022**	−0.004	−0.008
6. *Corr*(R_f,*Hou*)						1.000	−0.009	−0.005	−0.005	0.059**	−0.014*	0.003
7. *Std*(*Bus*)							1.000	0.167**	0.211**	0.022**	−0.026**	0.021**
8. *Corr*(R_s,*Bus*)								1.000	0.435**	0.015*	−0.023**	0.088**
9. *Corr*(R_f,*Bus*)									1.000	0.014*	−0.015*	0.010
10. *Corr*(*Lab*,*Hou*)										1.000	−0.005	−0.048**
11. *Corr*(*Lab*,*Bus*)											1.000	−0.049**
12. *Corr*(*Hou*,*Bus*)												1.000

NOTE: Panel A reports summary statistics of the explanatory variables in our regressions. Panel B reports the correlation matrix of background risk variables. *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. The data are a 9-year unbalanced panel for 4,756 households for the years 1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007, and 2009. * and ** denote statistical significance at the 5% and 1% levels, respectively.

median standard deviation of labor income growth is 19.5%. Similarly, for households with business income, the median standard deviation of business income growth is 21.6%. The bottom part of Panel A reports some demographic information. The average age of the heads of households is 48.196, the average family size is 2.682,

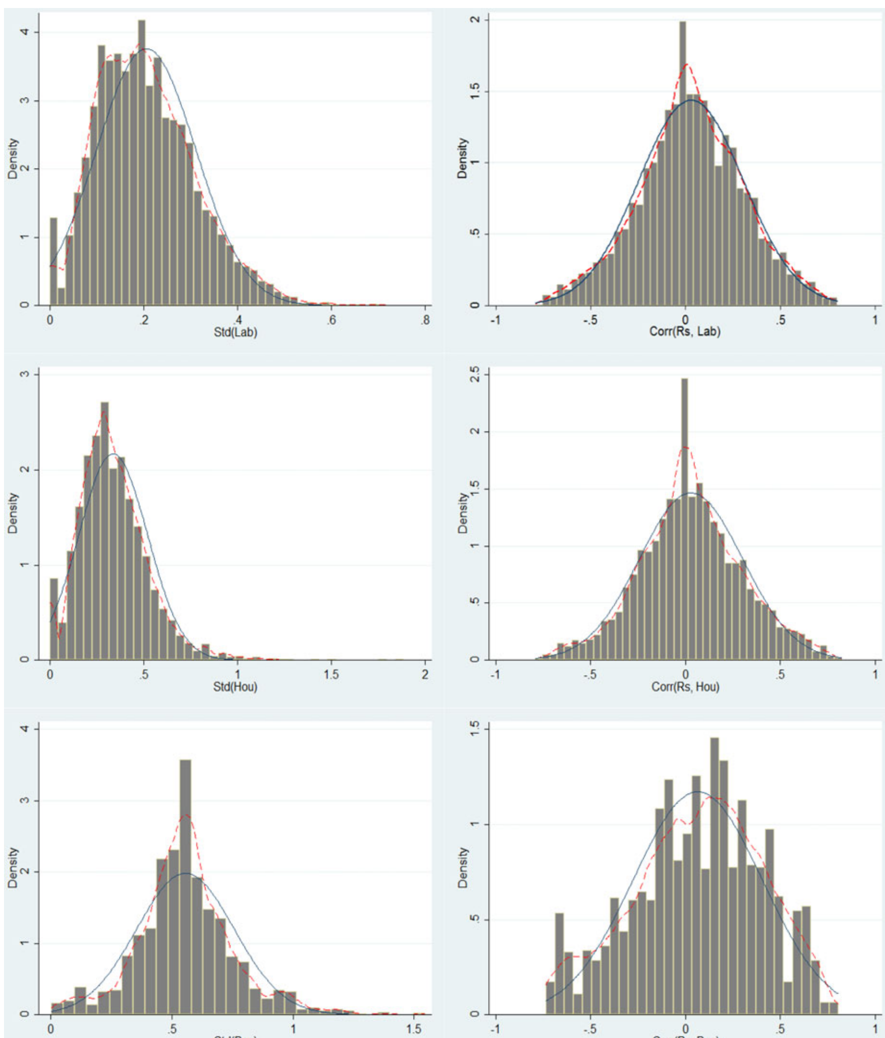

FIG. 1. Cross-Sectional Dispersion of Background Risk Factors. (*Continued*)

NOTE: This figure presents the cross-sectional distributions of 12 background risk variables. The sample includes observations for households that are exposed to the corresponding risks. The definitions of the variables are provided in Table 1. Gray bars represent the density, dashed line is the kernel density curve, and solid line is the normal density curve.

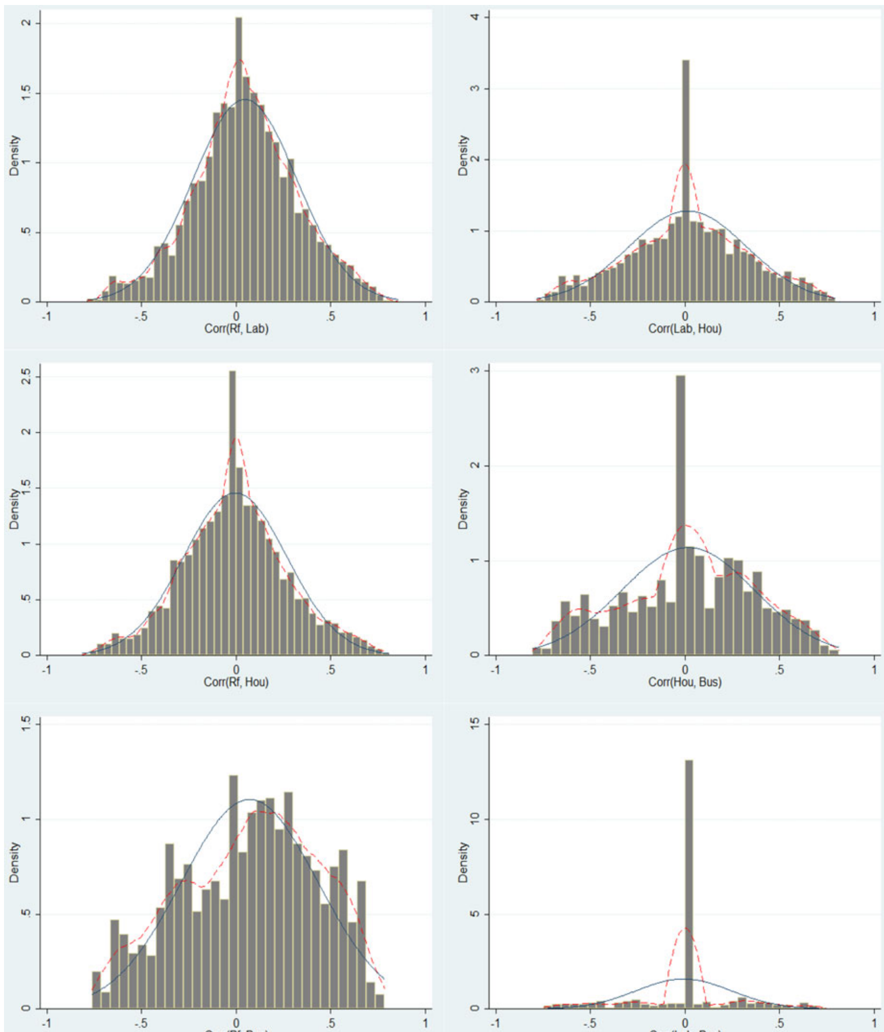

FIG. 1. Continued.

the average family income is $52,644, 30.9% of the heads of households have a college degree, while 52.7% have only a high school education.

Panel B of Table 2 presents the correlation matrix of the 12 background risk measures. The correlation between a background risk measure 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 by excluding the correlations between the risk-free rate and background risk assets and obtain similar results as our baseline analysis. The results using these measures are not reported but are available upon request.[20]

3. EMPIRICAL RESULTS

3.1 Statistical Significance

Table 3 presents maximum likelihood estimates of the Logit regressions. Five specifications are estimated, each with a different combination of the three types of background risks: (i) no background risk, (ii) with only labor income risk, (iii) with both labor income and housing risks, (iv) with both labor income and business risks, and (v) with all three types of background risks. The top part reports log likelihood ratio tests for various model comparisons.

Column (1) displays our benchmark model without considering background risks. We find strong explanatory power of education, race, income, and wealth for stock market participation, confirming the results of earlier studies. The positive coefficient on $Log(Age)$ and the negative coefficient on $(Log(Age))^2$ confirm the hump-shape pattern of stock market participation with age although these variables are not statistically significant. We find that the "house value" variable carries the expected negative sign and "unpaid mortgage" has the expected positive coefficient, consistent with Cocco (2005) and Campbell (2006). These parameters are statistically significant at the 1% level. 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 "head has a job" variable is positively related to stock market participation, but the effect is not statistically significant. The "owns a house" variable significantly increases the likelihood of stock market participation whereas the "has a business" variable significantly reduces participation. The "head in unemployment" is negatively related to participation but it is not statistically significant. "Head and wife in same industry" significantly reduces participation.

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 1% level. 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 that document that labor income reduces stockholdings when it is modeled as a risky asset, whereas it encourages

20. We also examine the correlations among time-invariant, forward-looking, and backward-looking background risk measures. We find that the time-invariant measure is more highly correlated with the backward measure than with the forward measure. The backward and forward measures of standard deviation variables are highly correlated. In contrast, the backward and forward measures of correlation variables are not closely associated.

TABLE 3

DETERMINANTS OF STOCK MARKET PARTICIPATION

	Baseline (1)	Labor risk (2)	Labor & house risk (3)	Labor & business risk (4)	All risks (5)
Likelihood ratio test		(2)–(1)	(3)–(2)	(4)–(2)	(5)–(1)
Chi-square of likelihood ratio test		32.000	17.000	5.000	55.000
p-value of likelihood ratio test		(0.00)	(0.00)	(0.17)	(0.00)
Std(*Lab*)		−1.210**	−1.131**	−1.187**	−1.105**
		(−4.36)	(−4.06)	(−4.30)	(−3.99)
Corr(R_s,*Lab*)		−0.308**	−0.316**	−0.314**	−0.321**
		(−2.91)	(−2.99)	(−2.96)	(−3.04)
Corr(R_f,*Lab*)		0.283**	0.299**	0.284**	0.298**
		(2.60)	(2.75)	(2.61)	(2.75)
Std(*Hou*)			−0.453**		−0.458**
			(−2.88)		(−2.91)
Corr(R_s,*Hou*)			−0.050		−0.047
			(−0.44)		(−0.41)
Corr(R_f,*Hou*)			0.195		0.192
			(1.72)		(1.69)
Std(*Bus*)				−0.350	−0.336
				(−1.86)	(−1.80)
Corr(R_s,*Bus*)				0.126	0.095
				(0.53)	(0.40)
Corr(R_f,*Bus*)				0.230	0.258
				(0.92)	(1.04)
Corr(*Lab*,*Hou*)			−0.200*		−0.194*
			(−2.18)		(−2.12)
Corr(*Lab*,*Bus*)				0.175	0.193
				(0.65)	(0.71)
Corr(*Hou*,*Bus*)					0.161
					(0.80)
Head has a job	0.092	0.339*	0.332*	0.370**	0.356**
	(0.75)	(2.48)	(2.43)	(2.71)	(2.60)
Owns a house	3.031**	3.044**	3.330**	3.087**	3.370**
	(6.17)	(6.18)	(6.62)	(6.25)	(6.69)
Has a business	−0.250**	−0.216**	−0.208**	−0.139	−0.134
	(−3.69)	(−3.20)	(−3.09)	(−1.73)	(−1.67)
Head in unemployment	−0.109	−0.082	−0.075	−0.082	−0.074
	(−1.29)	(−0.96)	(−0.88)	(−0.95)	(−0.87)
Head and wife in same industry	−0.253**	−0.245**	−0.247**	−0.240**	−0.243**
	(−2.74)	(−2.66)	(−2.70)	(−2.60)	(−2.65)
Log(*Age*)	1.928	1.609	1.956	1.695	2.052
	(1.14)	(0.95)	(1.15)	(1.00)	(1.20)
$(Log(Age))^2$	−0.308	−0.267	−0.312	−0.278	−0.324
	(−1.36)	(−1.17)	(−1.36)	(−1.22)	(−1.42)
Log(*Family size*)	−0.219**	−0.218**	-0.212^{-}	−0.222**	−0.216**
	(−4.26)	(−4.22)	(−4.10)	(−4.29)	(−4.15)
Race	0.709**	0.721**	0.723**	0.719**	0.719**
	(7.30)	(7.47)	(7.53)	(7.46)	(7.50)
High school	0.380**	0.370**	0.377**	0.369**	0.374**
	(4.84)	(4.73)	(4.82)	(4.71)	(4.78)
College	0.951**	0.931**	0.932**	0.931**	0.932**
	(10.8)	(10.6)	(10.6)	(10.6)	(10.6)
Log(*Income*)	0.374**	0.365**	0.369**	0.370**	0.374**
	(9.49)	(9.25)	(9.29)	(9.31)	(9.36)
Log(*Wealth*)	1.381**	1.387**	1.380**	1.390**	1.383**
	(30.0)	(30.2)	(29.9)	(30.1)	(29.8)
Log(*House value*)	−0.363**	−0.367**	−0.379**	−0.371**	−0.383**
	(−7.84)	(−7.92)	(−8.15)	(−7.98)	(−8.20)

(*Continued*)

TABLE 3

Continued

	Baseline (1)	Labor risk (2)	Labor & house risk (3)	Labor & business risk (4)	All risks (5)
Log(*Unpaid Mortgage*)	0.058**	0.057**	0.060**	0.058**	0.060**
	(9.12)	(9.01)	(9.47)	(9.06)	(9.50)
Log(*Head Labor Income*)	−0.012	−0.011	−0.011	−0.015	−0.014
	(−1.24)	(−1.12)	(−1.14)	(−1.51)	(−1.48)
Constant	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	21,938	21,938	21,938	21,938	21,938
Pseudo R^2	0.266	0.268	0.269	0.269	0.270

Note: 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. In each panel, coefficient estimates are reported with associated *t*-statistics in parentheses. Standard errors are estimated with cluster of households. *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 5% and 1% levels, respectively.

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 32 with degrees of freedom of 3, we reject specification (1) in favor of specification (2) at the 1% 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. *Std*(*Hou*) is significantly negatively related to stock market participation at the 1% level with the coefficient −0.453. The variable *Corr*(R_f,*Hou*) is positively related to stock market participation, but it is statistically significant only at the 10% level. The variable *Corr*(R_s,*Hou*) is negatively related to stock market participation, although it is not statistically significant. 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. This result suggests that the comovement of housing and labor income increases risk exposures, thus reducing 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% significance level, suggesting the importance of housing risk in stock market participation decision.

Column (4) shows that the standard deviation of business income has a negative impact on stock participation but only at the 10% significance level. Both the correlations of business income with the risk-free rate and with stock returns are insignificant. The log likelihood ratio test does not reject specification (2) in favor of (4) given the chi-square statistic of 5, suggesting that the overall impact of business risk on household stock market participation is not statistically significant.

In column (5), we report the results when all three types of background risks are jointly considered. All background risk variables that are significant in previous regressions continue to be statistically significant. Furthermore, this model outperforms specification (1) at the 1% significance level. Based on the likelihood ratio test, the three types of background risks are important to a household's decision to participate in the stock market.

Table 4 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 risks continue to have the expected signs in explaining portfolio choice in the Tobit regressions. The likelihood ratio tests confirm our previous findings that labor and housing risks appear to be more important than business risk.

In terms of the relative importance, we find labor income risk to be the most important, followed by housing risk, while business risk is less important. Three labor income risk factors are all statistically significant. The standard deviation of home equity growth, and the correlation between the risk-free rate and home equity growth are significant but the correlation between stock return and home equity growth is not significant. None of the three business risk variables is statistically significant at the 5% level or higher. Only the standard deviation of business income growth is marginally significantly negatively related to stock investment at the 10% level. In addition, the correlation between labor income and home equity is negatively related to stockholdings.

3.2 Economic Significance

Given the statistical significance of the background risk factors, we study the quantitative impact of these risk factors. For each type of risk, we estimate the change in a household's probability of stock market participation and proportion of stock to financial wealth by assuming the corresponding risk variables change one standard deviation in the unfavorable direction from their sample means while holding all other variables at their sample means. Table 5 reports the results.

The left part of Panel A reports the change in the probability of stock market participation. The calculation is based on the estimated coefficients in column (5) of Table 3. 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 of participating in the stock market by 6.26%. Similarly, for housing risk and business risk, the respective changes in probabilities are 3.41% and 1.63%. If all background risk variables change together, the probability of participation declines by 10.82%.[21]

The right part of Panel A in Table 5 provides the economic significance of background risk variables on the proportion of stockholdings. Using the estimated coefficients reported in column (5) of Table 4, we calculate the change of the

21. The overall effect need not equal the sum of the separate effects due to the nonlinearity of the Logit model.

TABLE 4

Determinants of Stockholdings

	Baseline (1)	Labor risk (2)	Labor & house risk (3)	Labor & business risk (4)	All risks (5)
Likelihood ratio test		(2)–(1)	(3)–(2)	(4)–(2)	(5)–(1)
Chi-square of likelihood ratio test		23.000	14.000	3.000	40.000
p-value of likelihood ratio test		(0.00)	(0.00)	(0.39)	(0.00)
Std(*Lab*)		−0.251**	−0.237**	−0.246**	−0.232**
		(−3.40)	(−3.19)	(−3.33)	(−3.12)
Corr(R_s,*Lab*)		−0.076**	−0.076**	−0.077**	−0.077**
		(−2.67)	(−2.69)	(−2.69)	(−2.71)
Corr(R_f,*Lab*)		0.069*	0.074*	0.069*	0.074*
		(2.33)	(2.50)	(2.33)	(2.49)
Std(*Hou*)			−0.089*		−0.090*
			(−2.10)		(−2.11)
Corr(R_s,*Hou*)			−0.031		−0.031
			(−1.00)		(−0.99)
Corr(R_f,*Hou*)			0.055		0.054
			(1.81)		(1.78)
Std(*Bus*)				−0.079	−0.075
				(−1.75)	(−1.67)
Corr(R_s,*Bus*)				0.024	0.022
				(0.40)	(0.37)
Corr(R_f,*Bus*)				0.049	0.053
				(0.86)	(0.92)
Corr(*Lab*,*Hou*)			−0.057*		−0.056*
			(−2.31)		(−2.28)
Corr(*Lab*,*Bus*)				0.013	0.017
				(0.20)	(0.25)
Corr(*Hou*,*Bus*)					0.016
					(0.35)
Head has a job	0.027	0.076*	0.075*	0.084*	0.081*
	(0.82)	(2.14)	(2.10)	(2.35)	(2.28)
Owns a house	0.595**	0.593**	0.646**	0.601**	0.654**
	(4.52)	(4.50)	(4.83)	(4.56)	(4.88)
Has a business	−0.065**	−0.057**	−0.055**	−0.040*	−0.039*
	(−3.90)	(−3.45)	(−3.35)	(−2.02)	(−1.98)
Head in unemployment	−0.033	−0.027	−0.026	−0.027	−0.026
	(−1.36)	(−1.13)	(−1.07)	(−1.13)	(−1.06)
Head and wife in same industry	−0.045	−0.043	−0.042	−0.042	−0.041
	(−1.93)	(−1.83)	(−1.83)	(−1.78)	(−1.77)
Log(*Age*)	0.805	0.719	0.779	0.743	0.806
	(1.69)	(1.50)	(1.63)	(1.55)	(1.68)
$(Log(Age))^2$	−0.114	−0.102	−0.110	−0.105	−0.114
	(−1.79)	(−1.61)	(−1.73)	(−1.65)	(−1.78)
Log(*Family size*)	−0.062**	−0.062**	−0.061**	−0.063**	−0.062**
	(−4.36)	(−4.35)	(−4.26)	(−4.40)	(−4.32)
Race—if white	0.213**	0.215**	0.216**	0.215**	0.215**
	(7.45)	(7.58)	(7.66)	(7.58)	(7.65)
High school	0.142**	0.140**	0.142**	0.140**	0.141**
	(6.39)	(6.33)	(6.42)	(6.29)	(6.38)
College	0.291**	0.287**	0.286**	0.286**	0.286**
	(11.9)	(11.7)	(11.7)	(11.7)	(11.7)
Log(*Income*)	0.085**	0.083**	0.083**	0.083**	0.084**
	(8.44)	(8.21)	(8.26)	(8.26)	(8.31)
Log(*Wealth*)	0.345**	0.345**	0.344**	0.346**	0.344**
	(28.7)	(28.7)	(28.5)	(28.7)	(28.5)
Log(*House value*)	−0.074**	−0.075**	−0.077**	−0.075**	−0.077**
	(−6.10)	(−6.13)	(−6.29)	(−6.18)	(−6.33)

(*Continued*)

TABLE 4

CONTINUED

	Baseline (1)	Labor risk (2)	Labor & house risk (3)	Labor & business risk (4)	All risks (5)
	(1)	(2)	(3)	(4)	(5)
Log(*Unpaid Mortgage*)	0.016**	0.015**	0.016**	0.016**	0.016**
	(9.43)	(9.33)	(9.63)	(9.37)	(9.67)
Log(*Head Labor Income*)	−0.003	−0.002	−0.002	−0.003	−0.003
	(−1.24)	(−1.06)	(−1.06)	(−1.44)	(−1.41)
Constant	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	21,938	21,938	21,938	21,938	21,938
Pseudo R^2	0.231	0.232	0.233	0.233	0.233

NOTE: 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. In each panel, coefficient estimates are reported with associated *t*-statistics in parentheses. Standard errors are estimated with cluster of households. *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 5% and 1% levels, respectively.

proportion of stockholdings 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 stockholdings by 1.92%. Similarly, for housing risk and business risk, the respective changes are 1.16% and 0.47%. If all background risk variables change together, the proportion of stockholdings declines by 3.69%.

Considering that the average stock market participation rate is 38.8%, the 10.82% decrease in the probability of participation due to the one standard deviation increase in the three background risks is a 28% (= 10.82/38.8) reduction in stock market participation in the sample. Similarly, as the sample average ratio of stock to financial wealth is 20.7%, the 3.69% decrease in stockholdings due to the one standard deviation increase in background risks implies a 18% (= 3.69/20.7) decline in stockholdings. These figures show that the effect of background risks on stock investments is economically important. The relative impact on market participation is especially pronounced.

In Panel B of Table 5, we examine the impact of education on the relationship between a household's stock market participation and stockholdings with 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 without a high school education will decrease its stock market participation probability by 8.43% and its proportion of stockholdings by 3.07%. In contrast, a household with a college education will reduce its stock market participation probability by 12.53% and its proportion of stockholdings by 4.24%.

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

TABLE 5

MARGINAL EFFECTS OF BACKGROUND RISKS FACTORS

	Stock market participation (in percent)			Stockholding relative to financial wealth (in percent)		
	At sample means (1)	Increase one std. dev. (2)	Change (3)	At sample means (4)	Increase one std. dev. (5)	Change (6)
Panel A. Marginal effect of three types of background risk factors						
Labor income risk						
$Std(Lab)$, $Corr(R_s,Lab)$, $Corr(R_f,Lab)$	34.21	27.95	−6.26	37.14	35.23	−1.92
Housing risk						
$Std(House)$, $Corr(R_s,House)$, $Corr(R_f,House)$	34.21	30.80	−3.41	37.14	35.99	−1.16
Business income risk						
$Std(Bus)$, $Corr(R_s,Bus)$, $Corr(R_f,Bus)$	34.21	32.58	−1.63	37.14	36.68	−0.47
All risks						
12 variables	34.21	23.39	−10.82	37.14	33.45	−3.69
Panel B. Marginal effect of 12 background risk factors for different education groups						
No high school	24.26	15.83	−8.43	32.71	29.63	−3.07
High school	31.78	21.47	−10.31	36.51	32.91	−3.60
College	44.85	32.32	−12.53	41.09	36.85	−4.24

NOTE: Panel A reports the impacts of background risks on stock market participation and stockholding for the baseline model, while Panel B reports these impacts for different education groups. In each panel, columns (1)–(3) report marginal effects of various background risks on stock market participation. Using estimated coefficients from the Logit regression (Table 3, 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. Columns (4)–(6) report the marginal effects of background risks on stockholdings relative to financial wealth conditional on participation. Using estimated coefficients from the Tobit regression (Table 4, 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.

TABLE 6

ESTIMATIONS USING ALTERNATIVE BACKGROUND RISK MEASURES

	Backward looking		Forward looking		Cross-sectional	
Dependent variable:	Participation Logit (1)	Portfolio Tobit (2)	Participation Logit (3)	Portfolio Tobit (4)	Participation Logit (5)	Portfolio Tobit (6)
Std(*Lab*)	-0.791^{**}	-0.162^{**}	-0.867^{**}	-0.192^{**}	-1.098^{*}	-0.110^{*}
	(−3.50)	(−2.76)	(−3.55)	(−2.89)	(−2.41)	(−2.26)
Corr(R_s,*Lab*)	-0.146^{*}	−0.036	−0.077	0.003	−0.226	-0.046^{*}
	(−1.97)	(−1.86)	(−0.94)	(0.14)	(−1.30)	(−2.46)
Corr(R_f,*Lab*)	0.089	0.025	0.176^{*}	0.030	0.399^{*}	0.052^{**}
	(1.18)	(1.27)	(1.98)	(1.20)	(2.25)	(2.73)
Std(*Hou*)	-0.460^{**}	-0.085^{*}	−0.053	−0.025	-0.839^{**}	−0.038
	(−3.83)	(−2.57)	(−0.34)	(−0.58)	(−2.95)	(−1.24)
Corr(R_s,*Hou*)	−0.064	−0.029	−0.082	−0.036	−0.186	−0.017
	(−0.81)	(−1.39)	(−1.02)	(−1.63)	(−1.03)	(−0.83)
Corr(R_f,*Hou*)	0.010	0.016	0.101	0.028	0.300	0.034
	(0.13)	(0.80)	(1.19)	(1.22)	(1.63)	(1.65)
Std(*Bus*)	0.069	0.018	−0.340	-0.124^{*}	−0.301	−0.011
	(0.35)	(0.38)	(−1.35)	(−1.97)	(−0.78)	(−0.25)
Corr(R_s,*Bus*)	0.383	0.092	−0.279	−0.123	0.444	0.051
	(1.73)	(1.76)	(−1.01)	(−1.76)	(0.91)	(0.92)
Corr(R_f,*Bus*)	0.111	−0.008	0.107	0.075	0.463	0.061
	(0.47)	(−0.16)	(0.39)	(1.13)	(1.02)	(1.20)
Corr(*Lab*,*Hou*)	−0.090	−0.038	−0.043	−0.040	−0.210	-0.041^{*}
	(−1.05)	(−1.68)	(−0.34)	(−1.20)	(−1.38)	(−2.47)
Corr(*Lab*,*Bus*)	-1.089^{*}	−0.143	0.211	0.026	−0.029	0.036
	(−2.13)	(−1.26)	(0.21)	(0.10)	(−0.068)	(0.79)
Corr(*Hou*,*Bus*)	0.446	0.057	0.313	0.049	0.161	0.008
	(1.51)	(0.82)	(0.56)	(0.46)	(0.53)	(0.24)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	No	No
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,298	19,298	9,336	9,343	4,716	4,726
Pseudo R^2	0.266	0.229	0.256	0.224	0.326	0.478

NOTE: This table reports the results using backward rolling-over, forward rolling-over background risk measures, and the cross-sectional 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. The data are a 9-year unbalanced panel for 4,756 households for the years 1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007, and 2009. * and ** denote statistical significance at the 5% and 1% levels, respectively.

(e.g., Vissing-Jorgensen 2002, Campbell 2006). 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 and information costs are lower.

3.3 Alternative Measures of Background Risks

Table 6 conducts more tests using alternative measures of background risks. In columns (1) and (2), we redo our tests using backward rolling-over measures for the Logit regression of stock market participation and for the Tobit regression of stockholdings, respectively. The standard deviation of labor income growth rate reduces stock market participation and the proportion of stock to financial wealth. The correlation between stock returns and labor income growth rate is negatively related to stock market participation and stockholdings, whereas the correlation between the risk-free rate and labor income growth is not significant. Housing risk is also important in that the standard deviation of home equity growth significantly decreases stock market participation and stockholdings.

In columns (3) and (4), we redo our regressions using forward rolling-over measures. For the stock market participation regression, the only two significant variables are the standard deviation of labor income growth and the correlation between the risk-free rate and labor income growth. As for the stockholdings regression, we find that two variables are statistically significant: the standard deviation of labor income growth and standard deviation of business income growth.

In columns (5) and (6), we consider cross-sectional regressions. For the Logit regression in column (5), we sum the stock market participation dummy variable over years and divide this variable by the number of years when the household appears in the sample. We classify a household as a stock market participant if it holds stocks in more than half of the time in the sample period. As for the Tobit regression in column (6), we regress the time average of stockholdings relative to wealth on the time-invariant background risk factors and the time-averages of other control variables.

As shown in column (5), the standard deviation of labor income growth significantly negatively impacts stock market participation, while the correlation of labor income and the risk-free rate significantly encourages stock market participation. The standard deviation of home equity growth rate also significantly decreases stock market participation. Column (6) confirms the importance of labor income risk variables in affecting a household's portfolio choice. Furthermore, the correlation of labor income and housing significantly decreases stockholdings.

In general, these tests using alterative measures of background risks yield weaker results than the baseline cases reported in Tables 3 and 4, primarily due to the less precise estimates of background risk measures with fewer observations. However, some observations can be made. Labor income risk is the most important one. The standard deviation of labor income growth is significant in all regressions. The correlation between stock returns and labor income growth carries the expected negative sign and is significant in two of six regressions. The correlation between labor income growth and the risk-free rate also has the expected positive sign in all regressions and is significant in three of six regressions. We therefore conclude that the volatility of labor income is an important factor that significantly affects household stock market participation and stockholdings. Moreover, households with risky (risk-free) labor income are less (more) likely to participation in stock market and to hold less (more) risky assets in their portfolios.

The standard deviation of home equity growth rate carries the expected negative sign and is significant in three of six regressions, suggesting that the volatility of home equity growth discourages stock market participation and stockholdings. However, results based on the correlation between home equity growth and financial asset returns are in general insignificant. Furthermore, we find that the business income risk factors that are estimated with the least observations yield the most mixed results.

3.4 Alternative Estimation Methods of Portfolio Choice

In Table 7, we compare the estimation results using the Tobit model, the Heckman selection model, and OLS regressions for the truncated sample consisting of only stockholders. We use two additional measures of the stock to wealth ratio: the ratio of stock to total wealth without home equity, denoted as *PflStk_2*, and the ratio of stock to total wealth including home equity, denoted as *PflStk_3*.

Column (1) in Table 7 is a repeat of the Tobit model in column (5) of Table 4 where the stock-to-wealth ratio is defined as a ratio of stock to total financial wealth (*Pflstk_1*). Columns (2) and (3) in Table 7 are Tobit models using alternative measures of the stock to wealth ratio (*Pflstk_2* and *Pflstick_3*). The results are very similar to previous findings in Table 4.

The next three columns in Table 7 present OLS regressions. In the OLS regressions, *Std*(*Lab*) is not significant. As for the correlation terms, *Corr*(R_s,*Lab*) is negatively related to stockholdings, and *Corr*(R_f,*Lab*) is positively related to stockholdings, consistent with findings in the Tobit regressions. Among the three housing risk variables, only *Corr*(R_s,*Hou*) is significantly negatively related to *PtfStk_1* and *PtfStk_2*. As for the business income risk, *Std*(*Bus*) has the expected negative sign, but it is statistically significant only in the *PtfStk_3* regression. Overall, the OLS regression results are qualitatively consistent with those using the Tobit model, but are statistically less significant.

As for Heckman selection model, we find that lagged stockholding has strong explanatory power for current stockholding. We report the *Lambda*, which would be 0 if stockholders were a random subgroup of the population. We reject the hypothesis that stockholders are random subgroup in favor of the alternative that stockholders are a selected group. Labor income risk appears less important in the Heckman model. In contrast, housing risk is relatively more important after controlling for sample selection. *Corr*(R_s,*Hou*) is significantly negatively related to stockholdings in the *PtfStk_1* regression, and *Corr*(R_f,*Hou*) is significantly positively related to stockholdings in the *PtfStk_1* and *PtfStk_3* regressions. As for business risk, consistent with previous findings, only *Std*(*Bus*) is important. In summary, the estimation of the Heckman model is in general consistent with the Tobit model, but is statistically less significant.

Overall, while we find that the results using OLS and Heckman models are weaker than those using the Tobit model, they still indicate the importance of background risks. Therefore, the significance of background risks in portfolio holdings is not primarily driven by the difference between stockholders and nonstockholders. We also note that the impact of background risks is relatively more important for stock participation than for stockholdings.

3.5 Other Robustness Checks

We conduct additional robustness checks. We first consider alternative ways to construct background risk factors. Specifically, we examine separate effects based on whether the correlation of a background risk factor with stock returns is positive or

TABLE 7

Alternative Estimations of Portfolio Holdings

	Tobit			OLS			Heckman		
Dependent variable:	*PflStk_1* (1)	*PflStk_2* (2)	*PflStk_3* (3)	*PflStk_1* (4)	*PflStk_2* (5)	*PflStk_3* (6)	*PflStk_1* (7)	*PflStk_2* (8)	*PflStk_3* (9)
Std(*Lab*)	−0.232**	−0.230**	−0.158**	0.024	−0.028	−0.022	0.03	−0.025	−0.043
	(−3.12)	(−3.85)	(−3.94)	(0.68)	(−0.87)	(−0.96)	(0.79)	(−0.69)	(−1.74)
Corr(R_s,*Lab*)	−0.077**	−0.064**	−0.039*	−0.026*	−0.024*	−0.014	−0.001	−0.01	0.003
	(−2.71)	(−2.81)	(−2.52)	(−1.97)	(−2.07)	(−1.69)	(−0.045)	(−0.68)	(0.32)
Corr(R_f,*Lab*)	0.074*	0.072**	0.047**	0.022	0.032*	0.022*	−0.004	0.023	0.006
	(2.49)	(2.96)	(2.84)	(1.55)	(2.48)	(2.37)	(−0.28)	(1.54)	(0.54)
Std(*Hou*)	−0.090*	−0.097**	−0.037	0.004	−0.028	0.011	0.026	−0.013	0.027
	(−2.11)	(−2.77)	(−1.61)	(0.18)	(−1.30)	(0.75)	(1.17)	(−0.63)	(1.89)
Corr(R_s,*Hou*)	−0.031	−0.027	−0.015	−0.033*	−0.028*	−0.015	−0.035*	−0.029	−0.017
	(−0.99)	(−1.05)	(−0.93)	(−2.11)	(−1.88)	(−1.53)	(−2.20)	(−1.93)	(−1.67)
Corr(R_f,*Hou*)	0.054	0.041	0.029	0.025	0.02	0.016	0.032*	0.021	0.022*
	(1.78)	(1.63)	(1.80)	(1.61)	(1.37)	(1.63)	(2.02)	(1.38)	(2.13)
Std(*Bus*)	−0.075	−0.076*	−0.058*	−0.024	−0.035	−0.032*	−0.019	−0.045*	−0.032*
	(−1.67)	(−2.06)	(−2.33)	(−1.01)	(−1.54)	(−2.04)	(−0.78)	(−1.96)	(−2.07)
Corr(R_s,*Bus*)	0.022	0.016	−0.004	0.022	0.013	−0.006	0.009	0.025	0.001
	(0.37)	(0.34)	(−0.13)	(0.64)	(0.40)	(−0.28)	(0.27)	(0.82)	(0.042)
Corr(R_f,*Bus*)	0.053	0.023	0.03	0.039	0.017	0.024	0.022	0.007	0.017
	(0.92)	(0.49)	(0.95)	(1.23)	(0.60)	(1.23)	(0.73)	(0.26)	(0.86)
Corr(*Lab*,*Hou*)	−0.056*	−0.045*	−0.025	−0.014	−0.012	−0.004	−0.014	−0.021	−0.004
	(−2.28)	(−2.23)	(−1.91)	(−1.10)	(−1.10)	(−0.48)	(−1.08)	(−1.73)	(−0.52)
Corr(*Lab*,*Bus*)	0.017	−0.002	−0.009	−0.012	−0.022	−0.016	−0.015	−0.016	−0.024
	(0.25)	(−0.028)	(−0.24)	(−0.36)	(−0.68)	(−0.71)	(−0.55)	(−0.61)	(−1.34)
Corr(*Hou*,*Bus*)	0.016	0.019	0.016	0.006	0.014	0.011	−0.008	0.000	−0.001
	(0.35)	(0.48)	(0.62)	(0.24)	(0.61)	(0.69)	(−0.35)	(−0.0083)	(−0.067)
Lagged *PtfStk*							0.321**	0.367**	0.363**
							(26.0)	(29.7)	(31.3)
Lamda							0.17	0.08	0.06
							(11.49)	(6.59)	(7.38)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,938	21,938	21,938	13,976	13,976	13,976	17,771	17,771	17,771
R^2	0.23	0.28	0.38	0.25	0.25	0.26			

Note: OLS regression is applied to a subsample of households that have participated in stock market in current and/or prior years. In the Heckman selection model, which is estimated using a two-stage method, we include lagged participation and stockholding in the participation and portfolio holding equations, respectively. Only the second-stage results are reported. *PflStk_1 (PflStk_2, PflStk_3)* stands for the ratio of stockholdings to financial wealth (total wealth excluding home equity, total wealth including home equity). *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. The data are a 9-year unbalanced panel for 4,756 households for the years 1984, 1989, 1994, 1999, 2001, 2003, 2005, 2007, and 2009. * and ** denote statistical significance at the 5% and 1% levels, respectively.

negative; that is, the explanatory variables are (standard deviation × positive correlation) and (standard deviation × negative correlation). This specification allows us to further examine the hedging motive hypothesis. We find that the standard deviation of labor income interacting with a positive correlation, ($Std(Lab) \times Corr(R_s,Lab)^{+}$), is significantly negatively related to stock participation while the impact of the standard deviation of labor income interacting with a negative correlation, ($Std(Lab) \times Corr(R_s,Lab)^{-}$), is not significant. We also consider the correlations of excess stock returns with the background risk variables, that is, ($Corr(R_s - R_f,X)$), where X is labor income, home equity, or business income growth. The results using this alternative measures are consistent with our baseline regressions.

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 heteroskedasticity or nonnormality (Amemiya 1985, pp. 378–81). We adopt three alternative specifications, which assume the residual standard errors to be an exponential function of total wealth, or total income, or both, respectively. These experiments produce similar results.

Since the PSID changes the definition of stockholdings in 1997. As a robustness check, we redo our baseline model by excluding observations for the years 1997 and 1999 and the qualitative results stay the same. Our baseline study uses *Filter2* to estimate background risk variables. As a robustness test, we apply *Filter3* and *Filter5* to filter our data and obtain similar results. We also redo our regressions using three subsamples of households that have labor income, housing, and business income, respectively. The results in these experiments confirm our previous findings. Following Angerer and Lam (2009), we decompose the background risks to expected (predictable) and unexpected (unpredictable) components. Specifically, we regress the growth rate of labor income (home equity, business income) on the lagged dependent variable and other explanatory variables, including the age of the head of household and its squared term, the age of wife and its squared term, and the two education variables. The regression residuals are regarded as the unexpected component and the fitted values of the regression are considered as the expected component of the background risk. We find that the expected labor income risk is positively related to stock market participation and stockholdings while the unexpected labor income risk is negatively related to stock market participation and stockholdings, consistent with Angerer and Lam (2009). We obtain a similar result for housing income risk. In contrast, the expected business income risk decreases stock investment while the unexpected business risk increases stock investment. Results obtained in this section are not reported to save space but are available upon request.

4. CONCLUSIONS

Using a sample of U.S. households with household-level background risk measures, we examine the empirical importance of background risks for a household's investment decision. We document significant heterogeneity of background risk exposures across households. The low stock market participation rates and the large variation of stockholdings are significantly related to the heterogeneity in background risks across households. Specifically, a household is more (less) likely to enter the stock market and invests a larger (smaller) fraction of wealth in stocks if its nonfinancial income (e.g., labor income) is less (more) volatile, is less (more) highly correlated with stock returns, or is more (less) highly correlated with the risk-free rate. In terms of relative importance, we find that labor income risk is the most important, followed by housing risk, while the impact of business income risk is limited.

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