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Household Portfolio Allocation, Uncertainty, and Risk

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Abstract Analysing the Panel Study of Income Dynamics and the Health and Retirement Study, we investigate the extent to which US households reduce their financial risk exposure when confronted with background risk. Our novel modelling approach – termed a deflated ordered fractional model – quantifies how the overall composition of a household portfolio with three asset classes adjusts with background risk, and is unique in recovering for any given risky asset class the shares that are reallocated to each safer asset category. Background risk exerts a significant impact on household portfolios, inducing a 'flight from risk' from riskier to safer assets.

Keywords Applied Econometrics • Asset Allocation • Background Risk • Fractional Models.
JEL Classification C33 • C35 • D14 • G11.

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1 Introduction and Background

This paper explores the extent to which households reallocate their financial assets due to background risk, which following Heaton and Lucas (2000b), derives from sources such as non-tradable labour income. Specifically, we investigate the degree to which uncertainty associated with labour income, house value, and health expenditure leads to households reallocating their financial assets towards less risky assets. A new econometric approach to the modelling of household portfolios is developed, which quantifies how the overall asset composition in a household portfolio adjusts due to background risk, and, for any given risky asset class, allows us to recover the precise share that is either retained or reallocated to each type of safer asset class. This latter innovation makes our contribution unique to the growing literature on household finance.

Extending the fractional models of Papke and Wooldridge (1996) and Kawasaki and Lichtenberg (2014) lies at the heart of our empirical strategy. These models are particularly well-suited to analysing the structure of financial portfolios, which in the context of our contribution, is captured by the fractions of financial assets belonging to different risk categories. To analyse these risk-based structures, methods from fractional data analysis are uniquely combined with those from the literature on category inflation following Harris and Zhao (2007). This leads to the development of a new econometric framework which we term a *deflated ordered fractional* model. The term 'deflated' captures a novel feature of our model, which, if supported by the data, allows for the fraction of risky asset holdings to be, *ceteris paribus*, lower than in the absence of unavoidable background risk, as predicted by economic theory (see for instance, Kimball 1993). The model is subsequently used to investigate the effects of uncertainty on financial portfolio allocation using panel data on US households.

We analyse data from the Panel Study of Income Dynamics (PSID) and the Health and Retirement Study (HRS), both of which have been extensively used in the household finance literature. Our modelling approach is highly flexible, and simultaneously allows for three data generating processes to capture household portfolio allocation decisions. These processes correspond to: portfolio allocation in the absence of background risk; asset reallocation due to background risk from high risk assets to medium risk and low risk assets; and, finally, asset reallocation due to background risk from medium risk assets to low risk assets. In setting out our modelling framework, we adopt terminology commonly used to describe financial market participants' decisions to move capital from riskier into safer investment vehicles, and refer to the effect of background risk on households as resulting in a 'flight from risk'.[1] Our empirical findings are then compared to the results from using alternative statistical frameworks to model the impact of background risk on household portfolio allocation. These include the Tobit model, which is commonly employed to analyse the structure of financial portfolios in the literature on household finance, and fractional modelling frameworks

[1] In a further extension discussed below, we allow for 'flight from risk' as well as exploring whether 'flight to risk' is observed in the context of household portfolio allocation.

(Papke and Wooldridge 1996, Kawasaki and Lichtenberg 2014) in which the explicit role for 'deflation' as described above is not taken into account. Significantly, we find that the *deflated ordered fractional* modelling approach yields a considerably more detailed picture of portfolio reallocation in the face of background risk than these alternative modelling frameworks. Hence, we find new evidence on the nature of household portfolio allocation that conventional methods are unable to detect.

A number of existing studies have used US survey data to examine the effect of background risk on household finances. Such studies have incorporated measures of background risk into the set of explanatory variables used to explain various aspects of household portfolios with a focus on the holding of stocks and shares. For example, analysing the Survey of Consumer Finances (SCF), Bertaut (1998) and Haliassos and Bertaut (1995) find that labour income risk is negatively related to the probability of stock-ownership, whilst Fratantoni (2001) reports that both labour income risk and committed expenditure risk associated with home-ownership induce a lower level of risky asset holding. Vissing-Jorgensen (2002) finds that a larger standard deviation of non-financial income reduces stock investment, but the covariance of income and stock returns has no impact. Moreover, Heaton and Lucas (2000a) show that investors invest less in stocks when they face more volatile business income, but labour income risk does not significantly affect stock investment. Analysing the PSID, Palia, Qi, and Wu (2014) report that labour income, housing value, and business income volatilities reduce a household's stock market participation and stockholding.[2]

In the context of older individuals, a variety of studies have exploited data from the HRS to explore the effect of health risks on portfolio allocation (see for example, Rosen and Wu (2004), Berkowitz and Qiu (2006), and Edwards (2008) amongst many others). This focus on older individuals is important given that there is a high concentration of asset holding amongst older households. This paper, therefore, focuses on asset holding across the entire age distribution, by considering two distinct data sources. This allows us to explore how specific background risks impact on risky asset holding at different parts of the life cycle.

In sum, existing studies have provided a range of interesting findings which shed light on how various measures of background risk affect the holding of risky assets. Such studies, however, do not uncover a detailed picture of how background risk affects reallocation between different aspects of a household's portfolio. In contrast, our new econometric framework, which is developed in the following section, unveils the extent to which background risk leads to reallocation between high risk, medium risk and safe assets.[3]

[2]Beyond the US, using Italian data, Guiso, Jappelli, and Terlizzese (1996) find that the presence of uninsurable income risk induces households to reduce risky asset holding in their financial portfolios, whilst for France Arrondel, Pardo, and Oliver (2010) report that the presence of non-negatively correlated earnings risks reduces households' willingness to hold risky financial assets, while negatively correlated income risks do not affect such choices. Cardak and Wilkins (2009), analysing Australian data, find that background risk factors of income uncertainty and health are important determinants of household risky asset holding.

[3]An oft-cited stylized fact in the household finance literature is the inclination of households to shun owning risky assets even in the presence of a historical equity premium, see for example, Fratantoni (2001) and Haliassos and

2 A Deflated Ordered Fractional (OF) Model

At the time of a survey questionnaire, household $i = 1, 2, ..., N$ reports the values of all assets in its portfolio, which are categorised as falling into one of three inherently ordered risk types: high; medium; and low.[4] For each asset, we denote the level of risk assigned to it as decreasing in the value of j, where $j = 0, 1, 2$. Let the reported value of each household's portfolio be measured in terms of its total dollar value D_i such that

$$D_i = \sum_{j=0}^{2} D_{ij}, \tag{1}$$

where D_{ij} denotes the total value of assets assigned to each risk class j. For household i's portfolio, the share of assets s_{ij} in each risk category j will therefore be given by

$$s_{ij} = \frac{D_{ij}}{D_i}, \tag{2}$$

where $s_{ij} = \{s_{i0}, s_{i1}, s_{i2}\}$ and $\sum_{j=0}^{2} s_{ij} = 1$. Our interest lies in modelling the determinants of households' asset shares as defined in expression (2), with particular attention paid to the impact of background risk on these quantities.

It would be possible to model the effects of drivers on each of the s_{ij} shares as a linear system, such that

$$s_{ij} = \mathbf{x}_i' \beta_j + u_{ij}, \tag{3}$$

where $\mathbf{x}_i$ is a matrix of (household) covariates and u_{ij} is a random error. However, as argued by Kawasaki and Lichtenberg (2014), this would effectively be an extension of the linear probability model, the shortcomings of which are well-known (Gujarati 1995): it would not guarantee that $0 \leq E(s_{ij} | \mathbf{x}_i) = \mathbf{x}_i' \beta_j \leq 1$; it would have repercussions on ensuring the adding-up constraint that $\sum_j = E(s_{ij} | \mathbf{x}_i) \equiv 1$; it would also be unable to handle boundary observations of 0 or 1 shares; and would likely embody heteroskedasticity in u_{ij}. Further, standard ordered choice models, which are characterised by mutually exclusive discrete outcomes, are unable to model this type of ordered data. Clearly, holding a high risk asset does not preclude a household from simultaneously owning a low or medium risk asset.

An ordered fractional modelling approach (Kawasaki and Lichtenberg 2014), which is a natural extension of the fractional estimator of Papke and Wooldridge (1996), is therefore appropriate. Using such a framework directly addresses the problems associated with the linear system captured by expression (3) whilst accounting for the inherent ordering of the asset shares. In addition to

Bertaut (1995). Our proposed model is able to shed some further light on the relationship between background risk and the low levels of risky asset holding.

[4] As discussed later, this parsimonious classification has precedence in the household portfolio literature (Carroll 2002).

using fractional estimation methods, a second, and novel, feature of our modelling framework is to treat the process underlying portfolio allocation decisions as one of partial observability, whereby the impact of background risk is allowed to 'deflate' the share of riskier assets held by a household relative to less risky assets. It is for this reason that our estimation framework is termed a *deflated ordered fractional* model. Here, households are characterised by a latent variable that determines the share allocation that would arise in the absence of background risk. This is referred to as a household's 'allocation equation'.[5] Additionally, we introduce latent variables termed 'background risk equations' that capture the extent to which background risk moves households away from the portfolio composition implied by the allocation equation. Partial observability implies that the combination of these unobserved processes, all of which take the form of fractional models, result in the household portfolio allocation observed in the data. We now set out the allocation equation.

2.1 The Allocation Equation

Our initial interest lies with modelling the drivers of household portfolio shares that are attributable to factors other than background risk. Specifically, let $E(s_{ij}|\mathbf{x}_i)$, $j = 0, 1, 2$, where $E(\cdot)$ denotes the expected value of the term in parentheses, s_{ij} represents the share of total assets in aggregate j for household i, and $\mathbf{x}_i$ is defined as a matrix of covariates that exclude background risk variables. The household allocation equation is characterised by a fractional model which embeds ordinality in the riskiness of asset shares *viz.*,

$$\begin{aligned} E(s_{i0}|\mathbf{x}_i) &= G(\mu_0 - \mathbf{x}_i'\beta) \\ E(s_{i1}|\mathbf{x}_i) &= G(\mu_1 - \mathbf{x}_i'\beta) - \Phi(\mu_0 - \mathbf{x}_i'\beta) \\ E(s_{i2}|\mathbf{x}_i) &= 1 - G(\mu_1 - \mathbf{x}_i'\beta) \end{aligned} \tag{4}$$

where: G is a known function satisfying $0 \leq G(z) \leq 1 \; \forall \; z = \mathbb{R}$ (Papke and Wooldridge 1996); $\sum_j = E(s_{ij}|\mathbf{x}_i) \equiv 1$; and $\mu_0 < \mu_1$ ensures that all of the asset shares are positive (Kawasaki and Lichtenberg 2014). As noted in Papke and Wooldridge (1996), $G(\cdot)$ is typically assumed to be a cumulative distribution function (CDF) based on the logit function or the standard normal distribution. As we assume that random factors in our model are normally distributed, this implies that the model in (4) can be more precisely described as an ordered fractional probit model. In analogous fashion to Mullahy (2015), who proposes a multivariate fractional model, we adopt the quasi-maximum likelihood estimation methods outlined in Papke and Wooldridge (1996) for the univariate fractional case, to define a quasi-likelihood function $L(\cdot)$ that embeds the expressions given in (4). In the context of our application, this involves replacing the binary indicators that

[5] The notion that the behaviour of economic agents may in part be driven by an unobserved behavioral equation (in this case what we term an 'allocation equation') is not specific to the literature on household finances. For instance, in the literature on monetary policy, Hu and Phillips (2004) and Kim, Jackson, and Saba (2009) assume that the US Federal Reserve has an unobserved optimal target federal funds rate which is determined by economic conditions.

populate a standard ordered probit model likelihood function with the observed household asset shares $s_{ij} = \{s_{i0}, s_{i1}, s_{i2}\}$.

The resulting likelihood function is given by

$$L = \prod_i \left(\Phi(\mu_0 - \mathbf{x}_i'\beta)\right)^{s_{i0}} \left(\Phi\left(\mu_1 - \mathbf{x}_i'\beta\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)\right)^{s_{i1}} \left(1 - \Phi\left(\mu_1 - \mathbf{x}_i'\beta\right)\right)^{s_{i2}} \tag{5}$$

where $\Phi(\cdot)$ denotes the standard normal CDF, and is consistent with the inherent risk ordering of the j asset bundles in the household's portfolio. Extending the arguments of Wooldridge (2010, p.751), we are therefore faced with an estimation problem identical to that associated with estimating a standard ordered response model. The corresponding log-likelihood function is given by

$$\log L = \sum_i \left(\sum_{j=0}^{2} s_{ij} \ln \gamma_{ij}\right) \tag{6}$$

where we have set $\gamma_{i0} = \Phi(\mu_0 - \mathbf{x}_i'\beta)$, $\gamma_{i1} = (\Phi\left(\mu_1 - \mathbf{x}_i'\beta\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right))$, and $\gamma_{i2} = (1 - \Phi\left(\mu_1 - \mathbf{x}_i'\beta\right))$. Accordingly, a consistent estimator for β can be obtained by solving

$$\frac{\partial \log L}{\partial \beta} = \sum_i \left(\sum_{j=0}^{2} s_{ij} \frac{\partial \ln \gamma_{ij}}{\partial \beta}\right) = \mathbf{0}. \tag{7}$$

The household allocation equation described by expressions (4) to (6) provides the basis for our analysis, where identification of the threshold parameters μ requires the omission of a constant term in $\mathbf{x}$. Monotonicity is ensured by setting $\mu_1 = \mu_0 + e^{\xi}$ during estimation, where μ_0 and ξ are freely estimated. It is possible to include background variables in $\mathbf{x}_i$, and estimate a stand-alone ordered fractional model with the full set of model variables. Significantly, our empirical results in Section 4, in which such an exercise is undertaken, strongly indicate that a modelling strategy which explicitly takes into account category deflation is more appropriate. Accordingly, we now extend the allocation equation to account for the impact of background risk.[6]

2.2 Modelling Background Risk

To gauge the degree to which background risk induces a 'flight from risk', we introduce background risk equations. Given a household's portfolio allocation, our approach provides a mechanism whereby households are able to move from higher risk asset bundles toward lower risk ones: shares

[6] Unlike the estimation approach in Kawasaki and Lichtenberg (2014), we do not use information on the size of household portfolios, D_i, during estimation. This would imply a likelihood function of the form $\frac{D_i!}{\Pi_{j=0}^{2} D_{ij}!}\Pi_{j=0}^{2}\gamma_{ij}^{D_{ij}}$. There are a number of reasons for not using such an expression: first, the sheer size of D_i makes this infeasible; second, using the extra information on D_i would not in any case affect the point estimates of β; and third, there is little evidence to suggest that conditioning on D_i will improve the efficiency of the estimator itself (Papke and Wooldridge 1993). In relation to this last point, the quasi-ML estimator will be consistent provided that the model in (4) is correctly specified, a result due to Gourieroux, Monfort, and Trognon (1984).

in higher-risk bundles are thus deflated. Two background risk equations are introduced, namely,

$$h_i^* = \mathbf{w}_i'\delta + \varepsilon_i \tag{8}$$

$$m_i^* = \mathbf{w}_i'\lambda + \varphi_i \tag{9}$$

where h_i^* and m_i^* represent unobserved latent propensities to move away from the choice of risky assets, $j = 0$ (high risk) and $j = 1$ (medium risk), respectively. We stress here that h_i^* has the same ordered fractional structure as in (4), whereas m_i^* is identical to the univariate fractional model of Papke and Wooldridge (1996).

Define these two equations as

$$h_i = \begin{cases} 0 & if \quad h_i^* < \mu_0^h \\ 1 & if \quad \mu_0^h \leq h_i^* < \mu_1^h \\ 2 & if \quad h_i^* \geq \mu_1^h \end{cases} ; \; m_i = \begin{cases} 1 & if \quad m_i^* > 0 \\ 2 & if \quad m_i^* \leq 0 \end{cases} \tag{10}$$

such that $j = 0, 1, 2$ corresponds to the risk ordering used in the asset allocation equation. That is, for all households we allow for the tempering of their 'allocated' portfolio bundle. We propose that h_i^* and m_i^* will be driven by a common set of observed variables ($\mathbf{w}_i$) - that proxy for background risk - with unknown weights (δ and λ) and random disturbance terms (ε and φ).

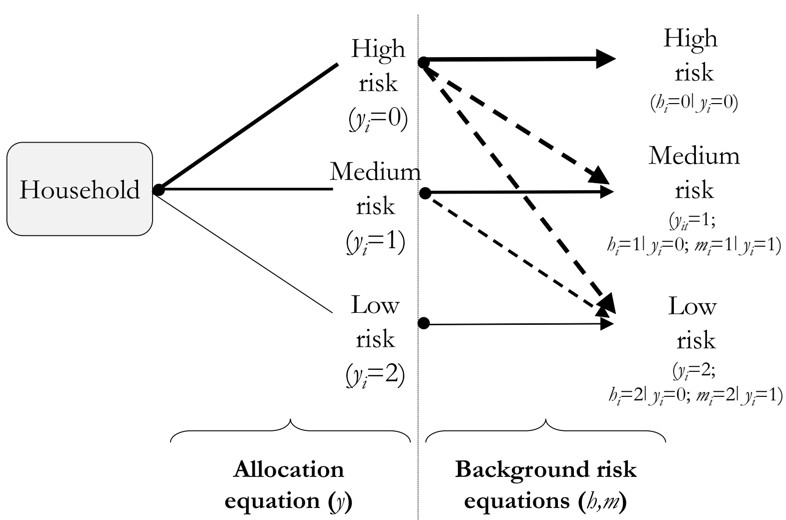

Figure 1: Branch diagram for the deflated ordered fractional model (with dotted lines depicting 'flights from risk' from riskier to less risky asset classes)

To shape intuition, Figure 1 depicts our modelling approach. When allocating asset shares, households are faced with choosing a bundle of high risk, medium risk, and low risk assets. The allocation equation depicts the portfolio share composition that would prevail in the absence of background risk; however, such a modelling strategy neglects the strong possibility that the decision to allocate shares may derive from more than a single data generating process. This gives rise to the presence of the background risk equations in (8) and (9), the effects of which are also depicted; the dotted lines represent 'flights from risk', from riskier to less risky assets.[7,8]

For h_i^*, under the usual assumption of normality of ε, and defining μ^h as the boundary parameters appertaining to the background risk equation (8), the expected value of the high risk asset share, s_{i0}, will be

$$E\left(s_{i,j=0}\,|\mathbf{x}_i, \mathbf{w}_i\right) = \underbrace{\Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)}_{\substack{\text{allocation}\\ \text{equation}}} \times \underbrace{\Phi\left(\mu_0^h - \mathbf{w}_i'\delta\right)}_{\substack{\text{background risk}\\ \text{equation (high risk assets)}}} \tag{11}$$

where the allocation from the high risk class, $\Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)$, in expression (4), is simply adjusted for the fraction of high risk assets the household decides to retain in this bundle. However, as depicted in Figure 1, the expected value of the medium risk share is more involved. In addition to the household's allocation, $\Phi\left(\mu_1 - \mathbf{x}_i'\beta\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)$, being (downward) adjusted by the binary background risk equation m_i^*, the decrease in this allocation share may be counterbalanced due to a reallocation from high risk to medium risk assets via h_i^*. Finally, as Figure 1 also shows, the expected share of low risk assets will be the sum of the household's allocation plus reallocated assets from the high and medium risk asset classes. Formally, the expected values for the medium and low risk asset bundles (with that for high risk asset bundles having been defined above) are given by

$$\begin{aligned}
E\left(s_{i,j=1}|\mathbf{x}_i, \mathbf{w}_i\right) &= \left(\begin{array}{c} \left[\Phi\left(\mu_1 - \mathbf{x}_i'\beta\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)\right] \times \Phi\left(\mathbf{w}_i'\lambda\right) \\ +\left\{\begin{array}{c} \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right) \times \\ \left[\Phi\left(\mu_1^h - \mathbf{w}_i'\delta\right) - \Phi\left(\mu_0^h - \mathbf{w}_i'\delta\right)\right] \end{array}\right\} \end{array}\right) & (12)\\
E\left(s_{i,j=2}|\mathbf{x}_i, \mathbf{w}_i\right) &= \left(\begin{array}{c} \left[1 - \Phi\left(\mu_1 - \mathbf{x}_i'\beta\right)\right] \\ +\Phi\left(\mu_0 - \mathbf{x}_i'\beta\right) \times \left[1 - \Phi\left(\mu_1^h - \mathbf{w}_i'\delta\right)\right] \\ +\left[\Phi\left(\mu_1 - \mathbf{x}_i'\beta\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\beta\right)\right] \times \left[1 - \Phi\left(\mathbf{w}_i'\lambda\right)\right] \end{array}\right). & (13)
\end{aligned}$$

In such a way, this model explicitly accounts for the hypothesized effect of background risk on household portfolio allocation; moreover, the estimates of the background risk shares in h_i^* and m_i^* provide direct estimates of the extent of this. In essence, this model allows for deflation of the

[7] It is conceivable that households may move a fraction of their share of safe assets into relatively riskier assets due to the presence of background risk (*i.e.*, a 'flight to risk'). In Figure 1, this would be depicted by upward sloping arrows in the background risk equations. Such a possibility, however, does not accord with the low levels of risky asset holding observed from an empirical perspective (Fratantoni 2001; Haliassos and Bertaut 1995; Bertaut 1998). However, to explore this possibility we also estimated a version of the model which allowed 'flights to risk', *i.e.*, reallocation from low risk holding to medium and high risk and from medium risk allocations to high risk. Generally, the findings indicated that there is no reallocation from medium to high risk asset allocation. For low risk assets, we found a similar lack of empirical support for a flight to risk. Such findings accord with the existing literature and our *a priori* expectations, thereby reinforcing our modelling approach.

[8] In an early microeconometric study of household portfolios, King and Leape (1998) found that most households own only a subset of the possible array of assets that they could hold. That is, their portfolios are 'incomplete'. Our modelling strategy directly addresses this phenomenon, which is characterised by a sizable proportion of households holding no risky assets in their financial portfolio. See Section 3.2 for discussion of household asset distributions.

respective high risk and medium risk asset share categories, and the reallocation of these assets to the remaining less risky categories. Following similar discrete choice literature, we term this a deflated ordered fractional probit model. In doing so, we emphasise that *ceteris paribus,* as $\Phi\left(\mu_1^h - \mathbf{w}_i'\delta\right) \to \Phi\left(\mu_0^h - \mathbf{w}_i'\delta\right) \to 1$ and $\Phi\left(\mathbf{w}_i'\lambda\right) \to 1$, the observed asset allocation will tend to the household's allocation without background risk. It is important to note that all of these quantities are freely estimated, such that the approach will not force any reallocation if this is not supported by the data.

With these modifications in place, the total log-likelihood now becomes

$$L = \prod_i E\left(s_{i0}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)^{s_{i0}} E\left(s_{i1}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)^{s_{i1}} E\left(s_{i2}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)^{s_{i2}}, \tag{14}$$

where $E\left(s_{ij}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)$ are given by equations (11) to (13). The likelihood for household i can be therefore be expressed as

$$\begin{aligned} L_i &= \prod_{j=0}^{2} E\left(s_{ij}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)^{s_{ij}} \\ &= \Lambda_i \end{aligned} \tag{15}$$

where Λ_i is used below as shorthand to denote the right hand side of expression (15). The parameters of the model are uniquely identified by the inherent non-linearities in equation (14); however, as discussed below, the choice of variables to enter $(\mathbf{x}_i, \mathbf{w}_i)$ will be important for identification.

A further refinement can be made to the model presented above. As all unobservables driving the system relate to the same household, there are strong *a priori* reasons for these to be correlated.[9] Generically, expressions for the expected values will now be functions of the bivariate normal cumulative distribution with integration limits a and b, and correlation coefficient ρ of the form $\Phi_2(a, b; \rho)$, where Φ_2 denotes the bivariate cumulative density function (CDF). Equations (11) to (13) now become

[9] All of the empirical results presented in this paper find empirical support for the presence of correlated residuals *vis-a-vis* the allocation equation and the background risk equations. However, results for the uncorrelated variants (not presented here) yield consistent results.

$$E\left(s_{i,j=0}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right) = \Phi_2\left(\mu_0-\mathbf{x}_i'\beta,\mu_0^h-\mathbf{w}_i'\delta;\rho\right) \tag{16}$$

$$E\left(s_{i,j=1}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right) = \begin{cases} \Phi_2\left(\mu_1-\mathbf{x}_i'\beta,\mathbf{w}_i'\lambda;-\rho\right) \\ -\Phi_2\left(\mu_0-\mathbf{x}_i'\beta,\mathbf{w}_i'\lambda;-\rho\right) \\ +\Phi_2\left(\mu_0-\mathbf{x}_i'\beta,\mu_1^h-\mathbf{w}_i'\delta;\rho\right) \\ -\Phi_2\left(\mu_0-\mathbf{x}_i'\beta,\mu_0^h-\mathbf{w}_i'\delta;\rho\right) \end{cases} \tag{17}$$

$$E\left(s_{i,j=2}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right) = \begin{cases} \left[1-\Phi\left(\mu_1-\mathbf{x}_i'\beta\right)\right] \\ +\Phi_2\left(\mu_0-\mathbf{x}_i'\beta,\mathbf{w}_i'\delta-\mu_1^h;\rho\right) \\ +\Phi_2\left(\mathbf{x}_i'\beta-\mu_1,-\mathbf{w}_i'\lambda;-\rho\right) \end{cases}. \tag{18}$$

We call the model delineated by expressions (16), (17), and (18) the *correlated deflated ordered fractional model* (hereafter deflated $OF(C)$).[10]

What emerges from the above analysis is that the overall partial effect for a given asset type, $E\left(s_{i,j=J}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)$, will be a composite of individual partial effect terms, which will in part correspond to a household's 'flight from risk'. For instance, if one takes the overall marginal effect for low risk assets associated with $\frac{\partial E(s_{i,j=2}|\mathbf{x}_i,\mathbf{w}_i)}{\partial \mathbf{x}^*}$, it is straightforward to show that it can be disaggregated into the sum of three constituent components, namely:

(*i*) 'Flight from risk' from high risk to low risk assets:

$$\left\{\begin{array}{l} \Phi\left(\frac{\mathbf{w}_i'\delta-\mu_1^h-\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)\phi\left(\mu_0-\mathbf{x}_i'\beta\right)\beta^* \\ +\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta-\rho(\mathbf{w}_i'\delta-\mu_1^h)}{\sqrt{1-\rho^2}}\right)\phi\left(\mathbf{w}_i'\delta-\mu_1^h\right)\delta^* \end{array}\right.$$

(*ii*) 'Flight from risk' from medium risk to low risk assets:

$$\left\{\begin{array}{l} \Phi\left(\frac{-\mathbf{w}_i'\lambda+\rho(\mathbf{x}_i'\beta-\mu_1)}{\sqrt{1-\rho^2}}\right)\phi\left(\mathbf{x}_i'\beta-\mu_1\right)\beta^* \\ +\Phi\left(\frac{\mathbf{x}_i'\beta-\mu_1+\rho(-\mathbf{w}_i'\lambda)}{\sqrt{1-\rho^2}}\right)\phi\left(-\mathbf{w}_i'\lambda\right)\lambda^* \end{array}\right.$$

(*iii*) Change in low risk assets in the allocation equation only:

$$\phi\left(\mathbf{x}_i'\beta-\mu_1\right)\beta^*.$$

The nature of this decomposition corresponds precisely to the structure of the deflated model in Figure 1; most significantly, both the sign and magnitude of an overall marginal effect will be a function of the signs and magnitudes of these individual components. Detailed derivations of the partial effects associated with a given expected share (EV) - which formally evaluate how much of a portfolio rebalancing effect is attributable to a 'flight from risk' - are provided in Appendix A.

[10] Although it would be theoretically possible to additionally allow the error terms in the background risk equations to be correlated with each other, to avoid over-parameterization and identification issues associated with $\mathbf{w}_i$ being the same in the h^* and m^* equations, we refrain from estimating such specifications.

2.3 Panel deflated ordered fractional model

Finally, to better exploit the information contained in the PSID and HRS, the deflated model can be extended by allowing for unobserved household heterogeneity - or unobserved effects - in all underlying equations, α. As is standard in the literature, it is assumed that $\alpha \sim N(0, \Sigma)$; and we denote the individual elements of Σ by y^*, h^* and m^*, respectively. The presence of such unobserved effects complicates evaluation of the resulting likelihood function, and to this extent we utilise the method of maximum simulated likelihood. Define $\mathbf{v}_i$ as a vector of standard normal random variates, which enter the model generically as $\mathbf{\Gamma v}_i$, such that for a single draw of $\mathbf{v}_i$, $\mathbf{\Gamma v}_i = (\alpha_{i,y^*}, \alpha_{i,h^*}, \alpha_{i,m^*})$. $\mathbf{\Gamma}$ is the *chol* (Σ) such that $\Sigma = \mathbf{\Gamma\Gamma}'$. Conditioned on $\mathbf{v}_i$, the sequence of T_i outcomes for household i are independent, such that the contribution to the likelihood function for a group of t observations is defined as the product of the sequence Λ_{it} - see equation (15) - which we denote e_i, corresponding to the observed outcome of shares, $e_i \mid \mathbf{v}_i$,

$$e_i \mid \mathbf{v}_i = \prod_{t=1}^{T_i} (\Lambda_{it} \mid \mathbf{v}_i) \,. \tag{19}$$

The unconditional log-likelihood function is found by integrating out these innovations such that

$$\log L(\theta) = \sum_{i=1}^{N} \log_{v_i} \prod_{t=1}^{T_i} (\Lambda_{it} \mid \mathbf{\Gamma v}_i) \, f(\mathbf{v}_i) d\mathbf{v}_i, \tag{20}$$

where all parameters of the model are contained in θ. Using the usual assumption of multivariate normality for $\mathbf{v}_i$ yields

$$\log L(\theta) = \sum_{i=1}^{N} \log_{v_i} \prod_{t=1}^{T_i} (\Lambda_{it} \mid \mathbf{\Gamma v}_i) \prod_{k=1}^{K} \phi(\mathbf{v}_{ik}) d\mathbf{v}_{ik} \tag{21}$$

where $k = 1, 2, ...K$ indexes the various stochastic unobserved effects in the model. The expected values in the integrals can be evaluated by simulation by drawing R observations on $\mathbf{v}_i$ from the multivariate standard normal population and we construct the simulated log-likelihood function as

$$\log L(\theta) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} (\Lambda_{it} \mid \mathbf{\Gamma v}_i) \,. \tag{22}$$

Halton sequences of length $R = 100$ were used (Train 2009), and this now feasible function is maximized with respect to θ.[11]

[11] As is common in the non-linear panel data literature, given that these unobserved heterogeneity terms are (potentially) correlated with observed heterogeneity terms, the correction proposed by Mundlak (1978) is applied in our empirical applications.

3 Data

As mentioned previously, this study analyses data drawn from two sources, namely the PSID and the HRS. The PSID has been used extensively in the existing literature on household finances (e.g. Kazarosian 1997; Carroll and Samwick 1998). Established in 1968, the PSID is a nationally representative survey of over 18,000 individuals, and collects information every two years on a wide variety of demographic and socioeconomic characteristics, in addition to collecting information about household wealth allocations.[12] This paper uses data from the 1999-2017 waves of the survey, resulting in information relating to 5,892 households, and which corresponds to 32,015 household/year observations.[13]

The PSID's household wealth module permits us to explore the household's portfolio allocation decisions, focusing on three distinct risk-based categories: high risk; medium risk; and low risk. Specifically, the allocation of assets into these three classes is determined by the structure of the questionnaire itself; asset categories are based on a range of questions where asset classes are grouped together. The taxonomy adopted in the PSID questionnaire corresponds closely to those used by Carroll (2002) and Hurd (2002). For example, low risk assets are defined from the question *"Do you [or anyone in your family living here] have any money in checking or savings accounts, money market funds, certificates of deposit, government savings bonds, or treasury bills, NOT including assets held in employer-based pensions or IRA's?"* High risk assets are defined using the question *"Do you [or anyone in your family living here] have any shares of stock in publicly held corporations, mutual funds, or investment trusts, not including stocks in employer-based pensions or IRA's?"* We also include the risky elements of a household's pension accounts. These are based on the question, *"(Do [you/you or your family living there] have) any money in private annuities or Individual Retirement Accounts (IRAs)?"* and then, "*Are they mostly in stocks, mostly in interest earning assets, split between the two, or what?"* Based on the response to the second question, we make the following assumptions about how these assets are allocated. Specifically, if the household reports *"mostly stocks"*, 100% of the value of pension assets are coded as high risk assets; if the response is "*split"*, 50% are allocated to high risk and medium risk; whilst if it is stated that the assets are *"mostly in interest earning"* accounts, 100% of pension assets are allocated to the medium risk asset category. This approach is consistent with Brunnermeier and Nagel (2008). Medium risk assets, in addition to non-risky pension accounts, are based on the question *"(Do [you/you or anyone in your family living there] have) any other savings or assets, such as cash value in a life insurance*

[12] A household wealth module was included every five years from 1984 through to 1999, and every two years thereafter.

[13] The panel structure of the PSID and HRS make them ideally suited for our purposes as compared to alternative surveys such as the SCF. Although the SCF is regularly used in the household portfolio allocation literature, its cross-sectional nature means that only relatively crude proxies of uncertainty are available. However, for completeness, we also applied our modelling approach to the SCF for a sample period encompassing the years 1998 to 2013. Our SCF findings are closely aligned with those from the PSID, thereby supporting the theory that uncertainty induces a flight from risk. These results are available on request.

policy, a valuable collection for investment purposes, or rights in a trust or estate that you haven't already told us about?" The total value of these assets is defined as medium risk assets.[14]

In addition to the PSID, we also analyse data from the HRS, which was compiled by the RAND Center for the Study of Aging. The HRS is a nationally representative biannual longitudinal survey of older Americans. It contains extensive information on a wide range of socioeconomic and demographic variables, including financial and housing wealth, income, and health status. In order to match the sample period of the PSID, we analyse data collected between 1998 to 2016.[15] Despite the survey focusing on older individuals, it is documented that this group owns a large percentage of the national wealth in the US and, hence, fully understanding the determinants of portfolio allocation of this specific group is of particular interest. The HRS sample contains information on $13,656$ households; this corresponds to $99,494$, household/year observations, where the median length of participation for individuals in the panel is seven years.

The HRS contains detailed information on a wide variety of financial assets, namely: checking, savings, and money market accounts, certificates of deposit, bonds and bond funds, government bonds and treasury bills, stocks, mutual funds, and retirement accounts including IRA and Keogh accounts. In line with the asset classification used for the PSID, we group these assets into three distinct categories based on their risk exposure. Details of this classification are presented in Table 3. High risk assets include stocks and shares, whilst medium risk assets include bonds and retirement accounts. Low risk assets include checking and current accounts and certificates of deposit, amongst others.[16]

Our estimation strategy controls for a wide range of demographic and socioeconomic characteristics that are commonly used in the existing literature, and which are assumed to influence asset shares in the household's allocation equation. These include head of household characteristics such as age, gender, education, race, marital status, and labour market status; and household composition controls such as whether there is a child present in the household. In addition, the allocation equation controls for measures capturing risk attitudes and the self-reported health status of the head of household, as well as the income and net wealth of the household, with the latter being defined net of total household debt. Furthermore, we control for the year of the survey in both the allocation and background risk equations. A full description of these variables is provided in Appendix B, Table B.1. The background risk equations contain year fixed effects, in conjunction with measures of household income uncertainty, house value uncertainty and health expenditure uncertainty, which are discussed in detail below. A complete description of these variables is pro-

[14]The composition of the three asset categories is summarised in Table 2.

[15]As described in Chien et al. (2014), the HRS comprises six distinct cohorts, each of which corresponds to a specific range of years in which an individual above the age of fifty years was born. Our estimations use information relating to all cohorts, meaning that our sample is representative of the US population aged over 50.

[16]Unfortunately, we are unable to classify retirement accounts into high and medium risk assets as in the PSID. The HRS, includes some information on the amount of retirement accounts allocated to interest bearing accounts and stocks and shares, from 2000 on wards. However, the nature of this question changes over time making comparisons across time problematic.

vided in Appendix B, Table B.1. Summary statistics for all of the explanatory variables used in our analysis are presented in Table 1 for the PSID and HRS samples.

3.1 Measuring Uncertainty

A notable feature of the PSID and the HRS is that both allow us to construct a range of uncertainty measures based on multiple observations of households over time. These measures capture uncertainty associated with household income, health expenditure and house value. As households are observed over an extended period, we are able to calculate the variability in these measures, which are consequently included in the background risk equations.

In the existing literature, a variety of measures capturing a household's income uncertainty have been used. For example, Cardak and Wilkins (2009) measure income uncertainty by using the coefficient of variation of an age and time adjustment of labour income over a five year period. Likewise, Guiso, Jappelli, and Terlizzese (1996) and Robst, Deitz, and McGoldrick (1999) use a coefficient of variation, constructed as the standard deviation of income divided by its average over that time period. In contrast, Heaton and Lucas (2000a) – and subsequently Bonaparte, Korniotis, and Kumar (2014) and Palia, Qi, and Wu (2014) – measure income uncertainty as the standard deviation of income growth across the time periods considered. Following the existing literature, we construct and incorporate measures of uncertainty based on the coefficient of variation (CV) and, where appropriate, the standard deviation (SD) into our empirical analysis.

Our uncertainty measures correspond to background risk deriving from the variability of income, house value, and out-of-pocket health expenditure. Hence, we explore the extent to which these three sources of background risk influence household portfolio allocation decisions. In line with the previous literature, for the PSID, we consider the uncertainty associated with the head of household's labour income (see for example Palia, Qi, and Wu 2014). House value is defined as being the self-reported current value of the main residence, based on the question: "*...what would it bring if it were sold today?*". Finally, in the PSID, out-of-pocket health expenditure is defined as the sum of the amount spent out-of-pocket for prescriptions, in-home medical care, special facilities, and other services, doctor, outpatient surgery, and dental bills in addition to nursing home and hospital bills.

For the PSID, following a similar approach to Palia, Qi, and Wu (2014), we exploit its long panel element to construct our income and house value uncertainty measures. Specifically, we exploit data spanning a 41 year period to construct measures of income and house value uncertainty faced by the household. Both the coefficient of variation, defined as the standard deviation of these measures divided by the average over time of these series, and, the standard deviations of the growth rates of household income and house value, are considered. These measures of background risk are constructed using data from the $1976 - 2017$ waves of the PSID, thereby exploiting information in the PSID that pre-dates the beginning of our sample period (the information on financial assets that we exploit is only included in the PSID from 1999 onwards). We also construct a measure of uncertainty capturing the coefficient of variation of out-of-pocket health expenditure for the $1999 - 2017$ period, using information reported in the PSID for these years; prior to 1999, the data used to construct these measures is not available. A measure capturing the standard deviation of growth for out-of-pocket health expenditure is not considered, due to the high proportion of zeros and the shorter time span for which this data is available.

For the HRS, we construct uncertainty measures in a similar manner to the PSID. However, due to the HRS only being established in 1992, our calculations are based on a relatively shorter sample window which encompasses the years $1992 - 2016$. As with the PSID, we measure the uncertainty associated with income and house value using both the coefficient of variation and the standard deviation in growth rates and, for health expenditure uncertainty, only the coefficient of variation is used. Due to the HRS having a large proportion of retired individuals relative to the PSID, we consider non-asset income opposed to labour income, which is in line with existing studies such as Vissing-Jorgensen (2002) and Massa and Simonov (2006). Out-of-pocket health expenditure in the HRS is measured in a similar way to the PSID and is defined as the sum of amongst other things: hospital and nursing home costs; doctor, dentist, and outpatient surgery costs; and average monthly prescription drug costs. Finally, house value in the HRS is measured in the same way as in the PSID. These measures are summarised in Table B.1.[17]

3.2 Asset Share Distributions

Figures B.1 and B.2 present the distributions of the dependent variables corresponding to our two samples. The distributions across the PSID and HRS are clearly non-normal suggesting that linear regression and Tobit specifications are not appropriate modelling approaches. There are also spikes at various parts of the distributions–particularly at 0 and 1–which are indicative of a large proportion of households not holding high risk assets in their financial portfolio. On average, PSID households hold 21% of financial wealth in high risk assets, as compared to 14% in the HRS.[18] Conditional on holding high risk assets, in the PSID, households allocate 56% of financial wealth to these assets compared to 42% in the HRS sample. Furthermore, in both samples, the majority of households hold some form of low risk asset, which accords with expectations as this asset category

[17] It is important to acknowledge that the correlation between the background risk measures and asset returns are potentially important for a household's asset allocation strategy (see for example, Heaton and Lucas 2000b and Palia, Qi, and Wu 2014). For example, a positive (negative) correlation between a background risk measure and risky asset returns is expected to induce households to substitute away from (towards) stock holding. In our setting, we are reluctant to include such correlations in the empirical analysis for several reasons. Incorporating the correlations between the background risk measures and asset returns along the lines of the theoretical literature would require more information than is available in our data. Specifically, the prices and returns of the assets held by the household are not contained in our data sources. Moreover, in our setting, due to data limitations, we analyse aggregated asset classes, as opposed to specific assets, meaning that any correlations would be crude approximations. More generally, we argue that we are capturing both demand and supply side factors which determine the asset market equilibrium.

[18] This disparity arises due to the PSID allowing us to allocate risky pension holdings to high risk assets. This is not possible in the RAND HRS sample.

includes checking and current accounts, with only 2.5% (2.8%) of households not holding any safe assets in the PSID (HRS) sample. In addition, for the PSID, 51% of households only hold low risk assets in their financial portfolio. The equivalent figure for the HRS is 35%.

4 Results

In this section, we present our empirical findings for the PSID and HRS. With respect to variable selection, our specifications fall into one of two types: those that model background risk using the coefficient of variation measures; and those for which background risk associated with income and house value is captured using the standard deviation measures. Recall that these measures are described in Section 3.1, and summarised in Table B.1.

For the purposes of comparison, we begin by briefly exploring the results relating to univariate models of portfolio allocation, in which the behavior of a single asset is the focus. For these specifications, the share of high risk assets in a household's portfolio is modelled using Tobit and univariate fractional response (Papke and Wooldridge 1996) frameworks. Drawing on the definitions corresponding to expressions (1) and (2), this is calculated for household i's portfolio as

$$s_{i0} = \frac{D_{i0}}{D_i}, \tag{23}$$

where s_{i0} denotes the share of assets in the high risk category. Modelling the share of high risk assets in expression (23) is quite common in the household finance literature. Following the univariate analysis, we present the results relating to both OF model estimation (Kawasaki and Lichtenberg 2014), and to our methodological contribution, the deflated $OF(C)$ model. Both of these modelling frameworks, the estimates of which are presented below in Section 4.2, differ from the univariate approaches, in that information pertaining to *all* asset risk categories, and not just the category associated with the highest risk are exploited in estimation. Finally, in accordance with the discussion in Section 2.3, random effects are used in all specifications. We turn first to the univariate models.

4.1 Univariate Models

All results relating to the Tobit and univariate fractional response (hereafter FR) models are presented in Table 4. Our estimated models use the full set of variables that feature in the deflated OF specifications, namely: all of the allocation equation variables described in Table B.1; and the set of uncertainty measures (either the CV or SD measures) described in Table B.1.

Panel A reports the model coefficients for specifications where background risk is proxied using the coefficient of variation measures, namely Income_{CV}, House_{CV} and Health_{CV}.[19] The results across

[19] For the univariate models, for brevity, we restrict ourselves to reporting the model coefficients, and not the marginal effects.

the Tobit and FR models are generally consistent with the existing literature in that education, household income, net wealth, subjective health measures and risk attitudes all have a significant impact on the share of risky assets. Being in better health and having higher levels of education are positively associated with the proportion of high risk assets in the financial portfolio. Similarly, income and net wealth are positively related to the proportion of high risk assets in the financial portfolios. These results are consistent across both the PSID and HRS samples. Interestingly, having children present in the household is inversely associated with the share of risky assets across both the Tobit and FR model specifications for the PSID; however, this household characteristic does not have a statistically significant impact on the share of risky assets for the HRS. This result is attributed to the fact that the HRS sample is, on average, older than the PSID sample.

Turning attention to the background risk measures, the PSID results indicate that labour income uncertainty fails to have a statistically significant impact on the risky asset share, whereas uncertainty relating to both house value and health expenditure reduce its share. A similar finding arises for the HRS sample, where both house value and health expenditure uncertainty reduce the share of high risk assets held, in line with our priors regarding the impact of background risk effects. Interestingly, the uncertainty corresponding to household non-asset income is positively associated with risky asset holding, potentially suggesting that non-financial asset income is not riskless and households are hedging using risky financial assets.

For the set of regressions where background risk associated with income and house value is proxied using the standard deviation (SD) measures, we turn to Panel B of Table 4. For brevity, only the estimated coefficients for the background risk variables are reported.[20] In line with the findings reported in Panel A, house value and health expenditure uncertainty reduce the share of risky assets held in both samples. In contrast to the CV measure of income uncertainty, which has a statistically insignificant impact on the risky asset share, the SD measure reduces the share of risky assets held for the PSID. This result is in line with existing studies (see, for example, Palia, Qi, and Wu 2014). This shows the importance of exploring a range of uncertainty measures and highlights that, in the context of labour income uncertainty in the PSID, which includes working age individuals, uncertainty as measured by growth rates induces a movement away from risky asset holding.

4.2 OF and deflated $OF(C)$ models

We now turn to the OF and deflated $OF(C)$ analysis. For the PSID, Table 5 presents the estimated model coefficients for these models. We then present the marginal effects for the deflated $OF(C)$ model in Table 6. All partial effects are evaluated at sample means. Similarly, for the HRS sample,

[20]For all sets of estimations (including for the OF and deflated $OF(C)$ estimations) our estimates of the allocation equation variables remain largely unchanged when the SD measures of background risk are used instead of the CV measures. This approach to reporting the results is thus adopted for the OF and deflated $OF(C)$ regressions below. The full set of estimation results is available from the authors on request.

Table 7 presents the estimated model coefficients for both the OF and deflated OF estimations, and Table 8 presents the marginal effects for the deflated OF model. In all tables, Panel A presents the full set of estimation results based on specifications that include proxies for income uncertainty, house value uncertainty, and health expenditure uncertainty, as measured by the coefficient of variation. For brevity, Panel B is restricted to reporting the comparable estimates for the background risk measures, where the SD measures of income and house value uncertainty were used instead of the CV measures.

PSID Results

As emphasised in the introduction, the *deflated* $OF(C)$ approach facilitates a more detailed picture of portfolio reallocation in the presence of background risk as compared to other modelling strategies. This is captured in Table 5. Compared to the OF model, which comprises a single (latent) estimation equation, the deflated model consists of three latent relationships: the allocation equation (y^*); and two background risk equations (m^* and h^*). This additional model complexity, which is central to recovering the precise asset share that is either retained or reallocated to each type of safer asset class, is reflected in the reported information criteria in Table 5: while the Akaike Information Criteria (AIC) is minimized for the deflated $OF(C)$ model, the Bayesian Information Criteria (BIC) is minimized for the OF. Given the well-known emphasis placed on parsimony by the latter measure, this result is not entirely unexpected. Nevertheless, given that our interest lies in uncovering evidence on the nature of household portfolio allocation that conventional methods are unable to detect, the support for the deflated $OF(C)$ in the form of a minimized AIC is highly encouraging.[21]

Turning to the extent to which our data is characterised by unobserved heterogeneity at the household level, Table 5 indicates that the random effects relating to the OF model, σ^2, are highly significant. Statistical significance in the random effects parameters is reported at the $p = 0.05$ level or lower for the deflated $OF(C)$ model with respect to the allocation equation ($\sigma^2_{y^*}$) and the respective correlation between random effects in the allocation equation and the high risk background risk equation (σ_{y^*,h^*}). In contrast, the estimated random effects in the background risk equations are statistically insignificant. This is true for the variance measures ($\sigma^2_{h^*}$ and $\sigma^2_{m^*}$) and the correlation between them (σ_{h^*,m^*}). It is encouraging that the common correlation term between the errors is found to be statistically significant.

Noting that negative (positive) coefficients are associated with riskier (safer) asset holding, we find that for the allocation equation, the OF and deflated $OF(C)$ results generally accord with

[21] Burnham and Anderson (2002) show that in practice, the BIC has a tendency to choose parsimonious models that under-fit the data. The same authors (see Burnham and Anderson 2002, p.66) also show that to mitigate the problem of selecting an 'over-fitted' model, the AIC can be modified to include an adjustment term to correct for small-sample bias. The authors refer to this adjusted measure as a second order criterion, or AIC_C. Such an adjustment is recommended when the sample size (n) is relatively small with respect to the number of model parameters (k), specifically, when $n/k < 40$. Whilst this condition is clearly not met in our empirical application, Burnham and Anderson (2004), p.270, argue that model over-fitting associated with the use of the AIC often arises because researchers fail to use the AIC_C.

the existing literature. For example, age, ethnicity, education, net wealth, income, health and risk attitudes are all statistically significant determinants of household portfolio decisions. However, as the marginal effects have a more meaningful interpretation, and given the specific contribution made by the deflated $OP(C)$ in accounting for household asset reallocations, we focus our discussion on Table 6, which presents the overall marginal effects associated with this model. As noted above, analytical expressions for these quantities are provided in Appendix A.

The ethnicity of the head of household is a statistically significant determinant of household asset allocation. For example, having a white head of household leads to a 7.9% higher high risk asset share compared to those with non-white household heads. Age and age-squared of the head of household are negatively and positively related to the share of low risk assets, respectively. In line with prior expectations, having children present in the household is inversely related to the share of risky assets, reducing the high risk asset share by 1.8%, whilst higher levels of education of the head of household are positively associated with the share of risky assets. Compared to having a head of household educated below high school level, a head of household possessing a college degree is associated with 15.7% and 9.8% higher high and medium risk asset shares, respectively, whilst a head of household with a college degree reduces the proportion of financial wealth allocated to low risk assets by 25.5%. In addition, better head of household health is positively associated with the share of risky assets. Increasing the self-assessed health of the head of household (measured on a 5-point scale) by one-unit increases the high risk asset share by 1.2%. In line with prior expectations, attitudes towards risk play an important role in portfolio allocation, such that having a more risk tolerant household head is positively associated with the share of risky assets. Here, a unit increase in the risk attitudes measure - which is increasing in risk tolerance - increases the shares of high risk and medium risk assets by 0.8% and 0.5%, respectively, and reduces the share of low risk assets by 1.2%.

Our uncertainty measures have mixed impacts on the household's portfolio allocation. CV based uncertainty relating to the head of household's labour income is not a statistically significant determinant of the share of riskier asset categories. In contrast, increased CV based uncertainty associated with house value and health expenditure moves households towards safer asset categories; households re-allocate their financial resources away from both high and medium risk asset categories, towards low risk assets. For example, a one-unit increase in house value uncertainty reduces the share of high risk assets by 1.9% and increases the low risk asset share by 3.6%. Similarly, a one unit increase in the coefficient of variation of health expenditure reduces the high risk asset share by 1.1%. For the SD based measures, Panel B of Table 5 reveals that house value uncertainty drives households away from high and medium risk assets towards low risk asset categories. A one-unit increase in house value uncertainty is associated with lowering the shares of high and medium risk assets by 3.4% and 5.6%, respectively. As a result of this reallocation, the share of low risk assets will correspondingly rise by 9.0%. The results suggest that the uncertainty around the growth rate of income–as opposed to the deviation in the level of income–influences the allocation to high risk assets. One possible explanation for this finding is that changes in this growth rate reflect potential uncertainty around the expectations of the income in the next period. Accordingly, this measure potentially captures the influence of expectations on portfolio allocation.

HRS Results

The HRS results generally accord with those for the PSID, and from the perspective of model fit and capturing unobserved heterogeneity, may be considered even stronger. Both the AIC and BIC are minimized for the deflated $OF(C)$ model, which provides additional support for using a deflated modelling framework to analyse household asset allocation decisions. From Table 7, we also observe that the household random effects have a significant impact on portfolio allocation decisions. The variance effects relating to the allocation and background risk equations ($\sigma^2_{y^*}$, $\sigma^2_{h^*}$, and $\sigma^2_{m^*}$), and the correlations between these effects (σ_{h^*,m^*} and σ_{y^*,m^*}) are statistically significant.

With respect to the determinants of portfolio allocation, our results generally accord with the existing literature. Ethnicity and marital status both influence household portfolio allocations. For example, compared to non-white headed households, having a white head of household is associated with 8.4% and 12.0% higher high risk and medium risk asset shares, respectively. In addition, relative to possessing below high school level education, having a head with college or high school level education increases the shares of high and medium risk assets, and thus lowers the share of low risk assets. Having a household head with a college degree increases the share of high risk assets by 15.1% and reduces the low risk asset share by 36.7%. Further, the results relating to health status, income, net wealth and subjective risk attitudes are all in line with the PSID results.

Turning to the background risk equations, Panel A reveals that households with a higher level of CV income uncertainty hold a higher share of risky assets. An explanation for this finding, which has been discussed in the existing literature (see, for example, Davis and Willen 2000), is that if the income and asset return correlation is low, then high risk assets can act as a means to hedge against income risk. In contrast, increasing house value uncertainty moves households away from high and medium risk assets towards safer ones: a one-unit increase in house value uncertainty reduces the shares of high and medium risk assets by 1.2% and 26.8%, respectively, whilst simultaneously increasing the share of low risk assets by 27.9%. In addition, a one-unit increase in health expenditure risk, as measured by the coefficient of variation, serves to reduce the medium risk asset share by 17.1% and to increase the low risk asset share by 17.3%. Arguably, the failure of health expenditure uncertainty measure to impact on high risk assets may be linked to the provision of health insurance in the older sample.

5 Asset Share Re-allocations

A key feature of our new model is its ability to quantify the deflating effects of background risk exposure on a household's observed asset allocation. In what follows, we explore how household asset allocations are affected both in the presence of background risk, and where such risk is absent. Doing so enables us to precisely determine if portfolio re-allocation occurs due to the combined effects of our background risk measures, as well as providing information on the size of such effects. Obtaining these estimated effects entails evaluating the relevant deflated OF equations and their subcomponents, described in Section 2, at the household level. These values are then averaged over all households in the sample.

Table 9 presents the overall reallocation percentages for the PSID and HRS samples for the deflated $OF(C)$ model. Our findings are reported for both the CV and SD measures of uncertainty. For the PSID, we find that for CV uncertainty, the presence of the background risk causes households to move away from the highest risk asset category. When background risk is present, the predicted proportions of high, medium and low risk assets are 19.3%, 15.8% and 64.9%, respectively. In contrast, the household's predicted allocations in the absence of such risk for high, medium and low risk assets are 22.8%, 35.5% and 41.6%, respectively. This indicates a clear movement away from high risk asset holding towards safer asset classes due to background risk. Approximately 6.1% of the share of high risk assets is reallocated to lower risk asset classes, with 4.4% being reallocated to medium risk assets and 1.6% being moved to low risk assets. Furthermore, we find that 48.4% of the share of medium risk assets is reallocated to low risk asset categories in the presence of background risk. Significantly, the nature of our reallocation results are qualitatively unchanged when the SD measures of income and health expenditure uncertainty are considered: with a modest amount of reallocation away from high risk assets. The results show similar large reallocations away from medium risk assets towards safe assets. Overall, the estimated allocation shares for the PSID - both with and without the presence of background risks - are similar in magnitude irrespective of whether the CV or SD measures are used to capture background risk.

For the HRS, Panel B of Table 9 indicates that, whilst background risk again induces households to hold relatively safer financial portfolios, its effects are considerably more potent. When the CV measures are considered, the predicted asset allocations in presence of background risk for high, medium and low risk assets are 11.7%, 34.3% and 54.1%, respectively. In the absence of the background risk, the predicted proportions of high, medium and low risk assets are 31.1%, 43.5%, and 25.5%, respectively. These results indicate that background risk leads to approximately 55.1% of the share of high risk assets being reallocated, with the majority, 45.6%, being reallocated to medium risk asset categories. Similar results are obtained when the SD measures of income and health expenditure uncertainty are used. Overall, our novel modelling approach enables us to highlight the significant role that background risk plays in shaping household portfolio allocation across the full spectrum of asset types.

6 Discussion

The aim of this section is to provide further discussion of our empirical results so as to better place them within the context of the extant literature. In doing so, it is important to recognise that our modelling framework is distinct from existing studies, not only in relation to our novel statistical approach, but with respect to how uncertainty is measured and how our assets types are defined. As part of our discussion, we also provide plausible explanations for the differences in findings across the PSID and HRS.

Overall, our findings are in line with the existing literature discussed in Section 1, in that background risk re-balances asset allocation away from high risk assets towards less risky ones. Whilst in the existing literature income uncertainty has attracted considerable attention, we explore three sources of background risk– income uncertainty, house value uncertainty, and health expenditure uncertainty–rather than a single source in isolation. This 'holistic' approach allows for the explicit consideration of the relative importance of different types of background uncertainty for asset allocation, which suggests that direct comparisons with many existing studies are not appropriate. An important possible implication stemming from our approach is that empirical studies that restrict themselves to considering the impact of single background risk measures may be susceptible to model mis-specification or omitted variable bias. This is particularly so if it is reasonable to hypothesize as we do, that in practice, US households are likely to be confronted with multiple sources of background risk, as opposed to a single source.

Interestingly, we find that the main drivers of asset reallocation are house value and health expenditure uncertainty. This suggests that future studies need to look beyond the effects of income uncertainty when accounting for asset allocation at the household level. The effects of house value and health expenditure uncertainty potentially have significant economic implications, especially in the arena of public policy. For instance, the significance of health expenditure uncertainty suggests that both the provision and nature of health insurance may play important roles in influencing a household's exposure to health expenditure uncertainty, and hence the structure of a household portfolio. Here, policies relating to healthcare coverage that reduce household exposure to such uncertainty may partially serve to mitigate the so-called stock-holding puzzle. In contrast to such implications at the microeconomic level, the importance of house value uncertainty highlights potential influences at the macroeconomic level, such as the interest rate and the role played by monetary policy in shaping borrowing conditions and US economic performance, which lie outside the household's control.

Another important difference between our modelling approach and the existing literature relates to the key finding from our analysis that background risk influences both medium and high risk asset allocations. In contrast, the existing literature predominantly explores risky asset holding or the share of financial wealth allocated to high risk assets in isolation of other types of assets. Our findings highlight the importance of adopting a holistic view of a household's portfolio in future research in this area. Our approach represents a step in this direction. It allows for the exploration of portfolio re-balancing across distinct asset classes as a result of changes in the explanatory variables, as well as allowing the identification of factors which result in households reallocating resources not only away from high risk, but also medium risk assets, towards low risk assets. Given that exposure to financial risk has implications for financial vulnerability, recognising that background risk has implications for this type of portfolio rebalancing reveals an important implication of our findings, especially as medium risk assets include pension wealth.

We also encountered differences in the results corresponding to the PSID and HRS data. When comparing the results across these two data sources, it is important to acknowledge that the PSID and the HRS collect information based on distinct demographic features, with the latter focusing on older individuals and the former being more representative of the adult population. The distinction is important in interpreting our results since the determinants of financial portfolio allocations are likely to evolve over the life course. For example, older age groups are likely to have accumulated more assets and, in addition, bequest motives and household time horizons may have more prominence in older age groups as compared to younger groups. Such considerations may lie behind the relatively large reallocation effects found for the HRS sample. Setting aside the differences in the sizes of the reallocation effects, it is interesting to note the consistency in the evidence supporting the importance of health expenditure and house value uncertainty in portfolio allocation across the two data sets.

As well as the sampling differences, it is also important to acknowledge limitations relating to the comparability of some dependent and independent variables across the two surveys. Perhaps the most notable difference relates to the fact that, for the PSID data, we are able to explore both direct and indirect stock holding, through, for example, retirement accounts, in the high risk asset share. In contrast, we are unable to capture indirect stock holding in the HRS. Estimating the effects of background risk across dependent variables that are not identical may partially explain the divergence in the reallocation effects across the two samples. In addition, the measure of income uncertainty is different across the two data sets. In order to tie in with existing studies, we follow the approaches applied to these two data sets in the existing literature so that we adopt the approach which is most appropriate for the sample under consideration. As explained previously, in the PSID, our income uncertainty measure is based on the head of household's labour income (also see Palia, Qi, and Wu 2014), whilst, for the HRS sample, it is based on the household's non-asset, rather than labour, income given the number of retirees in the sample (see e.g., Vissing-Jorgensen (2002) and Massa and Simonov (2006)).

Finally, in our analysis, we have incorporated a range of household random effects, and correlations between these, across the different methodologies. It is interesting to observe that the inclusion of these random effects significantly influences the impact of the background risk measures on the portfolio re-allocations. This suggests that, as in Fan and Zhao (2009) who find that individual heterogeneity significantly influences the estimated relationship between health status and risky asset holding, accounting for household heterogeneity when estimating models of portfolio allocation is important. In our estimations, the magnitudes of some of the estimated effects are significantly reduced upon the introduction of the correlated random effects. This suggests that careful consideration of the findings from studies based on cross-section data, as well as the findings from studies which do not appropriately account for the panel nature of the data, is warranted in order to avoid the effects of background risk on asset allocation being over-stated.

7 Conclusion

This paper contributes to the growing literature on household financial portfolio allocation. Exploiting data from the Panel Study of Income Dynamics and the Health and Retirement Study, we have developed a new empirical method to investigate the extent to which households facing background risk reduce their financial risk exposure. The deflated OF model is applicable to situations where there is a natural ordering to a series of proportions coupled with a prior belief that some of these proportions may be subject to category deflation. We explore the proportion of financial wealth allocated to three distinct risk-based asset categories and adopt a modelling strategy, which assumes that, given a range of observed and unobserved factors, households have an underlying portfolio allocation that would prevail in the absence of background risk. We explicitly quantify how the overall asset composition in a household's portfolio adjusts when exposed to such risk, and recover for, any given risky asset class, the shares that are either retained or reallocated to a relatively safer asset.

Our findings lead us to make a number of important conclusions. First, we present evidence which indicates that when confronted with background risk, households respond by attempting to reduce the overall risk that they face by reducing risky asset holding. Significantly, it is not only high risk asset holdings that are impacted by background risk; in practice, the 'flight from risk' from medium risk to safe assets is typically greater than the flight from high risk assets to less risky asset classes. This suggests that households are actively attempting to control the amount of financial risk and the associated financial vulnerability facing them. In addition, this finding serves to endorse our modelling approach which, in contrast to the existing literature, recognises that background risk may have an influence beyond risky asset holding. Such findings provide further support for the premise that the majority of households are risk averse, and aligns with studies which conclude that portfolio diversification is negatively related to the degree of household risk aversion (see for example King and Leape 1998; Barasinska, Schäfer, and Stephan 2012). Indeed, as noted by Barasinska, Schäfer, and Stephan (2012), a 'flight from risk' also accords with Keynes' precautionary motive for holding money, which in the context of our own findings can be interpreted as households preferring safety to higher returns on their investments when facing uncertainty.

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8 Tables

Table 1: PSID and HRS Summary Statistics[a]

	PSID[a]			HRS[b]		
Allocation Equation	Mean	Std. Dev	$[Min, Max]$	Mean	Std. Dev	$[Min, Max]$
Age	45.83	(14.45)	$[17, 97]$	66.37	9.08	$[34, 102]$
Age Squared	23.10	(14.21)	$[2.89, 94.09]$	44.87	12.13	$[11.56, 104.04]$
Male	0.79		$[0, 1]$	0.41		$[0, 1]$
Employed	0.81		$[0, 1]$	0.31		$[0, 1]$
Retired	0.12		$[0, 1]$	0.60		$[0, 1]$
White	0.77		$[0, 1]$	0.86		$[0, 1]$
Married	0.63		$[0, 1]$	0.74		$[0, 1]$
Child	0.40		$[0, 1]$	0.94		$[0, 1]$
Own	0.72		$[0, 1]$	0.89		$[0, 1]$
College Degree	0.37		$[0, 1]$	0.25		$[0, 1]$
High School	0.58		$[0, 1]$	0.56		$[0, 1]$
Net Wealth	0.94	(0.78)	$[-1.54, 1.93]$	1.24		$[-1.56, 1.93]$
Income	1.12	(0.08)	$[0.40, 1.58]$	1.09		$[0.41, 1.66]$
Subjective Health	2.71	(0.97)	$[0, 4]$	2.31		$[0, 4]$
Risk Attitudes	1.88	(1.60)	$[0, 5]$	0.70		$[0, 3]$
Background Risk Equations						
Income_{SD}	0.49	(0.19)	$[0.14, 1.35]$	0.73	0.61	$[0, 4.86]$
House_{SD}	0.42	(0.18)	$[0, 1.97]$	0.39	0.40	$[0, 5.39]$
Income_{CV}	0.60	(0.30)	$[0.08, 3.18]$	0.55	0.35	$[0.01, 3.41]$
House_{CV}	0.92	(0.57)	$[0.04, 5.56]$	0.40	0.34	$[0, 3.01]$
Health_{CV}	0.90	(0.42)	$[0, 3.00]$	0.93	0.46	$[0, 3.12]$
Dependent Variables						
High Risk	0.22	(0.33)	$[0, 1]$	0.14	(0.27)	$[0, 1]$
Medium Risk	0.15	(0.27)	$[0, 1]$	0.34	(0.37)	$[0, 1]$
Low Risk	0.64	(0.41)	$[0, 1]$	0.52	(0.41)	$[0, 1]$

[a]Number of observations = 32,015; Number of households = 5,892;
Median PSID participation per household = 5 years (max. 10).
[b]Number of observations = 99,494; Number of households = 13,656;
Median HRS participation per household = 7 years (max. 10).

Table 2: High Risk, Medium Risk, and Low Risk Asset Classifications in the PSID

Asset Category	PSID
High risk	Stock in publicly corporations Stock in mutual funds Stock in investment trusts Risky retirement accounts
Medium risk	Bonds (non Government) Non-risky pension accounts Life insurance policies
Low risk	Checking or savings accounts Money market funds Certificates of deposit Government bonds Treasury bills

Table 3: High Risk, Medium Risk, and Low Risk Asset Classifications in the HRS

Asset Category	HRS
High risk	Stock in publicly corporations Stock in mutual funds Stock in investment trusts
Medium risk	Bonds Pension accounts (IRA and Keogh) All other assets
Low risk	Checking or savings accounts Money market accounts Certificates of deposit Government bonds Treasury bills

Table 4: Random Effects Tobit and Fractional Response Models: PSID and HRS[a,b]

Panel A	PSID				HRS			
	Tobit Model		Fractional Model		Tobit Model		Fractional Model	
Age	0.0147***	(0.0039)	0.0223***	(0.0079)	-0.0342***	(0.0037)	-0.0759***	(0.0094)
Age Squared	-0.0904***	(0.0288)	-0.0014**	(0.0007)	0.0219***	(0.0023)	0.0565***	(0.0064)
Male	0.0502**	(0.0213)	0.0422	(0.0386)	-0.0029	(0.0097)	-0.0166	(0.0175)
Employed	-0.0360**	(0.0168)	-0.0862***	(0.0329)	0.0004	(0.0092)	-0.0314	(0.0216)
Retired	0.0414*	(0.0216)	0.0412*	(0.0433)	0.0153*	(0.0086)	0.0330*	(0.0198)
White	0.2630***	(0.0182)	0.3980***	(0.0314)	0.2600***	(0.0144)	0.3390***	(0.0275)
Married	0.0234	(0.0150)	-0.0194	(0.0301)	0.0196**	(0.0078)	-0.0365*	(0.0191)
Child	-0.0262**	(0.0102)	-0.0798***	(0.0210)	0.0291	(0.0180)	0.0122	(0.0361)
Homeowner	0.0140	(0.0130)	0.0144	(0.0261)	0.0530***	(0.0101)	0.0513*	(0.0266)
College Degree	0.4250***	(0.0320)	0.7300***	(0.0594)	0.4600***	(0.0157)	0.5490***	(0.0303)
High School	0.1600***	(0.0302)	0.2960***	(0.0570)	0.2720***	(0.0136)	0.3220***	(0.0271)
Net Wealth	0.1590***	(0.0075)	0.3030***	(0.0185)	0.0291***	(0.0031)	0.0683***	(0.0066)
Income	0.9890***	(0.0746)	2.2430***	(0.1660)	0.0846***	(0.0289)	0.0427***	(0.0059)
Subjective Health	0.0307***	(0.0052)	0.0660***	(0.0102)	0.0180***	(0.0026)	0.1950***	(0.0079)
Risk Attitudes	0.0259***	(0.0046)	0.0396***	(0.0074)	0.0137***	(0.0051)	0.0183**	(0.0091)
Year Dummies	Yes		Yes		Yes		Yes	
Income_{CV}	0.0206	(0.0252)	0.0517	(0.0449)	0.1460***	(0.0132)	0.1860***	(0.0237)
House_{CV}	-0.1260***	(0.0184)	-0.1660***	(0.0272)	-0.1220***	(0.0150)	-0.1320***	(0.0286)
Health_{CV}	-0.0720***	(0.0184)	-0.0662**	(0.0319)	-0.0569***	(0.0106)	-0.0517***	(0.0188)
Random effects								
σ^2	0.4300***	(0.0074)	-0.7070***	(0.0147)	0.4313***	(0.0045)	0.5859***	(0.0089)
Information criteria and log likelihood statistics								
AIC	35,820.04		28,173.52		92,067.68		72183.75	
BIC	36,088.00		28,433.12		92,371.94		72478.49	
LogL	-17,878.02		-14055.76		-46001.84		-36060.88	
Panel B								
Income_{SD}	-0.0829**	(0.0335)	-0.1130**	(0.0559)	0.0425***	(0.0075)	0.0509***	(0.0133)
House_{SD}	-0.2760***	(0.0438)	-0.3300***	(0.0711)	-0.0780***	(0.0119)	-0.1230***	(0.0214)
Health_{CV}	-0.0808***	(0.0184)	0.0743**	(0.0318)	-0.0579***	(0.0106)	-0.0500***	(0.0188)

[a]Standard errors in round $(\cdot)$ brackets.
[b]***/**/*Denotes two-tailed significance at one/five/ten percent levels.
PSID: Number of observations= $32,015$; Number of households = $5,836$.
HRS: Number of observations= $99,494$; Number of households = $13,656$.

Table 5: OF and Deflated $OF(C)$ Estimates, PSID, 1999-2017[a,b]

Panel A			Deflated OF Model with Correlated Errors					
	OF model		y^*		h^*		m^*	
Age	-0.2653***	(0.0758)	-0.2612***	(0.0836)				
Age Squared	0.1610***	(0.0611)	0.1653**	(0.0720)				
Male	-0.0188	(0.0363)	-0.0180	(0.0353)				
Employed	0.0365	(0.0306)	0.0418	(0.0414)				
Retired	-0.1207***	(0.0393)	-0.1214**	(0.0534)				
White	-0.3255***	(0.0288)	-0.3199***	(0.0325)				
Married	-0.0371	(0.0280)	-0.0393	(0.0321)				
Child	0.0730***	(0.0195)	0.0722***	(0.0231)				
Homeowner	-0.0115	(0.0238)	-0.0123	(0.0295)				
College Degree	-0.6443***	(0.0529)	-0.6336***	(0.0593)				
High School	-0.2141***	(0.0504)	-0.2119***	(0.0520)				
Net Wealth	-0.3414***	(0.0161)	-0.3201***	(0.0197)				
Income	-0.2062***	(0.0149)	-0.2028***	(0.0175)				
Subjective Health	-0.0478***	(0.0092)	-0.0472***	(0.0118)				
Risk Attitudes	-0.0315***	(0.0072)	-0.0308***	(0.0072)				
2001	0.0222	(0.0265)	0.0349	(0.1429)	-0.0858	(0.3759)	0.0469	(0.1562)
2003	0.0822***	(0.0313)	0.0955	(0.1417)	-0.0342	(0.3542)	-0.0144	(0.1518)
2005	0.0924***	(0.0360)	0.1613	(0.1383)	-0.2547	(0.3807)	-0.0165	(0.1516)
2007	0.1538***	(0.0426)	0.1891	(0.1378)	-0.2906	(0.3771)	0.1181	(0.1765)
2009	0.2550***	(0.0488)	0.2751**	(0.1400)	-0.1675	(0.3496)	0.0633	(0.1565)
2011	0.2326***	(0.0553)	0.3078**	(0.1397)	-0.3195	(0.3831)	-0.0039	(0.1500)
2013	0.2998***	(0.0626)	0.3399**	(0.1459)	-0.2302	(0.3759)	0.0501	(0.1573)
2015	0.3454***	(0.0704)	0.4570***	(0.1533)	-0.4327	(0.4422)	-0.0644	(0.1661)
2017	0.4242***	(0.0784)	0.4254***	(0.1583)	-0.2072	(0.3720)	0.1349	(0.1807)
Income_{CV}	-0.0032	(0.0402)			0.0013	(0.0990)	0.0472	(0.0617)
House_{CV}	0.1410***	(0.0243)			0.3139***	(0.0788)	0.1057	(0.0737)
Health_{CV}	0.0893***	(0.0298)			0.1905**	(0.0929)	0.1252	(0.0883)
μ_0	-5.0960***	(0.2213)	-4.9120***	(0.3043)	1.8470***	(0.4085)		
μ_1	-4.5160***	(0.2212)	-3.7970***	(0.9896)	2.0070***	(0.3749)		
Constant							-0.2048	(1.087)
Random effects and correlation parameters								
σ^2	0.3180***	(0.0136)						
$\sigma^2_{y^*}$					0.3940***	(0.0516)		
σ_{y^*,h^*}					-0.1991**	(0.0878)		
σ_{y^*,m^*}					-0.0043	(0.0359)		
$\sigma^2_{h^*}$					0.1127	(0.1257)		
$\sigma^2_{m^*}$					-0.0109	(0.0355)		
σ_{h^*,m^*}					0.0159	(0.0345)		
ρ					-0.6054***	(0.1301)		
Information criteria and log-likelihood statistics								
AIC	49601.05				49542.13			
BIC	49869.02				50061.32			
LogL	-24768.53				-24709.07			
Panel B								
Income_{SD}	0.1022**	(0.0528)			0.1374	(0.1594)	0.0684	(0.0907)
House_{SD}	0.3493***	(0.0658			0.8908***	(0.2029)	0.3954	(0.2593)
Health_{CV}	0.0975***	(0.0296)			0.1969**	(0.0966)	0.1528	(0.1061)

[a]Standard errors in round (·) brackets.

[b]***/**/*Denotes two-tailed significance at one/five/ten percent levels.

Number of observations $32,015$; Number of households $= 5,892$.

Table 6: Marginal Effects for PSID in the Deflated $OF(C)$ Model[a,b]

Panel A	Asset Class					
	High Risk		Medium Risk		Low Risk	
Age	0.0646***	(0.0206)	0.0405***	(0.0132)	-0.1051***	(0.0335)
Age Squared	-0.0409**	(0.0178)	-0.0256**	(0.0113)	0.0665**	(0.0289)
Male	0.0045	(0.0087)	0.0028	(0.0055)	-0.0072	(0.0142)
Employed	-0.0103	(0.0102)	-0.0065	(0.0064)	0.0168	(0.0167)
Retired	0.0300**	(0.0132)	0.0188**	(0.0086)	-0.0489**	(0.0215)
White	0.0791***	(0.0075)	0.0496***	(0.0057)	-0.1287***	(0.0122)
Married	0.0097	(0.0079)	0.0061	(0.0050)	-0.0158	(0.0129)
Child	-0.0179***	(0.0057)	-0.0112***	(0.0037)	0.0291***	(0.0092)
Homeowner	0.0030	(0.0073)	0.0019	(0.0045)	-0.0049	(0.0118)
College Degree	0.1567***	(0.0142)	0.0982***	(0.0107)	-0.2549***	(0.0228)
High School	0.0524***	(0.0128)	0.0329***	(0.0083)	-0.0853***	(0.0208)
Net Wealth	0.0792***	(0.0041)	0.0496***	(0.0040)	-0.1288***	(0.0066)
Income	0.0502***	(0.0042)	0.0315***	(0.0032)	-0.0816***	(0.0068)
Subjective Health	0.0117***	(0.0029)	0.0073***	(0.0019)	-0.0190***	(0.0047)
Risk Attitudes	0.0076***	(0.0018)	0.0048***	(0.0011)	-0.0124***	(0.0029)
2001	-0.0034	(0.0190)	-0.0151	(0.0175)	0.0186	(0.0263)
2003	-0.0216	(0.0189)	-0.0125	(0.0175)	0.0340	(0.0251)
2005	-0.0244	(0.0180)	-0.0245	(0.0169)	0.0489**	(0.0246)
2007	-0.0291	(0.0186)	-0.0545***	(0.0175)	0.0836***	(0.0260)
2009	-0.0579***	(0.0200)	-0.0563***	(0.0178)	0.1141***	(0.0281)
2011	-0.0567***	(0.0203)	-0.0503***	(0.0178)	0.1070***	(0.0295)
2013	-0.0701***	(0.0221)	-0.0645***	(0.0189)	0.1346***	(0.0321)
2015	-0.0867***	(0.0238)	-0.0632***	(0.0197)	0.1499***	(0.0344)
2017	-0.0926***	(0.0252)	-0.0935***	(0.0200)	0.1861***	(0.0377)
Income_{CV}	-0.0001	(0.0060)	-0.0089	(0.0102)	0.0090	(0.0122)
House_{CV}	-0.0191***	(0.0056)	-0.0167***	(0.0058)	0.0358***	(0.0081)
Health_{CV}	-0.0116**	(0.0052)	-0.0216***	(0.0071)	0.0332***	(0.0091)
Panel B						
Income_{SD}	-0.0052	(0.0064)	-0.0099	(0.0132)	0.0151	(0.0149)
House_{SD}	-0.0337**	(0.0137)	-0.0559***	(0.0169)	0.0897***	(0.0216)
Health_{CV}	-0.0075*	(0.0039)	-0.0237***	(0.0069)	0.0312***	(0.0083)

[a]Standard errors in round $(\cdot)$ brackets;

[b]partial effects calculated holding all variables at their means;

***/**/*denotes two-tailed significance at one/five/ten percent levels.

Table 7: OF and Deflated $OF(C)$ Estimates, HRS, 1998-2016[a,b]

Panel A			Deflated OF Model with Correlated Errors					
	OF Model		y^*		h^*		m^*	
Age	0.1965***	(0.0739)	0.2327*	(0.1203)				
Age Squared	0.3983	(0.4862)	1.1730	(0.8242)				
Male	-0.0004	(0.0153)	0.0040	(0.0209)				
Employed	0.0262	(0.0164)	0.0603*	(0.0325)				
Retired	-0.0565***	(0.0149)	-0.0752**	(0.0314)				
White	-0.4933***	(0.0231)	-0.6602***	(0.0325)				
Married	-0.0867***	(0.0154)	-0.1255***	(0.0220)				
Child	0.0271	(0.0299)	0.0300	(0.0412)				
Homeowner	-0.1236***	(0.0198)	-0.1728***	(0.0277)				
College Degree	-0.8239***	(0.0252)	-1.1860***	(0.0477)				
High School	-0.4707***	(0.0227)	-0.6174***	(0.0305)				
Net Wealth	-0.6011***	(0.0268)	-0.7013***	(0.0224)				
Income	-0.1338***	(0.0056)	-0.1948***	(0.0122)				
Subjective Health	-0.0477***	(0.0046)	-0.0708***	(0.0090)				
Risk Attitudes	-0.0263***	(0.0081)	-0.0431***	(0.0110)				
2000	-0.0564***	(0.0123)	0.0059	(0.0876)	-0.1155	(0.0790)	-0.0196	(0.3111)
2002	-0.0318*	(0.0174)	0.0465	(0.0847)	-0.1407*	(0.0764)	0.0167	(0.2936)
2004	-0.0659***	(0.0219)	0.0030	(0.0865)	-0.0855	(0.0747)	-0.2149	(0.2893)
2006	-0.0451	(0.0275)	0.0667	(0.0916)	-0.0793	(0.0788)	-0.4019	(0.2980)
2008	-0.0579*	(0.0332)	0.0836	(0.0980)	-0.1084	0.0844)	-0.5185*	(0.3144)
2010	-0.1401***	(0.0399)	-0.0342	(0.1045)	-0.0729	(0.0865)	-0.6206*	(0.3255)
2012	-0.1386***	(0.0453)	0.0077	(0.1136)	-0.0979	(0.0963)	-0.7713**	(0.3547)
2014	-0.1998***	(0.0506)	-0.0993	(0.1197)	-0.0923	(0.0967)	-0.7313**	(0.3471)
2016	-0.2393***	(0.0574)	-0.1941	(0.1242)	-0.0721	(0.0918)	-0.6675*	(0.3430)
Income_{CV}	-0.2328***	(0.0205)			-0.1863***	(0.0309)	-0.9548***	(0.2064)
House_{CV}	0.2260***	(0.0243)			0.1216***	(0.0327)	1.2990***	(0.2603)
Health_{CV}	0.1298***	(0.0169)			0.0174	(0.0249)	0.8201***	(0.1704)
μ_0	-4.8600***	(0.4503)	-5.9850***	(0.6176)	-0.2533***	(0.0732)		
μ_1	-3.5490***	(0.4499)	-4.5310***	(0.6071)	1.1900***	(0.0798)		
Constant							-0.1314	(0.2492)
Random effects and correlation parameters								
σ^2	0.4262***	(0.0102)						
$\sigma^2_{y^*}$					0.8742***	(0.0615)		
σ_{y^*,h^*}					0.0354	(0.0317)		
σ_{y^*,m^*}					-0.8038***	(0.2063)		
$\sigma^2_{h^*}$					0.1122***	(0.0180)		
$\sigma^2_{m^*}$					-0.8422***	(0.1477)		
σ_{h^*,m^*}					6.6560***	(2.3920)		
ρ					-0.2090***	(0.0674)		
Information criteria and log-likelihood statistics								
AIC	170,472.35				166,963.45			
BIC	170,776.60				167,552.94			
LogL	-85,204.17				-83,419.726			
Panel B								
Income_{SD}	-0.0259**	(0.0117)			-0.0249	(0.0180)	0.0333	(0.0537)
House_{SD}	0.1760***	(0.0201)			0.1103***	(0.0281)	0.8397***	(0.1338)
Health_{CV}	0.1277***	(0.0170)			0.0144	(0.0265)	0.7086***	(0.1171)

[a] Standard errors in round $(\cdot)$ brackets.

[b] ***/**/* denotes two-tailed significance at one/five/ten percent levels.

Number of observations $= 99,494$; Number of households $= 13,656$.

Table 8: Marginal Effects for the HRS in the Deflated $OF(C)$ Model[a,b]

Panel A	Asset class					
	High Risk		Medium Risk		Low Risk	
Age	-0.0297*	(0.0153)	-0.0423*	(0.0220)	0.0719*	(0.0373)
Age Squared	-0.1495	(0.1050)	-0.2131	(0.1500)	0.3626	(0.2546)
Male	-0.0005	(0.0026)	-0.0007	(0.0038)	0.0012	(0.0064)
Employed	-0.0077*	(0.0042)	-0.0110*	(0.0060)	0.0186*	(0.0101)
Retired	0.0096**	(0.0040)	0.0137**	(0.0058)	-0.0232**	(0.0098)
White	0.0841***	(0.0040)	0.1199***	(0.0096)	-0.2040***	(0.0119)
Married	0.0160***	(0.0028)	0.0228***	(0.0042)	-0.0388***	(0.0068)
Child	-0.0038	(0.0052)	-0.0054	(0.0075)	0.0093	(0.0128)
Homeowner	0.0220***	(0.0035)	0.0314***	(0.0055)	-0.0534***	(0.0088)
College Degree	0.1511***	(0.0052)	0.2154***	(0.0151)	-0.3666***	(0.0168)
High School	0.0787***	(0.0037)	0.1121***	(0.0089)	-0.1908***	(0.0109)
Net Wealth	0.0894***	(0.0028)	0.1274***	(0.0091)	-0.2167***	(0.0099)
Income	0.0248***	(0.0015)	0.0354***	(0.0031)	-0.0602***	(0.0041)
Subjective Health	0.0090***	(0.0011)	0.0129***	(0.0018)	-0.0219***	(0.0028)
Risk Attitudes	0.0055***	(0.0014)	0.0078***	(0.0022)	-0.0133***	(0.0034)
2000	0.0105	(0.0072)	-0.0013	(0.0486)	-0.0091	(0.0459)
2002	0.0077	(0.0073)	-0.0173	(0.0472)	0.0095	(0.0442)
2004	0.0079	(0.0075)	0.0412	(0.0446)	-0.0492	(0.0425)
2006	-0.0008	(0.0082)	0.0691	(0.0475)	-0.0683	(0.0450)
2008	-0.0001	(0.0088)	0.0893*	(0.0501)	-0.0892*	(0.0482)
2010	0.0114	(0.0100)	0.1335**	(0.0524)	-0.1449***	(0.0511)
2012	0.0085	(0.0106)	0.1565***	(0.0559)	-0.1650***	(0.0555)
2014	0.0216**	(0.0110)	0.1678***	(0.0567)	-0.1894***	(0.0568)
2016	0.0317**	(0.0129)	0.1724***	(0.0565)	-0.2041***	(0.0574)
Income_{CV}	0.0181***	(0.0030)	0.1930***	(0.0392)	-0.2111***	(0.0394)
House_{CV}	-0.0118***	(0.0032)	-0.2676***	(0.0483)	0.2794***	(0.0485)
Health_{CV}	-0.0017	(0.0024)	-0.1712***	(0.0318)	0.1729***	(0.0319)
Panel B						
Income_{SD}	0.0022	(0.0016)	-0.0082	(0.0113)	0.0060	(0.0115)
House_{SD}	-0.0098***	(0.0025)	-0.1727***	(0.0245)	0.1825***	(0.0248)
Health_{SD}	-0.0013	(0.0024)	-0.1495***	(0.0216)	0.1508***	(0.0218)

[a]Standard errors in round $(\cdot)$ brackets;
[b]partial effects calculated holding all variables at their means;
***/**/*denotes two-tailed significance at one/five/ten percent levels.

Table 9: Asset Share Reallocations

	Asset Type	Estimated shares without background risk	Reallocation Decomposition: High risk	Reallocation Decomposition: Medium risk	Reallocation Decomposition: Low risk	Estimated shares with background risk
Panel A- PSID, Panel Deflated $OF(C)$						
Coefficient of Variation	High risk	0.2283 (0.0186)	0.9395 (0.0294)	0.0164 (0.0197)	0.0440 (0.0207)	0.1936 (0.0052)
	Medium risk	0.3552 (0.2744)		0.5266 (0.3585)	0.4734	0.1579 (0.0035)
	Low risk	0.4164 (0.2824)			-	0.6485 (0.0059)
SD Growth†	High risk	0.2175 (0.0132)	0.9665 (0.0206)	0.0163 (0.0129)	0.0173 (0.0101)	0.1981 (0.0037)
	Medium risk	0.3353 (0.2529)		0.5076 (0.3510)	0.4924	0.1551 (0.0031)
	Low risk	0.4472 (0.2576)			-	0.6468 (0.0046)
Panel B- HRS, Panel Deflated $OF(C)$						
Coefficient of Variation	High risk	0.3107 (0.0130)	0.4490 (0.0208)	0.4560 (0.0153)	0.0951 (0.0106)	0.1168 (0.0024)
	Medium risk	0.4345 (0.0182)		0.5756 (0.0361)	0.4244	0.3427 (0.0101)
	Low risk	0.2547 (0.0114)				0.5405 (0.0099)
0.00 SD Growth†	High risk	0.2841 (0.0128)	0.4691 (0.0240)	0.4548 (0.0183)	0.07612 (0.0100)	0.1190 (0.0027)
	Medium risk	0.4326 (0.0178)		0.4679 (0.0415)	0.5321	0.3708 (0.0112)
	Low risk	0.2833 (0.0126)				0.5102 (0.0107)

[a] Standard errors in round $(\cdot)$ brackets.

†SD Growth refers to the specifications including the standard deviation of growth for income and house value, and the coefficient of variation for health expenditure.

Appendix

A Partial effects

Following estimation, several quantities of interest, and partial effects (PEs) of covariates on these, will be of interest. For example, PEs of the overall expected value (EV) for each asset type will be of interest, as will be the decomposition of this into its various components. The latter will estimate how much of the total effect is determined by a 'flight from risk'.

Below we derive analytical expressions for these for the correlated deflated OF model; those for the uncorrelated model would simply be achieved by setting $\rho = 0$. The required derivatives for the partial effects for the bivariate normal probabilities derived from expressions (16), (17), and (18) can be obtained using the generic result in Greene (2012), *viz.*

$$\frac{\partial \Phi_2 (a, b; \rho)}{\partial a} = \phi (a) \Phi \left(\frac{b - \rho a}{\sqrt{1 - \rho^2}} \right) \tag{A.1}$$

where $\phi(.)$ is the probability density function (PDF) of the standard univariate normal distribution.

To calculate the overall partial effects, begin by partitioning the explanatory variables and the associated coefficients as

$$\begin{gathered} \mathbf{x} = \begin{pmatrix} \mathbf{z} \\ \widetilde{\mathbf{x}} \end{pmatrix}, \ \beta = \begin{pmatrix} \beta_z \\ \widetilde{\beta} \end{pmatrix}, \ \mathbf{w} = \begin{pmatrix} \mathbf{z} \\ \widetilde{\mathbf{w}} \end{pmatrix}, \\ \delta = \begin{pmatrix} \delta_z \\ \widetilde{\delta} \end{pmatrix}, \ \lambda = \begin{pmatrix} \lambda_z \\ \widetilde{\lambda} \end{pmatrix}, \end{gathered} \tag{A.2}$$

where $\mathbf{z}$ represents the common variables that appear in both $\mathbf{x}$ and $\mathbf{w}$, with the corresponding coefficients β_z, δ_z and λ_z for the allocation, high risk background risk, and medium risk background risk equations, respectively. $\widetilde{\mathbf{x}}$ denotes the set of variables that appears solely in the allocation equation with associated coefficients $\widetilde{\beta}$, whereas $\widetilde{\mathbf{w}}$ denotes the set of variables both common and exclusive to the high and medium risk background risk equations, with respective coefficients $\widetilde{\delta}$ and $\widetilde{\lambda}$. Note that the explanatory variable of interest may appear in only one of $\mathbf{x}$ or $\mathbf{w}$, or in both. For a continuous variable x_k, the marginal effect on the high risk asset share in the allocation equation relating only to the explanatory variables in $\mathbf{x}$ is given by

$$\frac{\partial E \left(s_{i,j=0} \left| \mathbf{x}_i, \mathbf{w}_i \right. \right)}{\partial x_k} = \phi \left(\mathbf{x}' \beta \right) \beta_k. \tag{A.3}$$

Denoting the unique explanatory variables for the whole model as $\mathbf{x}^* = (\mathbf{z}', \widetilde{\mathbf{x}}', \widetilde{\mathbf{w}}')'$, and setting the associated coefficient vectors for $\mathbf{x}^*$ as $\beta^* = (\beta_z', \widetilde{\beta}', \mathbf{0}')'$, $\delta^* = (\delta_z', \mathbf{0}', \widetilde{\delta}')'$ and $\lambda^* = (\lambda_z', \mathbf{0}', \widetilde{\lambda}')$

implies that the partial effects of the explanatory variable vector $\mathbf{x}^*$ on each of the J overall asset shares in expressions (16), (17) and (18) are given by

$$\frac{\partial E\left(s_{i,j=0}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)}{\partial \mathbf{x}^*} = \begin{cases} \Phi\left(\frac{\mu_0^h-\mathbf{w}_i'\delta-\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)\phi\left(\mu_0-\mathbf{x}_i'\beta\right)\beta^* \\ +\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta-\rho(\mu_0^h-\mathbf{w}_i'\delta)}{\sqrt{1-\rho^2}}\right)\phi\left(\mu_0^h-\mathbf{w}_i'\delta\right)\delta^* \end{cases} \tag{A.4}$$

$$\frac{\partial E\left(s_{i,j=1}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)}{\partial \mathbf{x}^*} = \begin{cases} \left[\Phi\left(\frac{\mu_1-\mathbf{x}_i'\beta+\rho(\mathbf{w}_i'\lambda)}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta+\rho(\mathbf{w}_i'\lambda)}{\sqrt{1-\rho^2}}\right)\right]\phi\left(\mathbf{w}_i'\lambda\right)\lambda^* \\ +\Phi\left(\frac{\mathbf{w}_i'\lambda+\rho(\mu_1+\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)\phi\left(\mu_1-\mathbf{x}_i'\beta\right)\beta^* \\ +\left[\begin{array}{c}\Phi\left(\frac{\mu_1^h-\mathbf{w}_i'\delta-\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{\mu_0^h-\mathbf{w}_i'\delta-\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right) \\ -\Phi\left(\frac{\mathbf{w}_i'\lambda+\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)\end{array}\right]\phi\left(\mu_0-\mathbf{x}_i'\beta\right)\beta^* \\ +\left[\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta-\rho(\mu_1^h-\mathbf{w}_i'\delta)}{\sqrt{1-\rho^2}}\right)-\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta-\rho(\mu_0^h-\mathbf{w}_i'\delta)}{\sqrt{1-\rho^2}}\right)\right]\phi\left(\mu_1^h-\mathbf{w}_i'\delta\right)\delta^* \end{cases} \tag{A.5}$$

$$\frac{\partial E\left(s_{i,j=2}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)}{\partial \mathbf{x}^*} = \begin{cases} \phi\left(\mathbf{x}_i'\beta-\mu_1\right)\beta^* \\ +\Phi\left(\frac{\mathbf{w}_i'\delta-\mu_1^h-\rho(\mu_0-\mathbf{x}_i'\beta)}{\sqrt{1-\rho^2}}\right)\phi\left(\mu_0-\mathbf{x}_i'\beta\right)\beta^* \\ +\Phi\left(\frac{\mu_0-\mathbf{x}_i'\beta-\rho(\mathbf{w}_i'\delta-\mu_1^h)}{\sqrt{1-\rho^2}}\right)\phi\left(\mathbf{w}_i'\delta-\mu_1^h\right)\delta^* \\ +\Phi\left(\frac{-\mathbf{w}_i'\lambda+\rho(\mathbf{x}_i'\beta-\mu_1)}{\sqrt{1-\rho^2}}\right)\phi\left(\mathbf{x}_i'\beta-\mu_1\right)\beta^* \\ +\Phi\left(\frac{\mathbf{x}_i'\beta-\mu_1+\rho(-\mathbf{w}_i'\lambda)}{\sqrt{1-\rho^2}}\right)\phi\left(-\mathbf{w}_i'\lambda\right)\lambda^* \end{cases} . \tag{A.6}$$

Standard errors of all of these quantities can be obtained using the delta method.

B Variable definitions

Table B.1: Allocation Equation Variable Descriptions

Variable	Definition
Age	Age of household head in years.
Age Squared	Age of household head in years squared divided by 100.
Male	= 1 if head of household is male; 0 if female.
Employed	= 1 if head of household is employed or self-employed, 0 otherwise.
Retired	= 1 if head of household is retired, 0 otherwise.
White	= 1 if household head is white, 0 otherwise.
Married	= 1 if head of household married or in a relationship, 0 otherwise.
Child	= 1 if child present in the household, 0 otherwise.
Own	= 1 if the household owns their home or in process of purchasing, 0 otherwise.
College Degree	= 1 if household's head has at least college degree as highest educational qualification, 0 otherwise.
High School	= 1 if household's head has high school as highest educational qualification, 0 otherwise.
Net Wealth	Inverse hyperbolic sine transformation of household net wealth, that is, total assets minus total debt, divided by 10.
Income	Natural logarithmic transformation of total household income, divided by 10.
Subjective Health	Index of head of household's self-assessed health status measured on a 5 point scale increasing in better health.
Risk Attitudes	**PSID:** From the 1996 wave, a 6 point index, increasing in risk tolerance was based on the head of household's responses to the following series of questions: (M1): Suppose you had a job that guaranteed you income for life equal to your current total income. And that job was (your/your family's) only source of income. Then you are given the opportunity to take a new, and equally good, job with a 50–50 chance that it will double your income and spending power. But there is a 50–50 chance that it will cut your income and spending power by a third. Would you take the new job? The individuals who answered "yes" to this question, were then asked: (M2): Now, suppose the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it in half. Would you still take the job? The individuals who answered "yes" to this question were then asked: (M5): Now, suppose that the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it by 75 percent. Would you still take the new job? The individuals who answered "no" to Question M1 were asked: (M3): Now, suppose the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it by 20 percent. Then would you take the job? Those individuals who replied "no" were asked: (M4): Now, suppose that the chances were 50–50 that the new job would double your (family) income, and 50–50 that it would cut it by 10 percent. Then would you take the new job? **HRS:** Respondent is asked to choose between pairs of jobs where one guarantees current family income and the other offers a chance to increase income but also carries the risk of loss of income. If Respondent says s/he would take the risk, the same scenario but with riskier odds is presented. If Respondent says s/he would not take the risk, the same scenario with less risky odds is asked. The variable is set using the following four levels listed from least to most risk-averse: 1. Respondent would take a job with even chances of doubling income or cutting it in half. 2. Respondent would take a job with even chances of doubling income or cutting it by a third. 3. Respondent would take a job with even chances of doubling income or cutting it 20%. 4. Respondent would take or stay in the job that guaranteed current income given any of the above alternatives. We take an individual initial valuation of this question, and assume, like in the PSID, that this is time invariant over the time considered.
Year Fixed Effects	Binary variables capturing the survey time periods in the PSID 1999 - 2017 and 1998 - 2016 in the HRS.
Uncertainty Measures	
Coefficient of variation (CV) measures	
Income_{CV}	The coefficient of variation of a household's reported labour income (PSID) and non-capital income (HRS) over time; that is, the standard deviation of income divided by the household's average income.
House_{CV}	The coefficient of variation of the reported value of a household's home over time; that is, the standard deviation of the value of a household's home divided by its average value.
Health_{CV}	The coefficient of variation of a household's health expenditure; that is, the standard deviation of a household's health expenditure divided by its average value.
Standard deviation (SD) of growth rate measures	
Income_{SD}	Standard deviation of a household's income growth over time.
House_{SD}	Standard deviation of the growth in value of a household's home over time.

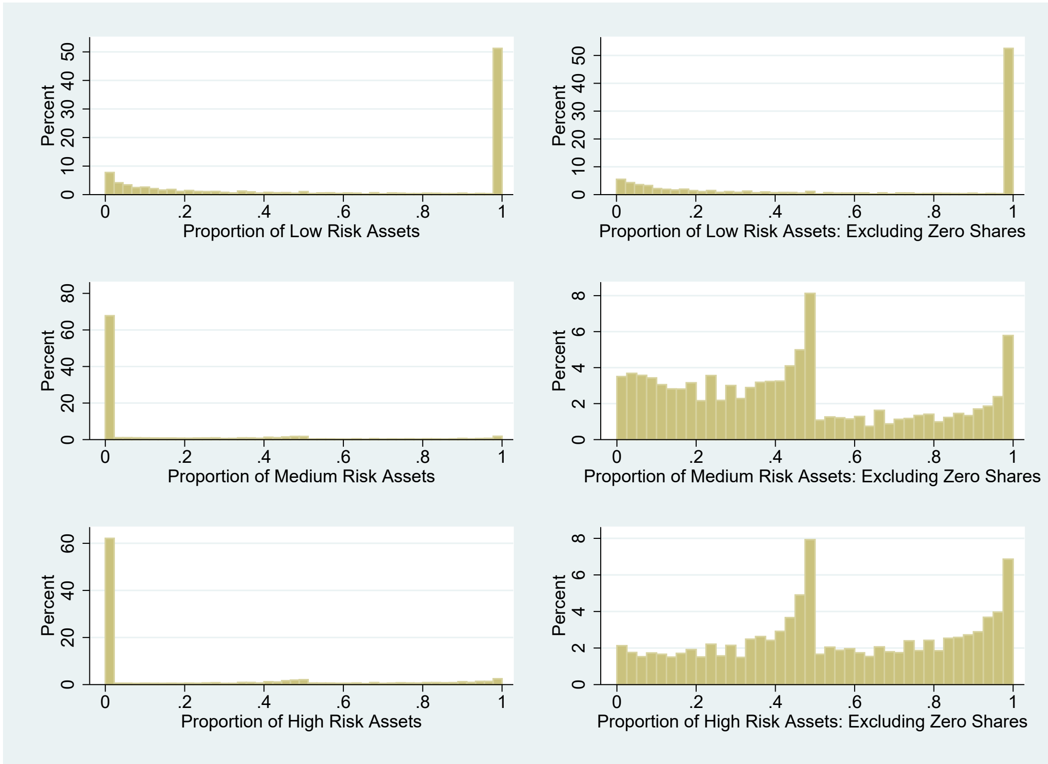

Figure B.1: Proportions of PSID households holding low risk, medium risk and high risk assets, with and without zero shares, 1999-2017

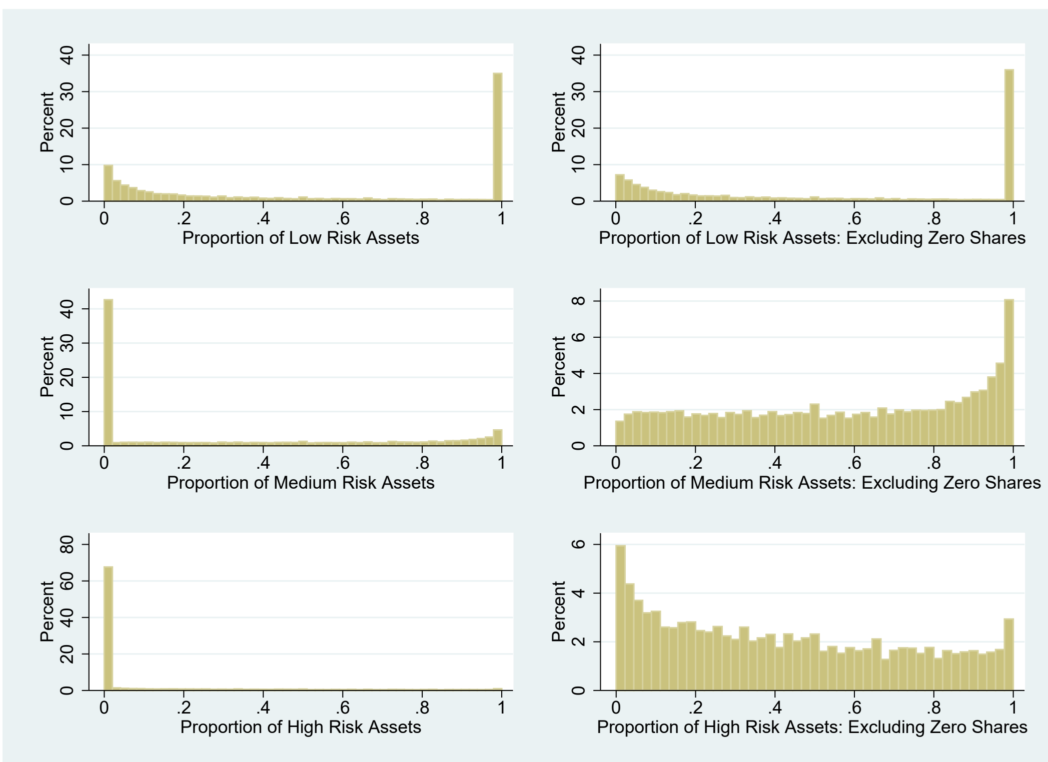

Figure B.2: Proportions of HRS households holding low risk, medium risk and high risk assets, with and without zero shares, 1998-2016