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Labor Income Risk and the Reluctance of Households to Invest in Risky Financial Assets: A Panel Data Analysis

by

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Labor income risk and the reluctance of households to invest in risky financial assets: A panel data analysis

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Abstract

We investigate the determinants of a household's decision on whether to invest in risky financial assets. Financial theory suggests that with increasing labor income risk, the reluctance of households to hold stocks increases. We propose to measure income risk as the observed variation of household income over a five year period. We find that indeed higher income risk reduces the propensity to invest in stocks. However, when controlling for household heterogeneity as well as subjective measures of a household's financial situation (income satisfaction, worries about financial situation), the impact of observed labor income variation vanishes.

Key words: household finance, risky asset market participation, labor income risk, behavioral finance, unobserved heterogeneity

JEL: D14, D81, G11

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1 Introduction

How households invest their earnings during their working life largely determines their welfare over the life cycle. Thus, it is of great interest to learn which factors determine how people allocate their funds to different asset classes. Historically, gains from investing in the stock market or in markets for similar financial instruments outperformed more conservative investment options like savings accounts or insurance plans by far. Yet, private investors largely forgo this equity premium as only a minority of households holds any stocks at all. This well-known reluctance is refered to as "stock market participation puzzle" (Haliassos and Bertaut 1995).

Underinvestment can also be observed for other types of risky securities both in the United States and in many European countries (Guiso, Haliassos and Jappelli 2002). For Germany, Börsch-Supan and Eymann (2000) note that the direct holding of risky financial assets has increased between the mid 1970s until the late 1990s. Still, like most continental European countries and in contrast to Anglo-Saxon countries, Germany has only a low share of households participating in risky asset markets.

One factor that potentially explains why households are less likely to hold risky assets than traditionally suggested by financial literature is labor income risk. Labor income is uncertain with respect to future income streams and it constitutes the primary source of income for most households. Higher levels of uncertainty in this income component might induce households to limit the deliberate exposure to other kinds of financial risk. In his 2006 presidential address to the American Financial Association John Campbell provides an intuitive explanation: *"[...] Households receive labor income but cannot sell claims to that income [...], much of the risk in labor income is idiosyncratic and therefore unhedgeable. This background risk increases effective risk aversion and leads households to invest more cautiously"* (Campbell 2006, p.1559). One should note, though, that the

effect could also be reversed if households hedge against labor income risk by investing into assets for which the return is negatively correlated with their own labor income (for an overview, see Campbell 2006).

A number of empirical studies assess whether labor income risk reduces the share of risky assets in a household's portfolio (Heaton and Lucas 2000, Hochguertel 2003, Cardak and Wilkins 2009), i.e. reducing the analysis to households that hold any kind of risky asset. For example, Betermier, Jansson, Parlour and Walden (2012) document a 20% decrease of a household's share in risky assets in its total portfolio composition when labor income risk rises by 20%. In contrast to the named studies we focus on the extensive margin, i.e. the overall propensity of households to hold any risky assets. The distinction between risk taking households and households that do not invest in risky securities can be regarded as the single largest determinant of the average risky asset share in the population.

The topic of private risky asset holding has received increasing attention in recent years and—besides labor income risk—several other influencing factors have been identified. For once, housing (Fratantoni 1998, Cocco 2004) and borrowing constrains (Guiso, Jappelli and Terlizzese 1996) play an important role as they limit the amount of money that is available for investments in risky assets. Also, Kaustia and Torstila (2011) find that political preferences have an effect on the investment decision. Financial literacy is identified by Christelis, Georgarakos and Haliassos (2011) and van Rooij, Lusardi and Alessie (2011) as a further determinant. More recently, behavioral factors have gained more attention as the traditional rational optimization theory is not able to fully explain the low stock market participation rate of households. Guiso, Sapienza and Zingales (2008) identify lack of trust in the stock market as a key to non-investment, for example. Hong, Kubik and Stein (2004) and Dierkes, Klos and Langer (2011) find social households—households

that frequently interact with neighbors or regularly go to church- –to invest more often in the stock market than other households.

We contribute to the existing literature by using data from the German Socio-Economic Panel which comprises approximately 12,000 households. Unlike most other studies which draw on cross-sectional data, we explicitly employ panel data methods in order to correct for household heterogeneity. Following Cardak and Wilkins (2009), we measure labor income risk by the coefficient of variation, relying on the normalized realized variability rather than deviation from some expected value of income. We find a significant negative effect of labor income variability on the propensity of households to hold risky securities. This effect remains robust even after accounting for a wide array of covariates, among them measures of perceived financial situation. However, once we control for unobserved heterogeneity between households, labor income risk does not seem to matter anymore. We attribute this outcome to the fact that labor market success and investment prowess are likely to be driven by the same household characteristics. Furthermore, it appears to be important to account for subjective assessment and expectation regarding the finances of a household.

The rest of the paper is organized as follows: Section 2 presents the dataset and illustrates the key variables of the analysis. We explain the estimation strategy in Section 3. Section 4 presents the empirical results. Section 5 summarizes our findings and concludes.

2 Data

The data for our analysis originates from the German Socio-Economic Panel (GSOEP), a panel study of German households, similar to the Panel Study of Income Dynamics (PSID) in the USA. It has been established in 1984 as a representative sample of approximately 4,500 West German households. The survey is conducted annually by the

German Institute for Economic Research (DIW) and is currently in its 27th wave. At present, it covers some 12,000 households with about 20,000 individuals. The GSOEP is one of the most extensive longitudinal micro datasets worldwide and covers a wide range of socio-economic variables such as employment status, income sources, education level or attitudes towards different aspects of life.[1]

More importantly for this study, the GSOEP covers several questions regarding the financial situation of the adult household members, both on the personal and the household level. Specifically, it is reported whether households invest in certain asset classes such as savings accounts, life insurance policies or securities. Since 2001 the question concerning the holding of securities distinguishes between fixed-interest securities and risky securities.[2] We use the latter variable to investigate whether a household invests in risky assets or not. We therefore employ a subsample of the data which covers the period 2001 (the first year for which our dependent variable exists) to 2010, the latest wave currently available.

The GSEOP reports the holding of risky securities at the household level. However, the corresponding investment decision is in large parts determined by personal characteristics such as age, gender, education or attitude towards risk which are individual, not household characteristics. To be able to combine household information with personal characteristics we choose the head of a household as unit of observation as is standard in the literature.

Our main interest lies in the effect of labor income risk on the decision to participate in risky asset markets. Yet, although labor income is measured on the personal level we are rather interested in the fluctuation of the combined labor income of the household. Thus, we aggregate the labor income of the household head and a potential spouse before

[1]For more information concerning the GSOEP see Haisken-DeNew and Frick (2005) or Wagner, Göbel, Krause, Pischner and Sieber (2008).

[2]The precise phrasing is "fixed interest securities (e.g. saving bonds, mortgage bonds, federal saving bonds)" and "other securities (e.g. stocks, funds, bonds, equity warrant)".

computing our measure of income risk. Labor income of children or other dependents is disregarded as these income streams are rather unsteady and are most likely not taken into account by the household head when taking investment decisions.

The classical measure of risk in the financial literature is the variance. However, the major drawback of this measure is that for highly skewed variables such as labor income the results would be largely driven by few households with very high labor income. We thus follow the approach of Cardak and Wilkins (2009) and use the coefficient of variation instead. The coefficient of variation is the ratio of the standard deviation to the mean. It is a normalized measure of variation which does not depend on the unit of measurement and is therefore not distorted by very high values of our labor income variable. We calculate the coefficient of variation for each household based on income data of the past five years prior to the time of observation.[3]

In addition to restricting the analysis to household heads, we also exclude pensioners because this group is not exposed to labor income risk in the usual sense. The final sample then comprises approximately 76,000 observations over the ten year observation period 2001-2010.

In our sample about one in three households invests in some kind of risky asset. One should note, though, that we see a constant decline in the participation rate over time. While in 2001 about 34 percent of all households participated in the asset market, this was true of only about 27 percent in 2010. This is probably due to the deterrent through the burst of the dot-com bubble right before the start of our sample period as well as the financial crisis starting in 2007. Besides this general pattern, one can observe huge disparities between household types. Especially income levels and wealth exhibit a strong positive correlation with the participation decision of a household. For instance, while only

[3]In order to check robustness of our findings, we varied the length of the window when calculating the coefficient of variation.

about 10 percent of the households in the lower tercile of the wealth distribution invest in risky assets, the corresponding fraction for households in the upper tercile is about 50 percent. Finally, most households adjust their portfolio composition only infrequently: between any two years about 80 percent of all households do not alter their participation decision.

Previous research has identified several socio-economic variables which strongly affect the participation decision of households.[4] In our model we try to account for as many of these influences as possible. Among the strongest predictors of stock market participation are wealth and income levels. Hence, we include the log of the net household income along with a one year lag as well as dummy variables which indicate to which tercile of the wealth distribution a household belongs. Moreover, more educated households are more likely to invest in this kind of assets, possibly because they are better able to understand sophisticated financial products. To capture this effect we use a dummy variable for college educated household heads in the model. It should be self-evident that the more comfortable someone is with taking financial risk, the more likely he or she will invest in stocks or other risky assets. We use the information provided by the GSOEP to account for self-assessed attitude towards financial risk of the household head. Also, age is an important factor as individuals face different goals, financial constraints and saving horizons in different phases of their life. On this account we include dummy variables for ten year age periods. We account for these influences in addition to our measure of labor income risk and time dummy variables (for every year but 2001) in our baseline model.[5]

In addition to these main determinants, we control for demographic characteristics which are likely to have an effect on the decision process. Men and women often behave

[4]For an overview, see Haliassos and Bertaut (1995), Campbell (2006) or Guiso and Sodini (2012).

[5]The variables household wealth and self-assessed risk aversion are only available for two years, respectively. We thus assume some stability over time for these factors. Further details about this approach are available upon request.

differently when it comes to personal finance decisions, and foreigners often face circumstances and constraints which differ from those of natives. It will also matter whether the household head is married and whether a minor lives in the household. Finally, we expect the investing behavior of people who where socialized in the GDR to deviate from that of individuals who where born in West Germany prior to 1990 due to the different socio-economic environment they were raised in.

Other aspects regarding a household's financial situation are likewise of importance. We include dummy variables which indicate whether a household is saving on a regular basis or holds loans. We also control for inheritance and whether the household head can be considered financially literate, i.e. whether he or she has ever received some kind of formal training in a finance related field. Lastly, we include the number of different asset classes that a household is holding besides risky assets.

Along with these objective measurable indicators of a household's financial situation, perception of the latter is most likely to be of importance as investment decisions depend on the expectations and concerns of the decision maker. The GSOEP offers two variables which measure this type of subjective perception of a household's finances. First, individuals are asked to rate their satisfaction with their income. Second, they state how worried they are about their financial situation. We expect these variables to capture the subjective factors which influence the investment decision which by nature cannot be covered by the (objective) income or wealth variables. We include the average of these two variables over the five years prior to the observation as we believe that subjective feelings are likely to have a long lasting impact on investment decisions.

A description of the variables can be found in Table 1 while summary statistics are provided in Table 2. We also present summary statistics by participation outcomes in Table 3. One can see that households which do invest in securities with variable rates are much more prosperous compared to their non-investing counterparts. Additionally,

their heads are on average better educated and more willing to take risks in financial matters. Also, the volatility of the labor income seems to be significantly lower for these households.

Insert Tables 1, 2 and 3 about here.

3 Estimation Strategy

In order to estimate the effect of an increase in the variation of household labor income on the probability that a household will hold risky financial assets, we employ a twofold estimation strategy to assure robustness of our findings: on the one hand, we subsequently add different control variables (as described in Section 2) to the baseline model. On the other hand, we use several econometric models in order to rule out that our results may be driven by unobserved heterogeneity.[6]

We are faced with a classical discrete choice problem in a panel data context where we model the latent utility y_{it}^* that household i receives in year t from investing in risky financial products as

$$y_{it}^* = \boldsymbol{x}_{it}\boldsymbol{\beta} + c_i + \varepsilon_{it} \ , \tag{1}$$

where $\boldsymbol{x}_{it}$ is the vector of covariates for household i in period t, as described in Section 2 and $\boldsymbol{\beta}$ is the corresponding coefficient vector. c_i denotes household heterogeneity and ε_{it} is a standard idiosyncratic error term. Define y_{it} as an observable binary variable which equals 1 if household i holds any form of risky asset in year t and 0 else. A household is said to invest in this asset type if the unobserved utility associated with holding the asset

[6] We also check for robustness by estimating the model on several sub-samples. Results are not reported as we do not find evidence for problems in this respect.

is positive, i.e. $y_{it} = 1[y_{it}^* > 0]$. Then the conditional probability for risky asset holding is given by

$$P(y_{it} = 1|\boldsymbol{x}_{it}, c_i) = F(\boldsymbol{x}_{it}\boldsymbol{\beta} + c_i) \qquad t = 1, \ldots, T.$$

$F(\cdot)$ is a cumulative density function (CDF) which is usually either a standard normal CDF $\Phi(\cdot)$ or a logistic CDF $\Lambda(\cdot)$. The former case leads to a probit model, the latter to a logit model. To obtain the standard random effects (RE) probit model, one assumes that the household fixed effects are conditionally normal distributed: $c_i|\boldsymbol{x}_i \sim \mathcal{N}(0, \sigma_c^2)$. One can then integrate out c_i to get consistent estimates and use σ_c^2 to compute marginal effects.

The RE assumption implies that household heterogeneity only affects the outcome of the dependent variable but is not related to the covariates. However, this assumption is unlikely to hold. Consider a household comprised of members with a long term committment. Such a household can (*ceteris paribus*) be expected to be more prone to invest in risky financial assets which entail a long investment horizon. At the same time, though, this type of household is also likely to have a smoother labor income stream compared to households which consist of less stable members. In such a situation, as long as we are not able to control for this characteristic, our estimate for the effect of labor income risk on investment decisions will be biased in a simple model. Given the panel data, we can address the problem of unobserved heterogeneity that is potentially correlated with explanatory variables by using a fixed effects logit model. The basic intuition behind this model is that by conditioning on the total number of years S in which a household actually held risky assets, we can eliminate the household fixed effects c_i in Equation (1). Thus, one can estimate the conditional probabilities for risky asset holding $P\left(y_{it} = 1 \mid \boldsymbol{x}_{it}, \sum_{t=1}^{T} y_{it} = S\right)$ while allowing for a relationship between c_i and bsx_{it}.

Yet, the fixed effects logit estimator has several disadvantages. First, we cannot estimate the coefficient for time invariant variables such as gender. Additionally, we can conduct the estimation only for households that exhibit some variation of the dependent variable within the observed time period. This leads to a significant loss of observations as the decision whether to invest in risky financial products or not is quite long-lasting in our sample. Finally, the estimation of marginal effects is unfeasible as it would require observation of c_i. Still, statistical significance, the sign of the estimates and the relative effect associated with two variables can be interpreted.

Another model which avoids most of the disadvantages of the fixed effect logit model, but still allows for some correlation between the unobservables c_i and the covariates $\boldsymbol{x}_{it}$, is Chamberlain's correlated random effects model. We employ the Mundlak (1978) version of this model, which assumes that part of the individual heterogeneity is a linear function of the time average of the covariates: $c_i = \psi + \bar{\boldsymbol{x}}_i\boldsymbol{\xi} + a_i$. The model presumes that most of the individual heterogeneity is captured by a linear combination of the time averages $\bar{\boldsymbol{x}}_i$. For the residual term a_i the usual random effects assumptions apply. The result is a random effects probit model which accounts for the potentially endogenous nature of the fixed effects and has the following form:

$$P(y_{it} = 1|\boldsymbol{x}_{it}, c_i) = F(\psi + \boldsymbol{x}_{it}\boldsymbol{\beta} + \bar{\boldsymbol{x}}_i\boldsymbol{\xi} + a_i) \qquad t = 1, \ldots, T.$$

In contrast to the fixed effects logit model, the form of the relationship between the individual heterogeneity and the covariates has to be specified explicitly and rather strictly. But, as mentioned above, these stronger assumptions yield the advantage that households which did not alter their investment decision over time remain in the sample and can be used for estimation. More importantly, we can compute marginal effects as in the standard random effects setting.

4 Empirical Results

In the following, we first present the results of the random effects probit estimation for the different model specifications. Afterwards, we compare these results to those obtained by controlling for unobserved heterogeneity via the fixed effects logit and the correlated random effects probit model.

4.1 Random Effects Probit Model

Estimation results based on the random effects probit model are summarized in Table 4.[7] Inference for the average marginal effects is based on clustered bootstrap samples.[8] We estimate four different specifications where we gradually add further control variables as outlined in Section 2. We can use 71,118 observations from 10,337 different households for the estimation of the base model. This number slightly decreases to 69,973 observations (10,313 households) for the full model.

Insert Table 4 about here.

The first column in Table 4 shows the average marginal effects of the main explanatory variables identified by the literature. The main focus of this study, the coefficient of variation, is highly statistically significant and exhibits the expected negative sign. Thus, higher income variability is associated with a reduction in the propensity to invest in risky assets. More precisely, a one unit increase in the variation of a a household's labor income, as measured by the coefficient of variation, reduces the probability that the household in question holds risky securities by 3.6 percentage points. The other variables are also statistically significant and display the expected sign. As reasoned in Section 2, we find that

[7] In all Tables 4, 5 and 6 coefficient estimates for the dummy variables for years and age groups are not reported to conserve space, but are available upon request.

[8] We draw 400 samples with replacement and calculate marginal effects for each bootstrap sample. The standard error of the marginal effect is then estimated by the standard deviation across all bootstrap repetitions.

indeed wealth, income, education level as well as risk appetite increase the likelihood of a risky investment. For instance, a household in the upper tercile of the wealth distribution has a 16.1 percentage point higher probability of holding stocks or the like as compared to a household in the lower tercile.

In the next step we add the demographic variables. Controlling for these household characteristics does not affect the coefficient estimate of our variable of interest: income variability is still significant and has the same sign and magnitude as before. The same holds more or less true for the other control variables. With respect to the demographic variables we find that men are somewhat less likely to invest in risky assets. Whether the household head is married seems not to be of importance while the presence of a minor in the household slightly reduces the propensity to invest in risky assets by 1.6 base points. The investment behavior of people born in the GDR does not differ from West Germans in this setting, but foreigners are decisively less likely to invest in risky assets: the likelihood is significantly reduced by 15.8 base points.

Continuing, we control for the financial behavior of households. The loan dummy variable has a very small, but as expected negative effect. All other financial variables (number of asset classes held, inheritance and finacial literacy) exhibit a strong positive influence on the probability to hold risky assets and are highly statistically significant. Accounting for the household's overall financial background leads to a decrease of the effect of a volatile labor income stream from -0.036 to -0.029. The estimate still remains highly statistically significant though. This reduced magnitude is probably due to the effect of different levels of labor income uncertainty on saving and investment patterns. For several of the other variables which are carried over from the previous model we see a decrease in the size of their effect as well. Again, this is likely due to correlation to a household's finances. This is particularly true for wealth and income effects as these are the most

important determinants of the financial behavior of a household. For instance, the effect of log-income declines from 7.4 % to 4.6 %.

The fourth column of Table 4 displays the full model after adding variables which pick up the household head's perception of the household's financial situation. The more satisfied a household's head is with its income the more likely (1.5 base points for a one unit increase) she or he is to invest in risky assets. Similarly, for a household which is less worried about the financial environment, the likelihood that this household holds risky assets is increased by 4.2 basis points for each one unit increase. Both variables are also statistically significant.

As before, the variables most affected by adding the subjective measures are wealth and income. A possible explanation would be that with increasing levels of income and wealth, the household will generally be more satisfied with and less worried about its financial situation. The subjective measures are highly important even though we control for the objectively measurable financial indicators. This reflects findings in the behavioral finance literature that people's expectations and concerns are very important determinants of the investment process.

Turning again to the coefficient of variation, we observe that while it is still significant, the marginal effect is now down to -2.2 percentage points. This leads us to conclude that objective factors are not the only driving force in the decision making process when it comes to investing in stocks. Perception of one's own financial situation and of the financial environment are likewise of importance. This conclusion is supported by the decreasing magnitude of the coefficient estimate of income variability across the four model specifications: If we account for the objective factors only (as in the baseline case), they will pick up a certain amount of the subjective influences. As soon as we control for these subjective factors, we get a more accurate estimate of how income variability affects the investment decision.

To sum up, the effect of realized labor income variation on the propensity to make risky financial investments is negative and highly significant. Controlling for a variety of variables does not change this finding. The magnitude of the effect, however, declines from -3.6 percentage points in the base model to -2.2 percentage points in the model with all control variables. One should note that this effect is not very large as the reported magnitude is associated with a one unit increase in the coefficient of variation. Yet, the measure is bound between 0 and 2.45 and exhibits a standard deviation of about 0.563. Thus, a one unit increase can be seen as a fairly large increase in the variability of the household labor income stream. Nevertheless, the magnitude of our results is in line with previous findings in the literature.

4.2 Accounting for unobserved heterogeneity

As outlined in Section 3, the results presented so far are potentially biased due to correlation of the covariates with unobserved household characteristics. In the following, we examine the results obtained after accounting for unobserved heterogeneity by means of fixed effects logit and correlated random effects probit. The approach of an incremental addition of control variables is the same as before.

One has to stress that these models cannot identify the effects of time-invariant variables such as gender in the fixed effects logit model.[9] The models do control for these variables, though. Variables which are not completely time-invariant but do change for only few households over the observed time span usually are statistically insignificant due to the lack of variation. In our model this is true for the dummy variables for college and foreign nationality which where highly significant in the random effects probit model but are not significant at all in the other two models.

[9]For the correlated random effects probit model the effect of variables with no or only little variation over time can be observed but are in fact indistinguishable from the effect of the corresponding time averages.

Coefficient estimates of the FE model are summarized in Table 5. Their interpretation is limited to statistical significance and their sign. The relative effect of two variables can also be compared to each other. This fact can be used to further compare the fixed effect logit model to the two models using the random effects assumption.

Insert Table 5 about here.

One should also note that we observe a very different sample for the FE logit model compared to the RE models. As mentioned before, we only observe results for households that switch at least once between holding and non-holding of risky assets in our sample period. Consequently, the number of observations decreases from about 70,000 (about 10,000 households) for the RE models to about 30,000 observations (about 4,000 households) for the FE logit model. More importantly, the composition of our sample is likely to change. For instance, as many low income, low wealth households never hold risky assets and many wealthy households always hold risky assets over the observed time period, the wealth and income distribution for the FE logit sample is more compressed compared to the RE sample. This will potentially affect the estimated coefficients for these variables. However, as we will see, the sign, significance and relative effects of the variables in this model are very similar to those for the correlated random effects model. We thus conclude that sample selection issues do not seem to matter much for the FE logit model in this context.

We find that the main determinants which exhibit some variation over time, such as wealth and income, are still highly statistically significant and exhibit the same sign as in the RE probit model. When we add the additional variables, the magnitude of these coefficients decreases but they remain significant, similar to what we observe for the random effects probit model. The same can be said for most of the additional variables where we observe significant positive effects of saving, number of asset classes held and satis-

faction with income, for example. Thus, even after we control for unobserved differences between households, many of the effects remain stable, at least in terms of direction and significance.

Now that we have eliminated inherent household differences, we are most interested in the impact of the coefficient of variation on the asset market participation probability. We find that the negative sign of our income risk measure remains unchanged with a coefficient equal to -0.174. However, the significance of the coefficient is lower than before with a p-value of about 3 percent. When adding the demographic and financial control variables, the magnitude of the coefficient estimate decreases only slightly which is in line with what we have seen before. Also, the variable remains significant at the 5 % significance level. Once we account for the measures of perceived financial situation, though, the coefficient of variation is no longer significant at any conventional significance level with a p-value of about 14 percent. The magnitude of the coefficient further decreases to -0.120. It thus seems that once we control for household heterogeneity along with all the other control variables—especially the ones capturing subjectivity—the effect of labor income variability seems negligible. However, before drawing conclusions we check the robustness of our results by turning to the CRE model.

Insert Table 6 about here.

The CRE model allows for computation of average marginal effects which enable us to interprete the size of the effects. From Table 6 we see that the estimates of the CRE model point towards the same conclusions as those of the FE logit model. For all four model settings, we find that significance of the estimates is quite similar to that of the corresponding estimators in the FE model. The signs are also identical. As in Table 5, the coefficient of variation is significant at the 5 % significance level for the first three model specifications. Once we add the variables which account for income

satisfaction and worries about financial situation, though, the income variation is not significant anymore. The observed t-statistic is almost identical to the one obtained in the fixed effects estimation. Furthermore, the relative effect of two variables is roughly comparable between the FE and the CRE model. These findings are reassuring as they indicate that the previous results are not driven by the characteristics of the FE logit model.

After controling for the unobserved heterogeneity, we find the effect of a one unit increase in the coefficient of variation to lead to a decrease in the participation probability by 1.4 percentage points in the base model. This is approximately two thirds of the magnitude of the effect in the fully specified RE model. Controlling for all variables in the CRE framework further reduces the marginal effect to less than one percentage point for a one unit increase of the coefficient of variation. Even though most variables exhibit a decrease in magnitude, this reduction is more important for the coefficient of variation as its effect was already rather small. However, the negligible size of its marginal effect together with the lack of significance in the fully specified model for both the FE logit and the CRE probit estimation strongly indicate that labor income risk at best plays a very small role in determining the propensity of a household to invest in risky asset classes.

Insert Table 7 about here.

The above findings are illustrated in Table 7 where we compare the results of all three models with all covariates. Note again that the columns RE and CRE contain marginal effects while the column FE contains parameter estimates only. The difference for the coefficient of variation is quite striking, while other important variables such as log of household income or saving behavior are not that different across models.

5 Conclusion

We investigate the determinants of a household's decision to invest in risky assets. Financial theory suggests that households which face higher labor income risk are less likely to hold risky financial assets. We model the probability of holding risky assets using the coefficient of variation of household labor income as a measure for labor income risk. Along with a large number of explanatory variables, which have already been considered in the literature, we include measures of a household head's income satisfaction and whether she or he is worried about her/his financial situation.

Our results do not contradict the predictions of financial theory, but also do not stress them. At first, we find a significant negative impact of income variability on the propensity to hold risky assets which is in accordance with previous research and theoretical predictions. This finding holds even after controlling for all our covariates, in particular the perception variables. The size of the effect is rather small but again the magnitude is in line with previously reported results. However, once we control for unobserved heterogeneity, we observe a sharp drop in the magnitude of the estimated effect. Income variability remains significant until we arrive at the fully specified model which accounts for the household head's income satisfaction and worries about the financial situation.

We therefore conclude that much of the previously observed effect of labor income risk may have been driven by underlying unobserved household characteristics as well as by the perception of the investment environment. It is thus not clear that less labor market uncertainty would lead to a higher level of investment in stocks by private households. Differences between household characteristics as well as confidence and trust in the financial system appear to play an important role. The latter, however, are hard to influence and in particular hard to build, but they are easily destroyed as the current situation of financial markets clearly demonstrates.

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Table 1: Variable description
This table presents the variables used in the estimation along with a description.

Variable	Description
risky	Dummy variable for household investment in risky assets (participation = 1)
male	Dummy for gender of head (male = 1)
age	Age of head
college	Years of education of head
married	Dummy variable for marital status of household head (married = 1)
minor	Dummy variable for minor living in household (minor present = 1)
east	Dummy variable for household head lived in GDR (lived in GDR = 1)
foreign	Dummy variable for household head is foreign (foreigner = 1)
finrisk	Attitude towards financial risk of head
	(0 = not willing to take risks at all - 10 = perfectly willing to take risks)
nethhinc	Net household income
netwealth	Net wealth
wealth_terc	Wealth terciles
savings	Dummy variable for household saves money (HH saves = 1)
loans	Dummy variable for household holds loan (HH holds loan = 1)
nasset	Number of different asset held
inher	Dummy variable for ever inherited money (inheritence = 1)
finlit	Dummy variable for financial literacy of household head (financial literate = 1)
incsat	Satisfaction with income of head
	(0 = not satisfied at all - 10 = perfectly satisfied)
worrfin	Worries about financial situation of head
	(1 = very concerned; 2 = somewhat concerned; 3 = not concerned at all)
coefvar	Coefficient of variation of total household labor income

Table 2: Summary statistics
This table presents summary statistics for the variables used in the estimation.

Variable	Mean	Std. Dev.	Min.	Max.	N
risky	0.308	0.462	0	1	76694
male	0.604	0.489	0	1	76694
age	44.394	12.242	18	88	76694
college	12.359	2.645	7	18	74999
married	0.497	0.500	0	1	76595
minor	0.310	0.463	0	1	76694
east	0.096	0.295	0	1	76694
foreign	0.082	0.274	0	1	76694
finrisk	2.497	2.276	0	10	76694
nethhinc	2301	1537	0	85000	76694
netwealth	135310	423939	-1452000	31665604	15325
wealth_terc	1.863	0.796	1	3	74463
savings	0.596	0.491	0	1	75757
loans	0.255	0.436	0	1	76181
nasset	2.264	1.456	0	6	76694
inher	0.236	0.425	0	1	76694
finlit	0.151	0.358	0	1	76694
incsat	5.936	2.371	0	10	76102
worrfin	1.961	0.699	1	3	76430
coefvar	0.502	0.563	0	2.449	76694

Table 3: Summary statistics by participation
This table presents summary statistics for the variables used in the estimation grouped by participation. The upper panel refers to households which hold risky assets, the lower panel refers to households who do not hold any risky assets throughout the sample period.

Variable	Mean	Std. Dev.	Min.	Max.	N
Panel 1: HH does not invest in risky assets					
male	0.587	0.492	0	1	50293
age	44.322	12.430	18	88	50293
college	11.885	2.431	7	18	49000
married	0.472	0.499	0	1	50212
minor	0.311	0.463	0	1	50293
east	0.099	0.298	0	1	50293
foreign	0.103	0.304	0	1	50293
finrisk	2.092	2.135	0	10	50293
nethhinc	2029	1254	0	85000	50293
netwealth	92775	284429	-1452000	22740000	10070
wealth_terc	1.696	0.772	1	3	48578
savings	0.497	0.500	0	1	49567
loans	0.275	0.447	0	1	49870
nasset	1.931	1.414	0	6	50293
inher	0.184	0.388	0	1	50293
finlit	0.116	0.320	0	1	50293
incsat	5.561	2.418	0	10	49872
worrfin	1.867	0.691	1	3	50099
coefvar	0.561	0.601	0	2.449	50293
Panel 2: HH does invest in risky assets					
male	0.641	0.480	0	1	26401
age	44.555	11.810	18	86	26401
college	13.41	2.793	7	18	25999
married	0.554	0.497	0	1	26383
minor	0.309	0.462	0	1	26401
east	0.090	0.287	0	1	26401
foreign	0.033	0.180	0	1	26401
finrisk	3.405	2.318	0	10	26401
nethhinc	2910	1897	0	85000	26401
netwealth	227846	618284	-223239	31665604	5255
wealth_terc	2.232	0.719	1	3	25885
savings	0.815	0.389	0	1	26190
loans	0.209	0.407	0	1	26311
nasset	3.009	1.260	0	6	26401
inher	0.353	0.478	0	1	26401
finlit	0.228	0.420	0	1	26401
incsat	6.776	2.024	0	10	26230
worrfin	2.170	0.669	1	3	26331
coefvar	0.369	0.439	0	2.449	26401

Table 4: Random Effects Probit Model Estimation Results
The table presents the calculated marginal effects based on the estimation results of the random effects probit model. Clustered bootstrap z-statistics are in parentheses. ***, ** and * denote significance on the 1%, 5% and 10% significance level, respectively.

	Base	Demographic	Financial	Perception
college	0.123***	0.115***	0.105***	0.095***
	(17.19)	(16.15)	(15.26)	(13.91)
finrisk	0.027***	0.028***	0.027***	0.026***
	(26.32)	(26.71)	(25.95)	(25.71)
wealth 2nd	0.107***	0.106***	0.077***	0.069***
	(19.57)	(19.23)	(13.81)	(12.54)
wealth 3rd	0.161***	0.160***	0.109***	0.095***
	(24.09)	(23.38)	(15.57)	(13.66)
loginc	0.071***	0.074***	0.046***	0.037***
	(15.64)	(15.94)	(9.568)	(7.731)
loginc lag	0.040***	0.043***	0.034***	0.022***
	(9.059)	(9.536)	(7.377)	(4.856)
coefvar	-0.036***	-0.037***	-0.029***	-0.022***
	(-7.631)	(-7.848)	(-6.104)	(-4.731)
male		-0.024***	-0.019***	-0.019***
		(-3.405)	(-2.723)	(-2.866)
married		-0.002	-0.011**	-0.009*
		(-0.277)	(-2.068)	(-1.696)
minor		-0.016***	-0.014***	-0.012*
		(-3.233)	(-2.990)	(-2.461)
east		0.013	0.011	0.030***
		(1.357)	(1.258)	(3.315)
foreign		-0.158***	-0.123***	-0.115***
		(-11.55)	(-9.108)	(-8.614)
savings			0.064***	0.056***
			(17.34)	(15.12)
loans			-0.009**	-0.005
			(-2.408)	(-1.402)
nasset			0.037***	0.035***
			(23.18)	(22.49)
inher			0.059***	0.056***
			(10.82)	(10.38)
finlit			0.096***	0.090***
			(11.17)	(10.60)
incsat				0.015***
				(8.901)
worrfin				0.042***
				(7.647)
Constant	–1.126***	-1.14***	-0.995***	-1.020***
	(-30.45)	(-29.78)	(-25.67)	(-26.30)
Observations	71,118	74,022	69,982	69,973
Number of HH	10,337	10,328	10,314	10,313

Table 5: Fixed Effects Logit Model Estimation Results
The table presents the coefficient estimates based on the fixed effects logit model. Clustered z-statistics are in parentheses. ***, ** and * denote significance on the 1%, 5% and 10% significance level, respectively.

	Base	Demographic	Financial	Perception
college	0.209	0.196	0.115	0.124
	(0.864)	(0.809)	(0.473)	(0.515)
finrisk	0.126***	0.128***	0.129***	0.130***
	(6.596)	(6.689)	(6.636)	(6.716)
wealth 2nd	0.393***	0.370***	0.289***	0.273***
	(4.013)	(3.781)	(2.928)	(2.754)
wealth 3rd	0.513***	0.478***	0.345***	0.318**
	(4.121)	(3.837)	(2.720)	(2.506)
loginc	0.505***	0.476***	0.292***	0.265***
	(8.842)	(8.247)	(4.913)	(4.418)
loginc lag	0.246***	0.225***	0.164***	0.124**
	(4.597)	(4.203)	(2.983)	(2.254)
coefvar	-0.174**	-0.175**	-0.161**	-0.120
	(-2.168)	(-2.190)	(-1.999)	(-1.470)
married		0.276***	0.192*	0.187*
		(2.865)	(1.954)	(1.899)
minor		0.009	0.002	-0.001
		(0.131)	(0.0266)	(-0.012)
foreign		0.352	0.377	0.380
		(0.985)	(1.021)	(1.022)
savings			0.426***	0.407***
			(9.448)	(9.040)
loans			0.004	0.013
			(0.096)	(0.280)
nasset			0.256***	0.253***
			(11.61)	(11.47)
inher			0.220**	0.211**
			(2.124)	(2.027)
incsat				0.082***
				(2.615)
worrfin				0.229**
				(2.253)
Observations	30,505	30,453	29,821	29,815
Number of HH	3,881	3,877	3,841	3,841

Table 6: Correlated Random Effects Probit Model Estimation Results
The table presents the calculated marginal effects based on the estimation results of the correlated random effects probit model. Clustered bootstrap z-statistics are in parentheses. ***, ** and * denote significance on the 1%, 5% and 10% significance level, respectively.

	Base	Demographic	Financial	Perception
college	0.021	0.019	0.013	0.013
	(0.826)	(0.809)	(0.688)	(0.614)
finrisk	0.011***	0.011***	0.011***	0.011***
	(6.311)	(6.426)	(6.518)	(6.585)
wealth 2nd	0.033***	0.031***	0.024***	0.023***
	(4.145)	(4.010)	(3.038)	(2.860)
wealth 3rd	0.043***	0.040***	0.029***	0.026***
	(4.218)	(4.015)	(2.774)	(2.525)
loginc	0.045***	0.043***	0.025***	0.022***
	(9.948)	(9.726)	(5.694)	(5.001)
loginc lag	0.022***	0.021***	0.014***	0.010**
	(4.905)	(4.599)	(2.976)	(2.245)
coefvar	-0.014***	-0.014**	-0.013**	-0.009
	(-2.228)	(-2.181)	(-1.973)	(-1.431)
married		0.024***	0.017**	0.017**
		(2.833)	(1.932)	(1.903)
minor		0.001	0.001	0.000
		(0.070)	(0.030)	(0.038)
foreign		0.027	0.030	0.030
		(0.905)	(0.956)	(0.948)
savings			0.037***	0.035***
			(9.130)	(9.350)
loans			0.002	0.002
			(0.714)	(0.531)
nasset			0.023***	0.023***
			(11.998)	(11.736)
incsat				0.008***
				(3.097)
worrfin				0.021***
				(2.556)
Constant	-1.366***	-1.554***	-1.348***	-1.340***
	(-21.07)	(-22.99)	(-20.59)	(-20.23)
Observations	71,118	71,022	69,982	69,973
Number of HH	10,337	10,328	10,314	10,313

Table 7: Model Comparison
The table presents the estimation results of the fully specified model for the random effects, the correlated random effects and the fixed effects specification. Columns "RE" and "CRE" hold marginal effects while column "FE" holds coefficient estimates. Clustered (bootstrap, if applicable) z-statistics are in parentheses. ***, ** and * denote significance on the 1%, 5% and 10% significance level, respectively.

	RE	CRE	FE
college	0.095***	0.013	0.124
	(13.91)	(0.614)	(0.515)
finrisk	0.026***	0.011***	0.130***
	(25.710)	(6.585)	(6.716)
wealth 2nd	0.069***	0.023***	0.273***
	(12.540)	(2.860)	(2.754)
wealth 3rd	0.095***	0.026***	0.318**
	(13.660)	(2.525)	(2.506)
loginc	0.037***	0.022***	0.265***
	(7.731)	(5.001)	(4.418)
loginc lag	0.022***	0.010**	0.124**
	(4.856)	(2.245)	(2.254)
coefvar	-0.022***	-0.009	-0.120
	(-4.731)	(-1.431)	(-1.470)
married	-0.009*	0.017**	0.187*
	(-1.696)	(1.903)	(1.899)
minor	-0.012*	0.000	-0.001
	(-2.461)	-(0.038)	(-0.012)
foreign	-0.115***	0.030	0.380
	(-8.614)	(0.948)	(1.022)
savings	0.056***	0.035***	0.407***
	(15.120)	(9.350)	(9.040)
loans	-0.005	0.002	0.013
	(-1.402)	(0.531)	(0.280)
nasset	0.035**	0.023***	0.253***
	(22.490)	(11.736)	(11.470)
inher	0.056***	0.016**	0.211**
	(10.380)	(1.992)	(2.027)
incsat	0.015***	0.008***	0.0824***
	(8.901)	(3.097)	(2.615)
worrfin	0.042***	0.021***	0.229***
	(7.647)	(2.556)	(2.253)
Observations	69,973	69,973	29,815
Number of HH	10,313	10,313	3,841