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ABSTRACT

Portfolio Allocation, Income Uncertainty and Households' Flight from Risk*

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

JEL Classification: C33, C35, D14, G11
Keywords: asset allocation, background risk, flight from risk, fractional models

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NON-TECHNICAL SUMMARY

Since the 2008 global financial crisis, much attention has been paid to the behaviour of banks and investors following significant events such Brexit and the US elections. In particular, a 'flight to safety' has been observed, whereby depositors invest their money in relatively safe assets in times of uncertainty. Using data on a large sample of US households, we find that when faced with income uncertainty, households behave in a similar way. Household income uncertainty could be driven by many factors ranging from a reduction in the availability of overtime hours to job loss, which could be due to, for example, ill health or redundancy. Our empirical analysis of 4,257 households, over the time period 1999-2013, reveals that household income uncertainty leads to households holding less risky assets such as stocks and shares and more low risk assets such as savings accounts. We also find that it is not only high-risk asset holdings that are reduced by income uncertainty; but also the holding of medium risk assets such as bonds and non-risky pension accounts. Such income uncertainty therefore leads to an aggregate picture whereby we observe very few households holding financial assets associated with risk and a very high proportion of household wealth held in safe assets with relatively low rates of return. This suggests that households are actively attempting to control the amount of financial risk and the associated financial vulnerability facing them. Such findings provide further support for the premise that the majority of households are risk averse. A flight from risk also accords with Keynesian 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.

1 Introduction and Background

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. Named the 'stockholding puzzle', this phenomenon has received significant attention in the existing literature; see for example, Fratantoni (2001), Haliassos and Bertaut (1995) and Bertaut (1998) amongst many others. Furthermore, households that do own risky assets are often characterized by holding undiversified portfolios. While these observations may initially appear uncontroversial, they constitute examples of empirical 'puzzles' that have traditionally sat uncomfortably with the predictions of classical financial and economic theory: that is, what households actually do is quite often inconsistent with formal theories prescribing what they ought to do, highlighting the disconnect between 'positive' and 'normative' household finance (Campbell 2006).

An influential strand of literature that attempts to account for these empirical puzzles draws on the notion of 'background risk', which is hypothesised to induce households to reduce their total desired risk exposure by reducing their exposure to avoidable risks, by, for example, holding increased amounts of safe assets. Such behaviour has been termed 'temperance' in a number of important theoretical contributions (Pratt and Zeckhauser 1987; Kimball 1991; Gollier and Pratt 1996; Heaton and Lucas 2000b). Using this prediction as an intuitive starting point, this paper presents a new approach to the modelling of household portfolios, termed a *deflated fractional ordered probit* ($DFOP$) model. We uniquely combine methods from the literature on category inflation following Harris and Zhao (2007) with that of compositional data analysis (Papke and Wooldridge 1996; Kawasaki and Lichtenberg 2014). In the context of our empirical application, the word 'deflated' refers to the prediction that the fraction of risky assets held in household financial portfolios will, *ceteris paribus*, be lower than would be the case in the absence of background risk. Its usage has close parallels with the discrete-choice literature on category inflation which sets out to model a build-up or 'excess' of observations in a given choice category.

In what follows, we quantify how the overall asset composition in a household portfolio adjusts due to background risk, focusing on income uncertainty; and for any given risky asset class, recover the precise share that is reallocated to a safer asset due to its presence. This latter innovation makes our contribution unique to the growing literature on household finances. As will become apparent in later sections, our method is also readily applicable to the analysis of financial portfolios other than those pertaining to households.

In setting out our arguments, we adopt terminology commonly used to describe financial market participants' decisions to move capital from riskier into safer investment vehicles, referring to the effect of background risk on households as resulting in a 'flight from risk'. The $DFOP$ model is used to investigate the extent of this phenomenon for the US exploiting the 1999-2013 waves of the *Panel Study of Income Dynamics* (PSID). Our model is able to explicitly explore why US households' shares of risky assets are observed to be so low.

Whilst this paper models household portfolio allocation and background risk in a novel way, it is not alone in exploiting US survey data to examine the effect of background risk on household finances. 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.[1] Our study combines insights from much of the aforementioned literature; in doing so our analysis controls for the effects of income uncertainty, as well as a wide range of other economic factors and individual characteristics.

2 A Deflated Fractional Ordered Probit ($DFOP$) Model

Consider a situation where financial assets are classified into three different risk types: high, medium and low. As discussed later, this parsimonious classification has precedence in the household portfolio literature (Carroll 2002). In what follows, we treat the process underlying portfolio allocation decisions as one of partial observability: households are characterised by an unobserved portfolio allocation equation that captures the allocation that would arise in the absence of background risk; we call this a household's allocation equation. Additionally, we introduce what we term background risk equations - also unobserved - that capture the extent to which background risk factors move households away from this allocation. The observed household portfolio allocation is therefore the combination of these two unobserved processes.

2.1 The Allocation Equation

Our initial interest lies with modelling the share of the household portfolio allocated to each type of financial asset - which is assumed to prevail in the absence of background risk - and the partial effects of observed covariates on these. To model this relationship we use the fractional ordered probit (FOP) model of Kawasaki and Lichtenberg

[1] 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. Other notable work explores the effects of health risks on portfolio allocation (Rosen and Wu 2004, Edwards 2008, Berkowitz and Qiu 2006, Fan and Zhao 2009 and Spaenjers and Spira 2015), in which poor health is associated with lower levels of risky asset holding.

(2014), which is a hybrid of the ordered probit model and the fractional response model of Papke and Wooldridge (1996).[2] With no loss of generality we label household portfolio shares, $j = 0, 1, 2$, such that they decrease with risk as j increases.

In setting out the allocation equation it is intuitive to relate it to the standard ordered probit (OP) model (Greene 2012). Households are assumed to have an underlying latent variable, y_i^*, related to observed characteristics with unknown weights ($\boldsymbol{\beta}$), and a random, normally distributed error term u_i, such that

$$y_i^* = \mathbf{x}_i'\boldsymbol{\beta} + u_i. \tag{1}$$

Denoting the total number of outcomes available as J (here $J = 3$, such that $j = 0, 1, 2$), the outcome j that household i chooses will depend on the relationship between y_i^* and the inherent boundary parameters in the OP model according to

$$y_i = \begin{cases} 0 \quad if & y_{it}^* < \mu_0 \\ 1 \quad if & \mu_0 \leq y_{it}^* < \mu_1 \\ 2 \quad if & y_{it}^* \geq \mu_1 \end{cases} \tag{2}$$

where μ_0 and μ_1 are boundary parameters. Household i's corresponding likelihood when $J = 3$ is

$$\ell_i = \prod_{j=0}^{J-1=2} (\Phi(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}))^{d_{i0}} \left(\Phi\left(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}\right)\right)^{d_{i1}} \left(1 - \Phi\left(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}\right)\right)^{d_2} \tag{3}$$

where $\Phi(.)$ is the standard normal cumulative distribution function. The indicator function d_{ij} is such that $d_{ij} = 1\left(y_j = j\right)$ where the household can be in only one of the $j = 0, 1, 2$ outcomes. However, as it is possible for households to hold assets belonging to different classes at the same time, that is the risk-ordered categories are not mutually exclusive - equations (1) and (3) are not sufficient to model fractional

[2] Whilst a fractional multinomial logit approach may seem appropriate for modelling our data, this is not the case as our household portfolio shares have an inherent ordering based on risk.

data.

Specifically, we require

$$E\left(s_{ij}\left|\mathbf{x}_i\right.\right),\ j=0,1,2 \tag{4}$$

where E denotes the expected value of the term in parentheses and s_{ij} represents the share of total assets in aggregate j for household i. This instead implies a likelihood function given by

$$\ell_i=\prod_j\left(\Phi(\mu_0-\mathbf{x}_i'\boldsymbol{\beta})\right)^{s_{i,j=0}}\left(\Phi\left(\mu_1-\mathbf{x}_i'\boldsymbol{\beta}\right)-\Phi\left(\mu_0-\mathbf{x}_i'\boldsymbol{\beta}\right)\right)^{s_{i,j=1}}\left(1-\Phi\left(\mu_1-\mathbf{x}_i'\boldsymbol{\beta}\right)\right)^{s_{i,j=2}}. \tag{5}$$

and is consistent with the inherent ordering, in risk, of the j asset bundles in the household's portfolio (and not of the value of the shares themselves). The household allocation equation is characterised by

$$\begin{aligned} E\left(s_{i,j=0}\left|\mathbf{x}_i\right.\right) &= \Phi\left(\mu_0-\mathbf{x}_i'\boldsymbol{\beta}\right) \\ E\left(s_{i,j=1}\left|\mathbf{x}_i\right.\right) &= \Phi\left(\mu_1-\mathbf{x}_i'\boldsymbol{\beta}\right)-\Phi\left(\mu_0-\mathbf{x}_i'\boldsymbol{\beta}\right) \\ E\left(s_{i,j=2}\left|\mathbf{x}_i\right.\right) &= 1-\Phi\left(\mu_1-\mathbf{x}_i'\boldsymbol{\beta}\right) \end{aligned} \tag{6}$$

which by construction all satisfy $0\le E\left(s_{i,j}\left|\mathbf{x}_i\right.\right)\le 1$ (Kawasaki and Lichtenberg 2014). The (fractionally ordered) household allocation equation provides the baseline starting point for our analysis, which we now extend.

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

$$h_i^* = \mathbf{w}_i'\boldsymbol{\delta} + \varepsilon_i \tag{7}$$

$$m_i^* = \mathbf{w}_i'\boldsymbol{\lambda} + \varphi_i \tag{8}$$

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.

Define these two equations as

$$h_i = \begin{cases} 0 \quad if \quad\quad h_i^* < \mu_0^h \\ 1 \quad if \quad \mu_0^h \leq h_i^* < \mu_1^h \\ 2 \quad if \quad\quad h_i^* \geq \mu_1^h \end{cases} ; m_i = \begin{cases} 1 \quad if \quad m_i^* > 0 \\ 2 \quad if \quad m_i^* \leq 0 \end{cases} \tag{9}$$

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 ($\boldsymbol{\delta}$ and $\boldsymbol{\lambda}$) and random disturbance terms (ε and φ).

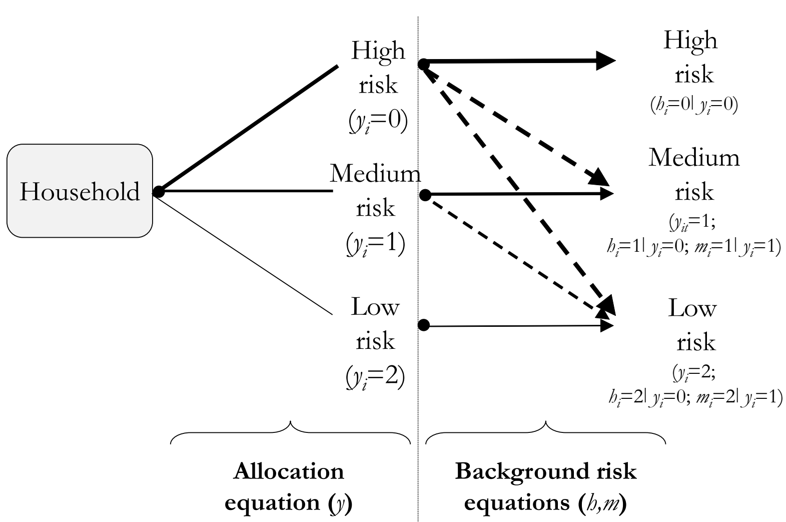

Figure 1: Branch diagram for the $DFOP$ model (with dotted lines depicting 'flights from risk' from riskier to less risky asset classes)

To shape intuition, Figure 1 depicts our 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 (7) and (8), the effects of which are also depicted; the dotted lines represent 'flights from risk', from riskier to less risky assets.[3]

For h_i^*, under the usual assumption of normality of ε, and defining $\boldsymbol{\mu}^h$ as the boundary parameters appertaining to the background risk equation (7), the expected value of the high-risk asset share, s_{i0}, will be

$$E\left(s_{i,j=0}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right) = \underbrace{\Phi\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}\right)}_{\substack{\text{allocation}\\ \text{equation}}} \times \underbrace{\Phi\left(\mu_0^h - \mathbf{w}_i'\boldsymbol{\delta}\right)}_{\substack{\text{background risk}\\ \text{equation (high-risk assets)}}} \tag{10}$$

where the allocation from the high-risk class, $\Phi\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}\right)$ - in expression (6) - 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, $\Phi\left(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}\right) - \Phi\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}\right)$, 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

[3] 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 estimate a version of the model, which also allows 'flights to risk', *i.e.*, reallocation from low risk holding to medium and high risk and from medium risk allocations to high risk. For the PSID, the findings indicate that there is no reallocation from medium to high risk asset allocation. For safe assets, we find a similar lack of empirical support for a flight to risk. Such findings accord with the existing literature and our *a priori* expectations and therefore reinforce our modelling approach.

the medium- and low-risk asset bundles (with that for high-risk asset bundles having been defined above) are given by

$$E\left(s_{i,j=1}|\mathbf{x}_i,\mathbf{w}_i\right) = \left(\begin{array}{c} \left[\Phi\left(\mu_1-\mathbf{x}_i'\boldsymbol{\beta}\right)-\Phi\left(\mu_0-\mathbf{x}_i'\boldsymbol{\beta}\right)\right]\times\Phi\left(\mathbf{w}_i'\boldsymbol{\lambda}\right) \\ +\left\{\begin{array}{c} \Phi\left(\mu_0-\mathbf{x}_i'\boldsymbol{\beta}\right)\times \\ \left[\Phi\left(\mu_1^h-\mathbf{w}_i'\boldsymbol{\delta}\right)-\Phi\left(\mu_0^h-\mathbf{w}_i'\boldsymbol{\delta}\right)\right] \end{array}\right\} \end{array}\right) \tag{11}$$

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

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^* will provide direct estimates of the extent of this. In essence, this model allows deflation of the respective high-risk and medium-risk asset share categories, and reallocation of these assets to the remaining less-risky categories. Following similar discrete choice literature, we term this a deflated fractional ordered probit ($DFOP$) model. In doing so, we emphasise that *ceteris paribus,* as $\Phi\left(\mu_1^h-\mathbf{w}_i'\boldsymbol{\delta}\right)\rightarrow\Phi\left(\mu_0^h-\mathbf{w}_i'\boldsymbol{\delta}\right)\rightarrow 1$ and $\Phi\left(\mathbf{w}_i'\boldsymbol{\lambda}\right)\rightarrow 1$, 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 not supported by the data.

With these modifications in place, the log-likelihood for a household now becomes

$$\begin{aligned} \ell_i &= \prod_j E\left(s_{i,j=0}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)^{s_{i,j=0}} E\left(s_{i,j=2}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)^{s_{i,j=1}} E\left(s_{i,j=2}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)^{s_{i,j=2}} \\ &= E_i \end{aligned} \tag{13}$$

where $E\left(s_{i,j}\left|\mathbf{x}_i,\mathbf{w}_i\right.\right)$ are given by equations (10) to (12); note that we will use the shorthand RHS of equation (13), E_i, later on. The parameters of the model are uniquely identified by the inherent nonlinearities in equation (13); however, as discussed below, the choice of variables to enter $(\mathbf{x}_i, \mathbf{w}_i)$ will be important for identification. This is discussed in detail below.

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.[4] Generically, expressions for the expected values will now be functions of the bivariate normal cumulative distribution (*cdf*'s) with integration limits a and b, and correlation coefficient ρ of the form $\Phi_2(a, b; \rho)$, where Φ_2 denotes the bivariate *cdf*. Equations (10) to (12) now become

$$E\left(s_{i,j=0}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right) = \Phi_2\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}, \mu_0^h - \mathbf{w}_i'\boldsymbol{\delta}; \rho\right) \tag{14}$$

$$E\left(s_{i,j=1}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right) = \begin{cases} \Phi_2\left(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}, \mathbf{w}_i'\boldsymbol{\lambda}; -\rho\right) \\ -\Phi_2\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}, \mathbf{w}_i'\boldsymbol{\lambda}; -\rho\right) \\ +\Phi_2\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}, \mu_1^h - \mathbf{w}_i'\boldsymbol{\delta}; \rho\right) \\ -\Phi_2\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}, \mu_0^h - \mathbf{w}_i'\boldsymbol{\delta}; \rho\right) \end{cases} \tag{15}$$

$$E\left(s_{i,j=2}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right) = \begin{cases} \left[1 - \Phi\left(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}\right)\right] \\ +\Phi_2\left(\mu_0 - \mathbf{x}_i'\boldsymbol{\beta}, \mathbf{w}_i'\boldsymbol{\delta} - \mu_1^h; \rho\right) \\ +\Phi_2\left(\mathbf{x}_i'\boldsymbol{\beta} - \mu_1, -\mathbf{w}_i'\boldsymbol{\lambda}; -\rho\right) \end{cases} . \tag{16}$$

We label the correlated version of the $DFOP$ model, $DFOPC$. Standard model inference is straightforward as $DFOPC$ estimation is a routine application of maximum likelihood (ML) estimation (Wooldridge 2010), full derivations of which are provided in Appendix A.

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 $\frac{\partial E\left(s_{i,j=2}\left|\mathbf{x}_i, \mathbf{w}_i\right.\right)}{\partial \mathbf{x}^*}$, it is

[4] 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) yielded consistent results.

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:

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

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

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

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

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

The nature of this decomposition corresponds precisely to the structure of the $DFOP$ 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 B.

2.3 Panel $DFOP$ model

Finally, to better exploit the information contained in the PSID, the $DFOPC$ model can be extended by allowing for unobserved household heterogeneity - or unobserved effects - in all underlying equations, $\boldsymbol{\alpha}$.[5] As is standard in the literature, it is assumed that $\boldsymbol{\alpha} \sim N(0, \Sigma)$; 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 $\boldsymbol{\Gamma}\mathbf{v}_i$, such that for a single draw of $\mathbf{v}_i$, $\boldsymbol{\Gamma}\mathbf{v}_i = (\alpha_{i,y^*}, \alpha_{i,h^*}, \alpha_{i,m^*})$. $\boldsymbol{\Gamma}$ is the $chol(\Sigma)$ such that $\Sigma = \boldsymbol{\Gamma}\boldsymbol{\Gamma}'$. Conditioned on $\mathbf{v}_i$, the

[5] In the context of household financial decision making, there exist potentially substantial amounts of (unobserved) heterogeneity. For example, Fan and Zhao (2009) find that individual heterogeneity significantly influences the estimated relationship between health status and risky asset holding.

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 E_{it} - see equation (13) - which we denote e_i, corresponding to the observed outcome of shares, $e_i \mid \mathbf{v}_i$,

$$e_i \mid \mathbf{v}_i = \prod_{t=1}^{T_i} \left(E_{it} \mid \mathbf{v}_i\right). \tag{17}$$

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

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \int_{v_i} \prod_{t=1}^{T_i} \left(E_{it} \mid \boldsymbol{\Gamma}\mathbf{v}_i\right) f(\mathbf{v}_i) d\mathbf{v}_i, \tag{18}$$

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

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \int_{v_i} \prod_{t=1}^{T_i} \left(E_{it} \mid \boldsymbol{\Gamma}\mathbf{v}_i\right) \prod_{k=1}^{K} \phi(\mathbf{v}_{ik}) d\mathbf{v}_{ik}. \tag{19}$$

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

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \left(E_{it} \mid \boldsymbol{\Gamma}\mathbf{v}_i\right). \tag{20}$$

Halton sequences of length $R = 100$ were used (Train 2009), and this now feasible function is maximized with respect to $\boldsymbol{\theta}$.

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. Consequently we include averages of the continuous covariates of household i as a set of explanatory variables, $\overline{x_i} = \frac{1}{T} \sum_{t=1}^{T} x_{it}$.[6]

[6] We include the mean of the following time varying continuous variables: age; age-squared;

3 Data

The PSID has been used extensively in the existing literature on household finances (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 the household wealth allocations.[7] This paper uses data from the 1999-2013 waves of the survey, resulting in information relating to $4,257$ households, and which corresponds to $22,854$ household/year observations.[8]

The 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: here, asset categories are based on a range of questions where asset classes are grouped together. The taxonomy adopted in the PSID questionnaire also corresponds closely to those used in the contributions of 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*

income; and net wealth.

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

[8] The panel structure of the PSID makes it ideally suited for our purposes as compared to alternative surveys such as the SCF. Although the SCF is regularly used in the existing household portfolio allocation literature, its cross-section nature means that only relatively crude proxies of income uncertainty are available in the SCF. However, we have also applied our modelling approach to the SCF, 1998 to 2013, and we find evidence in accordance with that from the PSID, supporting flight from risk. These results are available on request.

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 to be 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 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 to be medium-risk assets.[9]

Our estimation strategy controls for a wide range of demographic and socioeconomic characteristics which are common in the existing literature and 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, as well as household composition controls such as whether there is a child present in the household. In addition, the allocation equation also controls for measures capturing risk attitudes and 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 C, Table C.1. The background-risk equations contain, in conjunction with measures of household income uncertainty which are discussed in detail below, a set of state-level variables which aim to capture exogenous exposure to potential sources of background risks. These are namely: state-level changes in unemployment; changes in state-level GDP; a state-level house price index;

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

and changes in state-level consumption expenditure. A complete description of these variables is provided in Appendix C, Table C.2, and summary statistics for all of the explanatory variables used in our analysis are presented in Table 1.

3.1 Measuring income uncertainty using PSID data

A notable feature of the PSID data is that it allows us to construct a range of income uncertainty measures based on multiple observations of households over time. As households are observed over an extended period, we can calculate measures of variability in household income to include in the background risk equations. In the existing literature, a variety of measures that capture 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) – measure income uncertainty as the standard deviation of income growth across the time periods considered. In order to evaluate the robustness of our findings, we explore four measures of income uncertainty and estimate four different models, each including a different measure of income uncertainty. Our first measure of income uncertainty is the coefficient of variation of the household's income, that is the standard deviation over time divided by the average income over the time period (referred to as CV Income).

The three remaining measures of the household's level of income uncertainty, in line with the existing literature, see for example, Gorbachev (2011), Blundell, Pistaferri, and Preston (2008) and Blundell, Low, and Preston (2013), are based on the assumption of the income process for household i being given by

$$Ln(Y_{it}) = \mathbf{X}_{it}'\boldsymbol{\beta} + P_{it} + \partial_{it} \tag{21}$$

where Y_{it} is household income at time t, while X_{it} is a set of observable income characteristics which are anticipated by the household and are allowed to change over time. In the existing literature, many studies focus on labour income uncertainty, see for example, Robst, Deitz, and McGoldrick (1999), where typical income characteristics include education, experience, occupation, tenure, gender and hours worked. Given that we are analysing household portfolio allocation, we focus on household characteristics which may influence the household income process. Specifically, we use the following household characteristics: head of household's education, employment status, gender, ethnicity and birth cohort; the spouse's level of education and employment status; and the number of children and the number of adults in the household, whether there are additional income earners in the household, and, finally, year and state controls.[10] The income process decomposes the remaining income into a permanent component, P_{it}, and a transitory, mean reverting, component, ∂_{it}. It is assumed that permanent income evolves following

$$P_{it} = P_{it-1} + \theta_{it} \tag{22}$$

where θ_{it} is assumed to be serially uncorrelated.

Measures of income uncertainty used in the existing literature are often based on the residuals of the above income process equation. Our second measure of income uncertainty, similar to Robst, Deitz, and McGoldrick (1999), uses the standard deviation of the residuals of the above equation estimated by linear regression, that is $Ln(Y_{it}) = \mathbf{X}_{it}'\boldsymbol{\beta} + \epsilon_{it}$, where the measure of income uncertainty is captured by $Std.Dev(\epsilon_{it})$, referred to as SDHHRES.

[10] We find that the explanatory variables have the expected impacts on household income. Specifically, gender, ethnicity, education level, maritial status, additional income earners, in additon to partner's employment status and education level are all found to be significant determinants of household income.

We also estimate the above using a random effects regression model of household income, in order to account for the panel nature of the data, and subsequently construct proxies for permanent and transitory income using the income process $Ln(Y_{it}) = \mathbf{X}'_{it}\boldsymbol{\beta} + u_i + \epsilon_{it}$: here, the individual systematic component u_i can be removed from the residual, ϵ_{it}, and added to the estimated household income, in order to proxy permanent income. This method is similar to that used by Diaz-Serrano (2005). We assume, as above, that permanent income follows an auto-regressive process with a one period lag, so permanent income uncertainty is measured by the standard deviation of the residual of the following process, $P_{it} = P_{it-1} + \theta_{it}$. We initially include only the standard deviations of transitory income, that is $Std.Dev(\epsilon_{it})$, referred to as SDTRANS. Our final specification includes uncertainty relating to permanent income (referred to as SDPERM) and uncertainty relating to transitory income, $\sigma_i^{Perm} = Std.Dev(\theta_{it})$ and $\sigma_i^{Trans} = Std.Dev(\epsilon_{it})$, respectively. As mentioned above, full details of the variables corresponding to these different measures are found in Appendix C, Table C.2. All income uncertainty measures are estimated using panel data from the 1999-2013 waves of the PSID and, once calculated, missing values are omitted leaving the final sample of $22,854$ observations.[11]

3.2 Asset share distributions

Figure 2 presents the distributions of the dependent variables corresponding to our sample. The distributions are clearly non-normal suggesting that linear regression and Tobit specifications are not appropriate modeling approaches. It is also apparent that there are spikes at various parts of the distributions, particularly at 0 and 1. For example, it is clear that a large proportion of households do not hold risky assets in their financial portfolio. On average, households hold 21% of financial wealth in high

[11] The pairwise correlations between the measures of income uncertainty indicate a high degree of correlation between the measures except for the measure of permanent income uncertainty. Specifically, CV Income displays pairwise correlations between SDHHRES and SDTRANS of 0.894 and 0.917, respectively, whilst the correlation between SDHHRES and SDTRANS is 0.993. The correlations between SDPERM and CV Income, SDHHRES and SDTRANS are significantly lower; specifically, 0.204, 0.178 and 0.157, respectively.

risk assets, whilst those households that hold risky assets allocate 54% of financial wealth to risky assets. Furthermore, the majority of households hold some form of safe asset - which accords with expectations as this asset category includes checking and current accounts - with only 2.6% of households not holding any safe assets. In addition, 48% of households only hold low risk assets in their financial portfolio.

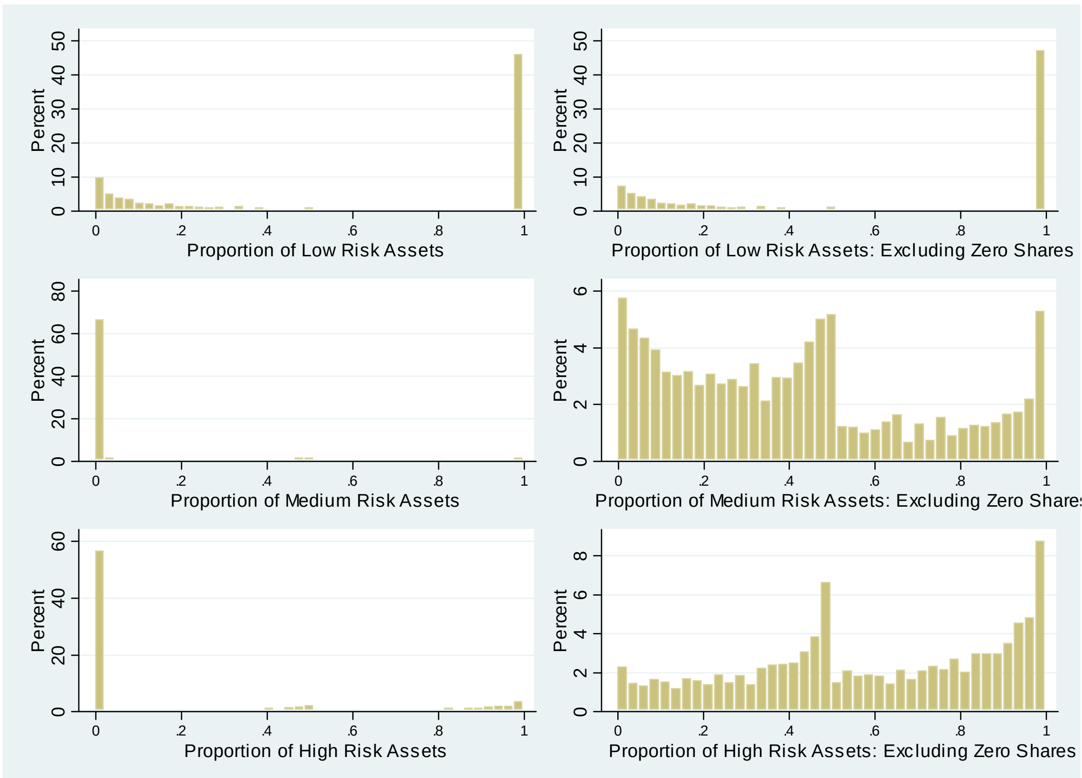

Figure 2: Proportions of PSID households holding low-risk, medium-risk and high-risk assets, with and without zero shares, 1999-2013

4 Results

Our estimation results are presented in Tables 3, 4 and 5 relating to the $DFOPC$ model extended to account for the panel structure of our data (*i.e.*, the $DFOPC$ with correlated random effects across the asset allocation equation and the background risk equations).[12] The estimated coefficients and corresponding partial effects

[12]For brevity, we only present results relating to the panel variant of the $DFOPC$ model. We have estimated versions of the model for pooled data as well as for uncorrelated errors. Comparing

evaluated at sample means relating to the panel $DFOPC$ model are presented in Tables 3 and 4, respectively. In Tables 3 and 4, Panel A presents the results relating to the specification which includes proxies for permanent and transitory income. This is our preferred specification as it aligns with the large theoretical and empirical literatures relating to household income processes and income uncertainty (see for instance: Blundell and Preston 1998; Arellano 2014; Diaz-Serrano 2005), in which income shocks are decomposed into their permanent and transitory components. Panel B of Tables 3 and 4 summarises the results relating to the other measures of income uncertainty, which are included independently of each other, and presents the coefficients and marginal effects relating to the alternative income uncertainty measures, respectively. Additionally, in Table 3, we present results relating to the standard FOP model for comparison purposes. Finally, central to our contribution is the analysis of the overall predicted impact of background risk exposure on household portfolio reallocation in the US, the estimates of which are presented in Table 5. Initially, we will discuss the effects of individual variables on the overall allocation (i.e. Tables 3 and 4) before focusing on the reallocation effects arising due to background risk exposure (Table 5).

Turning firstly to the ancillary parameters in Table 3, it is apparent that ρ is statistically significant, advocating the use of the $DFOPC$ over the $DFOP$ one. The parameters relating to the variances and covariances of the household random effects are also presented in Table 3. The results indicate that the household random effects relating to the allocation equation, $\sigma^2_{y^*}$, and the correlations between the allocation equation and the background risk equations, σ_{y^*,h^*} and σ_{y^*,m^*}, are statistically significant. Specifically, there exist unobserved characteristics which influence the asset allocation equation and there is a positive correlation between the unobserved characteristics in the allocation equation and the background risk equations. The results suggest that there are household unobserved characteristics which move households

various information criteria across a range of model specifications reveals that the panel $DFOPC$ is the preferred specification.

towards safer asset allocations in the asset allocation equation. Furthermore, these unobserved characteristics are associated with households having a higher propensity to move away from high risk and medium risk asset holdings. Conversely, the results suggest that household random effects have an insignificant impact on the background risk equations, $\sigma^2_{h^*}$ and $\sigma^2_{m^*}$, or the correlation between them, σ_{h^*,m^*}. Finally, upon comparing the various information criterion, the $DFOPC$ model consistently outperforms the FOP model; advocating the use of the $DFOPC$ approach.

Turning our attention to the estimated coefficients of the allocation model presented in Table 3 reveals that, recalling that negative (positive) coefficients are associated with riskier (safer) asset holding, the FOP and $DFOPC$ results generally accord with the existing literature. For example, age, ethnicity, education, net wealth, health and risk attitudes are all statistically significant determinants of household portfolio decisions. Given that the marginal effects have a more straightforward interpretation, we focus our discussion on Table 4 which presents the marginal effects associated with the $DFOPC$ model.

The allocation equation reveals that the ethnicity and marital status of the head of household are significant determinants of the household's asset allocation. For example, households with a white head hold 8.9% more high risk assets compared to those with non-white household heads, whilst having a divorced head of household is associated with holding 5.2% less high-risk assets and 8.9% more safe assets. Age and age-squared of the head of household are negatively and positively related to low-risk asset holding, respectively. In line with prior expectations, having children present in the household is inversely related to risky asset holding, whilst higher levels of education of the head of household are positively associated with risky asset holding. For example, compared to having a head of household with below high school level education, a head of household possessing a college degree is associated with holding 6.2% and 3.5% more high- and medium-risk assets respectively, whilst a head of household with a college degree reduces the proportion of financial wealth allocated to safe assets by 9.7%. In addition, better health of the head of household is positively associated with risky asset holding. Increasing the self-assessed health of the head of household (measured on a 4-point scale) by one unit, increases high risk asset holding by 1.1%. In line with prior expectations, attitudes towards risk play an important role in portfolio allocation; having a more risk tolerant household head is positively associated with risky asset holding. Specifically, a unit increase in the risk attitudes measure - which is increasing in risk tolerance - increases high-risk and medium-risk asset holding by 0.7% and 0.4%, respectively, and reduces low-risk assets by 1.1%.

Considering the effects of the variables in the background risk equations in Table 4 reveals some interesting results. For example, the results indicate that relative to 1999, there was a shift away from risky asset holding in 2007, as demonstrated by the positive and statistically significant coefficient on this year control. Specifically, the estimated effect of the 2007 control is associated with households reducing high risk asset holding by 7.3% and increasing safe asset holding by 9.0%, which coincides with the start of the financial crisis. This result highlights the importance of the prevailing macroeconomic climate for household financial portfolio allocation. The measures of income uncertainty have statistically significant impacts on the household's portfolio allocation (see Table 4 Panels A and B). Specifically, uncertainty with respect to the household's income stream is positively associated with holding riskier asset categories. One potential explanation for this finding, which has been discussed in the existing literature, relates to the possibility that if the income and asset return correlation is low, then high-risk assets can act as a means to hedge against income risk (Davis and Willen 2000).

Having estimated the parameters of the $DFOPC$ model, we now turn to the issue of asset share reallocation. In what follows, we calculate the household portfolio shares that for any given risky asset class, are either retained or reassigned to a comparatively safer asset.

5 Asset share (re)allocations

A salient feature of our new model is its ability to quantify the deflating effects of a household's exposure to a variety of sources of background risk on its observed asset allocation. Accordingly, we estimate overall expected values, expected values purged of reallocation effects and reallocation effects, by evaluating the relevant equations (14) to (16) and their appropriate subcomponents. These are evaluated at an individual household level and then averaged over households. Table 5 presents the overall reallocation percentages for the PSID for the panel variant of the $DFOPC$ model. The results relating to the panel $DFOPC$ with both permanent and transitory income risk included, indicate that the introduction of the background risk equation causes households to move away from high risk asset categories. In the presence of background risk, the predicted proportions of high-, medium- and low-risk assets are 20.3%, 16.5% and 63.2%, respectively. In contrast, the household's predicted allocations in the absence of background risk to high-, medium- and low- risk assets are given by 38.7%, 13.4% and 47.9%, respectively. This indicates a clear movement away from high-risk asset holding towards safer asset classes, once we allow background risk to influence the household's asset allocation. Allowing the deflation of high- and medium-risk asset classes reveals that approximately 29.5% of high-risk assets are reallocated, with 17.3% being reallocated to medium-risk assets and 12.2% being moved to low-risk assets. Furthermore, we find that 46.5% of medium-risk assets are reallocated to low-risk asset categories in the presence of background risk. The relatively small standard errors associated with these reallocation percentages lead us to be confident that these parameters are precisely estimated.

The reallocation results relating to the other income uncertainty measures suggest that the results are robust across a variety of specifications of income uncertainty. Our results indicate that, across the four specifications, between 70.5% and 74.7% of high risk assets are retained in the high risk category, with between 11% and 12% of the reallocated risky assets moved to low-risk assets. Moreover, the results show similar reallocations away from medium-risk assets towards safer assets, and that the estimated allocation shares - both with and without the presence of background risks - are similar in magnitude across the models considered. Overall, our empirical findings highlight the significant role that background risk plays in shaping household portfolio allocation.

6 Conclusion

This paper contributes to the growing literature on household financial portfolio allocation. Exploiting data from the Panel Study of Income Dynamics, we develop a new empirical method to investigate the extent to which US households facing background risk reduce their financial risk exposure. The $DFOP$ 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 indicating that when confronted with background risk, households respond by attempting to reduce the overall risk that they face by reducing risky asset holding. Significantly, we show that it is not only high-risk asset holdings that are significantly 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. Such a finding provides further support for the premise that the majority of households are risk averse, and aligns with studies whose conclusions are that portfolio diversification is negatively related to the degree of household risk aversion (see for instance 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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7 Tables

Table 1: PSID Summary statistics[a]

Allocation equation	Mean	Std. Dev	$[Min, Max]$
Age	44.951	13.405	$[17, 97]$
Age Squared	2200.35	1277.99	$[289, 9409]$
Male	0.794	0.404	$[0, 1]$
Employed	0.740	0.438	$[0, 1]$
Retired	0.074	0.261	$[0, 1]$
White	0.779	0.415	$[0, 1]$
Married	0.628	0.483	$[0, 1]$
Widowed	0.025	0.158	$[0, 1]$
Divorced	0.171	0.377	$[0, 1]$
Child	0.417	0.493	$[0, 1]$
Own	0.720	0.449	$[0, 1]$
College Degree	0.627	0.484	$[0, 1]$
High School	0.299	0.458	$[0, 1]$
Net Wealth	0.942	0.757	$[-1.512, 1.920]$
Household Income	1.121	0.078	$[0.169, 1.569]$
Subjective Health	2.763	0.949	$[0, 4]$
Risk Attitudes	1.890	1.605	$[0, 5]$
Background risk equations			
SDPERM	0.193	0.127	$[0.001, 1.366]$
SDTRANS	0.339	0.261	$[0.004, 4.204]$
SDHHRES	0.351	0.260	$[0.008, 4.202]$
CV Income	0.033	0.027	$[0.0005, 0.413]$

[a]Number of observations = 22,854; Number of households = 4,257; Median PSID participation per household = 5 years (max. 8).

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: *FOP* and *DFOPC* estimates, PSID, 1999-2013[a,b]

					DFOPC			
					Background risk equations			
Panel A	*FOP*		*Allocation equation*		*OP-BR*		*P-BR*	
	Coef.	**SE**	**Coef.**	**SE**	**Coef.**	**SE**	**Coef.**	**SE**
Age	-0.456***	(0.084)	-0.571***	(0.149)	–		–	
Age Squared	0.467***	(0.073)	0.587***	(0.140)	–		–	
Male	0.090***	(0.026)	0.140***	(0.044)	–		–	
Employed	0.019	(0.033)	0.031	(0.058)	–		–	
Retired	-0.120***	(0.041)	-0.133**	(0.079)	–		–	
White	-0.320 ***	(0.019)	-0.356***	(0.044)	–		–	
Married	0.096***	(0.028)	0.103**	(0.049)	–		–	
Widowed	0.065	(0.049)	0.093	(0.093)	–		–	
Divorced	0.154***	(0.028)	0.209***	(0.051)	–		–	
Child	0.108***	(0.017)	0.097***	(0.031)	–		–	
Homeowner	-0.033*	(0.021)	-0.020	(0.035)	–		–	
College Degree	-0.219***	(0.030)	-0.248***	(0.056)	–		–	
High School	0.021	(0.031)	0.030	(0.053)	–		–	
Net Wealth	-0.266***	(0.018)	-0.289***	(0.032)	–		–	
Household Income	-0.309*	(0.191)	-0.498	(0.308)	–		–	
Subjective Health	-0.045***	(0.008)	-0.045***	(0.015)	–		–	
Risk Attitudes	-0.023***	(0.004)	-0.027***	(0.009)	–		–	
2001	0.026	(0.038)	-0.002	(0.249)	0.041	(0.354)	0.281	(0.979)
2003	0.015	(0.037)	0.032	(0.237)	0.042	(0.338)	-0.200	(0.915)
2005	-0.005	(0.041)	0.017	(0.254)	0.018	(0.356)	0.049	(0.963)
2007	0.266***	(0.052)	-0.167	(0.265)	0.686**	(0.316)	0.854	(1.061)
2009	0.178**	(0.100)	0.115	(0.259)	0.131	(0.456)	0.619	(1.370)
2011	0.049	(0.060)	0.118	(0.257)	-0.020	(0.375)	-0.139	(0.997)
2013	0.073	(0.073)	0.258	(0.252)	-0.190	(0.410)	-0.700	(1.111)
Constant							0.256	(1.024)
Boundary parameters								
μ_0	-6.719***	(0.181)	-7.524***	(0.699)	0.430	(0.282)	–	
μ_1	-6.195***	(0.181)	-7.118 ***	(0.736)	1.054***	(0.284)	–	
Background risk variables								
SDPERM	0.084	(0.059)	–		0.112	(0.167)	0.404	(0.654)
SDTRANS	-0.216***	(0.030)	–		-0.402***	(0.108)	-0.617	(0.501)
ρ	–				-0.588***		(0.139)	
Ancillary statistics								
AIC	37821.528		$\sigma^2_{y^*}$	0.148***	(0.055)	*AIC*	36985.266	
BIC	38110.856		σ_{y^*,h^*}	0.071***	(0.023)	*BIC*	37515.701	
CAIC	38146.856		σ_{y^*,m^*}	0.374*	(0.238)	*CAIC*	37581.701	
HQIC	37915.580		$\sigma^2_{h^*}$	0.034	(0.030)	*HQIC*	37157.694	
Log L	-18874.764		$\sigma^2_{m^*}$	0.178	(0.157)	*Log L*	-18426.633	
			σ_{h^*,m^*}	0.949	(1.224)			
Panel B								
CV Income	-0.218***	(0.030)			-0.727	(0.898)	-0.451	(2.227)
SDHHRES	-0.203***	(0.029)			-0.378***	(0.118)	-0.329	(0.288)
SDTRANS	-0.210***	(0.029)			-0.385***	(0.130)	-0.273	(0.227)

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

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

Number of observations$= 22,854$; number of households$= 4,257$.

All regressions control for state level GDP growth, consumption expenditure growth, the house price index and unemployment growth.

Table 4: Marginal Effects for PSID data in the *DFOPC* model[a,b]

	Asset class					
Panel A	High-risk		Medium-risk		Safe	
Age	0.143***	(0.035)	0.081***	(0.020)	-0.224***	(0.054)
Age Squared	-0.147***	(0.032)	-0.083***	(0.018)	0.230***	(0.050)
Male	-0.035***	(0.011)	-0.020***	(0.006)	0.055***	(0.017)
Employed	-0.008	(0.015)	-0.004	(0.008)	0.012	(0.023)
Retired	0.033*	(0.020)	0.019*	(0.011)	-0.052*	(0.031)
White	0.089***	(0.009)	0.050***	(0.005)	-0.140***	(0.014)
Married	-0.026**	(0.012)	-0.015**	(0.007)	0.040**	(0.019)
Widowed	-0.023	(0.027)	-0.013	(0.017)	0.037	(0.037)
Divorced	-0.052***	(0.012)	-0.030***	(0.007)	0.082 ***	(0.019)
Child	-0.024***	(0.007)	-0.014***	(0.004)	0.038***	(0.012)
Homeowner	0.005	(0.009)	0.003	(0.005)	-0.008	(0.014)
College Degree	0.062***	(0.013)	0.035***	(0.007)	-0.097***	(0.021)
High School	-0.007	(0.013)	-0.004	(0.008)	0.012	(0.021)
Net Wealth	0.072***	(0.006)	0.041***	(0.003)	-0.113***	(0.009)
Household Income	0.124	(0.077)	0.070	(0.043)	-0.195	(0.120)
Subjective Health	0.011***	(0.004)	0.006***	(0.002)	-0.018***	(0.006)
Risk Attitudes	0.007***	(0.002)	0.004***	(0.001)	-0.011***	(0.003)
2001	-0.006	(0.023)	-0.020	(0.040)	0.027	(0.041)
2003	-0.015	(0.021)	0.013	(0.038)	0.003	(0.037)
2005	-0.007	(0.022)	-0.006	(0.038)	0.013	(0.039)
2007	-0.073**	(0.031)	-0.018	(0.048)	0.090**	(0.052)
2009	-0.051	(0.053)	-0.060	(0.085)	0.110	(0.094)
2011	-0.026	(0.028)	-0.007	(0.043)	0.033	(0.053)
2013	-0.033	(0.037)	0.011	(0.055)	0.021	(0.068)
Background risk variables						
SDTRANS	0.067***	(0.016)	0.033	(0.030)	-0.100***	(0.035)
SDPERM	-0.019	(0.028)	-0.027	(0.048)	0.046	(0.057)
Panel B						
CV Income	0.097	(0.117)	0.171	(0.081)	-0.113	(0.217)
SDHHRES	0.061***	(0.016)	0.016	(0.021)	-0.077***	(0.027)
SDTRANS	0.060***	(0.016)	0.014	(0.018)	-0.074***	(0.025)

[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.
All regressions control for state level GDP growth, consumption expenditure growth, the house price index and unemployment growth.

Table 5: Asset share reallocations

	Asset type	Estimated shares without background risk	Reallocation decomposition High-risk	Reallocation decomposition Medium-risk	Reallocation decomposition Safe	Estimated shares with background risk	Observed sample shares
Panel B - PSID Panel DFOPC							
Coefficient of Variation	High-risk	0.342*** (0.038)	0.747*** (0.068)	0.145*** (0.045)	0.108*** (0.032)	0.202*** (0.004)	0.219
	Medium-risk	0.177*** (0.039)	–	0.546	0.454*** (0.154)	0.164*** (0.004)	0.156
	Low-risk	0.481*** (0.043)	–	–	1	0.634*** (0.005)	0.625
SDHHRES	High-risk	0.375*** (0.044)	0.730*** (0.063)	0.153*** (0.041)	0.117*** (0.033)	0.202*** (0.004)	0.219
	Medium-risk	0.155*** (0.045)	–	0.5265	0.474*** (0.137)	0.164*** (0.005)	0.156
	Low-risk	0.471*** (0.047)	–	–	1	0.633*** (0.005)	0.625
SDTRANS	High-risk	0.365*** (0.040)	0.740*** (0.065)	0.144*** (0.043)	0.117*** (0.032)	0.203*** (0.004)	0.219
	Medium-risk	0.177*** (0.054)	–	0.502	0.498*** (0.117)	0.163*** (0.004)	0.156
	Low-risk	0.458*** (0.054)	–	–	1	0.635*** (0.005)	0.625
SDTRAN *and* SDTRANS	High-risk	0.387*** (0.037)	0.705*** (0.053)	0.173*** (0.032)	0.122*** (0.032)	0.203*** (0.006)	0.219
	Medium-risk	0.134*** (0.036)	–	0.535	0.465*** (0.139)	0.165*** (0.004)	0.156
	Low-risk	0.479*** (0.038)	–	–	1	0.632*** (0.007)	0.625

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

Appendix

A Inference

If we allow $\boldsymbol{\theta}_0$ to denote the true, unknown, parameters of the model, such that Q defines the total number of model parameters, the $Q \times 1$ score of the log-likelihood for observation i can be expressed as

$$S_i(\boldsymbol{\theta}) = \nabla_\theta \ell_i(\boldsymbol{\theta})' = \left(\frac{\partial \ell_i}{\partial \theta_1}(\boldsymbol{\theta}), \frac{\partial \ell_i}{\partial \theta_2}(\boldsymbol{\theta}), \frac{\partial \ell_i}{\partial \theta_3}(\boldsymbol{\theta}), \ldots, \frac{\partial \ell_i}{\partial \theta_Q}(\boldsymbol{\theta}),\right)'. \tag{A.1}$$

Defining the Hessian $\mathbf{H}_i(\boldsymbol{\theta})$ as the matrix of second partial derivatives of $\ell_i(\boldsymbol{\theta})$ such that

$$\mathbf{H}_i(\boldsymbol{\theta}) = \nabla_\theta S_i(\boldsymbol{\theta}) \tag{A.2}$$

holds the implication that ML estimators will be asymptotically normally distributed as

$$\sqrt{N}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) \overset{a}{\sim} N\left(\mathbf{0}, \mathbf{A}_0^{-1}\mathbf{B}_0\mathbf{A}_0^{-1}\right) \tag{A.3}$$

where

$$\mathbf{A}_0 = -E\left[\mathbf{H}_i(\boldsymbol{\theta}_0)\right] \tag{A.4}$$

$$\mathbf{B}_0 = E\left[S_i(\boldsymbol{\theta}_0) S_i(\boldsymbol{\theta}_0)'\right]. \tag{A.5}$$

It is straightforward to demonstrate (Wooldridge 2010) that under standard regularity conditions: (i) $\mathbf{A}_0 = \mathbf{B}_0$; and (ii) the distribution of the ML estimates $\widehat{\boldsymbol{\theta}}$ converge to

$$\sqrt{N}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0\right) \xrightarrow{d} N\left(\mathbf{0}, \mathbf{A}_0^{-1}\right). \tag{A.6}$$

The asymptotic variance of $\widehat{\boldsymbol{\theta}}$ will therefore be

$$Avar\left(\widehat{\boldsymbol{\theta}}\right) = \mathbf{A}_0^{-1}/N\ . \tag{A.7}$$

All of the matrices

$$N^{-1}\sum_{i=1}^{N}-E\left[\mathbf{H}_i\left(\widehat{\boldsymbol{\theta}}\right)\right];\; N^{-1}\sum_{i=1}^{N}S_i\left(\widehat{\boldsymbol{\theta}}\right)S_i\left(\widehat{\boldsymbol{\theta}}\right)';\; \text{and } N^{-1}\sum_{i=1}^{N}\mathbf{A}\left(\mathbf{x}_i,\widehat{\boldsymbol{\theta}}\right) \tag{A.8}$$

converge to $\mathbf{A}_0$ - where $\mathbf{A}\left(\mathbf{x}_i,\widehat{\boldsymbol{\theta}}\right) = -E\left[\mathbf{H}\left(y_i,\mathbf{x}_i,\boldsymbol{\theta}_0|\mathbf{x}_i\right)\right]$). It follows from this that the asymptotic variance of $\left(\widehat{\boldsymbol{\theta}}\right)$ can be estimated using any of the following three quantities:

$$\left[N^{-1}\sum_{i=1}^{N}-E\left[\mathbf{H}_i\left(\widehat{\boldsymbol{\theta}}\right)\right]\right]^{-1};\; \left[N^{-1}\sum_{i=1}^{N}S_i\left(\widehat{\boldsymbol{\theta}}\right)S_i\left(\widehat{\boldsymbol{\theta}}\right)'\right]^{-1};\; \text{and } \left[N^{-1}\sum_{i=1}^{N}\mathbf{A}\left(\mathbf{x}_i,\widehat{\boldsymbol{\theta}}\right)\right]^{-1}. \tag{A.9}$$

Finally, the Delta method can be exploited to estimate the standard errors of partial effects, summary probabilities, and any other quantities of interest derived from $\widehat{\boldsymbol{\theta}}$.

B 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 $DFOPC$ model; those for the uncorrelated $DFOP$ would simply be achieved by setting $\rho = 0$. The required derivatives for the partial effects for the bivariate normal probabilities derived from expressions (14), (15), and (16) can be obtained using the generic result in Greene (2012), *viz.*

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

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

$$\begin{gathered} \mathbf{x} = \begin{pmatrix} \mathbf{z} \\ \widetilde{\mathbf{x}} \end{pmatrix}, \ \boldsymbol{\beta} = \begin{pmatrix} \boldsymbol{\beta}_z \\ \widetilde{\boldsymbol{\beta}} \end{pmatrix}, \ \mathbf{w} = \begin{pmatrix} \mathbf{z} \\ \widetilde{\mathbf{w}} \end{pmatrix}, \\ \boldsymbol{\delta} = \begin{pmatrix} \boldsymbol{\delta}_z \\ \widetilde{\boldsymbol{\delta}} \end{pmatrix}, \ \boldsymbol{\lambda} = \begin{pmatrix} \boldsymbol{\lambda}_z \\ \widetilde{\boldsymbol{\lambda}} \end{pmatrix}, \end{gathered} \tag{B.2}$$

where $\mathbf{z}$ represents the common variables that appear in both $\mathbf{x}$ and $\mathbf{w}$, with the corresponding coefficients $\boldsymbol{\beta}_z$, $\boldsymbol{\delta}_z$ and $\boldsymbol{\lambda}_z$ 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 $\widetilde{\boldsymbol{\beta}}$, 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 $\widetilde{\boldsymbol{\delta}}$ and $\widetilde{\boldsymbol{\lambda}}$. 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

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

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 $\boldsymbol{\beta}^* = (\boldsymbol{\beta}_z', \widetilde{\boldsymbol{\beta}}', \mathbf{0}')'$, $\boldsymbol{\delta}^* = (\boldsymbol{\delta}_z', \mathbf{0}', \widetilde{\boldsymbol{\delta}}')'$ and $\boldsymbol{\lambda}^* = (\boldsymbol{\lambda}_z', \mathbf{0}', \widetilde{\boldsymbol{\lambda}}')$ implies that the partial effects of the explanatory variable vector $\mathbf{x}^*$ on each of the J overall asset shares in expressions (14), (15) and (16) are given by

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

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

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

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

C Variable definitions

Table C.1: PSID 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.
Widowed	= 1 if head of household widowed, 0 otherwise.
Divorced	= 1 if head of household is divorced or separated, 0 otherwise.
Child	= 1 if child present in the household, 0 otherwise.
Own	= 1 if head of household owns own 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 net wealth, that is, total assets minus total debt, divided by 10.
Household Income	Natural Logarithm transformation of total household income, divided by 10.
Health	Index of self-assessed health status measured on a 5 point scale increasing in better health.
Risk Attitudes	From the 1996 wave of the PSID, a 6 point index, increasing in risk tolerance was based on 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?
2001	= 1 if survey year is 2001, 0 otherwise.
2003	= 1 if survey year is 2003, 0 otherwise.
2005	= 1 if survey year is 2005, 0 otherwise.
2007	= 1 if survey year is 2007, 0 otherwise.
2009	= 1 if survey year is 2009, 0 otherwise.
2011	= 1 if survey year is 2011, 0 otherwise.
2013	= 1 if survey year is 2013, 0 otherwise.

Table C.2: PSID Income Uncertainty Descriptions

Variable	Definition
CV Income	Defined to be the standard deviation of household income over time, divided by the average household income over time.
SDHHRES	Based on the standard deviation of the residuals of a linear household income equation estimated by OLS. The dependent variable is the natural logarithm of household income independent variables include: the household head education level, employment status, gender, and ethnicity and cohort; the spouse's education and employment status; general household characteristics including number of children and the number of adults in the household; whether there are additional earners in the household; year and time controls.
SDTRANS	Based on the standard deviation of the time varying residuals of a household income equation as outlined above estimated by a random effects model. Specifically, using a random effects element allows us to separate the individual component of the following equation, $Ln(Y_{ht}) = BX_{ht} + u_i + e_{ht}$. Therefore the transitory income measure is given by the $SD(e_{it})$.
SDPERM	$SDPERM$ (permanent income uncertainty): Permanent income was approximated by adding individual specific effort term to the households predicted household income from the above household income equation estimated by random effects. We then allow permanent income to follow an auto-regressive process with one lag, that is, $P_{ht} = P_{ht-1} + d_{ht}$. The uncertainty regarding permanent income is then $SD(d_{it})$.