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Income hedging and portfolio decisions☆

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ABSTRACT

We examine whether the decision to participate in the stock market and other related portfolio decisions are influenced by income hedging motives. Economic theory predicts that the market participation propensity should increase as the correlation between income growth and stock market returns decreases. Surprisingly, empirical studies find limited support for the income hedging motive. Using a rich, unique Dutch data set and the National Longitudinal Survey of the Youth (NLSY) from the United States, we show that when the income-return correlation is low, individuals exhibit a greater propensity to participate in the market and allocate a larger proportion of their wealth to risky assets. Even when the income risk is high, individuals exhibit a higher propensity to participate in the market when the hedging potential is high. These findings suggest that income hedging is an important determinant of stock market participation and asset allocation decisions.

1. Introduction

One of the key risks that most households face is income risk. Standard economic theory posits that unless income risk is uninsurable and non diversifiable, the stock market participation decisions should depend upon the correlation between income risk and stock market returns (e.g., Heaton and Lucas, 1996, 2000b; Campbell and Viceira, 2002; Haliassos and Michaelides, 2003; Cocco, Gomes, and Maenhout, 2005; and Gomes and Michaelides, 2005). If the income-return correlation is low, then stocks can serve as a good hedge against income risk, which should induce individuals to participate in the market. Consequently, market participation should increase as the correlation between income growth and stock market return decreases.

Because this is an intuitive conjecture, it is puzzling that previous empirical studies find limited support for income hedging motives in market participation and asset allocation decisions, especially because some previous studies also demonstrate that a considerable part of income risk can be hedged using financial assets (e.g., Davis and Willen, 2000a, 2000b). For example, Heaton and Lucas (2000a) find only weak evidence in support of the hedging motive, perhaps because they use imputed measures of stock market participation.[1] Similarly, Vissing-Jorgensen (2002) finds no evidence that the correlation

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[1] Heaton and Lucas (2000a) use tax return data that include no information on asset holdings. They infer who owns stocks and the level of their asset holdings using tax information on dividends, interest, and capital gains.

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between income growth and market returns influences portfolio decisions. She suggests that this lack of evidence is likely to be driven by the short sample period used to estimate income growth.[2] Most recently, Massa and Simonov (2006) show that income hedging motives do not influence the portfolio decisions of Swedish investors.

In this paper, unlike the evidence from these earlier empirical studies, we find strong support for income hedging motives in market participation and asset allocation decisions. We utilize a rich, unique Dutch data set (the Dutch National Bank (DNB) Household Survey) that enables us to better examine whether the relation between income growth and financial market returns affects portfolio decisions. This data choice is based on the belief that the unavailability of a long time series of good quality income data could be one of the main reasons for the lack of empirical support for the income hedging motive.

The main advantage of the DNB Household Survey is that it is a large annual panel covering the 1993–2011 period. The sample contains individuals across a wide age range from 18–94 years. Further, the data set includes information about income, taxes paid, and market participation, as well as a number of important traditional determinants of portfolio decisions such as age, education, risk aversion, and health status. Having multiple years of data for each individual allows us to obtain more precise estimates of the correlation between income growth and stock market returns.[3] Overall, the DNB Household Survey provides significantly richer information than commonly used US data sets such as the Survey of Consumer Finances (SCF) or the Panel Study of Income Dynamics (PSID). We exploit this richness of the DNB Household Survey to provide stronger support for the income hedging motive in stock market participation and asset allocation decisions.

Our empirical analysis combines the economic intuition from the capital asset pricing models (CAPM) that includes human capital (Mayers, 1972, 1973; Fama and Schwert, 1977; Jagannathan and Wang, 1996; Campbell and Viceira, 2002; and Eiling, 2012) and the literature on limited stock market participation (e.g., Vissing-Jorgensen, 2002). Specifically, following the limited participation literature, we conjecture that individuals with low income growth-market return correlation would perceive the net benefit of market participation to be high because that low correlation would suggest that the market offers high income hedging potential. Consequently, individuals who experience an income process that is not strongly positively correlated with the market would exhibit a stronger propensity to participate in the stock market. And according to human capital CAPM, upon participation, these investors are likely to choose a larger equity portfolio to maximally exploit the income hedging benefits offered by the stock market (Campbell and Viceira, 2002).

Our empirical evidence supports these key conjectures. In probit participation regressions, the probability of participation in the stock market is higher when the correlation of income growth with the Dutch stock market return is lower. The propensity to participate in the stock market increases significantly when the hedging potential is high, even when the level of income risk is very high. For example, a 1 standard deviation decrease in the correlation leads to about an 11 percentage point increase in the probability of investing in stocks and mutual funds. Similarly, individuals with low (bottom quartile) income-return correlation are about 12 percentage points more likely to own stocks, but individuals with low (bottom quartile) correlation and high (top quartile) income risk are about 24 percentage points more likely to own stocks.

Using Tobit and Heckman (1979) regressions, we find similar results for asset allocation decisions of households. The proportional allocation to risky assets increases when the market return is more negatively correlated with income growth. In particular, the Tobit regression estimates indicate that a 1 standard deviation decrease in the correlation is associated with a 5 and 3 percentage point increase in the wealth allocated to stocks and mutual funds, respectively.

These empirical findings are robust to several variations to the baseline estimation framework. In particular, the economic importance of the income-return correlation is strong for both direct and indirect market participation decisions. Our results are also qualitatively similar for risk seeking investors who hold only stocks but no mutual funds and for investors who are tax-sensitive and invest in funds that reinvest all distributions. Further, our findings are not driven by very young or very old investors because we find similar results for the middle-aged cohort. In additional tests, we find that the significance of the income-return correlation remains high even when we account for entrepreneurial risk. Last, we demonstrate that the correlation between income growth and market returns also affects the decision to remain in the market. Individuals with low income-return correlation own stocks in most of the survey years.

In most of our analysis, we use after-tax income derived from all sources. We focus on this comprehensive measure of income because canonical models of portfolio choice suggest that the risks from all sources of disposable income should affect portfolio decisions. However, to draw connection with existing studies that use before-tax labor income (e.g., Betermier, Jansson, Parlour, and Walden, 2012), we repeat our analysis using before-tax labor income. We find very similar results using this alternate measure of income. A lower correlation between market return and labor income growth is associated with higher market participation rates and larger allocation to risky assets.

Using the before-tax labor income measure, we are able to test finer theoretical predictions based on the

[2] Vissing-Jorgensen (2002) uses the Panel Survey of Income Dynamics (PSID). Given the limitations of the PSID, she computes the income growth-market return covariance using a relatively shorter period from 1982–1992.

[3] Due to data limitations, many existing studies on income risk either use synthetic cohorts (e.g., Davis and Willen, 2000a) or focus on income risk related to demographic characteristics such as occupation, education, and gender (e.g., Davis and Willen, 2000b). Other studies, such as Heaton and Lucas (2000a), have accurate income data from Internal Revenue Service tax filings but need to infer who owns stocks based on reported dividend income.

permanent income hypothesis (PIH). Specifically, consistent with the PIH, we find that the correlation with the deterministic component of labor income growth does not affect investment decisions. Instead, what matters for portfolio decisions is the return correlation with the stochastic component of labor income growth. In addition, consistent with this theory, we find that the return correlation with permanent labor income shocks has a larger effect on investor decisions than the return correlation with temporary labor income growth shocks (e.g., see Heaton and Lucas, 2000a; Haliassos and Michaelides, 2003; Cocco, Gomes, and Maenhout, 2005; and Gomes and Michaelides, 2005).

In the last set of tests, we repeat our analysis using US data from the National Longitudinal Survey of the Youth (NLSY). Specifically, we consider the NLSY labor income data and find a similar hedging motive among US households. In this sample, a 1 standard deviation decrease in the income-return correlation implies a 13 percentage point increase in the ownership of stocks, mutual funds, and bonds. These results indicate that our key findings obtained using the Dutch data are likely to generalize to US households.

Collectively, these results indicate that the income hedging motive is a strong determinant of stock market participation and asset allocation decisions of both Dutch and US households. Consistent with the predictions of the standard economic theory, we show that the propensity to participate in the market is higher when the correlation between income growth and market returns is low. We do not establish that individuals optimally hedge their income risks, but we do show that individuals are at least sensitive to their income risk when they make investment decisions. In particular, they recognize that financial assets can serve as a good hedge against labor income risk and adopt broader decision frames to evaluate their income and stock market risks.[4]

Our findings contribute to the broader literature on household finance, especially to the debate on whether rational or behavioral factors are more important determinants of portfolio decisions and low levels of market participation rates. Rational determinants of portfolio decisions include age, education, marital status, wealth, and income (Campbell, 2006). More recently, the literature has considered behavioral factors of participation such as social interactions (Hong, Kubik, and Stein, 2004), optimism (Puri and Robinson, 2007), personal experiences (Malmendier and Nagel, 2011), and political activism (Bonaparte and Kumar, 2012). Our paper adds an intuitive and economically important factor (i.e., income hedging motive) to the list of rational determinants of market participation decisions.

Previous studies have also examined the potential link between various dimensions of income risk and financial decisions. For example, Guiso, Jappelli, and Terlizzese (1996) find that Italian households with more background income risk hold more liquid assets and invest less in risky assets. Heaton and Lucas (2000a) show that market participation rates are lower for business owners because entrepreneurial income is positively correlated with market returns. More recently, Angerer and Lam (2009) demonstrate that investors with higher permanent income risk allocate a smaller fraction of their wealth in risky assets. Similarly, Betermier, Jansson, Parlour, and Walden (2012) show that wage volatility influences the financial decisions of Swedish households. Individuals who move to riskier jobs reduce their holdings of risky assets. None of these papers examines the impact of the correlation between labor income growth and stock market return on portfolio decisions, which is the main focus of our paper.

The rest of the paper is organized as follows. Section 2 provides a brief description of our data sources. Section 3 reports our main empirical results and Section 4 provides additional supporting evidence. Section 5 concludes with a brief discussion.

2. Data and summary statistics

In this section, we describe our main data sets. We also provide summary statistics of the main variables included in our empirical analysis.

2.1. The Dutch National Bank Household survey

Our main data are from the 1993–2011 waves of the Dutch National Bank Household Survey. We use the DNB data for our main empirical analysis because it offers several advantages over US data sets that have been typically used in the household finance literature. For example, the Panel Survey of Income Dynamics includes panel information about income, but it reports information about stock market participation in the 1984 and 1989 waves. In contrast, the DNB Household Survey provides detailed information about both income and financial decisions in every survey wave.

The DNB Household Survey has been used by previous studies, including Alessie, Hochguertel, and Soest (2004) and Guiso, Sapienza, and Zingales (2008). The data are organized in a panel that includes information for about two thousand households. For each member of the household that is interviewed, the DNB Household Survey reports information such as age, education, and total income. Our sample focuses on individuals who are older than 18. Altogether, we consider 1763 respondents for whom we have detailed information in multiple waves of the survey. Table 1 reports the participation and summary statistics for the survey data.

In most of our analysis, we use the after-tax income from all sources to measure the correlation between income growth and market returns. But, as part of our robustness analysis we also use the before-tax labor income measure. We also use a measure of after-tax total income that does not include a special savings tax, which

[4] In an informal conversation, a bartender told us that he does not invest in the stock market because his income is positively correlated with the stock market performance. When the stock market performs poorly, has fewer customers and his income falls considerably. This kind of awareness of the link between income and stock market performance could influence people's market participation decisions even if they are not consciously optimizing by combining the various types of risks they face.

Table 1
Summary statistics: Dutch National Bank Household Survey.

This table reports the summary statistics for the key variables used in the empirical analysis. The data are from the DNB Household Survey and cover all the waves from 1993–2011. *n* is the number of individuals, and *T* is the average number of years in which those individuals participated in the survey. The definitions of all variables are in Appendix Table A1.

Variable	Mean	Standard Deviation	Percentiles					Observations		
			10th	25th	50th	75th	90th	$N=n\times T$	*n*	Average T
OwnSTK	0.120	0.325	0	0	0	0	1	15,459	1,763	8.8
PropSTK	0.036	0.135	0	0	0	0	0.0507	13,999	1,736	8.1
OwnMF	0.185	0.388	0	0	0	0	1	15,459	1,763	8.8
PropMF	0.068	0.180	0	0	0	0	0.278	13,999	1,736	8.1
OwnSTKMF	0.272	0.445	0	0	0	1	1	13,999	1,736	8.1
PropSTKMF	0.104	0.226	0	0	0	0.032	0.444	13,999	1,736	8.1
OwnGF	0.045	0.208	0	0	0	0	0	12,235	1,762	6.9
PropGF	0.015	0.087	0	0	0	0	0	10,995	1,730	6.4
Business Owner	0.019	0.138	0	0	0	0	0	9,538	1,232	7.7
Corr(*Rm*, *dy*)	−0.071	0.409	−0.628	−0.382	−0.091	0.202	0.522	17,718	1,763	10.0
Corr(*Rm*, *d*(*Labor Inc*))	−0.054	0.439	−0.649	−0.385	−0.086	0.257	0.583	8,638	953	9.1
Cov(*Rm*, *dy*)	−0.004	0.036	−0.039	−0.017	−0.003	0.008	0.030	17,718	1,763	10.0
Ln(*y*)	9.75	0.841	8.760	9.470	9.950	10.300	10.500	14,303	1,762	8.1
St. Dev(*dy*)	0.259	0.181	0.064	0.107	0.215	0.374	0.526	17,718	1,763	10.0
St. Dev(*d*(*Labor Inc*))	0.128	0.093	0.034	0.055	0.098	0.179	0.272	8,638	953	9.1
Ln(*Net Worth*)	10.90	2.07	7.95	9.43	11.60	12.50	13.00	14,390	1,742	8.3
HH size	2.450	1.190	1	2	2	3	4	16,984	1,763	9.6
Age	53.9	13.7	35	44	54	64	72	17,461	1,763	9.9
Age^2	181	212	3.24	22.9	98.3	273	476	17,461	1,763	9.9
Education	0.564	0.496	0	0	1	1	1	16,433	1,754	9.4
Male	0.613	0.487	0	0	1	1	1	17,461	1,763	9.9
Unemployed	0.117	0.322	0	0	0	0	1	15,470	1,763	8.8
Retired	0.284	0.451	0	0	0	1	1	15,470	1,763	8.8
Good health	3.910	0.693	3	4	4	4	5	15,396	1,763	8.7
Risk aversion	4.400	2.05	1	3	4	6	7	14,425	1,745	8.3

is a fixed proportion of the market value of individual stock holdings. This type of tax was introduced in 2001 and implemented in 2002.

Table 1 reports the summary statistics for the key variable in the DNB Household Survey. Table A1 in the Appendix provides a detailed description of all those variables. The descriptive statistics in Table 1 show that 12% of the sample owns stocks, 19% owns mutual funds, and total market participation, which includes ownership of stocks or mutual funds or both, is about 27%. Examining the asset allocation decisions, we find that, on average, households invest about 10% of their financial wealth in stocks and mutual funds. However, the households with the largest portfolios (i.e., 90th percentile) invest about 44% of their wealth in stocks and mutual funds.

In our empirical analysis, we follow Guiso, Jappelli, and Terlizzese (1996) and Heaton and Lucas (2000a) and measure income risk as the standard deviation of income growth. Income is the total income after taxes, and it does not include financial income from dividends and interest payments.[5] The summary statistics reported in Table 1 show substantial cross-sectional variation in income risk. The standard deviation of income growth ranges from 0.064 (=10th percentile) to 0.526 (=90th percentile).

Following Massa and Simonov (2006), we investigate how income risk comoves with market returns using the correlation of income growth with market returns. Specifically, we compute the correlation between income growth and the return of the AEX index, which is a market index of all stocks traded on the Amsterdam stock exchange.[6] To minimize measurement error, we follow the literature and compute one correlation for each respondent for the entire sample period (e.g., Vissing-Jorgensen, 2002; and Massa and Simonov, 2006). We find that the correlation of income growth with the market return has substantial variation across households. It ranges from −0.624 (=10th percentile) to 0.522 (=90th percentile). Therefore, the potential of households to mitigate their income risks using financial assets varies considerably.

The DNB Household Survey is representative of the Dutch population. The average age is 54, about half of the sample participants are males, and about half of them are college graduates. Also, one-third of the survey participants are retired and only 10% of them are unemployed. Most of the participants are in good health and on average exhibit moderate levels of risk aversion. Overall, the sample covers a large cohort of investors and is

[5] In Section 3.5, we find similar results when we use labor income before taxes in our empirical analysis.

[6] When we compute the correlations, we consider individuals with a minimum of four waves of valid income growth data. We obtain similar results if we require a minimum of ten waves of valid income growth data. However, in the latter case we lose a large portion of our sample.

Table 2
Correlation matrix: DNB Household Survey.

This table reports the correlation matrix of the key variables. The data are from the 1993–2011 waves of the DNB Household Survey. The definitions of all variables are in Appendix Table A1. The first part of the table reports the correlation coefficients for the first 11 variables, whereas the second part of the table reports the correlation coefficients for variables 12–23.

	Variable	1	2	3	4	5	6	7	8	9	10	11
1	*OwnSTK*	1										
2	*PropSTK*	0.65	1									
3	*OwnMF*	0.32	0.13	1								
4	*PropMF*	0.13	0.03	0.71	1							
5	*OwnSTKMF*	0.66	0.43	0.83	0.59	1						
6	*PropSTKMF*	0.47	0.59	0.65	0.83	0.72	1					
7	*OwnGF*	0.13	0.03	0.11	0.03	0.12	0.04	1				
8	*PropGF*	0.08	0.00	0.04	−0.01	0.06	−0.01	0.76	1			
9	*Business owner*	−0.03	−0.02	−0.04	−0.03	−0.05	−0.03	−0.02	−0.02	1		
10	*Corr(Rm, dy)*	−0.06	−0.06	−0.05	−0.06	−0.08	−0.08	−0.02	−0.01	0.00	1	
11	*Cov(Rm, dy)*	−0.07	−0.08	−0.03	−0.03	−0.06	−0.07	0.01	0.00	−0.03	0.77	1
12	*Ln(y)*	0.16	0.10	0.16	0.09	0.19	0.13	0.06	0.03	−0.05	−0.02	0.05
13	*St. Dev(dy)*	−0.02	0.06	−0.09	−0.05	−0.09	0.00	−0.04	−0.02	0.15	0.10	−0.06
14	*Ln(Net Worth)*	0.26	0.16	0.28	0.18	0.33	0.24	0.09	0.07	−0.03	−0.01	0.03
15	*HH size*	0.00	−0.02	−0.09	−0.07	−0.04	−0.07	−0.02	−0.01	0.02	0.00	−0.03
16	*Age*	0.08	0.08	0.11	0.11	0.11	0.14	−0.02	−0.02	−0.04	−0.02	−0.02
17	*Age*^{2}	0.01	0.05	0.04	0.05	0.03	0.07	0.01	0.03	−0.04	−0.02	0.02
18	*Education*	0.06	0.03	0.06	0.04	0.08	0.05	0.03	0.04	0.03	−0.05	−0.02
19	*Male*	0.17	0.10	0.14	0.09	0.18	0.13	0.06	0.07	−0.03	0.02	0.01
20	*Unemployed*	−0.01	−0.02	−0.01	−0.03	−0.01	−0.04	−0.02	−0.03	−0.03	0.05	0.00
21	*Retired*	0.04	0.08	0.06	0.09	0.05	0.12	−0.02	−0.01	−0.04	−0.05	−0.06
22	*Good health*	0.01	0.05	0.01	0.00	0.02	0.03	0.02	0.02	0.02	−0.04	−0.02
23	*Risk aversion*	−0.42	−0.28	−0.38	−0.28	−0.48	−0.38	−0.10	−0.05	−0.02	0.02	0.02

	Variable	13	14	15	16	17	18	19	20	21	22	23
13	*St. Dev(dy)*	1										
14	*Ln(Net Worth)*	−0.16	1									
15	*HH size*	0.00	−0.01	1								
16	*Age*	0.08	0.16	−0.34	1							
17	*Age*^{2}	0.07	−0.09	−0.08	−0.05	1						
18	*Education*	−0.11	0.20	0.07	−0.23	0.05	1					
19	*Male*	−0.19	0.42	0.03	0.16	−0.03	0.09	1				
20	*Unemployed*	0.08	−0.01	−0.12	0.11	−0.18	−0.04	0.04	1			
21	*Retired*	0.17	−0.05	−0.16	0.59	0.31	−0.18	−0.06	−0.24	1		
22	*Good health*	−0.03	0.07	0.13	−0.16	0.01	0.09	0.03	−0.19	−0.08	1	
23	*Risk aversion*	0.06	−0.19	−0.05	0.09	−0.05	−0.08	−0.19	0.06	0.08	−0.08	1.00

appropriate for analyzing the impact of income hedging on portfolio decisions.

Table 2 reports univariate correlations among the key variables used in the empirical analysis. The correlation estimates show that the stock market participation decision is negatively correlated with the income growth-market return correlation. This evidence suggests that as this correlation decreases, the propensity to participate in the stock market rises.

2.2. National longitudinal survey of the youth data

In addition to the DNB Household Survey, we use data from the National Longitudinal Survey of the Youth to examine the robustness of our findings. The NLSY sample contains individuals who were 14–22 years old in 1979. The survey respondents were followed annually from 1979 to 1994 and biannually from 1996 onward. In our analysis, we use the data until 1994 because we want to compute annual income growth rates using consecutive annual income observations. To compute the return correlations with income growth, we use the labor income data provided by the NLSY.

One weakness of the NLSY is that it does not collect detailed information about the ownership of risky assets. From 1988 onward, it only asks respondents if they own stocks or mutual funds or bonds, or some combination. However, the survey includes important demographic information such as age, gender, education, wealth, marital status, health, and risk aversion. We use these demographic variables as control variables in our analysis. Appendix Table A2 provides brief definitions of all these variables.

We present summary statistics and correlation estimates for the NLSY variables in Appendix Table A3. The NLSY focuses on a younger cohort of the US population with an average age of about 30 years. The sample is evenly split between men and women. About 47% of the participants are single and about one fourth of them are college graduates. Examining the financial decisions of NLSY respondents, we find that about 15% of them hold stocks, bonds and mutual funds. Similar to the DNB Household Survey, we find an unconditional negative

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correlation between income growth and the US stock market returns.

3. Main empirical results

In this section we present our main empirical findings. We begin with a summary of the theoretical motivation for our empirical analysis. Then, we present baseline results from direct and indirect market participation regressions. We also examine the asset allocation decisions of investors and show that the proportion of financial wealth allocated to stocks and mutual funds is influenced by income hedging motives.

3.1. Theoretical motivation

We develop our estimation framework using the economic intuition from capital asset pricing models that includes human capital (Mayers, 1972, 1973; Fama and Schwert, 1977; Jagannathan and Wang, 1996; Campbell and Viceira, 2002; and Eiling, 2012) and the stock market participation literature (e.g., Vissing-Jorgensen, 2002). Specifically, we consider the Campbell and Viceira (2002) model of portfolio choice, which features labor income and fixed labor supply. In their model, there is a risk-averse investor with constant relative risk aversion preferences. The investor cannot trade her labor income, and she has access to a risk-free asset and a risky asset. Through a series of log-linearizations, Campbell and Viceira (2002, pp. 170) show that the optimal weight on the risky portfolio is

$$w = \frac{1}{\rho}\left(\frac{\mu+\sigma_r^2/2}{\gamma\sigma_r^2}\right)+\left(1-\frac{1}{\rho}\right)(corr_{yr})\left(\frac{\sigma_y}{\sigma_r}\right) \tag{1}$$

where γ is the coefficient of relative risk aversion, μ is the expected log excess return, σ_y is the standard deviation of income risk, σ_r is the standard deviation of the return of the risky portfolio, $corr_{yr}$ is the correlation between income growth and stock market returns, and ρ is a positive constant less than one. ρ is the steady state portion of financial wealth to total wealth (i.e., human and financial wealth).[7]

The optimal portfolio demand in Eq. (1) has two components. The first component is related to the Sharpe ratio of the risky asset and the level of risk aversion. This term reflects the demand for risky assets when income risk is idiosyncratic (i.e., $corr_{yr}=0$). The second term in the equation is the income hedging component, and it is driven by the correlation between the return of the risky asset and income growth. This hedging demand component indicates that when the correlation between income growth and financial market returns is low, stocks would serve as a good hedge against income risk and investors should increase their optimal allocation to financial assets.[8]

Most previous studies focus on the setting in which the income risk is idiosyncratic (i.e., $corr_{yr}$ is set to zero) and asset demand is driven by the Sharpe ratio component. The main finding from these studies is that as income risk rises, the allocation to risky assets decreases. This finding is consistent with the optimal allocation relation in Eq. (1) when $corr_{yr}$ is set to zero.[9] In another related study, Heaton and Lucas (2000a) take a different approach and conjecture that entrepreneurial income is likely to be correlated with stock market wealth and, thus, it might not be idiosyncratic. Using Internal Revenue Service (IRS) data, they demonstrate that entrepreneurs allocate a smaller proportion of their wealth to risky assets.

In our study, we use a new data set and re-examine whether income risk is purely idiosyncratic. Specifically, we focus on the hedging potential of financial assets and test whether income hedging concerns affect the participation and asset allocation decisions of investors. As predicted by Eq. (1), when income risk is not idiosyncratic, an increase in income risk does not necessarily lead to lower asset demand. In fact, a higher level of income risk could be associated with higher asset demand if the correlation between income growth and asset returns is negative. This key prediction is one of the hypotheses we test in this paper.

Our data do not contain information about the stocks held by investors and, therefore, we cannot compute the correlation between income growth and portfolio returns. To overcome this hurdle, we use the correlation between income growth and the market return as a proxy for the correlation between income growth and portfolio return. This approximation is reasonable under the assumption that the CAPM captures most of the systematic risks in investor portfolios.

Beyond this theoretical argument, we use data from a US discount brokerage house for the 1991–1996 period to demonstrate that the mean correlation between realized portfolio returns and market returns is 0.511.[10] This evidence of high correlation between portfolio and market returns suggests that our assumption that households would be sensitive to the correlation between income growth and market returns is reasonable. Further, for households that do not own stocks, the correlation between income growth and market returns might be a good signal of potential income hedging opportunities offered by financial markets.

[7] The original formulation developed in Campbell and Viceira (2002) uses the covariance measure instead of the correlation measure. We replace the covariance measure with the correlation term for easier interpretation. Nevertheless, as expected, using the correlation term instead of the covariance measure does not change our findings. In our robustness analysis (see Sections 3.3 and 3.4), we find that the individuals with lower covariance participate more in the market and allocate more of their wealth to risky assets.

[8] Conditional on participation, this economic intuition generalizes to more realistic inter-temporal life-cycle models (e.g., Heaton and Lucas, 2000b; Haliassos and Michaelides, 2003; Cocco, Gomes, and Maenhout, 2005; and Gomes and Michaelides, 2005) in which a positive correlation between income shocks and stock returns can lower investment in risky assets.

[9] When $corr_{yr}$ is zero, Campbell and Viceira (2002) show (see pp. 171–173) that as income risk σ_y rises, ρ increases, $(1/\rho)$ decreases, and, consequently, the weight allocated to risky asset (i.e., w) decreases.

[10] See Korniotis and Kumar (2011) for details about the brokerage data.

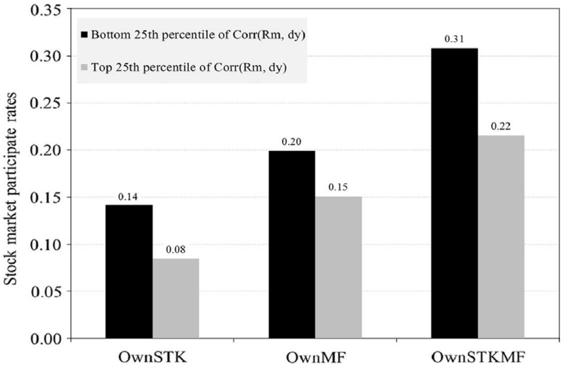

Fig. 1. Market participation rates for low and high correlation subsamples. The figure presents the average participation rates for the low and high correlation subsamples. Low (high) is defined as bottom (top) quartile of correlation between income growth and market returns. The data are from the DNB Household Survey and cover all the waves from 1993–2011. The definitions of all variables are in Appendix Table A1.

3.1.1. Importance of market participation costs

While the Campbell and Viceira (2002) framework highlights the importance of income hedging, their model does not explain why most households do not participate in the stock market. The market participation costs can be significant and related to the costs associated with getting informed about the investment opportunities available in the stock market, the opportunity cost of time spent to maintain an equity portfolio, and various types of trading costs (Vissing-Jorgensen, 2002). Participation costs could also vary across individuals when, compared with the general population, more resourceful investors (e.g., educated or wealthy investors) could have easier access to financial markets and could also have lower trading costs. An investor would compare the total (fixed and variable) cost of participation with the expected benefit from participation to determine whether or not to participate in the market.

To account for the important role of these costs associated with market participation, in our empirical analysis, we consider a host of demographic variables that are likely to be correlated with the cost of participation.

3.2. Graphical evidence

We begin our empirical analysis by examining graphically how market participation propensity is influenced by the income growth-market return correlation. Fig. 1 shows the participation rates, conditional upon the level of income-return correlation. We present the average participation rates for respondents with the lowest correlation (bottom quartile) and highest correlation (top quartile). Significant cross-sectional variation exists in the income-return correlation levels. The average correlations for the low and high correlation subsamples are -0.58 and 0.50, respectively. Further, we find that respondents with low correlation participate more in the market compared with those in the high correlation subsample. This evidence is consistent with our main conjecture and suggests that investment decisions of individuals are sensitive to income-return correlations.

3.3. Baseline market participation regression estimates

Next, we estimate stock market probit participation regressions. For this analysis, we define an indicator function I as

$$I = \begin{cases} 1 & \text{if investor participates, or} \\ 0 & \text{if investor does not participate,} \end{cases} \tag{2}$$

and we estimate the propensity to participate in the stock market, which we denote by $p(I=1)$. Following the related portfolio choice literature, in our empirical analysis, we assume that the decision to own risky assets depends upon household-level variables such as income, wealth, education, gender, and risk aversion. These household-level variables would serve as a reasonable proxy for the real and perceived market participation costs.

In Table 3, we report the marginal effects from probit market participation regressions. The dependent variable in these regressions is an ownership binary variable that takes the value of one if the individual owns financial assets and zero otherwise. We separately examine the decision to hold stocks directly and indirectly through mutual funds. We also examine the total market participation decisions. In Panel A, our key independent variable is the income growth-return correlation. For robustness, in Panel B, we replace the correlation term with the covariance measure between income growth and market returns. Our control variables are the level of income and wealth, the standard deviation of income growth, the household's size, the age and squared age of the respondent, various dummy variables related to gender, employment and retirement status, and categorical variables related to health and risk aversion.

Our results indicate that the correlation between income growth and market returns affects the decision to participate in the stock market. In particular, we find that when the correlation between income growth and the Dutch market index return is low, the market participation propensity increases. This result is strong and statistically significant in regressions with and without control variables. For example, in the stock ownership multivariate regression 3 that includes all control variables, the marginal effect of the correlation is -0.338 and its t-statistic is -6.53.[11]

The effect of income-return correlation remains statistically significant when we look at the mutual fund participation decisions, but the marginal effect weakens. For example, in the multivariate regression 6, the marginal effect of the correlation term is -0.162 and its t-statistic is -3.72. The different estimates between the decision to hold stocks directly and indirectly suggest that investors are likely to consider individual stocks as more effective instrument for hedging income risk than mutual funds. In regression 9, we examine the decision to hold stocks directly and indirectly through mutual funds and find a

[11] Our t-statistics are based on robust heteroskedasticity-consistent standard errors. When we compute clustered standard errors based on age, gender, and education clusters, we find very similar results. See Appendix Table A4.

Table 3

Probit participation regression estimates.

This table reports marginal effects from probit regressions. The dependent variables are the direct market participation dummy (Columns 1–3), indirect market participation dummy (Columns 4–6), and total market participation dummy (Columns 7–9). In Panel A (B), the main explanatory variable is the correlation (covariance) between income growth and market returns. In Panel C, we report estimates using before-tax income data. Robust *t*-statistics are reported in parentheses below the coefficient estimates. The data are from the 1993–2011 waves of the DNB Household Survey. All regressions include time (year) fixed affects. In regressions 3, 6, and 9, in Panels B and C, the coefficient estimates for the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed. The definitions of all variables are in Appendix Table A1.

	OwnSTK (1–3)			OwnMF (4–6)			OwnSTKMF (7–9)		
Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Estimates using correlation between income growth and market returns									
Corr(Rm, dy)	−0.237	−0.284	−0.338	−0.156	−0.179	−0.162	−0.239	−0.255	−0.279
	(−7.17)	(−7.64)	(−6.53)	(−5.29)	(−5.35)	(−3.72)	(−8.35)	(−7.95)	(−6.57)
Ln(y)		0.440	0.015		0.436	−0.012		0.410	−0.015
		(15.27)	(0.42)		(16.75)	(−0.40)		(17.34)	(−0.53)
St. Dev(dy)		0.571	0.182		−0.093	−0.613		0.164	−0.392
		(6.81)	(1.56)		(−1.17)	(−5.68)		(2.17)	(−3.84)
Ln(Net Worth)			0.256			0.255			0.288
			(16.32)			(20.60)			(24.08)
HH size			0.019			−0.117			−0.065
			(1.01)			(−7.27)			(−4.22)
Age			0.010			0.006			0.009
			(4.04)			(3.35)			(5.17)
Age^2 × 100			0.017			0.020			0.024
			(1.61)			(2.19)			(2.77)
Education			0.014			0.140			0.116
			(0.34)			(3.89)			(3.29)
Male			0.064			−0.031			−0.026
			(1.17)			(−0.71)			(−0.62)
Unemployed			0.031			0.018			0.033
			(0.44)			(0.32)			(0.58)
Retired			0.083			0.056			0.078
			(1.12)			(0.94)			(1.34)
Good health			−0.042			0.004			−0.008
			(−1.41)			(0.16)			(−0.32)
Risk aversion			−0.349			−0.237			−0.313
			(−31.51)			(−28.98)			(−37.08)
N	15,459	13,139	9,351	15,459	13,139	9,351	13,999	11,961	9,133
pseudo R^2	0.011	0.056	0.288	0.011	0.060	0.206	0.008	0.047	0.270
Panel B: Estimates using covariance between income growth and market returns									
Cov(Rm, dy)	−3.590	−4.654	−5.747	−1.355	−2.595	−2.564	−2.980	−3.864	−4.415
	(−7.05)	(−7.68)	(−6.80)	(−3.05)	(−4.56)	(−3.53)	(−6.69)	(−7.17)	(−6.31)
Ln(y)		0.445	0.019		0.438	−0.011		0.414	−0.014
		(15.40)	(0.51)		(16.80)	(−0.36)		(17.42)	(−0.48)
St. Dev(dy)		0.486	0.053		−0.133	−0.661		0.103	−0.475
		(5.72)	(0.45)		(−1.67)	(−6.11)		(1.36)	(−4.62)
N	15,469	13,148	9,354	15,469	13,148	9,354	14,004	11,965	9,136
Pseudo R^2	0.010	0.056	0.289	0.010	0.060	0.206	0.007	0.046	0.270
Panel C: Estimates using before-tax income measure									
Corr(Rm, dy)	−0.235	−0.273	−0.311	−0.138	−0.149	−0.125	−0.225	−0.231	−0.250
	(−7.08)	(−7.26)	(−5.98)	(−4.65)	(−4.44)	(−2.90)	(−7.85)	(−7.14)	(−5.91)
Ln(y)		0.474	0.035		0.454	−0.005		0.430	−0.005
		(16.03)	(0.93)		(17.23)	(−0.15)		(17.92)	(−0.18)
St. Dev(dy)		0.555	0.180		−0.102	−0.617		0.159	−0.389
		(6.52)	(1.53)		(−1.27)	(−5.71)		(2.08)	(−3.79)
N	15,459	13,152	9,359	15,459	13,152	9,359	13,999	11,974	9,141
Pseudo R^2	0.010	0.061	0.288	0.010	0.063	0.205	0.008	0.050	0.270

negative and statistically significant marginal effect (estimate= −0.279, *t*-statistic= −6.57).

In economic terms, the impact of income-return correlation is also significant. Based on the estimates in the multivariate regression 3, we find that a 1 standard deviation decrease in the correlation (=0.409) is associated with a 14 percentage point ($= -0.338 \times -0.409 \times 100$) increase in the probability of owning stocks directly. Similarly, the estimates from the multivariate regression 6 suggest that the probability of investing in mutual funds increases by 7 percentage points ($= -0.162 \times -0.409 \times 100$). And based on the total ownership regression 9 estimates, we find that the probability of investing in either stocks or mutual funds increases by 11 percentage points ($= -0.279 \times -0.409 \times 100$).

These economic significance estimates are comparable to the economic impact of education (i.e., being a college graduate) on participation, which is one of the most important determinants of portfolio decisions. Specifically, the estimates in regression 9 indicate that college graduates have an 11 percentage point higher chance of participating in the market.

Beyond our main variables, the coefficient estimates of the control variables are consistent with the evidence in the existing literature. For example, older, wealthy, less risk averse, and more educated individuals tend to participate more in the market. We also find that individuals with high income risk (i.e., high standard deviation of income growth) have a higher chance of investing in individual stocks directly. However, high income risk investors have a lower propensity to invest in mutual funds.

For robustness, in Panel B, we replace the income-return correlation term with the covariance between the two measures and obtain similar results. For example, in the multivariate probit regression 9 with the total (direct plus indirect) participation as the dependent variable, the marginal effect estimate of the covariance term is -1.679 and its *t*-statistic is -5.77. This marginal effect is not only statistically significant but also economically significant. A 1 standard deviation decrease in the covariance measure ($=0.036$) is associated with about a 16 percentage point increase in the total participation propensity ($=4.415 \times 0.036 \times 100$).[12]

3.4. Baseline asset allocation regression estimates

Our next set of results is related to the asset allocation decisions of households. We first estimate Tobit regressions that include both equity owners and non-owners. We also estimate Heckman (1979) regressions that focus on only market participants where we explicitly model the decision to participate. The basis of our asset allocation analysis is the optimal portfolio demand Eq. (1).

In Table 4, we report estimates from Tobit regressions in which the dependent variable is the fraction of wealth invested in financial assets. We consider direct investment in stocks, indirect investment in equities using mutual funds, and total investment in equities. In Panel A, the main independent variable is the income growth-return correlation and in Panel B, the main independent variable is the covariance between income growth and market returns. Like the probit market participation regression specifications, we consider a rich set of control variables. The choice of these control variables is partially motivated by the optimal weight expressions in Eq. (1), which suggest that income, wealth and risk aversion would be important determinants of the asset allocation decision.

The Tobit regression estimates are broadly consistent with the estimation results from the market participation regressions. Specifically, in Panel A, we find that investors with low income growth-return correlation allocate more of their wealth to risky assets. For example, in the multivariate regression 3 where we consider allocations to stocks only, the coefficient estimate of income-return correlation is -0.110 (*t*-statistic$=-5.55$). Similarly, in the multivariate regression 6 where we consider allocations to mutual funds only, this estimate is -0.076 (*t*-statistic$=-3.74$). These coefficient estimates imply that a 11 standard deviation decrease in the correlation term ($=0.409$) is related to a 5 and 3 percentage points increase in the wealth allocated to stocks and mutual funds, respectively. These economic effects are meaningful relative to the average share of wealth invested in stocks (4%) and in mutual funds (7%).

The coefficient estimates of other variables are consistent with the previous evidence. For example, we find that wealthier or older individuals with lower levels of risk aversion allocate more of their wealth to risky assets. Further, we find that individuals with larger income risk (i.e., higher standard deviation of income growth) invest more in individual stocks but allocate less of their wealth in mutual funds. This evidence suggests that individual investor-specific income risk might be better hedged using individuals stocks than mutual funds.

At first glance, these finding could appear inconsistent with the evidence in Angerer and Lam (2009), who report that permanent income risk reduces the fraction of wealth invested in risky assets. However, they examine the joint decision to own stocks and mutual funds whereas we separate the two decisions.[13]

In Panel B, we replace the correlation variable with the covariance measure and find that the proportion of wealth allocated to risky assets is higher when the income-return covariance is lower. When the dependent variable is the proportion of wealth allocated to individual stocks, the coefficient estimate of covariance measure is -1.924 (*t*-statistic$=-7.00$). This estimate implies that a 1 standard deviation decrease in the income-return covariance ($=0.036$) is associated with about a 7 percentage point increase ($=1.924 \times 0.036 \times 100$) in wealth allocated to individual stocks. We obtain similar results in regression 6 where we focus on the proportion of wealth allocated to mutual funds (estimate$=-1.125$, *t*-statistic$=-3.32$). Overall, the results in Panel B are qualitatively similar and suggest that hedging motives are strong determinants of asset allocation decisions of households.

3.5. Income hedging motives or effects of taxes?

Our baseline estimates are determined by the after-tax total income measure, which excludes any income from

[12] The estimates of the marginal effects with the covariance term are larger than those with the correlation term because the range of values for the covariance is lower than the range for the correlation. For example, the 10th percentile for the correlation (covariance) is -0.628 (-0.039) and the 90th percentile is 0.522 (0.030). Nevertheless, the economic effects based on 1 standard deviation changes in the covariance or the correlation terms are similar.

[13] We also show in Section 3.7 that high income risk need not be necessarily associated with lower investment in risky assets because of the potential hedging benefits of the market.

Table 4
Tobit and Heckman asset allocation regression estimates.

This table reports estimates from Tobit and Heckman regressions. The dependent variables are the portfolio shares in stocks (*PropSTK*), mutual funds (*PropMF*), and stocks and mutual funds (*PropSTKMF*). The control variables in regressions 3, 6, and 9 in Panels B and C are the same as in corresponding specifications in Panel A. Panel C reports estimates with before-tax income. All regressions include year fixed affects. In regressions 3, 6, and 9, in Panels B and C, the coefficient estimates for the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed. Regressions 10 and 11 of Panel A report estimates from a Heckman model.

Panel A: Estimates using correlation between income growth and market returns

	PropSTK (1–3)			PropMF (4–6)			PropSTKMF (7–9)			PropSTKMF Heckman (10–11)	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Corr(*Rm*, *dy*)	−0.124	−0.129	−0.110	−0.098	−0.103	−0.075	−0.128	−0.130	−0.102	−0.030	−0.022
	(−6.52)	(−6.53)	(−5.55)	(−5.71)	(−5.54)	(−3.74)	(−7.75)	(−7.39)	(−5.82)	(−5.40)	(−3.86)
Ln(*y*)		0.191	0.011		0.190	−0.008		0.211	0.000	0.037	0.003
		(13.56)	(0.82)		(14.19)	(−0.56)		(17.38)	(0.03)	(13.64)	(0.90)
St. Dev(*dy*)		0.359	0.153		−0.026	−0.234		0.163	−0.075	0.069	0.028
		(8.01)	(3.42)		(−0.62)	(−4.80)		(4.01)	(−1.81)	(5.22)	(2.08)
Ln(*Net Worth*)			0.088			0.101			0.107		0.018
			(14.93)			(18.51)			(22.37)		(17.58)
HH size			0.005			−0.044			−0.027		−0.005
			(0.70)			(−6.08)			(−4.45)		(−2.70)
Age			0.004			0.003			0.004		0.002
			(4.30)			(3.92)			(5.83)		(6.97)
Age^2 × 100			0.009			0.009			0.011		0.004
			(2.43)			(2.11)			(3.21)		(3.30)
Education			0.004			0.073			0.057		0.016
			(0.29)			(4.46)			(4.03)		(3.48)
Male			0.008			−0.007			−0.012		0.001
			(0.39)			(−0.37)			(−0.69)		(0.15)
Unemployed			0.012			−0.014			−0.009		−0.004
			(0.49)			(−0.54)			(−0.39)		(−0.59)
Retired			0.058			0.046			0.068		0.038
			(2.26)			(1.73)			(3.01)		(5.27)
Good health			−0.006			0.006			0.005		0.006
			(−0.53)			(0.56)			(0.56)		(1.91)
Risk aversion			−0.130			−0.102			−0.127		−0.036
			(−27.32)			(−27.38)			(−38.36)		(−31.62)
N	13,999	11,961	9,133	13,999	11,961	9,133	13,999	11,961	9,133	2,004	205
Pseudo R^2	0.011	0.047	0.326	0.010	0.044	0.197	0.010	0.045	0.273		
Lamda										−0.06	−0.040
										(−12.56)	(−5.48)

Panel B: Estimates using covariance between income growth and market returns

	PropSTK (1–3)			PropMF (4–6)			PropSTKMF (7–9)		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cov(*Rm*, *dy*)	−2.193	−2.266	−1.924	−0.966	−1.481	−1.125	−1.778	−2.081	−1.679
	(−7.06)	(−7.00)	(−5.89)	(−3.63)	(−4.68)	(−3.32)	(−6.69)	(−7.03)	(−5.77)
Ln(*y*)		0.193	0.012		0.191	−0.007		0.213	0.001
		(13.71)	(0.94)		(14.26)	(−0.51)		(17.50)	(0.11)
St. Dev(*dy*)		0.319	0.110		−0.052	−0.257		0.129	−0.108
		(7.06)	(2.47)		(−1.20)	(−5.26)		(3.17)	(−2.60)
N	14,004	11,965	9,136	14,004	11,965	9,136	14,004	11,965	9,136
Pseudo R^2	0.012	0.048	0.327	0.009	0.043	0.197	0.009	0.044	0.273

Panel C: Estimates using before-tax income measures

Independent variable	PropSTK (1–3)			PropMF (4–6)			PropSTKMF (7–9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Corr(Rm, dy)	−0.128	−0.129	−0.103	−0.082	−0.081	−0.054	−0.120	−0.115	−0.086
	(−6.75)	(−6.48)	(−5.16)	(−4.80)	(−4.39)	(−2.71)	(−7.26)	(−6.57)	(−4.91)
Ln(y)		0.207	0.012		0.198	−0.007		0.220	0.001
		(14.16)	(0.84)		(14.68)	(−0.51)		(17.92)	(0.04)
St. Dev(dy)		0.355	0.155		−0.036	−0.243		0.156	−0.080
		(7.77)	(3.40)		(−0.82)	(−4.95)		(3.80)	(−1.91)
N	13,999	11,974	9,141	13,999	11,974	9,141	13,999	11,974	9,141
Pseudo R^2	0.011	0.052	0.326	0.010	0.046	0.196	0.009	0.047	0.273

financial assets. In Netherlands, a new tax law, introduced in 2001 and implemented in 2002, required all Dutch households to pay a tax that is a fixed proportion of the market value of their stock holdings. Consequently, the tax payment of all households since 2001 is inversely proportional to the size of their financial portfolios. This inverse relation implies that for households with relatively stable income streams, the variability in after-tax income could be driven significantly by stock market performance.

The 2001 tax change could potentially introduce a bias in our results. In particular, individuals with larger financial portfolios would have larger taxes and the correlation between their after-tax income growth and market returns would be lower or even more negative. To ensure that our results are robust to this potential reverse causality concern, we obtain a new after-tax income measure that does not include the savings tax. The new income measure is gross income minus taxes that do not include taxes on savings based on the 2001 law.

We estimate our participation and asset allocation regressions with the new income measure. The estimation results are presented in Panel C of Tables 3 and 4. We find that the negative estimates of our key income growth-market return correlation variable remain virtually unaffected. We continue to find that income hedging motives are strong determinants of portfolio decisions. This evidence indicates that our main findings are not mechanically induced by the tax changes introduced in 2001.

3.6. *Asset allocation decisions of market participants*

We estimate Tobit regressions using a sample of both stockholders and nonstockholders. These Tobit regression estimates could be driven entirely by the participation decision of households. In this subsection, we examine whether the Tobit regression estimates capture any additional information beyond what is reflected in the probit regression estimates.

Specifically, we follow Vissing-Jorgensen (2002) and Fagereng, Gottlieb and Guiso (2011), and we estimate Heckman (1979) type models, where we simultaneously consider the market participation and asset allocation decisions. Like Vissing-Jorgensen (2002), the control variables in the selection model (i.e., the participation regression) are the same as the control variables used in the asset allocation regression. We include lagged financial wealth and lagged squared financial wealth as additional control variables.[14] We estimate the system of equations with maximum likelihood and report the estimates of

[14] Our regression specifications for the participation and asset allocation regressions are motived by the economic intuition in Vissing-Jorgensen (2002). In particular, we include lagged wealth and squared wealth variables in the participation regression because these variables would be associated with resourceful individuals who have already incurred the cost of participation. Those wealthy and more resourceful individuals are more likely to own stocks. Thus, we expect lagged wealth to be an important determinant of participation decisions. In contrast, the lagged financial wealth controls are excluded from the equity share regressions because, conditional on current wealth, there is no obvious economic reason that lagged wealth would affect the current equity share of market participants.

asset allocation regressions in Columns 10 and 11 of Table 4, Panel A.[15]

The Heckman regression estimates show that the subsample of market participants is not random because our lambda estimate is statistically different from zero (see the last two rows of Panel A). A lambda estimate that is statistically indistinguishable from zero indicates that the sample of market participants is drawn randomly from the population and, therefore, ordinary least squares (OLS) could be used for the estimation. In contrast, a non-zero lambda indicates that it is more appropriate to use the Heckman estimation method instead of the OLS because OLS would yield biased and inconsistent estimates.

Examining the estimation results, we find that the coefficient estimates of the correlation term are significantly negative. For example, in regression specification 10 that includes the baseline control variables, its estimate is −0.030 (t-statistic = −4.40). In the regression specification that includes all the control variables (See regression 11) its estimate is −0.022 (t-statistic = −3.86). Similar to the findings in the related literature, the estimated coefficient estimates in the asset allocation regressions are smaller than those in the probit and Tobit regressions.[16] But, this evidence is not surprising because our sample of market participants is relatively small. Overall, the Heckman regression estimates suggest that market participants allocate a greater proportion of their wealth to risky assets when the correlation between income growth and market returns is lower.

Examining the economic significance of the Heckman regression estimates, we find that the predicted equity share differential between investors with low (10th percentile) and high (90th percentile) income growth-return correlation is about 3.5 percentage points in the regressions with the baseline control variables and 2.5 percentage points in the regressions with all control variables. These estimates of economic significance are weaker than those obtained using probit and Tobit regressions, but this finding is not surprising. Other household finance studies report similar results and demonstrate that investor characteristics typically do not have a very strong impact on the asset allocation decision when the estimation procedure considers only the subsample of market participants (e.g., Brunnermeier and Nagel, 2008; Curcuru, Heaton, Lucas and Moore, 2009; and Malmendier and Nagel, 2011). Therefore, interpreted within the broader context of the existing household finance literature, the economic impact of the income growth-market return correlation is reasonable.

3.7. *Importance of hedging when income risk is high*

In this subsection, we examine how hedging motives interact with the level of income risk to influence people's market participation and asset allocation decisions. While high income risk is associated with lower exposure to risky assets (e.g., Heaton and Lucas, 2000b; Vissing-Jorgensen, 2002; and Angerer and Lam, 2009), individuals with high income risk have more to gain by exploiting potential risk hedging investing opportunities offered by the market. Such investors could be more willing to invest in the market, especially if the correlation between their income growth and market returns is negative.

This prediction is motivated by our theoretical model. Specifically, the model in Section 3.1 [see Eq. (1)] illustrates how the intensity of income hedging motives depends on the level of income risk. Specifically, the component of asset demand related to hedging depends on the $[(corr_{yr})(\sigma_y/\sigma_r)]$ term. This expression indicates that when income risk σ_y is high, the demand for risky assets would be high when the income growth-market return correlation $corr_{yr}$ is negative.

To examine the interaction between income risk and the income-return correlation, we estimate expanded regression specifications that include three additional variables: a high income risk dummy variable that is set to one if the standard deviation of income growth is in the top quartile, a low correlation dummy variable that is set to one if the income-return correlation is in the bottom quartile, and an interaction between the high income risk and low correlation dummy variables.[17] We present these regression estimates in Table 5.

Consistent with the previous evidence in the literature, we find that individuals with high income risk do participate less in the market and allocate less of their wealth in risky assets. Specifically, when we examine the decision to directly own stocks (see Column 1), the coefficient estimate of the high income risk dummy is −0.407 (t-statistic = −4.78). This estimate suggests that an individual with income risk in the highest quartile is about 8 percentage points less likely to own stocks.[18] We also find a similar effect when we examine allocations to risky assets. For example, the estimate of the high income risk dummy in Column 6 is −0.118 (t-statistic = −3.97), which implies that individuals with high income risk invest about 6.6 percentage points less in stocks and mutual funds.[19]

[15] One weakness of the Heckman estimation method is that the maximum likelihood estimation (MLE) requires a large sample. Otherwise, the MLE does not converge. To ensure convergence, we estimate the Heckman model using only the before-tax total income measure that provides the largest sample.

[16] For example, Vissing-Jorgensen (2002), Campbell (2006), and Malmendier and Nagel (2011) also report coefficient estimates that are significantly smaller in the asset allocation regressions when they are estimated using only the subsample of market participants.

[17] To define the interaction term, we do not directly interact the correlation measure with the income risk variable because such an interaction would reflect the covariance between income growth and return (by definition, $cov_{ry} = corr_{ry}\ \sigma_r \sigma_y$). And, we have already shown in Panel B of Tables 3 and 4 that the covariance is a significant predictor of portfolio decisions. To ensure that we are not merely restating those findings, we define the interaction term using dummy variables for high income risk and low correlation.

[18] To compute the total marginal effect for an individual with high income risk, we take the estimate of the high income risk dummy variable (−0.407) and add the product between the standard deviation (0.869) and the top 25th percentile of the standard deviation of income growth (0.374), i.e., $100 \times (-0.407 + 0.869 \times 0.374) = -8$.

[19] The total −6.6 percentage points marginal effect for an individual with high income risk is computed as $100 \times (-0.118 + 0.138 \times 0.374)$, where −0.118 is the estimate of the high income risk dummy variable,

Table 5
Participation and asset allocation regression estimates using extended specifications.

The table reports the marginal effects from extended specifications of market participation and asset allocation regressions. The regression specifications are similar to those used in Tables 4 and 5 with the following additional explanatory variables: a dummy variable for individuals with high income risk (standard deviation of income growth is in the top quartile), a dummy variable for individuals with low income growth-market returns correlation (bottom quartile), and a low correlation-high income risk interaction term. Robust t-statistics are reported in parentheses below the coefficient estimates. The data are from the DNB Household Survey and cover all the waves from 1993–2011. All regressions include time (year) fixed affects. The coefficient estimates for the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed. The definitions of all variables are presented in Appendix Table A1.

	Probit (1-3)			Tobit (4-6)		
	OwnSTK	OwnMF	OwnSTKMF	PropSTK	PropMF	PropSTKMF
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(*Rm*, *dy*)	−0.303	−0.174	−0.255	−0.079	−0.078	−0.086
	(−3.98)	(−2.66)	(−4.02)	(−2.73)	(−2.62)	(−3.32)
Low Corr × *High Inc Risk*	0.203	0.024	0.090	0.078	−0.016	0.034
	(1.85)	(0.23)	(0.96)	(1.83)	(−0.35)	(0.87)
Low Corr	0.003	−0.018	0.013	0.019	−0.001	0.013
	(0.04)	(−0.30)	(0.23)	(0.78)	(−0.03)	(0.57)
High Inc Risk	−0.407	−0.188	−0.290	−0.165	−0.057	−0.118
	(−4.78)	(−2.56)	(−4.04)	(−5.10)	(−1.66)	(−3.97)
Ln(*y*)	0.013	−0.013	−0.017	0.009	−0.008	−0.000
	(0.36)	(−0.41)	(−0.57)	(0.72)	(−0.58)	(−0.03)
St. dev(*dy*)	0.869	−0.258	0.132	0.432	−0.116	0.138
	(4.42)	(−1.48)	(0.78)	(5.79)	(−1.49)	(2.02)
N	9,351	9,351	9,133	9,133	9,133	9,133
Pseudo R^2	0.291	0.206	0.272	0.331	0.197	0.275

From our perspective, more importantly, we find that the hedging motives are stronger among individuals with high income risk when they consider investing in individual stocks. When we examine the decision to directly own stocks (see Column 1), the coefficient estimate of the interaction term between low correlation and high income risk is 0.203 (t-statistic = 1.85). This evidence indicates that individuals with high income risk exhibit a higher incremental propensity to invest in the stock market when the potential hedging benefits are high. These results are similar when we examine the stock allocation decisions (see Column 4).

This incremental effect of the income hedging motive is economically significant. The estimate of the interaction term in Column 1 implies that individuals with low correlation are about 12 percentage points more likely to own stocks while individuals with low correlation and high income risk are about 24 percentage points more likely to own stocks. Thus, when the hedging potential is high, the market participation propensity increases significantly, even when income risk is very high.[20]

(*footnote continued*)
0.138 is the estimate of the standard deviation, and 0.374 is the top 25th percentile of the standard deviation of income growth.

[20] The total 12 percentage points effect for low correlation individuals is computed as $100 \times (-0.303 \times -0.382 + 0.003)$, where −0.303 is the marginal effect of the correlation term, −0.382 is the bottom 25th percentile of the correlation term, and 0.003 is the estimate of the low correlation dummy. The 24 percentage points effect of the low correlation and high income risk individuals is given by the 12 percentage points low correlation total effect minus the 8 percentage points high income effect plus the 20.3 percentage points effect from the interaction term between low correlation and high income risk variables.

3.8. Estimates using labor income measures

In our baseline analysis, we focus on after-tax total income because in the canonical model of consumption and portfolio decisions, the sum of risks from all sources of disposal income is what should determine household behavior. However, many previous studies focus on only before-tax labor income (e.g., Meghir and Pistaferri, 2004; and Betermier, Jansson, Parlour, and Walden, 2012). To draw a better connection with this literature, we estimate our baseline regressions using before-tax labor income instead of total income.

We present the estimation results with labor income growth in Table 6, Panel A. We find that a high positive correlation between labor income growth and returns is associated with lower stock market participation. Specifically, the coefficient estimates for the correlation between stock market returns and labor income growth in the probit regressions are negative. For example, the coefficient estimate on the labor income-return correlation coefficient in Column 3 of Panel A is −0.171 (t-statistic = −3.25). Similarly, the labor income-return correlation coefficient estimates in Tobit regressions reported in Columns 4–6 are also negative. In particular, the estimate of the labor income-return correlation coefficient in the stocks and mutual funds asset allocation regression is −0.089 (t-statistic = −4.06).

The statistical significance of estimates with before-tax labor income are slightly weaker compared with those with total after-tax income reported in Panel A of Tables 3 and 4. This is especially true when the dependent variable is the direct ownership in stocks. The estimates associated with the ownership of mutual funds are similar regardless of the definition of income. A potential reason for the

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lower significance is that the subsample of respondents with labor income is substantially smaller (only about nine hundred respondents) compared with the total sample of about 17 hundred respondents with valid total income data.[21]

Nevertheless, the implied economic significance of the estimates obtained using the labor income data is high. Specifically, in the participation regressions, a 1 standard deviation decrease in the labor income risk-return correlation (0.439) is related to a 4.56 ($0.104 \times 0.439 \times 100$), 5.84 ($0.133 \times 0.439 \times 100$) and 7.51 ($0.171 \times 0.439 \times 100$), percentage point increase in the ownership of stocks, mutual funds, and stocks or mutual funds or both, respectively. These effects are comparable to the economic impact of labor risk. A 1 standard deviation decrease in the labor income growth standard deviation (0.093) is associated with a 7.54 ($0.807 \times 0.093 \times 100$), 9.13 ($0.977 \times 0.093 \times 100$) and 10.38 ($1.111 \times 0.093 \times 100$) percentage point increase in the ownership of stocks, mutual funds, and stocks or mutual funds or both, respectively. Overall, these findings suggest that the income hedging motive is strong even when we focus exclusively on labor income.

3.9. *Estimates using components of labor income*

Next, motivated by the literature on the Permanent Income Hypothesis (PIH), we estimate participation and asset allocation regressions using various components of labor income. The main finding from the PIH literature (e.g., Hall, 1978) is that the labor income shocks that should matter the most for investment decisions are the permanent income shocks. Similarly, Hall and Mishkin (1982) find that temporary income shocks might affect consumption decisions but their effect is smaller than that of permanent shocks. More recently, Heaton and Lucas (2000a), Haliassos and Michaelides (2003), Cocco, Gomes and Maenhout (2005), and Gomes and Michaelides (2005) argue that a positive correlation between permanent labor income shocks and stock returns can decrease the asset allocation to equity.

Following the PIH literature, we decompose labor income growth into deterministic and stochastic components. The stochastic component can be further decomposed into permanent and temporary components.[22] Motivated by the labor income literature going back to Ben-Porath (1967) and Griliches (1977), we assume that deterministic income growth can be predicted by age, education, and gender. Specifically, we measure deterministic income growth with the explained part from a regression of income growth on survey year (time trend), age, age^2, age^3, age^4, male dummy, education (college dummy), the interaction term between the male dummy and education, and the interactions of the male dummy with age, age^2, age^3, and age^4.[23] The stochastic component of labor income is the residual labor income growth from this regression.

We further decompose stochastic labor income growth into permanent and temporary (transitory) components. Typically, such decompositions are based on structural models that require a long time-series of labor income data for estimation (e.g., Carroll, 1992, 1997; and Meghir and Pistaferri, 2004). Instead, we follow Kopczuk, Saez, and Song (2010), who propose measuring permanent shocks using moving averages.[24] Specifically, our measure of the permanent component of income growth in year t is the equal weighted average of the stochastic income growth rates in years $(t-1)$, t, and $(t+1)$. The transitory component at year t is the difference between the year t stochastic labor income growth and the permanent component of income growth at year t. We follow the Kopczuk, Saez, and Song (2010) approach because its nonparametric nature does not involve specifying a fully structural model of income shocks that might not be appropriate for all respondents in our sample.[25]

After we decompose the labor income growth measure, we compute correlations between the components of labor income growth and stock returns. We then estimate the baseline market participation and asset allocation regressions with the new correlations. We present these results in Panels B and C of Table 6.

Our estimates are consistent with the theoretical predictions. Examining the probit regression estimates in Panel B, we find that the correlation of returns with the deterministic component of labor income growth is not significant in explaining the decision to own stocks (in regression 2, its estimate is -0.028 and its t-statistic is -0.53). In contrast, the estimate of the correlation between returns and stochastic labor income growth is negative and relatively more significant (in regression 3, its estimate is -0.078 and its t-statistic is -1.61). And, when we estimate the participation regression using the

[21] In the NLSY data set, we have a substantially larger sample of respondents with valid labor income data and we find that the impact of the labor-income growth-market return correlation is always statistically significant. Please see Panel A of Table 8.

[22] We use the income decomposition method that is standard in the literature and has been previously used by Gomes and Michaelides (2005). Specifically, the evolution of income Y is based on two laws of motion: $Y_t = P_t U_t$ and $P_t = \exp[(f(t, X_t))P_{t-1}N_t]$. The function $f(t, X_t)$ is a deterministic function of household demographic characteristics X_t. The process P_t is a permanent component with innovation N_t and U_t is a transitory component. This specification implies that the log difference in income ($\Delta \log Y_t$) has three components: the deterministic component $f(t, X_t)$, the transitory component $\Delta \log U_t$, and the permanent component $\Delta \log N_t$. We define the stochastic component of income growth as the sum of $\Delta \log U_t$ and $\Delta \log N_t$.

[23] The specification chosen for defining the deterministic component of income growth is supported empirically. We find that all chosen variables in the income growth decomposition regression are statistically significant. The only exception is the education dummy and its interaction with the male dummy. We still keep these two variables in the model because intuitively being a college graduate should be important for the income process.

[24] DeBacker, Heim, Panousi and Vidangos (2013) compare the structural approach to decomposing income shocks as in Gottschalk and Moffitt (1994, 2009) with the nonparametric approach of Kopczuk, Saez, and Song (2010). They find that the two methodologies produce very similar empirical results because mathematically the two methods are almost identical.

[25] We use one lag and one lead growth rate to compute the permanent income growth rate due to data constraints. In this case, we are considering only respondents that have valid labor income information for five consecutive surveys. If we add another lead and lag growth rate terms in the definition of the permanent income variable, we have to focus on respondents that have valid labor income information for seven consecutive surveys, a requirement that decreases our sample size significantly.

Table 6
Participation and asset allocation regression estimates using components of labor income.

The table reports marginal effects from market participation and asset allocation regressions using components of before-tax labor income. The specifications are similar to those used in Tables 4 and 5. We exclude respondents who are retired or unemployed. Robust *t*-statistics are reported in parentheses below the coefficient estimates. The data are from the DNB Household Survey. In Panels B and C, we decompose labor income growth into deterministic and stochastic components and then decompose the stochastic component into transitory and permanent components. All regressions include time fixed effects. In Panel A, the coefficient estimates for the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed. In Panels B and C, we present only the coefficient estimates related to the correlation terms. All regressions in Panels B and C include all the controls as in Panel A.

Panel A: Baseline estimates

	Probit (1–3)			Tobit (4–6)		
	OwnSTK	OwnMF	OwnSTKMF	PropSTK	PropMF	PropSTKMF
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(*Rm*, *dy*)	−0.104	−0.133	−0.171	−0.036	−0.089	−0.089
	(−1.61)	(−2.45)	(−3.25)	(−1.51)	(−3.59)	(−4.06)
Ln(*y*)	0.053	0.093	0.107	−0.003	0.028	0.021
	(0.72)	(1.68)	(1.97)	(−0.13)	(1.13)	(0.93)
St. Dev(*dy*)	−0.807	−0.977	−1.111	−0.141	−0.317	−0.291
	(−2.23)	(−3.20)	(−3.77)	(−1.05)	(−2.22)	(−2.33)
N	4,835	4,835	4,730	4,730	4,730	4,730
Pseudo R^2	0.279	0.183	0.242	0.304	0.183	0.245

Panel B: Income risk decomposition and participation decisions

	OwnSTKMF						
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(*Rm*, *Total dy*)	−0.171						
	(−3.25)						
Corr(*Rm*, *Deterministic dy*)		−0.028				−0.018	
		(−0.53)				(−0.34)	
Corr(*Rm*, *Stochastic dy*)			−0.078			−0.080	
			(−1.61)			(−1.66)	
Corr(*Rm*, *Transitory dy*)				−0.035			−0.053
				(−0.92)			(−1.35)
Corr(*Rm*, *Permanent dy*)					−0.081		−0.081
					(−2.16)		(−2.10)
N	4,730	4,729	4,728	3,898	3,898	4,728	3,898
Pseudo R^2	0.242	0.237	0.240	0.251	0.250	0.240	0.253

Panel C: Income risk decomposition and asset allocation decisions

	PropSTKMF						
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(*Rm*, *Total dy*)	−0.089						
	(−4.06)						
Corr(*Rm*, *Deterministic dy*)		−0.026				−0.025	
		(−1.19)				(−1.18)	
Corr(*Rm*, *Stochastic dy*)			−0.057			−0.058	
			(−2.83)			(−2.89)	
Corr(*Rm*, *Transitory dy*)				0.001			−0.004
				(0.07)			(−0.27)
Corr(*Rm*, *Permanent dy*)					−0.025		−0.022
					(−1.71)		(−1.43)
N	4,730	4,729	4,728	3,898	3,898	4,728	3,898
Pseudo R^2	0.245	0.240	0.243	0.260	0.259	0.243	0.261

correlations between market returns and both the deterministic and stochastic components of labor income growth, we find that the correlation with the stochastic component has a higher and more significant estimate (see regression 6).

Next, we separate stochastic income growth into transitory and permanent components. Consistent with the theoretical predictions, we find that the correlation with the temporary component has a weaker impact on participation decisions than the impact of the correlation with the permanent component. Specifically, in regression 4, the estimate of the correlation with the temporary component is −0.035 and its *t*-statistic is −0.92. In regression 5, the estimate of the correlation with the permanent component is −0.081 and its *t*-statistic is −2.16. We find similar results in regression 7 that includes both correlation terms.

In Panel C of Table 6, we present estimates from Tobit asset allocation regressions in which we vary the component of labor income growth used to define the correlation with market returns. We find that the impact of return correlation with deterministic income growth is small and insignificant (in regression 2, its estimate is −0.026 and its t-statistic is −1.19). In contrast, the impact of the return correlation with stochastic income growth is strong and significant (in regression 3, its estimate is −0.057 and the t-statistic is −2.83). Also, the return correlation with transitory income growth is small and insignificant (in regression 4, its estimate is −0.001 and the t-statistic is 0.07), while the return correlation with permanent income growth is negative and significant (in regression 5, its estimate is −0.025 and the t-statistic is −1.71).

Overall, the findings from our market participation and asset allocation regressions suggest that individuals are likely to consider the joint dynamics between their income and the stock market returns when making financial decisions. Individuals whose income grows when the stock market returns are low exhibit a higher propensity to participate in the market and allocate more of their wealth to risky assets. It is likely that these individuals recognize that risky assets could serve as a good hedge against their labor income risk.

4. Additional empirical evidence

In this section, we report additional evidence to support our main finding that the income-return correlation is an important determinant of portfolio decisions.

4.1. Estimates using restricted Dutch sample

In our baseline analysis, we impose minimal restrictions on the data so that we have the largest possible sample, which allows us to exploit the richness of our data set more effectively. However, this raises the potential concern that some of our results could be driven by extreme outliers. To ensure that our results are robust to this potential concern, we restrict our sample using several standard filters. All our choices are motivated by the selection criteria used in the Angerer and Lam (2009) study. Specifically, we exclude all individuals who are unemployed or reported income of less than 100 euros. We also remove individuals from the sample if the standard deviation of their income growth is above 3. Last, we focus only on individuals who have income growth data for at least ten years.[26]

The results from market participation probit and asset allocation Tobit regressions with the restricted sample are presented in Table 7. Not surprisingly, the sample size decreases significantly when we apply the various filters. Specifically, in the multivariate regressions the sample size decreases from about 91 hundred observations to about 15 hundred. In spite of this severe reduction in the sample size, our key results remain unaffected. Consistent with our baseline estimates, we find that the lower is the correlation between income growth and market returns, the higher is the individual's propensity to participate in the market and the higher is the allocation to risky assets.

4.2. Estimates using the NLSY data

In the next set of tests, we use data from the 1979 NLSY and examine whether our main conclusions derived using the Dutch data generalize to US households. The choice of the NLSY data is motivated by Angerer and Lam (2009), who use them to examine the significance of income risk for portfolio decisions.

In Panel A of Table 8, we report the estimates from market participation and asset allocation regressions using the NLSY data. The main independent variable is the correlation between income growth and stock market returns. The income measure is the before-tax labor income. The control variables are log of income, log of net worth, age and age squared, education (college graduate dummy variable), male dummy, single dummy, health proxy, and risk aversion.

The NLSY estimates show that individuals with lower labor income-return correlations are more likely to participate in the market and allocate a larger proportion of their wealth in stocks, mutual funds, and bonds. Specifically, the marginal probability estimate for labor income-return correlation in Column 3 is −0.058 (t-statistic = −2.09). This estimate implies that a 1 standard deviation decrease in correlation (=0.372) is associated with about a 2 percentage point (=0.058 × 0.372 × 100) increase in the market participation propensity. Relative to the mean participation rate of 15 percentage points, this represents more than a 13 percentage point increase.

We find similar estimates in the Tobit asset allocation regressions. For example, the estimate of labor income-return correlation in regression 6 is −0.018 (t-statistic = −2.42). This estimate implies that a 1 standard deviation decrease in labor income-return correlation (=0.372) leads to an increased allocation in stocks, mutual funds, and bonds by about 0.67 percentage points (=0.372 × 0.018 × 100). Compared with the mean allocation of 1.66 percentage points, this represents an increase of about 40 percentage points [=100 × (0.67/0.0166)].

4.3. Labor income decomposition using the NLSY data

The income measure in the NLSY data is the before-tax labor income. We follow the PIH literature and decompose labor income growth into deterministic and stochastic components. For this income decomposition, we follow the same approach as in Section 3.9. We recompute the income-return correlations using these labor income components and report the regression estimates in Panels B and C of Table 8.

In the market participation probit regressions in Panel B, the coefficient estimate of the return correlation with the deterministic component of labor income growth is insignificant (in regression 2, its estimate is −0.042 and its t-statistic is −0.67). In contrast, the coefficient estimate of the market return correlation with the stochastic

[26] Angerer and Lam (2009) require having at least 14 years of income growth data. When we impose this restriction we lose almost all households in the sample and cannot estimate any of our regressions meaningfully.

Table 7
Participation and asset allocation regression estimates using a restricted sample.

The table reports the marginal effects from market participation and asset allocation regressions. The regression specifications are similar to those used in Tables 4 and 5. We restrict the sample by excluding individuals who make less than 100 euros, are unemployed, have a standard deviation of income growth higher than 3, and have valid income growth data for less than ten years. We suppress the estimates for the control variables that include log net worth, age, age squared, education, male, unemployed, and retired dummy variables, good health index, and risk aversion index. Robust *t*-statistics are reported in parentheses below the coefficient estimates. The data are from the DNB Household Survey and cover all the waves from 1993 to 2011. The coefficient estimates for the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed. The definitions of all variables are in Appendix Table A1.

	Probit (1–3)			Tobit (4–6)		
	OwnSTK	OwnMF	OwnSTKMF	PropSTK	PropMF	PropSTKMF
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(*Rm*, *dy*)	−0.517	−0.831	−1.059	−0.177	−0.355	−0.402
	(−3.31)	(−6.29)	(−7.88)	(−4.00)	(−6.85)	(−8.86)
Ln(*y*)	−0.150	−0.171	−0.099	−0.047	−0.063	−0.050
	(−1.41)	(−2.16)	(−1.17)	(−1.57)	(−1.95)	(−1.71)
St. Dev(*dy*)	−0.191	−1.861	−1.320	0.108	−0.665	−0.387
	(−0.41)	(−4.49)	(−3.25)	(0.90)	(−4.05)	(−2.86)
N	1,561	1,556	1,549	1,549	1,549	1,549
Pseudo R^2	0.366	0.226	0.294	0.465	0.224	0.313

component of labor income growth is significant (in regression 3, its estimate is −0.058 and its *t*-statistic is −3.37). When we estimate a regression with both return correlation measures, we find the stochastic labor income growth-return correlation has a larger and more significant estimate (see regression 6).

Next, we separate the stochastic labor income growth measure into transitory and permanent components. Consistent with the theoretical predictions, we find that the correlation with the temporary component of labor income growth has a weaker impact on participation decisions than the impact of the correlation with the permanent component. In regression 4, for instance, the coefficient estimate of the market return correlation with temporary income growth is −0.017 and its *t*-statistic is -1.58. In regression 5, however, the coefficient estimate of the return correlation with permanent income growth rises to −0.038 and its *t*-statistic is −3.48. The Tobit asset allocation regressions presented in Panel C yield very similar results. Overall, consistent with our evidence using the DNB Household Survey, we confirm that what matters for portfolio decisions is the correlation between stochastic labor income growth and market return, especially the correlation with the permanent component of labor income growth.

4.4. Frequency of participation decisions

In our next test, we examine whether income hedging motives influence people's propensity to stay in the market. If individuals participate in the market motivated by the potential income risk hedging opportunities offered by the market, they should exhibit a lower propensity to exit the market and should always allocate some of their wealth in risky assets.

In our frequency of participation test, we count the number of survey years in which respondents reported owning stocks or mutual funds or both. Table 9 reports the estimates from cross-sectional Poisson regressions where the number of periods in which an individual owned stocks is the dependent variable. Our estimation results show that individuals whose income growth is more negatively correlated with market returns participate in the market more often. For example, in the multivariate regression 6, the coefficient estimate of the income-return correlation is negative (= −0.305) and statistically significant (*t*-statistic= −4.34). This evidence provides additional support to our key conjecture.

4.5. Evidence from other tests

In our final set of tests, we examine several auxiliary hypotheses and conduct additional tests to examine the robustness of our findings. For brevity, these results are summarized in Appendix Tables A5 and A6 and discussed in Appendix Sections A.1–A.5.

In the first set of tests, we compare our findings more closely with the evidence in Angerer and Lam (2009) and show that our results are different from theirs because of the stricter sample selection criteria used in their study. Second, we examine whether income risk reduction motives are more important during periods when investors are more risk averse. When we focus on subperiods when the respondents report to be the most risk averse across the various waves of the DNB Household Survey, we find that the income-return correlation is an even stronger determinant of stock market participation decisions. In the third test, we show that our results do not capture the known effects of entrepreneurial risk on portfolio decisions (Heaton and Lucas, 2000a). In the next set of results, we show that the choice of income hedging instruments depends crucially on the income-return correlation.

Last, we demonstrate that our main findings are not driven by the behavior of very young and the very old investors. This test is motivated by the evidence in Agarwal, Driscoll, Gabaix, and Laibson (2009) and Korniotis and

Table 8

Market participation and asset allocation regression estimates using the National Longitudinal Survey of the Youth.

The table reports the marginal effects from market participation and asset allocation regressions using the NLSY data. In Panel A, we present estimates from regressions in which the main explanatory variable is the correlation between labor income growth and stock market returns. In the probit (Tobit) regressions 1–3 (4–6), the dependent variable is a dummy variable for owning (equity share in) stocks, or mutual funds, or bonds, or some combination. In the multivariate regressions 3 and 6, we suppress the estimates for the control variables (log net worth, age, age squared, education, male, unemployed, and retired dummy variables, good health index, and risk aversion index). In Panels B and C, we decompose labor income growth into a deterministic and a stochastic component and then decompose the stochastic component into a transitory and permanent component. Robust t-statistics are reported in parentheses below the coefficient estimates. All the regressions include time (year) fixed effect. The definitions of all variables are in Appendix Table A2. In regressions 3 and 6 in Panel A, the coefficient estimates for the control variables (log of net worth, age, age2, education, male, single, number of health problems, and risk aversion) are suppressed. In Panels B and C, we present only the coefficient estimates related to the correlation terms. All regressions in Panels B and C include all the controls as in the multivariate regressions 3 and 6 in Panel A.

Panel A: Baseline estimates

	Probit (1–3)			Tobit (4–6)		
	Own STKMFB	Own STKMFB	Own STKMFB	Prop STKMFB	Prop STKMFB	Prop STKMFB
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(Rm, dy)	−0.037	−0.055	−0.058	−0.021	−0.026	−0.018
	(−2.09)	(−2.59)	(−2.09)	(−3.74)	(−4.02)	(−2.42)
Ln(y)		0.363	0.156		0.106	0.044
		(25.53)	(10.54)		(22.86)	(10.49)
St. Dev(dy)		−0.099	−0.104		−0.027	−0.025
		(−5.49)	(−4.40)		(−4.88)	(−4.07)
N	50,224	43,746	29,526	49,705	43,260	29,554
Pseudo R^2	0.001	0.050	0.127	0.002	0.077	0.148

Panel B: Income risk decomposition and participation decisions

	OwnSTKMFB						
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(Rm, Total dy)	−0.058						
	(−2.09)						
Corr(Rm, Deterministic dy)		−0.042				−0.011	
		(−0.67)				(−0.16)	
Corr(Rm, Stochastic dy)			−0.058			−0.056	
			(−3.37)			(−3.26)	
Corr(Rm, Transitory dy)				−0.017			−0.022
				(−1.58)			(−2.08)
corr(Rm, Permanent dy)					−0.038		−0.040
					(−3.48)		(−3.69)
N	29,526	29,739	29,011	19,851	19,851	29,011	19,851
Pseudo R^2	0.127	0.127	0.126	0.115	0.115	0.127	0.116

Panel C: Income risk decomposition and asset allocation decisions

	PropSTKMFB						
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Corr(Rm, Total dy)	−0.018						
	(−2.42)						
Corr(Rm, Deterministic dy)		−0.019				−0.016	
		(−1.18)				(−0.98)	
Corr(Rm, Stochastic dy)			−0.012			−0.011	
			(−2.62)			(−2.55)	
Corr(Rm, Transitory dy)				−0.005			−0.006
				(−1.79)			(−2.21)
Corr(Rm, Permanent dy)					−0.008		−0.009
					(−3.02)		(−3.27)
N	29,554	29,767	29,038	19,863	19,863	29,038	19,863
Pseudo R^2	0.148	0.148	0.148	0.138	0.138	0.148	0.139

Kumar (2011), who find that middle-age respondents are financially more sophisticated. It is possible that only those sophisticated middle-aged investors would engage in income risk hedging. We find very similar results when we focus on the middle-age cohort, i.e., individuals who are between the ages of 36 and 64.

Taken together, the results from these additional sets of tests further demonstrate that individuals are sensitive to the interaction between their income growth and market return when they make their financial decisions. These results in conjunction with our baseline evidence provide strong support for our key conjecture, which posits that

Table 9
Frequency of market participation: Poisson regression estimates.

This table reports the marginal effects from cross-sectional Poisson regressions. The dependent variable is the number of waves in which a respondent reported investing in stocks (N periods STK), mutual funds (N periods MF), and stocks or mutual funds or both (N periods STKMF). The control variables are averaged across all the waves. Robust t-statistics are reported in parentheses below the coefficient estimates. The data are from the DNB Household Survey and cover all the waves from 1993–2011. The definitions of all variables are in Appendix Table A1.

	N periods STK	N periods MF	N periods STKMF	N periods STK	N periods MF	N periods STKMF
Indep. variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(Rm, dy)	−0.513	−0.348	−0.393	−0.437	−0.256	−0.305
	(−4.14)	(−3.92)	(−4.90)	(−3.80)	(−3.14)	(−4.34)
Ln(y)	0.943	0.772	0.734	−0.032	−0.123	−0.099
	(8.25)	(8.71)	(9.68)	(−0.30)	(−1.36)	(−1.32)
St. Dev(dy)	1.182	0.241	0.539	0.043	−0.750	−0.433
	(4.27)	(1.07)	(2.75)	(0.16)	(−3.31)	(−2.42)
Ln(Net Worth)				0.330	0.374	0.340
				(7.44)	(11.54)	(12.30)
HH size				0.043	−0.134	−0.069
				(0.75)	(−3.24)	(−1.95)
Age				0.011	0.010	0.009
				(1.52)	(2.08)	(2.09)
$Age^2 \times 100$				−0.000	−0.000	−0.000
				(−1.19)	(−0.59)	(−0.97)
Education				0.026	0.218	0.145
				(0.23)	(2.40)	(1.91)
Male				−0.079	−0.055	−0.082
				(−0.47)	(−0.49)	(−0.85)
Unemployed				0.445	0.246	0.297
				(1.72)	(1.29)	(1.88)
Retired				0.631	0.253	0.382
				(2.48)	(1.34)	(2.31)
Good health				−0.103	−0.014	−0.031
				(−0.92)	(−0.21)	(−0.51)
Risk aversion				−0.662	−0.351	−0.407
				(−18.36)	(−14.15)	(−18.47)
N	1,762	1,762	1,762	1,716	1,716	1,716
Pseudo R^2	0.082	0.071	0.075	0.392	0.275	0.327

income hedging motives are among the most important determinants of stock market participation and asset allocation decisions of households.

5. Summary and conclusion

Limited stock market participation is one of the most pervasive features of household portfolio decisions. In this study, we investigate whether the decision to participate in the stock market and other related portfolio decisions are influenced by income hedging motives. Standard economic theory predicts that the market participation propensity should be higher if the correlation between income growth and stock market returns is strongly negative. Surprisingly, limited empirical support exists for this income hedging motive in market participation and asset allocation decisions.

Using a rich, unique Dutch data set and the NLSY data from the US, we show that when the income-return correlation is more negative, individuals exhibit a greater propensity to participate in the market. And conditional upon participation, they allocate a larger proportion of their wealth to risky assets. Even when the income risk is high, individuals exhibit a higher propensity to participate in the market when the hedging potential is high. These findings suggest that income hedging is an important determinant of stock market participation and asset allocation decisions. Our evidence complements existing studies on household finance and highlights the importance of income hedging in participation and asset allocation decisions.

One limitation of our study is that we do not observe the composition of investor portfolios. To hedge their income risk more effectively, investors could choose specific portfolios that are more negatively correlated with their income process. With the availability of better data sets, we might be able to better quantify the impact of income hedging on the composition of investor portfolios. Further, the hedging induced demand shifts could influence asset prices, where assets that are more effective for income hedging could demand higher prices when hedging-induced demand is high. We hope to explore these questions in our future research.

Appendix A

In this appendix we present tables that include detailed definitions of all the variables we use in the paper as well as results from auxiliary tests. The variable definitions are in Tables A1 and A2. Summary statistics for the NLSY data set are in Table A3 and estimation results using clustered standard errors are in Table A4.

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A.1. Comparisons with previous evidence using the NLSY data

For robustness, we compare our results with previous evidence in the related portfolio choice literature. In particular, Angerer and Lam (2009) use the NLSY data and estimate asset allocation regressions similar to ours. In some of their asset allocation regression specifications they include the covariance between income growth and the US market return as an explanatory variable and find that it has a negative but insignificant coefficient estimate. Their evidence could appear inconsistent with our findings.

A potential explanation for this lack of statistical significance in their study is the restrictions they impose on their sample. Specifically, in the Appendix of their paper, Angerer and Lam (2009) mention that the base sample has 12,687 respondents, but they use only 1909 individuals in their empirical analysis. Because their objective was to separate income risk into permanent and idiosyncratic components using a structural model of income risk, strict sample selection criteria were necessary. But such strict sample selection criteria are not necessary for our study.

Nevertheless, to allow for proper comparisons between our results, we estimate our baseline regression specifications using a restricted sample that is very similar to the Angerer and Lam (2009) study. In particular, we consider a sample of individuals with reported income over 100 dollars, income growth standard deviation less than 3, and valid income growth data for at least 14 waves. We report these estimates in Table A5, Panel A. These results are similar to the evidence reported in the Appendix of Angerer and Lam (2009). The coefficient estimates of the key labor income-return correlation variable are negative, but they are statistically insignificant. This evidence indicates that the difference between our findings is primarily due to the filters used to define the sample.

To examine the sensitivity of these results to various sample restrictions, we relax one of the restrictions used in Angerer and Lam (2009) and require valid income growth data for at least ten waves instead of 14. We still require income to be higher than 100 dollars and income growth standard deviation to be less than 3. The estimation results are reported in Panel B of Table A5. In this slightly less restrictive sample, we find that the coefficient estimates of the labor income-return correlation are negative and statistically significant. Compared with the statistical significance in Panel A, the significance of coefficient estimates in Panel B rises considerably. This evidence indicates that the strict sample restriction is the main reason for the difference in the findings between our study and those reported in the Appendix of Angerer and Lam (2009).

A.2. Impact of time-varying risk aversion

Our main conjecture is that investors with income growth that is low or negatively correlated with market returns should exhibit a higher propensity to invest in the stock market. An auxiliary hypothesis is that income risk reduction motives would be more important in periods

Table A1
Variable definitions: Dutch National Bank (DNB) Household Survey.

Variable	Definition
OwnSTK	One if own stocks and zero otherwise.
PropSTK	Value of stock holdings to total financial wealth.
OwnMF	One if own mutual funds and zero otherwise.
PropMF	Value of mutual fund holdings to total financial wealth.
OwnSTKMF	One if own stocks or mutual funds and zero otherwise.
PropSTKMF	Value of stocks and mutual fund holdings to total financial wealth.
OwnGF	One if own mutual funds that reinvest distributions (i.e., dividends and capital gains) and zero otherwise.
PropGF	Value of growth mutual funds to financial wealth. Growth funds reinvest all distributions (i.e., dividends and capital gains).
OwnSTKnotMF	One if own stocks but does not own mutual funds and zero otherwise.
PropSTKnotMF	Value of stock holdings to total financial wealth of those who own only individual stocks but no mutual funds.
Business Owner	One if reported business income and zero otherwise.
Ln(*y*)	Log of total after tax income excluding interest and dividend payments.
dy	Income growth rate. Income is total after tax income excluding dividend and interest payments.
Corr(*Rm*, *dy*) *Cov*(*Rm*, *dy*)	Correlation between Dutch market return (based on the AEX index) and income growth rate. To compute the correlation, we require that a respondent has at least four years of income growth data. If not, then the correlation value is set to missing. To minimize measurement error we compute one correlation estimate per respondent using the full sample. We use the same approach to compute the covariance between income growth and market returns.
St. Dev(*dy*)	Standard deviation of income growth. To compute the standard deviation, we require that a respondent has at least four years of income growth data. If not, then the standard deviation value is set to missing. To minimize measurement error, we compute 1 standard deviation estimate per respondent using the full sample.
Ln(*Net Worth*)	Log of net worth (assets minus liabilities).
HH size	Household size.
Age	Years old.
Education	One if graduated from college and zero otherwise.
Male	One if male and zero otherwise.
Unemployed	One if unemployed and zero otherwise.
Retired	One if retired and zero otherwise.
Good health	Health rating from 1–5, with 5 being very healthy.
Risk aversion	Perception of risk related to investing from 1–7 where 7 is belief that investing is very risky.
High RA	One if risk aversion is in the top 75th percentile and zero otherwise.

Table A2
Variable definitions: National Longitudinal Survey of the Youth (NLSY).

Variable	Definition
OwnSTKMFB	One if own stocks or mutual funds or both and zero otherwise. Only available in 1988, 1989, 1990, 1992, 1993 and 1994.
PropSTKMFB	Value of stock, bond, and mutual fund holdings to total financial wealth. Available in 1988, 1989, 1990, 1992, 1993 and 1994.
Ln(y)	Log of annual labor income.
dy	Income growth rate. Income is annual labor income.
Corr(Rm, dy)	Correlation between US market return (based on value-weighted index of all stocks listed on Center for Research Securities Prices) and income growth rate. To compute the correlation, we require that a respondent has at least four years of income growth data. If not, then the correlation value is set to missing. To minimize measurement error, we compute one correlation estimate per respondent using the full sample.
St. Dev(dy)	Standard deviation of income growth. To compute the standard deviation, we require that a respondent has at least four years of income growth data. If not, then the standard deviation value is set to missing. To minimize measurement error, we compute 1 standard deviation estimate per respondent using the full sample.
Ln(Net Worth)	Log of net worth (assets minus liabilities).
Age	Years old.
Education	One if graduated from college and zero otherwise.
Male	One if male and zero otherwise.
Number of health problems	Number of health conditions that the respondent suffers from including heart disease and diabetes.
Risk aversion	The risk aversion proxy is based on three hypothetical lotteries. In the first lottery (lottery 1), the respondents are given a 50/50 chance to double their family income or reduce their family income by one-half. If they accept lottery 1, they are offered a riskier lottery (lottery2) with a 50/50 chance they can double their family income or reduce their family income by one third. If they reject lottery 1, they are offered a less risky lottery (lottery 3) with a 50/50 chance they can double their family income or reduce their family income by 20%. Based on these responses, we generate a risk aversion proxy that takes a value of two if the respondent rejects lotteries 1 and 3; a value of one if she accepts lottery 1 but rejects 2 or rejects 1 but accepts 3; and a value of zero if she accepts lotteries 1 and 2.

when investors report being more risk averse compared with the average level of risk aversion across the survey years. Specifically, when risk aversion rises, investors who choose a high equity share must be those with the highest hedging potential. The high hedging potential must be strong enough to counteract the potential adverse impact of an increase in risk aversion on allocation to risky assets.

We test the conditional risk aversion hypothesis in Panel A of Table A6, when we add the interaction between income-return correlation and a high risk aversion dummy variable to the baseline specifications. The high risk aversion dummy variables identifies the survey years in which the respondents report being the most risk averse (i.e., the respondent's risk aversion is in the top quartile across all survey years). The interaction term measures the additional significance of the hedging motive in periods when investors are most risk averse.

We find that the interaction term has a negative and statistically significant estimate. For example, when we examine the decision to invest in stocks or mutual funds, the estimated results in Column 3 indicate that the marginal probability estimate of the interaction term is -0.510 (t-statistic $=-2.54$). This estimate suggests that in the years when investors are most risk averse, a 1 standard deviation decrease in the correlation ($=0.409$) is associated with about 30% increase in market participation propensity [$=-(0.241+0.510)\times 0.409\times 100$)]. We find similar results for the asset allocation decisions. In particular, when we examine the decision to allocate wealth to stocks and mutual funds (see Column 6), the coefficient estimate of the interaction term is -0.243 (t-statistic $=-2.80$). This estimate implies that when investors are very risk averse, a 1 standard deviation decrease in the income-return correlation term ($=0.409$) is associated with about 14% increase in wealth allocation to risky assets [$=-(0.085+0.243)\times 0.409\times 100$].

Overall, our evidence is consistent with the hypothesis that more risk averse investors have a stronger motivation to hedge their income risk and, therefore, the income-return correlation is a more important determinant of their portfolio decisions.

A.3. Control for entrepreneurial risk

Next, we examine whether our results somehow capture the known effects of entrepreneurial risk on portfolio decisions. Heaton and Lucas (2000a) find that business owners tend to allocate less of their wealth to risky assets because entrepreneurial risk is typically positively correlated with financial risk. To account for this potential channel on participation and asset allocation decisions, we estimate our baseline regressions by adding a business owner dummy variable as a control variable. The results are reported in Panel B of Table A6. We find that the addition of the business owner dummy variable does not significantly affect the statistical and economic significance of the income-return correlation variable.

A.4. Hedging motives and the choice of hedging instruments

Our baseline results suggest that individuals are likely to find stocks to be better income hedging instruments as compared with mutual funds. This evidence is consistent with the conjecture that riskier assets serve as more effective hedging instruments. In the next set of tests, we examine how the income-return correlation affects the choice of riskier financial assets. First, we examine whether a negative income growth-return correlation affects the decision of investors to specialize in stocks only. This set contains investors who report owning stocks but not mutual funds. We also examine the decision to own riskier mutual funds

Table A3
Summary statistics of key variables in the National Longitudinal Survey of the Youth.

This table reports summary statistics and the correlation estimates for the key variables in the 1979 NLSY data set. The sample covers the waves from 1979–1994. The definitions of all variables are in Appendix Table A2.

Panel A: *Univariate summary statistics*

Variable	Mean	Standard Deviation	Percentile					N
			10th	25th	50th	75th	90th	
OwnSTKMFB	0.153	0.360	0	0	0	0	1	54,510
PropSTKMFB	0.017	0.077	0	0	0	0	0.0162	53,984
Corr(*Rm*, *dy*)	0.009	0.372	−0.484	−0.254	0.020	0.271	0.479	155,141
Ln(*y*)	0.800	0.502	0.271	0.432	0.688	1.058	1.473	155,141
St. Dev(*dy*)	8.930	1.297	7.090	8.294	9.210	9.852	10.310	118,706
Ln(*Net Worth*)	9.477	1.784	7.090	8.294	9.596	10.740	11.580	41,891
Age	30.630	3.110	26	28	31	33	35	68,667
Education	0.190	0.393	0	0	0	0	1	54,571
Male	0.509	0.500	0	0	1	1	1	68,667
Single	0.469	0.499	0	0	0	1	1	54,667
Number of health problems	0.064	0.388	0	0	0	0	0	47,597
Risk aversion	1.214	0.818	0	0	1	2	2	50,332

Panel B: *Correlation matrix*

	Variable	1	2	3	4	5	6	7	8	9	10	11
1	*OwnSTKMFB*	1										
2	*PropSTKMFB*	0.54	1									
3	*corr*(*Rm*, *dy*)	−0.01	−0.01	1								
4	*Ln*(*y*)	−0.08	−0.04	−0.04	1							
5	*St. Dev*(*dy*)	0.18	0.11	0.01	−0.36	1						
6	*Ln*(*Net Worth*)	0.28	0.04	0.01	−0.16	0.32	1					
7	*Age*	0.04	0.01	0.01	−0.05	0.17	0.23	1				
8	*Edu*	0.23	0.15	−0.03	−0.01	0.24	0.23	0.03	1			
9	*Male*	0.01	0.03	−0.02	−0.11	0.25	−0.01	−0.01	−0.04	1		
10	*Single*	−0.10	0.01	−0.02	0.09	−0.06	−0.37	−0.13	−0.02	0.03	1	
11	*Number of health problems*	−0.01	−0.01	0.02	0.05	−0.04	−0.03	−0.02	0.01	−0.09	0.01	1
12	*Risk aversion*	−0.01	−0.01	0.00	−0.02	−0.01	0.02	0.03	−0.05	−0.09	−0.09	0.00

Table A4

Estimation results based on clustered standard errors.

The table reports marginal effects from market participation and asset allocation regressions using total after-tax income. The specifications are similar to those used in Tables 4 and 5. The definitions of all variables are presented in Appendix Table A1. The main explanatory variable is the correlation between income growth and stock market returns. In Columns 1–3, we present probit regression estimates. In Columns 4–6, we present Tobit regression estimates. The *t*-statistics of the regression estimates, reported in parentheses beneath the estimates, are based on clustered standard errors. The clusters are defined based on age, gender, and education. The data are from the 1993–2011 waves of the DNB Household Survey. All regressions include time fixed effects. The coefficient estimates of the control variables (log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed.

	Probit (1–3)			Tobit (4–6)		
	OwnSTK	OwnMF	OwnSTKMF	PropSTK	PropMF	PropSTKMF
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(*Rm*, *dy*)	−0.338	−0.162	−0.279	−0.110	−0.075	−0.102
	(−6.87)	(−3.50)	(−6.60)	(−5.61)	(−3.70)	(−5.84)
Ln(*y*)	0.015	−0.012	−0.015	0.011	−0.008	0.000
	(0.41)	(−0.38)	(−0.49)	(0.85)	(−0.54)	(0.03)
St. Dev(*dy*)	0.182	−0.613	−0.392	0.153	−0.234	−0.075
	(1.46)	(−5.17)	(−4.13)	(2.93)	(−4.49)	(−1.89)
N	9,351	9,351	9,133	9,133	9,133	9,133
Pseudo R^2	0.288	0.206	0.270	0.326	0.197	0.273

Table A5

Market participation and asset allocation regression estimates using restricted National Longitudinal Survey of the Youth.

The table reports marginal effects from probit and Tobit regressions. In Panel A (B), the sample excludes those with income less than 100 dollars, income growth standard deviation higher than 3, and valid income growth data for less than 14 (ten) waves. In regressions 3 and 6, the coefficient estimates for control variables (net worth, age, squared age, male, single, number of health problems, and risk aversion) are suppressed. Robust *t*-statistics are reported in below the coefficient estimates. All regressions include time fixed effects.

Panel A: *Estimates using a sample with at least 14 years of labor income growth data*						
	Probit (1–3)			Tobit (4–6)		
	OwnSTKMFB	OwnSTKMFB	OwnSTKMFB	PropSTKMFB	PropSTKMFB	PropSTKMFB
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(*Rm*, *dy*)	−0.024	−0.033	−0.042	−0.014	−0.017	−0.006
	(−0.51)	(−0.69)	(−0.79)	(−1.25)	(−1.47)	(−0.57)
Ln(*y*)		0.496	0.239		0.110	0.054
		(16.45)	(7.45)		(14.65)	(7.08)
St. Dev(*dy*)		−0.094	−0.219		−0.023	−0.055
		(−2.19)	(−4.28)		(−2.17)	(−4.94)
N	10,964	10,910	9,167	10,864	10,808	9,173
Pseudo R^2	0.002	0.049	0.119	0.004	0.078	0.154
Panel B: *Estimates using a sample with at least 10 years of income growth data*						
Corr(*Rm*, *dy*)	−0.062	−0.055	−0.061	−0.027	−0.025	−0.015
	(−2.36)	(−1.97)	(−1.82)	(−3.48)	(−3.16)	(−1.78)
Ln(*y*)		0.437	0.208		0.120	0.058
		(23.85)	(11.04)		(21.50)	(11.21)
St. Dev(*dy*)		−0.085	−0.138		−0.015	−0.028
		(−3.40)	(−4.50)		(−2.02)	(−3.63)
N	31,945	30,704	22,739	31,596	30,353	22,758
Pseudo R^2	0.001	0.049	0.116	0.002	0.074	0.134

that re-invest all their distributions. These funds are identified in the DNB Household Survey as growth funds.

We report the probit and Tobit regression estimates for these two scenarios in Panel C of Table A6. Consistent with our previous results, we find that the income growth-market return correlation has a negative and statistically significant estimate in both the probit and Tobit regressions. Specifically, in probit regression 2 where we study the decision to hold stocks only, the marginal probability estimate of the correlation variable is −0.288 (*t*-statistic = −5.00). Similarly, in probit regression 4 where we study the decision to hold growth funds, this marginal probability estimate is −0.167 (*t*-statistic = −2.45).

These marginal effects indicate that a 1 standard deviation decrease in the correlation term (=0.409) is associated with about a 12 percentage point (= −0.288 × −0.409 × 100) increase in the sole ownership of stocks and about a 7 percentage point (= −0.167 × −0.409 × 100) increase in the ownership of growth funds. The Tobit regression estimates in Columns 5–8 portray a similar

Table A6

Participation and asset allocation regression estimates: additional robustness checks.

The table reports marginal effects from market participation and asset allocation regressions. The estimation details are similar to those in Tables 4 and 5. In Panel A, High RA Period takes the value of one in survey years when the individual reported to be the most risk averse across all survey years. In Panel B, the Business Owner Dummy takes the value of one for individuals with positive entrepreneurial income. In Panel C, we focus on two subsamples: investors who participate in the stock market only directly (i.e., own stocks but not mutual funds) and investors in the middle-age cohort. Robust t-statistics are reported in parentheses below the coefficient estimates. The data are from the 1993–2011 waves of the DNB Household Survey. The definitions of all variables are in Appendix Table A1. All regressions include time fixed effects. The coefficient estimates of the control variables (log of income, standard deviation of income growth, log of net worth, household size, age, age^2, education, male, unemployed, retired, good health, and risk aversion) are suppressed.

Panel A: High risk aversion periods

	Probit (1–3)			Tobit (4–6)		
	OwnSTK	OwnMF	OwnSTKMF	PropSTK	PropMF	PropSTKMF
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Corr(Rm, dy)	−0.305	−0.016	−0.142	−0.094	−0.013	−0.050
	(−4.62)	(−0.31)	(−2.73)	(−3.98)	(−0.55)	(−2.41)
N	6,456	6,456	6,305	6,305	6,305	6,305
Pseudo R^2	0.307	0.202	0.271	0.340	0.199	0.274

Panel B: Role of entrepreneurial risk

	Probit (1–3)			Tobit (4–6)		
Independent variable	OwnSTK (1)	OwnMF (2)	OwnSTKMF (3)	PropSTK (4)	PropMF (5)	PropSTKMF (6)
Corr(Rm, dy)	−0.439	−0.207	−0.387	−0.144	−0.085	−0.135
	(−6.92)	(−3.79)	(−7.26)	(−6.66)	(−3.87)	(−6.88)
Business owner dummy	−0.296	−0.067	−0.277	−0.128	0.039	−0.036
	(−1.66)	(−0.43)	(−1.78)	(−2.28)	(0.59)	(−0.60)
N	6,771	6,771	6,648	6,648	6,648	6,648
Pseudo R^2	0.297	0.237	0.300	0.352	0.246	0.318

Panel C: Type of risk assets (only direct ownership and growth funds) and middle-aged subsample

	Probit (1–2)		Tobit (3–4)		Probit	Tobit
Independent variable	OwnSTKnotMF (1)	OwnGF (2)	PropSTKnotMF (3)	PropGF (4)	OwnSTKMF 35 < age < 65 (5)	PropSTKMF 35 < age 65 (6)
Corr(Rm, dy)	−0.288	−0.167	−0.147	−0.078	−0.142	−0.050
	(−5.00)	(−2.45)	(−4.14)	(−1.90)	(−2.73)	(−2.41)
N	9,351	7,024	9,133	6,850	6,305	6,305
Pseudo R^2	0.152	0.123	0.165	0.122	0.271	0.274

picture. The proportions of wealth allocated to stocks and growth funds are higher when the income-return correlation is lower. Together, these results are consistent with our main conjecture, which posits that income-return correlation influences the market participation and asset allocation decisions of individuals.

A.5. Estimates for the middle-age cohort

Our sample is representative of the Dutch population, and it includes respondents between the ages of 18–93. But, Agarwal, Driscoll, Gabaix, and Laibson (2009) and Korniotis and Kumar (2011) find that middle-age respondents are financially more sophisticated. Therefore, to ensure that our main findings are not driven by the very young and the very old, in our final test, we focus on the middle-age cohort, i.e., individuals who are between the ages of 36 and 64.

Panel C of Table A6 reports the estimates from market participation and asset allocation regressions. We find that the effect of income hedging motives on portfolio decisions among the subsample of relatively more sophisticated middle-age cohort of investors is similar to those in the full sample. Specifically, investors whose income growth is negatively correlated with the market return invest more in individual stocks and allocate more of their wealth to individual stocks.

Further, in contrast to our full sample estimates, we find that the decision to invest in mutual funds is not related to the income-return correlation. The coefficient estimate of the income-return correlation is insignificant in both probit and Tobit regression specifications. This evidence is consistent with our observation that sophisticated investors are likely to recognize that mutual funds could have limited ability to hedge investor-level income risk, which can be highly idiosyncratic. Another possibility is that middle-aged investors hold mutual funds as part of their retirement account and, thus, in their private portfolios they shy away from mutual funds.

Taken together, the results from the additional set of tests further demonstrate that individuals are sensitive to the interaction between their income growth and market return when they make their financial decisions. These results in conjunction with our baseline evidence strong support for our key conjecture, which posits that income hedging motives are among the most important determinants of market participation and asset allocation decisions of individuals.

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