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Household Portfolios and Monetary Policy

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ABSTRACT

We show that expansionary monetary policy is positively (negatively) associated with household portfolio allocation to high-risk (low-risk) assets, in line with 'reaching for yield' behaviour. Our main findings are based on an analysis of US household-level data using alternative measures of monetary policy shifts over the period 1999–2007. Using the two-part Fractional Response Model, we show that changes in the Federal Funds Rate (FFR) have a stronger impact on the decision to hold high-risk assets relative to the impact on the decision to hold low-risk assets. In addition, our findings indicate that the impact of FFR changes is stronger for active investors. Finally, our findings are robust over an extended time period (1999–2019) that includes the global financial crisis using a monetary policy measure that accounts for the post-crisis ZLB period.

JEL Classification: D14, G11, E52

1 | Introduction and Background

We find that monetary policy conditions matter for household asset allocation. The recent experience of historically low interest rates in the United States, as well as in other countries, has stimulated a body of research on the effects of monetary policy on financial markets and the real economy. A widely held view is that by reducing interest rates, central banks have increased the appetite of investors for risk-taking, the so-called 'reaching-for-yield', in an effort to improve financial market conditions and support economic activity. Reaching-for-yield is a double-edged sword since it distorts asset allocations in favour of risky assets, which can have adverse consequences for financial stability (Rajan 2006; Borio and Zhu 2012). In the aftermath of the 2007–2008 global financial crisis, policymakers have often called for vigilance regarding emerging risks to the financial system from highly accommodative monetary policy (Yellen 2011). Ultra-low interest rates have depressed returns from savings and fuelled a debate on whether they discourage households from saving.

A body of literature has emerged on the important implications of reaching-for-yield. Previous studies typically focus on the behaviour of financial institutions (e.g., Jiménez et al. 2014; Di Maggio and Kacperczyk 2017; Alzuabi, Caglayan, and Mouratidis 2020) and little is known about how households respond to monetary policy. Specifically, it remains unclear as to whether the composition of household portfolios across high-risk and low-risk assets changes in response to monetary policy shifts. The main contribution of our paper lies in tackling this question by conducting an empirical analysis of the effects of monetary policy actions on the asset allocation of US households.

We analyse household-level data drawn from the biennial US Panel Study of Income Dynamics (PSID). For our main analysis, we utilise five waves of the PSID survey covering the period 1999–2007. We focus on the pre-crisis period since, post-crisis, the level of the Federal Fund Rate (FFR) was zero. For robustness, we also analyse 11 waves of the PSID, covering the period 1999–2019, which includes the global financial crisis. We explore the determinants of the share of low-risk assets and the share of high-risk assets in the household portfolio.

For 1999–2007, changes in monetary policy are measured using two approaches. The first uses changes in the effective FFR prior to each survey and provides an intuitive measure of monetary policy shifts that does not rely upon sophisticated econometric analysis. The second approach uses the methodology of Romer and Romer (2004), as refined by Caglayan, Kandemir Kocaaslan, and Mouratidis (2017), to obtain unexpected FFR changes. Both approaches are based on the idea that the FFR is the key US monetary policy indicator, with unexpected FFR changes providing reliable estimates of policy shocks, over a long period stretching from the mid-1980s to the 2007–2008 financial crisis (Romer and Romer 2004).[1]

Our main modelling approach is a Fractional Response Model (FRM), with portfolio shares regressed on monetary policy shifts and a range of household and macroeconomic controls. The FRM, which is ideally suited to modelling dependent variables that lie on the unit interval, has only recently been used in the household finance literature (see, e.g., Bucciol, Cavasso, and Zarri 2019; Stavrunova and Yerokhin 2012). We find that expansionary monetary policy is positively (negatively) associated with higher (lower) allocation to high-risk (low-risk) assets. Hence, our empirical evidence suggests that 'reaching-for-yield' is not confined to financial institutions, and also characterises the financial behaviour of households.

To further explore the link between household portfolios and monetary policy, we use the two-part FRM estimation method following Schwiebert and Wagner (2015). This is motivated by the fact that zero and non-zero values of the asset shares are included in the sample, since some households do not hold any low-risk and/or high-risk assets. The two-part FRM approach allows us to evaluate the effects of monetary policy on whether high and/or low-risk assets are held and, conditional on holding an asset type, the impact of monetary policy on the portfolio share. Interestingly, while the monetary policy effects on portfolio shares in the fractional part accord with the findings from the standard FRM approach, an important difference arises in the participation equation. Specifically, the findings indicate that the decision to hold high-risk assets and the decision to hold low-risk assets are both related to actual FFR changes, rather than policy shocks. Furthermore, the impact of actual FFR changes on the decision to hold high-risk assets is much stronger than its impact on the decision to hold low-risk assets.

An important caveat underlying our findings is related to the distinction between active portfolio rebalancing versus passive valuation effects (Bucciol and Miniaci 2015), since even the portfolio share of a household with full inertia in its investment behaviour may display variation over time, driven by valuation changes. To explore the implications of this, we separate our sample into households classified as active and inactive investors and we still find that expansionary policy has a positive (negative) effect on high (low) risk asset shares, endorsing the robustness of our findings.

Our study is relevant to several strands of the existing literature. A key related strand is concerned with the risk-taking channel of monetary policy. Previous empirical studies have examined the behaviour of banks (Alzuabi, Caglayan, and Mouratidis 2020), mutual funds (Di Maggio and Kacperczyk 2017), and pension funds (Joyce, Liu, and Tonks 2017). These studies typically provide evidence suggesting a greater propensity for undertaking riskier investments by financial institutions when interest rates are low.

We contribute to the risk-taking channel literature by empirically modelling the link between portfolio allocation and monetary policy using household-level data, where there is a distinct lack of existing research. For example, although Lian, Ma, and Wang (2019) conclude that US household investment decisions are characterised by reaching-for-yield when monetary policy is expansive (low short-term interest rates), their empirical analysis is conducted at the aggregate, rather than the household-level data, using Flow of Funds data on household sector flows into stocks and interest-bearing safe assets. Hence, their econometric analysis does not model actual household behaviour and cannot account for household characteristics. As acknowledged by Lian, Ma, and Wang (2019), their aggregate time series evidence can only be suggestive when revealing the behaviour of households. Hence, our use of household-level data lies at the heart of our contribution. The recent study by Luetticke (2021) is also relevant for our analysis although it focuses on the choice between liquid and illiquid assets and the potential heterogeneity in portfolio responses to policy shocks across households with different levels of wealth.[2]

Finally, our study is informative about the effects of monetary policy on saving behaviour as savings form a significant part of low-risk asset holding for households. Theoretically, the effect of interest rates on savings is ambiguous (Attanasio and Weber 2010).[3] Furthermore, the empirical evidence on the interest rate elasticity of savings is mixed. Some studies support the substitution effect (Horioka and Wan 2007), especially when nominal rates are very low (Aizenman, Cheung, and Ito 2019), while others find little/no effect (Beer et al. 2016), or even a negative relationship consistent with the income effect (Nabar 2011). Importantly, many of these studies use data at the macroeconomic level, and, therefore, cannot shed light on household behaviour.

2 | Data

2.1 | Household-Level Data

Our household-level data are drawn from the US PSID, a longitudinal survey, which began in 1968 and initially included ~5000 families and 18,000 individuals. The PSID has been used extensively in the existing household finance literature (e.g., Carroll and Samwick 1998; Guiso and Sodini 2013).

We focus on the information contained in the supplementary Wealth Modules, which were collected biennially from 1999 onwards. Specifically, our main analysis covers the following 5 waves of the survey: 1999, 2001, 2003, 2005 and 2007 and the sample comprises 15,650 ($N \times T$) observations, where N denotes 5328 households.

The information provided in the Wealth Modules allows us to explore the allocation of financial assets into low-risk and high-risk categories. Low-risk assets are defined from the responses to 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?' On the other hand, high-risk assets are defined from the responses to: ‘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 firstly on the question: ‘Do [you/or your family living there] have any money in private annuities or Individual Retirement Accounts (IRAs)?’ We then use responses to the follow-up question: ‘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 assumption 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; and if the response is ‘split’, 50% are allocated to high-risk.[4] This approach is consistent with Brunnermeier and Nagel (2008).

We explore the impact of monetary policy on the share of assets held in each category, with the numerator of the low-risk (high-risk) asset share being defined as the dollar value of all financial assets held as asset types defined as low-risk (high-risk) and the denominator for both asset shares is the dollar value of all financial assets held at the time of the survey. Non-financial assets (e.g., housing wealth) are not included in the denominator as we control for them in the analysis as detailed below. Therefore, the values for the low-risk and high-risk asset shares are constrained to lie between zero and one. On average and in accordance with expectations, see Table 1, the low-risk asset share is considerably higher (62.7%) than the high-risk asset share (21.3%). Figure 1 presents the distributions of the two dependent variables considered in our analysis, the shares of high and low-risk assets, including and excluding the cases of zero holdings. The distributions are clearly non-normal, and it is also apparent that there are spikes at 0 and 1. Specifically, 3% of households report zero low-risk asset share and 48% report 100% low-risk asset share. Whereas 61% of households report zero high-risk asset share and only 1% report 100% high-risk asset share. Clearly, most households in our sample do not hold any high-risk assets, which, as discussed below, is common in the literature.

The PSID contains an extensive range of household characteristics that are commonly controlled for in the existing household finance literature (see, e.g., Guiso, Jappelli, and Terlizzese 1996; Dohmen et al. 2011). These include: household net worth, defined as an inverse hyperbolic sine transformation of the difference between total assets and total liabilities including the net value of real estate; total family (household) income in the previous year; whether the respondent is a homeowner (i.e., whether they or anyone else in the family living there owns or is buying the home, either fully or jointly); whether the respondent owns a business or has a financial interest in any business; the head of household's gender, age, race, labour market status, education, marital status and self-assessed health.

The PSID includes a measure of the respondent's risk attitudes based on the 1996 PSID Survey, which includes five questions on hypothetical gambles with respect to lifetime income. The series of questions enables us to place respondents into one of six categories of risk attitudes, where, faced with a 50–50 gamble of doubling income or cutting it by some given factor, the

TABLE 1 | Summary statistics: 1999–2007.

	Mean	SD	Min	Max
Dependent variables				
Low-risk asset share	0.627	0.413	0	1
High-risk asset share	0.213	0.325	0	1
Macro variables				
Changes in the Federal Fund Rate (FFR)	0.001	0.117	−0.215	0.128
Romer and Romer's shocks (RR-shock)	−0.001	0.069	−0.091	0.059
Real GDP growth	3.229	1.210	1.125	4.687
Chicago Fed National Activity Index (CFNAI)	0.042	0.373	−0.69	0.4
Independent variables				
Age	43.50	13.26	18	96
Female	0.231			
White	0.764			
Business owner	0.159			
Homeowner	0.705			
Log networth	9.663	6.998	−13.73	19.01
Risk attitudes	1.862	1.612	0	5
Health index	2.792	0.967	0	4
Income quartiles				
First quartile	9.919	0.582	4.925	10.514
Second quartile	10.811	0.162	10.515	11.080
Third quartile	11.355	0.159	11.080	11.643
Fourth quartile (omitted)	12.135	0.445	11.643	15.921
Employment status				
Employed (omitted)	0.867			
Unemployed	0.029			
Not in labour force	0.037			
Retired	0.067			
Marital status				
Single (omitted)	0.186			

(Continues)

TABLE 1 | (Continued)

	Mean	SD	Min	Max
Married	0.598			
Divorced	0.186			
Widowed	0.029			
Education				
High school and below (omitted)	0.686			
College degree	0.314			
Observations	15,650			

individual will accept the risky job if the expected utility from the job change exceeds that of the utility from remaining with the current job where income is certain (for full details, see, e.g., Kimball, Sahm, and Shapiro 2008). We construct a risk tolerance index, which can take any integer value between 0 and 5, and is increasing in risk tolerance.

As the risk aversion questions were only asked in 1996, in our empirical analysis, there is no variation in risk attitudes within households over time and, hence, this variable should be regarded as other time-invariant variables such as gender. However, although the time invariance of our measure of risk attitudes is data-driven, based on the current literature, while individual risk preferences may exhibit small fluctuations due to external influences, the underlying disposition towards risk generally remains stable. This is supported by the literature advocating the stability of personality traits (Frey et al. 2017) and empirical research. For example, Dohmen et al. (2011) concluded that individual risk attitudes tend to remain consistent even across different domains of life and across different time periods. Schildberg-Hörisch (2018, 148) argues that 'individual risk preferences appear to be persistent and moderately stable over time'. There is some evidence of risk aversion increasing slightly with age (see, e.g., Sahm 2012; Schurer 2015; and Dohmen et al. 2017), particularly around retirement. However, the changes are typically gradual and predictable rather than erratic. For example, Dohmen et al. (2017) find that willingness to take risks decreases linearly with age until approximately the age of 65 after which the slope becomes flatter. However, Schildberg-Hörisch (2018) argues that the correlation over time of risk attitudes found in the literature supports the stability of risk attitudes, at least partly, as the strict stability of risk attitudes cannot be empirically supported given that the correlation coefficient is low in many studies.

2.2 | Monetary Policy Measures

To identify monetary policy shifts, we use two approaches. First, we calculate the average change in the monthly value of the effective FFR across the 2 years preceding each survey.[5] This approach has the benefit of simplicity and is consistent with the idea that most households are not sophisticated enough to rely upon advanced econometric models in order to evaluate the stance of monetary policy. Second, to isolate the unexpected component of FFR changes, we use monetary policy shocks that account for the Federal Reserve Board's response to expected economic conditions. Policy shocks are calculated using a well-established methodology proposed by Romer and Romer (2004). The calculation of Romer and Romer's shocks (*RR-shock*) involves two steps. First, intended FFR changes around the Federal Open Market Committee (FOMC) meetings are identified. Second, the intended FFR changes are regressed on the internal FOMC forecasts for inflation and real economic activity, that is, the Greenbook forecasts, around the dates of these forecasts. The residuals from the regression represent the monetary policy shocks. This methodology has been further developed by Caglayan, Kandemir Kocaaslan, and Mouratidis (2017) by introducing time-varying parameters and regime shifts into their model and our measure is based on this extended methodology.[6,7]

Our main analysis of the impact of monetary policy shifts on household portfolios focuses on the period 1999–2007, motivated by the fact that, while there is wide agreement regarding the identification of monetary policy shocks before 2007, there is still no consensus on this issue for the period that includes the 2007–2008 crisis and the ensuing zero lower bound (ZLB). Furthermore, during the period of the ZLB, there is limited variation in the change in the monthly effective FFR.[8] Moreover, the existing literature on the effects of monetary policy on financial markets during the crisis/ZLB period often uses VAR-based (Gertler and Karadi 2015) and/or event study approaches (Gagnon et al. 2011) along with high-frequency data. These methods are not compatible with the lower frequency at which household survey data are generally available. However, as discussed in Section 5.2, in order to examine the robustness of our findings over a longer time period, which includes the global financial crisis, we use a new measure of monetary policy shocks. This measure is based on Hanson and Stein (2015) and uses the change in the two-year nominal Treasury yield around FOMC announcement dates to capture news about the expected medium-term path of interest rates.

3 | Modelling Asset Shares

The asset shares are defined on the closed interval $y_{it} \in [0, 1]$, with a significant portion of observations falling at one of the two extremes. Using linear models, such as OLS, for bounded dependent variables can produce predicted values that lie outside these bounds. Furthermore, linear models will not account for the fact that bounded variables are subject to floor and ceiling effects. Hence, the results will be biased as they will reflect constant partial effects of changes in the explanatory variables even when the dependent variable approaches one of the bounds (Gallani and Krishnan 2017).

Nonlinear models, for example, logit and probit models, can be used to prevent predicted values from falling outside the closed interval of such bounded variables, but these models are appropriate for binary response variables. Nonlinear models that are frequently used to model continuous variables that are bounded in nature, for example, Tobit models, censored regressions and truncated models, also have limitations when a significant portion of observations falls at one of the extremes.[9] While the truncated models suffer from sample selection bias

(Maddala 1991), the Tobit model is sensitive to heteroscedasticity (Arabmazar and Schmidt 1981) and relies on distributional assumptions that are frequently not reflected in survey data (Gallani and Krishnan 2017). The FRM, developed by Papke and Wooldridge (1996, 2008), provides an effective approach to overcome these limitations and it has been only recently employed in the area of household finance (see, e.g., Bucciol, Cavasso, and Zarri 2019; Stavrunova and Yerokhin 2012). The results discussed in this paper are based on a cross-sectional specification of the FRM and the other modelling techniques used. However, the results from the random effects specification of the FRM (Papke and Wooldridge 2008) are reported in Tables A1 and A2 of Appendix A as a robustness check.

The FRM approach assumes that the conditional mean of the fractional response variable, y_{it}, given a set of explanatory variables, X_{it}, is specified as:

$$E(y_{it} | X_{it}) = G(X_{it}\boldsymbol{\theta}) \tag{1}$$

The FRM requires a functional form for y_{it} that ensures the fitted values lie on the unit interval. Papke and Wooldridge (1996) suggest any cumulative distribution function (logit or probit) as possible specifications for $G(.)$. We use the fractional probit specification where the probit function will map X_{it} onto the (0, 1) interval,

$$G(X_{it}\boldsymbol{\theta}) = \Phi(X_{it}\boldsymbol{\theta}) \tag{2}$$

where Φ is the standard normal cumulative distribution function and $\boldsymbol{\theta}$ is a vector of unknown parameters. The explanatory variables included in the vector X_{it} are: the household and head of household-specific covariates, see Section 2.1; macroeconomic controls, discussed below; and the measure of monetary policy, see Section 2.2. The measures of monetary policy are our key parameters of interest, which will capture the relationship between monetary policy and household portfolio allocation.

Papke and Wooldridge (1996) propose estimating FRM by quasi-maximum likelihood (QML) based on the Bernoulli log-likelihood function given by:

$$l_{it}(\boldsymbol{\theta}) = y_{it}\ \log\left[G(X_{it}\boldsymbol{\theta})\right] + (1 - y_{it})\ \log\left[1 - G(X_{it}\boldsymbol{\theta})\right] \tag{3}$$

The marginal effects of a unitary change in x_k in the standard FRM are given by:

$$\frac{\partial E(y_{it} | X_{it})}{\partial x_k} = \theta_k g(X_{it}\boldsymbol{\theta}) \tag{4}$$

We control for macroeconomic conditions using the average quarterly percentage change in real GDP over the 2 years preceding each survey. For robustness, we also use the average of the Chicago Fed National Activity Index (CFNAI) across the 2 years before each survey. The CFNAI is a monthly index designed to gauge overall economic activity, and related inflationary pressures, by combining 85 existing monthly indicators.

Prior to including monetary policy measures and any macroeconomic controls, in Table 2, we present the marginal effects for

TABLE 2 | Micro determinants of household portfolios—FRM.

	Low-risk asset share	High-risk asset share
Female	−0.010	−0.003
	(0.013)	(0.011)
Age	−0.013***	0.008***
	(0.002)	(0.002)
Age squared	0.001***	−0.001***
	(0.000)	(0.000)
White	−0.101***	0.104***
	(0.010)	(0.009)
Business owner	−0.040***	0.025***
	(0.010)	(0.008)
Homeowner	−0.016	0.016*
	(0.010)	(0.008)
Log networth	−0.011***	0.008***
	(0.001)	(0.001)
Risk index	−0.006**	0.008***
	(0.003)	(0.002)
Health attitudes	−0.009**	0.015***
	(0.004)	(0.003)
Income quartiles		
First quartile	0.158***	−0.136***
	(0.014)	(0.011)
Second quartile	0.108***	−0.099***
	(0.011)	(0.009)
Third quartile	0.054***	−0.052***
	(0.009)	(0.007)
Employment status		
Unemployed	0.011	0.003
	(0.020)	(0.016)
Not in labour force	0.031	0.010
	(0.021)	(0.016)
Retired	−0.031*	0.040***
	(0.017)	(0.013)
Marital status		
Married	0.029**	−0.039***
	(0.015)	(0.012)
Divorced	0.058***	−0.039***
	(0.015)	(0.012)

(Continues)

TABLE 2 | (Continued)

	Low-risk asset share	High-risk asset share
Widowed	0.033	−0.039*
	(0.029)	(0.023)
Education		
College degree	−0.111***	0.096***
	(0.009)	(0.007)
Wave controls		
Wave	−0.166***	0.147***
	(0.010)	(0.008)
Wave	−0.197***	0.182***
	(0.011)	(0.009)
Wave	−0.170***	0.151***
	(0.010)	(0.008)
Wave	−0.104***	0.105***
	(0.008)	(0.007)
Observations	15,650	15,650

Note: (*i*) This table presents estimates of the household level determinants of the low and high-risk asset shares based on the FRM model, 1999–2007, where the dependent variable is constrained to be between zero and one. (*ii*) The results shown in the table refer to the average marginal effect (AME) of a one-point change of the explanatory variable in question on the expected value of the dependent variable. (*iii*) Standard errors pertaining to these AMEs are clustered at the household level and shown in parenthesis. (*iv*) *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

all the household and head of household controls for the low-risk asset share and high-risk asset share equations. These controls are included in all models, but, for brevity, we only present them in full in Table 2. Overall, the findings tie in with previous studies with, for example, income and net worth being positively (negatively) related to the share of high (low) risk assets. In terms of magnitude, compared to those in the fourth quartile, the omitted category, those in the first quartile hold a 15.8 pp. greater share of low-risk assets and a 13.6 pp. lower share in high-risk assets. Households with heads at the early stages of the life cycle appear to be less inclined to hold high-risk assets, as is also the case for having relatively low levels of education. White heads of household are more likely to hold high-risk assets and, in terms of magnitude, they hold a 10.4 pp. higher share of high-risk assets. Similarly, business owners hold a 2.5 pp. higher share of risky assets. These findings accord with the existing literature (see, e.g., Guiso, Jappelli, and Terlizzese 1996; Ampudia and Ehrmann 2017), thereby endorsing our baseline specification.

Table 3 reports estimates of the model described in Equation (2), which includes the monetary policy measures and the macroeconomic controls. With respect to the macroeconomic controls, to explore the robustness of our findings, we estimate three different specifications: In Specification 1, we do not include any macroeconomic controls (Panel A); Specification 2 controls for past GDP growth (Panel B); and in Specification 3, we replace GDP growth with the CFNAI (Panel C).

Across all specifications in Table 3, the two measures of monetary policy, capturing actual FFR and unexpected FFR changes (*RR-shock*), are statistically significant at the 1% level. The negative sign of the estimated parameters associated with the monetary policy changes for the share of high-risk assets indicates that expansionary monetary policy, as captured by interest rate cuts, is positively associated with allocation to high-risk assets. In contrast, monetary policy easing is associated with lower allocation to low-risk assets. In terms of magnitude, Panel A of Table 3 shows that a 1% decrease in the FFR is associated with, on average, a 19.6 pp. increase in the share of high-risk assets and a 19.6 pp. decrease in the share of low-risk assets. These findings accord with the argument that low interest rates discourage households from saving, while encouraging them to hold relatively risky assets in accordance with reaching-for-yield behaviour.[10]

Overall, the magnitude of the estimated parameters in Table 3 differs substantially across the actual and unexpected interest rate changes with the former having a stronger impact. For example, in the case of the high-risk asset share in Panel B, the marginal effects for FFR changes and the *RR-shock* are −0.314 and −0.260, respectively. The difference in magnitudes accords with intuition and our expectations since most households do not rely on econometric models to evaluate the stance of monetary policy.

The robustness of this pattern of results to the inclusion of the macroeconomic controls is noteworthy. The findings in Panels B and C indicate that a growing economy is associated with a higher (lower) share of high (low) risk assets. Overall, our findings, which accord with reaching-for-yield behaviour among households, are consistent across a range of specifications.[11] We now turn to exploring robustness via alternative econometric modelling approaches.

4 | A Two-Part Modelling Approach

As shown in Figure 1, the majority of households do not hold high-risk assets. Indeed, the 'stock-holding puzzle' whereby households appear disinclined to hold risky assets even in the presence of a historical equity premium, is well-known in the existing literature (Haliassos and Bertaut 1995). The inclusion of households with zero holdings of high-risk assets may lead to biased estimates of the effect of monetary policy on portfolio allocation.[12] Hence, we explore the robustness of our findings using the two-part FRM estimation method, which allows us to examine the impact of monetary policy shifts on the two different parts of the distribution of the asset share variables. Specifically, we evaluate monetary policy effects on whether high and/or low-risk assets are held and, conditional on holding an asset type, the amount of the asset share.

The two-part FRM was introduced by Ramalho and Silva (2009) as an extension of the Papke and Wooldridge (1996) FRM approach. However, the two-part model proposed by Ramalho and Silva (2009) assumes independence between the decision to hold an asset type and the decision related to the level of holding. Schwiebert and Wagner (2015) proposed a generalisation of the two-part model allowing for dependence between each part of the model. We use the 'Conditional Mixed Process' (CMP)

TABLE 3 | Monetary policy shifts and household portfolios: FRM.

	Low-risk asset share		High-risk asset share	
Panel A: No macro controls				
	(1)	(2)	(3)	(4)
FFR	0.248***		−0.196***	
	(0.023)		(0.018)	
RR shock		0.411***		−0.306***
		(0.038)		(0.031)
Panel B: GDP growth				
	(5)	(6)	(7)	(8)
FFR	0.366***		−0.314***	
	(0.029)		(0.022)	
RR shock		0.349***		−0.260***
		(0.039)		(0.030)
GDP	−0.029***	−0.012***	0.027***	0.012***
	(0.003)	(0.002)	(0.002)	(0.002)
Panel C: CFNAI				
	(9)	(10)	(11)	(12)
FFR	0.487***		−0.399***	
	(0.038)		(0.030)	
RR shock		0.409***		−0.305***
		(0.041)		(0.033)
CFNAI	−0.093***	0.001	0.078***	−0.001
	(0.012)	(0.008)	(0.009)	(0.006)
Observations	15,650	15,650	15,650	15,650

Note: (*i*) See notes (*i*) to (*iv*) in Table 2. (*ii*) Each specification in each panel represents a separate regression and each regression includes the set of micro determinants as in Table 2.

framework developed by Roodman (2011) to allow for contemporaneous cross-equation error correlation. The CMP approach is based on a general seemingly unrelated regression (SUR) framework, in which, although the dependent variables are independent from each other, the correlation between their error terms is allowed for.[13]

The first part of the generalised two-part FRM models the probability of a household holding an asset type using a binary choice framework defined as:

$$Pr\left(y_{it}^{*}=1 \mid Z_{it}\right)=Pr\left(y_{it} \in \left(0,1\right] \mid Z_{it}\right)=\Phi\left(Z_{it}\boldsymbol{\theta}\right) \tag{5}$$

where Φ is the standard normal cumulative distribution function, Z_{it} is a vector of covariates, which influence the decision to hold the specific asset type, and y_{it}^{*} is defined as follows:

$$y_{it}^{*}=\begin{cases}0 & \text{for } y_{it}=0\\ 1 & \text{for } y_{it}\in(0,1]\end{cases} \tag{6}$$

The second part of the generalised two-part FRM relates to positive holding of the asset type, that is, the magnitude of the asset share. The specification for this part is:

$$E\left(y_{it} \mid X_{it}, Z_{it}, y_{it}^{*}=1\right)=\frac{\Phi 2\left(X_{it}\boldsymbol{\gamma}, Z_{it}\boldsymbol{\theta}; \rho\right)}{\Phi\left(Z_{it}\boldsymbol{\theta}\right)} \tag{7}$$

where $\Phi 2(.;\rho)$ denotes the bivariate standard normal distribution function with correlation coefficient, ρ, between participation and the level of the asset share. X_{it} is a vector of explanatory variables, which influence this part of the distribution. Standard errors are clustered at the household level.[14]

In addition to the controls in Equation (5) (i.e., the first part of the model), a dummy variable indicating whether the household has received a financial windfall is included as an over-identifying variable. This variable indicates whether the household has received a financial windfall during the previous 2 years in the form of an inheritance or gift worth \$10,000 or more. We need

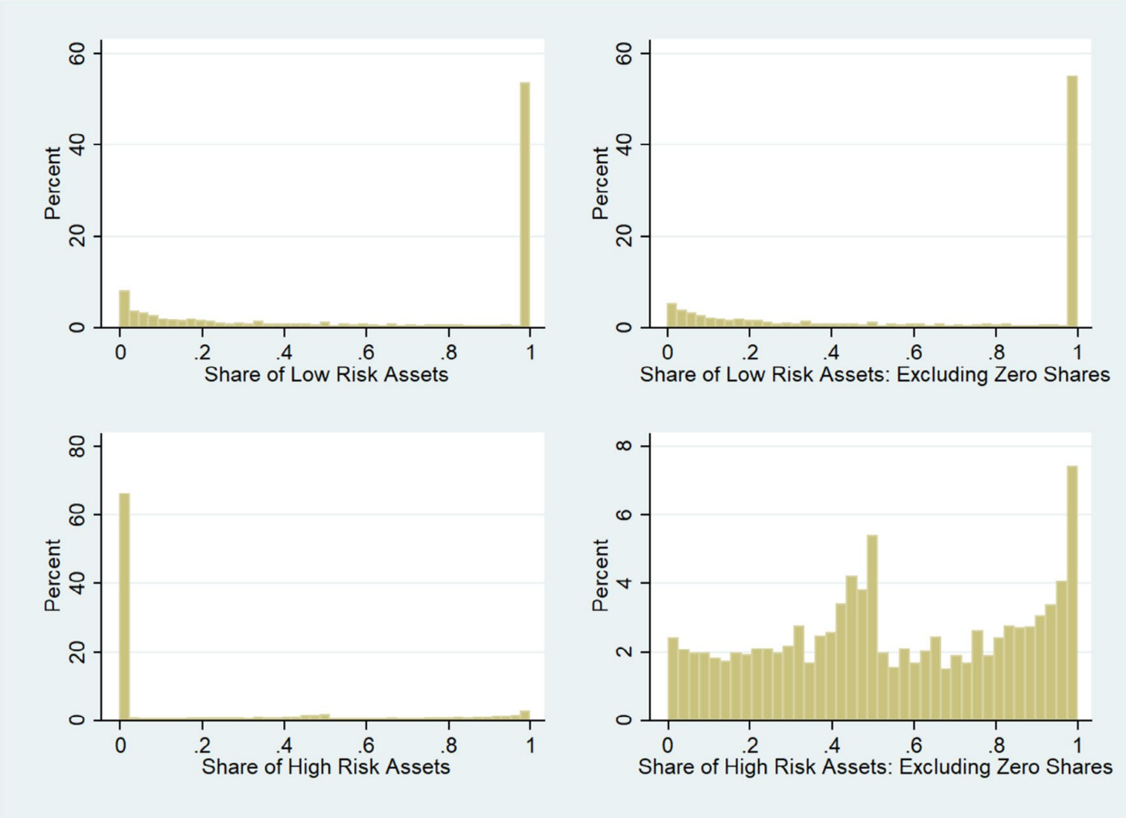

FIGURE 1 | Household portfolios: The asset shares. [Colour figure can be viewed at wileyonlinelibrary.com]

to select a suitable identifying variable for the first stage, specifically a variable which influences the probability of holding an asset type but does not influence the shares of high-risk and low-risk assets held.[15]

The results from estimating the generalised two-part FRM are presented in Table 4. In Panel, A no macroeconomic controls are included; in Panel B, we control for past GDP growth; and, in Panel C, we replace GDP growth with the CFNAI. For each specification, in each panel, we report the marginal effects relating to our key variables of interest for the probit part of the model (i.e., the decision to hold) and the fractional part (i.e., the asset share) and the associated correlation coefficient, ρ, between the error terms of the two equations. As in the case of the FRM in Section 3, marginal effects are obtained to assess the effect of a change in the explanatory variables on the probability of holding an asset type and on the asset share.

The measures of monetary policy shifts are negatively associated with the decision to hold and the level of holding high-risk assets across most specifications. However, the impact on the low-risk asset share is only statistically significant for the level of holding but not the decision to hold. A possible explanation for this finding is that, when the Fed increases the interest rate, households will realise that the return on safe assets is close to the return on risky assets after adjusting for the level of risk. Hence, these households will reduce holdings of risky assets and increase the share of safe assets.

Comparing the magnitudes of the effects related to the participation equation and the level of holding equation reveals some important differences. The results in Table 4 show that changes in monetary policy have a larger impact on the level of the shares of high and low-risk assets compared to the decision to hold these assets. For example, Panel C of Table 4 shows that a 1% increase in the FFR is associated with, on average, an 83.4 pp. decrease in the share of high-risk assets compared to, on average, only a 45.8 pp. increase in the probability of holding high-risk assets.

Furthermore, a difference in the magnitude of the effects of the two measures of monetary policy, the actual FFR and the unexpected FFR changes, on the high-risk assets is apparent. Specifically, changes in the actual FFR have a stronger effect on both the decision to hold and the level of holding high-risk assets than the impact of the unexpected FFR changes. This suggests that the household's financial decisions are more influenced by monetary policy actions as measured by actual FFR changes. Furthermore, this finding accords with the results presented in Table 3 and suggests that household financial behaviour is mostly influenced by a simple measure of interest rates rather than a measure that is based on econometric models designed to isolate the unexpected component of monetary policy.

The impacts of the macroeconomic controls on the asset shares accord with expectations. Specifically, an increase in economic activity, whether measured by GDP growth or the CFNAI, is associated with an increase in the household's share of high-risk assets and a decrease in the share of low-risk assets.

Finally, the correlation between the error terms of the two equations, ρ , is reported for each specification in Table 4. These

TABLE 4 | Monetary policy shifts and household portfolios: Two-part FRM.

	Low-risk asset share				High-risk asset share			
Panel A: No macro controls								
Specification	(1)		(2)		(3)		(4)	
	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part
FFR	0.002	0.750***			−0.321***	−0.110		
	(0.011)	(0.067)			(0.026)	(0.143)		
RR shock			0.002	1.272***			−0.415***	−0.435***
			(0.020)	(0.117)			(0.044)	(0.164)
Windfall	0.000		0.006		0.069***		0.067***	
	(0.006)		(0.007)		(0.018)		(0.018)	
ρ	0.371***		0.353**		0.667**		0.683**	
	(0.138)		(0.147)		(0.206)		(0.204)	
Panel B: GDP growth								
Specification	(5)		(6)		(7)		(8)	
	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part
FFR	0.026*	1.410***			−0.519***	−0.622***		
	(0.015)	(0.090)			(0.033)	(0.145)		
RR shock			0.008	1.371***			−0.432***	−0.589***
			(0.020)	(0.119)			(0.045)	(0.151)
GDP	−0.003**	−0.102***	−0.002*	−0.038***	0.031***	0.076***	0.007***	0.047***
	(0.001)	(0.008)	(0.001)	(0.006)	(0.003)	(0.008)	(0.002)	(0.007)
Windfall	0.007		0.007		0.063***		0.066***	
	(0.007)		(0.007)		(0.017)		(0.018)	
ρ	0.398***		0.379***		0.735**		0.716**	
	(0.111)		(0.119)		(0.180)		(0.194)	
Panel C: CFNAI								
Specification	(9)		(10)		(11)		(12)	
	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part	Probit part	Frac. part
FFR	0.025	1.474***			−0.458***	−0.834***		
	(0.019)	(0.116)			(0.043)	(0.128)		
RR shock			0.006	1.261***			−0.347***	−0.640***
			(0.021)	(0.125)			(0.047)	(0.132)
CFNAI	−0.008	−0.278***	−0.002	0.006	0.053***	0.277***	−0.038***	0.114***
	(0.006)	(0.035)	(0.004)	(0.023)	(0.013)	(0.037)	(0.009)	(0.037)
Windfall	0.007		0.006		0.066***		0.069***	
	(0.007)		(0.007)		(0.018)		(0.018)	
ρ	0.380***		0.362***		0.722**		0.699**	
	(0.117)		(0.127)		(0.181)		(0.194)	
Observations	15,650	15,197	15,650	15,197	15,650	6059	15,650	6059

Note: (*i*) This table presents estimates of the two-part FRM, 1999–2007, where the probit part of the equation refers to the probability of holding the asset type and the Frac. Part of the equation refers to the level of holding. (*ii*) The coefficient ρ represents the associated correlation between the error terms of these two equations. (*iii*) Each specification in each panel represents a separate regression and each regression includes the set of micro determinants as in Table 2. (*iv*) The results shown in the table refer to the average marginal effect (AME) of a one-point change of the explanatory variable in question on the expected value of the dependent variable. (*v*) Standard errors pertaining to these AMEs are clustered at the household level and shown in parenthesis.

results support a statistically significant relationship between the unobserved characteristics of the decision to hold an asset type and the asset share. Such findings imply that there is interdependence between these decisions and endorse the use of a modelling approach that allows for such interdependence, as it will lead to more efficient coefficient estimates.

5 | Robustness Checks

5.1 | Active Investors

The main finding of our analysis so far is that expansionary monetary policy is associated with higher allocation to high-risk assets and lower allocation to low-risk assets in household financial portfolios. It is important to acknowledge a potential caveat related to the fact that portfolio shares may be shifting over time not only due to active portfolio rebalancing but also as a result of passive valuation effects (Bucciol and Miniaci 2015). Thus, the increase in the share of high-risk assets following expansionary monetary policy shifts may reflect an increase in the value of stock-holdings, as opposed to, or in addition to, active portfolio rebalancing towards stocks. Generally, even the portfolio share of a household characterised by full inertia in its investment behaviour may display variation over time, driven by such valuation changes.

To gain further insight into how this affects our findings, we repeat our analysis for a sub-sample of active investors.[16] Active investors are defined as households which indicate that someone (in the household) has bought or sold 'any shares of stock in publicly held corporations, stock mutual funds, or investment trusts, including any automatic reinvestments not including any IRAs' over the previous year. The active investors' sample corresponds to 19% of the sample analyzed in Sections 3, 4 and 5. This low proportion accords with previous studies which report that, whereas the majority of households exhibit inertia in their investment behaviour, a minority of sophisticated households (generally the wealthy and the better educated) engage in active portfolio rebalancing (Brunnermeier and Nagel 2008; Calvet, Campbell, and Sodini 2009). Indeed, Table A3 in Appendix A presents summary statistics for the sample of active investors, where distinct differences can be seen across the sample of active investors and the whole sample: For example, the heads of active investor households are more likely to be male, more risk tolerant and more highly educated.

Table 5 reports the FRM estimates for the sample of active investors. The monetary policy effects, as measured by actual changes in FFR, remain highly statistically significant and are consistently positively associated with the low-risk asset share and inversely associated with the high-risk asset share. The sensitivity of the high-risk asset share to monetary policy shifts

TABLE 5 | Household portfolios for active investors: FRM.

	Low-risk asset share		High-risk asset share	
Panel A: No macro controls				
FFR	0.225***		−0.260***	
	(0.050)		(0.054)	
RR shock		0.364***		−0.330***
		(0.075)		(0.081)
Panel B: GDP growth				
FFR	0.485***		−0.572***	
	(0.059)		(0.063)	
RR shock		0.380***		−0.347***
		(0.076)		(0.082)
GDP	−0.044***	−0.022***	0.051***	0.025***
	(0.005)	(0.004)	(0.006)	(0.005)
Panel C: CFNAI				
FFR	0.533***		−0.588***	
	(0.074)		(0.079)	
RR shock		0.387***		−0.347***
		(0.077)		(0.083)
CFNAI	−0.127***	−0.023	0.133***	0.016
	(0.022)	(0.015)	(0.024)	(0.016)
Observations	2900	2900	2900	2900

Note: See notes in Table 3.

TABLE 6 | Household portfolios for active investors: Heckman selection model.

	Low-risk asset share		High-risk asset share	
Panel A: No macro controls				
Second stage				
FFR	0.222***		−0.264***	
	(0.053)		(0.059)	
RR shock		0.366***		−0.359***
		(0.093)		(0.107)
First stage (active)				
Windfall	0.382***	0.361***	0.382***	0.361***
	(0.047)	(0.047)	(0.047)	(0.047)
ρ	0.032	0.005	0.029	0.062
	(0.122)	(0.111)	(0.141)	(0.138)
Panel B: GDP growth				
Second stage				
FFR	0.503***		−0.610***	
	(0.070)		(0.080)	
RR shock		0.386***		−0.388***
		(0.093)		(0.108)
GDP	−0.045***	−0.022***	0.055***	0.027***
	(0.007)	(0.005)	(0.008)	(0.006)
First stage (active)				
Windfall	0.346***	0.342***	0.346***	0.342***
	(0.047)	(0.047)	(0.047)	(0.047)
ρ	−0.012	−0.009	0.097	0.086
	(0.102)	(0.106)	(0.126)	(0.132)
Panel C: CFNAI				
Second stage				
FFR	0.544***		−0.632***	
	(0.090)		(0.104)	
RR shock		0.392***		−0.384***
		(0.098)		(0.115)
CFNAI	−0.129***	−0.023	0.146***	0.020
	(0.027)	(0.017)	(0.031)	(0.019)
First stage (active)				
Windfall	0.350***	0.349***	0.350***	0.349***
	(0.047)	(0.047)	(0.047)	(0.047)
ρ	−0.009	−0.001	0.087	0.071
	(0.106)	(0.110)	(0.130)	(0.137)
Observations	15,650	15,650	15,650	15,650

Note: (*i*) The table reports the results of the Heckman estimations for Equation (8), 1999–2007. (*ii*) Both the selection equation and the outcome equation include the set of micro determinants as in Table 2. ρ is the coefficient of correlation between the first and the second stage errors. (*iii*) Standard errors are clustered at the household level and shown in parenthesis. (*iv*) Each specification in each panel represents a separate regression and each regression includes a set of micro determinants as in Table 2.

TABLE 7 | Monetary policy shifts and household portfolios: FRM (1999–2019).

	Low-risk asset share	High-risk asset share
Panel A: No macro controls		
	(1)	(2)
2Y-treasury yield	0.874***	−0.563***
	(0.147)	(0.114)
Panel B: GDP growth		
	(3)	(4)
2Y-treasury yield	1.243***	−0.809***
	(0.152)	(0.117)
GDP	−0.016***	0.011***
	(0.001)	(0.001)
Panel C: CFNAI		
	(5)	(6)
2Y-treasury yield	1.128***	−0.749***
	(0.165)	(0.128)
CFNAI	−0.016***	0.011***
	(0.004)	(0.003)
Observations	40,178	40,178

Note: (*i*) See notes in Table 3. (*ii*) The sample used in this table covers 11 waves of the PSID survey (1999–2019).

for the sample of active investors is much larger relative to the equivalent effects estimated for the whole sample, see Table 3. For example, focusing on the results in Panel B of Table 5, the estimated parameter associated with actual changes in the FFR for the high-risk asset share is −0.572 for active investors compared to −0.314 for the whole sample, as reported in Panel B of Table 3. The fact that active investors react more strongly to changes in monetary policy suggests that while part of the overall shift in portfolio holdings may be due to passive valuation effects, a significant portion of that shift is likely to be driven by a minority of investors who are financially sophisticated, knowledgeable, and closely monitor economic conditions and policy changes. These investors actively adjust their portfolios in response to such factors, contributing to the observed portfolio allocation changes.

Since active investors are likely to differ systematically from inactive investors, selection bias in the results in Table 5 may arise in splitting the sample in this way. To further explore the robustness of our findings and to address such potential bias from splitting the sample, we adopt the Heckman selection estimation approach for the sample of active investors. The first stage models the probability of being an active investor, the results of which are used to calculate an inverse Mills ratio term, which is included in the second stage asset share equations to control for potential sample selection bias. Specifically, we re-estimate our share equations, with the standard errors clustered at the household level, for the sample of active investors, as follows:

$$y_{it} = \boldsymbol{X}'_{it}\boldsymbol{\beta} + \boldsymbol{M}'_{t}\boldsymbol{\gamma} + \pi r_t + \lambda \delta_{it} + \varepsilon_{it} \tag{8}$$

where $\delta_{it} = \phi(H_{it}) / \Phi(H_{it})$ is the standard inverse Mills ratio term estimated from a probit model used to determine the probability of being an active investor, $H_{it} = \Phi^{-1}(P_{it})$ and P_{it} denotes the predicted probability of household i at time t having an active investor in the household, $\phi(.)$ represents the probability density function of the standard normal distribution and $\Phi(.)$ denotes the cumulative density function of the standard normal distribution. Finally, r_t is the measure of monetary policy, as previously defined, and π is the key coefficient of interest. To identify the model, given the link between holding assets and being an active investor, we follow Section 4 and control for receiving a financial windfall during the previous 2 years in the form of an inheritance or gift worth $10,000 or more in the probit part of the model. Our findings endorse our choice of instrument being statistically significant in the probit model, yet statistically insignificant if included in the second stage of the model.

Table 6 presents the Heckman estimation results from modelling the low-risk asset share and the high-risk asset share following the specifications used in Table 5. From the second stage regression, we can see that the Heckman results accord with our previous findings with expansionary monetary policy shifts increasing (decreasing) the share of high (low) risk assets in household portfolios. Furthermore, the sensitivity of the financial portfolios of active investor households to monetary policy shifts, mainly in the case of actual FFR changes, is apparent in the estimated coefficients from the Heckman estimation approach, see Table 6. Thus, the findings presented in Table 6 accord with the findings in Table 5. In addition, to provide a basis for comparison, Table A4 in Appendix A presents the OLS estimation results for the 1999–2007 period for all households to shed light on the relative magnitudes of the estimated coefficients from the Heckman approach. The results reported in Table A4 confirm that the response of active investors to shifts in monetary policy is large. For example, focusing on the results in Panel B of Table 6, the estimated parameter associated with actual changes in the FFR for the high-risk asset share is −0.610 for active investors compared to −0.401 for the OLS estimation, as reported in Panel B of Table A4. Overall, such findings provide additional support for the pattern of results presented in Section 3, which further endorses the important role played by monetary policy in household portfolio allocation decisions.

5.2 | Accounting for the Financial Crisis

This section explores the robustness of the estimated effects of monetary policy shifts on household portfolios over a longer time period. We extend the sample by adding the following six waves of the PSID survey, thereby covering the global financial crisis and its aftermath: 2009, 2011, 2013, 2015, 2017 and 2019. Hence, the extended sample used for the analysis in this section covers 11 waves (1999–2019), comprising 40,178 ($N \times T$)

TABLE 8 | Monetary policy shifts and household portfolios: Two-part FRM (1999–2019).

	Low-risk asset share			High-risk asset share		
Panel A: No macro controls						
	Probit part		Frac. part	Probit part		Frac. part
2Y-treasury yield	0.183**		2.489***	−0.571***		−1.505***
	(0.076)		(0.467)	(0.163)		(0.406)
Windfall	0.006			0.051***		
	(0.004)			(0.010)		
ρ		0.491***			0.729***	
		(0.092)			(0.113)	
Panel B: GDP growth						
	Probit part		Frac. Part	Probit part		Frac. part
2Y-treasury yield	0.224***		3.637***	−0.813***		−2.136***
	(0.075)		(0.485)	(0.169)		(0.420)
GDP	−0.002***		−0.048***	0.010***		0.027***
	(0.001)		(0.004)	(0.002)		(0.004)
Windfall	0.006			0.050***		
	(0.004)			(0.010)		
ρ		0.495***			0.737***	
		(0.093)			(0.112)	
Panel C: CFNAI						
	Probit part		Frac. Part	Probit part		Frac. part
2Y-treasury yield	0.156*		3.384***	−0.586***		−2.473***
	(0.082)		(0.526)	(0.184)		(0.451)
CFNAI	0.002		−0.055***	0.001		0.062***
	(0.002)		(0.013)	(0.004)		(0.012)
Windfall	0.005			0.051***		
	(0.004)			(0.010)		
ρ		0.489***			0.735***	
		(0.093)			(0.112)	
Observations	40,178		39,263	40,178		14,175

Note: (*i*) See notes in Table 4. (*ii*) The sample used in this table covers 11 waves of the PSID survey (1999–2019).

observations. Since data on the RR shock is not available over this extended period and the FFR has remained stable at the ZLB for several years since December 2008, we use a recently proposed measure of monetary policy shifts to cover the longer period.[17] The new measure of monetary policy shocks is based on Hanson and Stein (2015). Specifically, we measure news about the expected medium-term path of interest rates using the change in the two-year nominal Treasury yield around FOMC announcement dates. In particular, for a FOMC meeting on day t, we compute yield changes from day t–1 to $t+1$. As Hanson and Stein (2015) argue, this accounts for the possibility that the full market reaction to a FOMC announcement might not be instantaneous. They argue that this may be the case particularly for long-term yields, as investors can take some time to digest the information content of the FOMC announcement.[18]

To compare the two samples used in our study, Table 1 presents the summary statistics for the 1999–2007 period, whereas Table A5 presents the corresponding statistics for the longer time period, 1999–2019. The mean of the high-risk asset share for the longer time period is lower (19.2%) than that for the shorter time period (21.3%), which might reflect the impact of the global financial crisis. Similarly, the log of net wealth is also lower for the samples based on the longer time period.

To examine the robustness of our findings related to the period 1999–2007, we re-estimate the models reported in Tables 3 and 4 for the extended time period using the new measure of monetary policy shocks. The results are reported in Tables 7 and 8. The results accord with the findings estimated over the shorter time period. Hence, our findings are robust over the longer time period that covers the global financial crisis as well as to using the change in the two-year nominal Treasury yield as a proxy for changes in expectations regarding the medium-term path of interest rates.

Specifically, the results presented in Table 7 indicate that an increase in the two-year treasury yield is associated with a higher (lower) share of low (high) risk assets and, in addition, the results are robust to the inclusion of the macroeconomic controls. Furthermore, Table 8 shows that this pattern of results is robust to using the two-part FRM.[19]

6 | Conclusion

We have analyzed data on US household financial portfolios and two measures of monetary policy shifts, based on actual and unexpected changes in the FFR, over the period 1999–2007, to explore how households react to changes in monetary policy. Our FRM findings show that expansionary monetary policy is associated with higher household portfolio allocation to high-risk assets and lower allocation to low-risk assets. The findings from the two-part modelling approach show that monetary policy shifts are only statistically significant for the decision to hold high-risk assets but not the decision to hold low-risk assets. Our findings for active investors reveal that the impact of monetary policy changes on household portfolio allocation is stronger, relative to the sample of all households, which accords with the view that passive valuation effects on their own cannot fully explain the overall changes in household portfolio shares. Finally, our findings are robust over an extended time period (1999–2019) using a monetary policy measure that accounts for the post-crisis ZLB period.

This study brings together two important strands of the existing literature, related to the risk-taking channel of monetary policy and household financial portfolios. It informs and extends both strands by demonstrating the existence of an empirical link between household portfolio allocation and monetary policy shifts. This link suggests that, in addition to financial institutions, households may also reach-for-yield. Our findings have important policy implications since they empirically verify the intuition of policymakers related to reaching-for-yield behaviour on the part of households. Our findings suggest that this type of behaviour should be accounted for when calibrating the appropriate monetary policy response to economic and financial developments. There are a couple of caveats that we should acknowledge when considering the results, which limit the interpretability of the results. First, it would have been ideal to be able to measure household financial portfolios at a higher frequency. This is a general limitation that encompasses the majority of studies analysing household finance. Second, albeit arguably less problematic, it would have been interesting to be able to measure risk attitudes more frequently to explore the argument that risk preferences are persistent over time.

Finally, our findings suggest several avenues for future work including further exploring the relationship between appetite for financial risk-taking at the household level and monetary policy as well as examining whether these results hold in a non-US context.

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Data Availability Statement

The data that support the findings of this study are openly available in The Panel Study of Income Dynamics at https://simba.isr.umich.edu/data/data.aspx.

Endnotes

[1] For the extended time period, 1999–2019, we use the change in the two-year nominal Treasury yield around the Federal Open Market Committee (FOMC) announcement dates to capture news about the expected medium-term path of interest rates, see Section 5.2.

[2] Luetticke (2021) uses repeated cross-sectional data on household portfolios from the Survey of Consumer Finances (SCF). By sorting households across different percentiles of net liquid wealth, the study finds that monetary policy tightening shocks lead to a reduction (increase) in the portfolio liquidity of households below (above) median wealth.

[3] A decrease in the interest rate represents an increase in the price of future consumption (relative to current consumption), generating an increase in current consumption and a decline in current savings. This substitution effect may be offset by an income effect since, given the lower interest rate, a target level of future consumption requires more savings. A wealth effect, arising from asset revaluation, due to lower interest rates, can also lead to an increase in consumption and a decrease in saving, reinforcing the substitution effect.

[4] The remaining 50% is allocated to medium-risk assets. If it is stated that the assets are 'mostly in interest earning' accounts, 100% of pension assets are allocated to a medium-risk asset category. Although our focus here lies on the effect of monetary policy on the shares of low and high-risk assets, it is important to acknowledge the existence of medium-risk assets, which form part of the denominator of the asset shares. The value of which is elicited from the following survey 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 have not already told us about? The total value of the medium-risk assets is defined from the responses to this question plus the value of non-risky pension accounts, as outlined above, which forms part of the denominator used to construct the low and high-risk asset shares.

[5] There is substantial empirical evidence indicating that the FFR has been the key US monetary policy indicator since the mid-1980s (Romer and Romer 2004).

[6] The frequency of this data is quarterly and the series ends at 2008Q4. In line with our approach for the simple measure of monetary policy shifts, we average the quarterly shocks across the 2 years preceding each survey.

[7] The results (available on request) are robust to using alternative measures of monetary policy shocks. Specifically, the results are robust to the shock of Bauer and Swanson (2023), which is derived from professional forecasters, and the Jarociński and Karadi (2020) shock, which is derived using both interest rate surprises and stock price changes as it distinguishes monetary policy shocks from information shocks. We thank an anonymous referee for proposing these two alternative measures.

[8] The 2007–2008 financial crisis had a significant impact on the Federal Reserve Board's approach to monetary policy implementation. Following a series of FFR cuts, commencing in Autumn 2007, the ZLB was reached by the end of 2008.

[9] The results presented in Sections 3 and 5 are robust to using a Tobit estimator and these results are available on request.

[10] For all estimations, to aid comparison with the existing literature, we frame the discussion of the results in terms of expansionary monetary policy.

[11] We also investigate possible mechanisms that might explain the response of household portfolios to changes in monetary policy. Our results, available on request, suggest that attitudes towards risk play an important role. The relationship between monetary policy shifts and household portfolio allocation appears to be stronger for households that are the most tolerant towards risk.

[12] In the FRM analysis in Section 3, zero and non-zero values of the asset shares are included in the estimations. Hence, the findings reveal the effect of monetary policy on the expected value of the asset share, which could be operating at zero or positive values of the asset share.

[13] Wulff (2019) provides an illustration of how the CMP suite of tools can be used to fit the generalised two-part FRM in STATA.

[14] See Schwiebert and Wagner (2015) for full formulations of the generalised two-part FRM.

[15] This approach is similar to Spaenjers and Spira (2015) and Guiso, Haliassos, and Jappelli (2003), where income and wealth quartiles are included in the equation of the stock market participation decision, following the argument that the relationship between the decision to participate in the stock market and wealth is non-linear. This is because changes in wealth at very low or very high wealth quantiles arguably will not have a pronounced impact on the probability of stock market participation. The results of the two-part FRM support the validity of the identifying variable. Specifically, the probit regression results for all specifications show that the windfall variable is statistically significant in the first part of the model, thereby supporting its validity. Furthermore, if the windfall variable is included in the second part of the model, it is statistically insignificant.

[16] We have investigated the robustness of our findings to controlling for valuation changes by adding past stock market returns to the set of controls, as defined by the average monthly stock market return for the 2 years preceding the survey data. The pattern of results is robust to its inclusion.

[17] The target FFR reached the ZLB (in fact, a range between 0% and 0.25%) in December 2008 and remained there until the FOMC meeting of 16 December 2015, when it was first raised (to 0.25%–0.5%). The change in the monthly effective FFR, upon which our first measure of monetary policy shifts is based, is, on average, 0 during the ZLB period. Hence, there is limited variation in this measure over the extended time period.

[18] To transform these high-frequency yield changes into monthly observations, we follow the approach of Guo, Kontonikas, and Maio (2020). In particular, the yield change that occurs in the FOMC meeting of a given month is kept constant for 30 calendar days, followed by 0 until the new FOMC meeting takes place.

[19] We also explore the role of risk attitudes and active investment over the time period 1999–2019 using the new measure of monetary policy shocks. The results accord with the findings discussed in Sections 5 and 6.

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Appendix A

Additional Tables

TABLE A1 | Micro determinants of household portfolios—Cross-sectional and random effects specifications.

	Cross-sectional specification		Random effects specification	
	Low-risk asset share	**High-risk asset share**	**Low-risk asset share**	**High-risk asset share**
Female	−0.024*	0.009	−0.021	0.012
	(0.014)	(0.011)	(0.013)	(0.010)
Age	−0.020***	0.018***	−0.020***	0.017***
	(0.004)	(0.003)	(0.004)	(0.003)
Age squared	0.002***	−0.002***	0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
White	−0.095***	0.097***	−0.095***	0.094***
	(0.010)	(0.009)	(0.010)	(0.008)
Business owner	−0.034***	0.019**	−0.026***	0.012*
	(0.010)	(0.008)	(0.009)	(0.007)
Homeowner	−0.010	0.009	−0.008	0.003
	(0.010)	(0.009)	(0.009)	(0.008)
Log networth	−0.010***	0.005***	−0.010***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Risk attitudes	−0.006**	0.008***	−0.006**	0.007***
	(0.003)	(0.002)	(0.003)	(0.002)
Health index	−0.005	0.011***	−0.004	0.008***
	(0.004)	(0.003)	(0.004)	(0.003)
Income quartiles				
First quartile	0.071***	−0.061***	0.041***	−0.036***
	(0.016)	(0.013)	(0.014)	(0.012)
Second quartile	0.054***	−0.051***	0.036***	−0.033***
	(0.012)	(0.010)	(0.011)	(0.009)
Third quartile	0.023**	−0.023***	0.012	−0.016**
	(0.009)	(0.007)	(0.008)	(0.006)
Employment status				
Unemployed	−0.000	0.012	0.004	0.004
	(0.020)	(0.016)	(0.017)	(0.014)
Not in labour force	0.019	0.020	0.001	0.023
	(0.021)	(0.016)	(0.019)	(0.015)
Retired	−0.033*	0.040***	−0.013	0.028**
	(0.017)	(0.013)	(0.015)	(0.011)
Marital status				
Married	0.037**	−0.045***	0.033**	−0.033***
	(0.015)	(0.012)	(0.013)	(0.011)

(Continues)

TABLE A1 | (Continued)

	Cross-sectional specification		Random effects specification	
	Low-risk asset share	**High-risk asset share**	**Low-risk asset share**	**High-risk asset share**
Divorced	0.056***	−0.036***	0.054***	−0.029**
	(0.015)	(0.013)	(0.014)	(0.012)
Widowed	0.033	−0.039*	0.028	−0.032
	(0.028)	(0.023)	(0.026)	(0.021)
Education				
College degree	−0.095***	0.083***	−0.097***	0.085***
	(0.009)	(0.007)	(0.009)	(0.007)
1999 Wave	−0.142***	0.125***	−0.133***	0.118***
	(0.013)	(0.010)	(0.012)	(0.010)
2001 Wave	−0.159***	0.147***	−0.143***	0.133***
	(0.013)	(0.010)	(0.012)	(0.010)
2003 Wave	−0.139***	0.123***	−0.124***	0.110***
	(0.011)	(0.009)	(0.011)	(0.009)
2005 Wave	−0.096***	0.098***	−0.093***	0.093***
	(0.008)	(0.007)	(0.008)	(0.007)
Observations	15,650	15,650	15,650	15,650

Note: (*i*) This table presents estimates of the household level determinants of the low and high-risk asset shares based on a random effects FRM model, 1999–2007, where the dependent variable is constrained to be between zero and one. (*ii*) The correction proposed by Mundlak (1978) is applied by including the means of the following time-varying continuous variables: age, age squared, income and net wealth. (*iii*) The results shown in the table refer to the average marginal effect (AME) of a one-point change of the explanatory variable in question on the expected value of the dependent variable. (*iv*) Standard errors pertaining to these AMEs are clustered at the household level and shown in parenthesis. (*v*) *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE A2 | Monetary policy shifts and household portfolios: Random effect FRM.

	Low-risk asset share		High-risk asset share	
Panel A: No macro controls				
	(1)	(2)	(3)	(4)
FFR	0.116***		−0.073***	
	(0.022)		(0.017)	
RR shock		0.120***		−0.047
		(0.039)		(0.032)
Panel B: GDP growth				
	(5)	(6)	(7)	(8)
FFR	0.298***		−0.238***	
	(0.032)		(0.025)	
RR shock		0.189***		−0.111***
		(0.044)		(0.036)
GDP	−0.026***	−0.009***	0.023***	0.008***
	(0.003)	(0.002)	(0.003)	(0.002)
Panel C: CFNAI				
	(9)	(10)	(11)	(12)
FFR	0.247***		−0.176***	
	(0.042)		(0.034)	
RR shock		0.095**		−0.031
		(0.046)		(0.038)
CFNAI	−0.050***	0.009	0.039***	−0.006
	(0.014)	(0.008)	(0.011)	(0.007)
Observations	15,650	15,650	15,650	15,650

Note: (*i*) See notes (*i*) to (*iv*) in Table A1. (*ii*) Each specification in each panel represents a separate regression and each regression includes the set of micro determinants as in frm_micro except wave dummies.

TABLE A3 | Summary statistics: Active investors.

	1999–2007 sample	Active investors
Dependent variables		
Low-risk asset share	0.627	0.300*
High-risk asset share	0.213	0.522*
Independent variables		
Age	43.504	46.277*
Female	0.231	0.124*
White	0.764	0.921*
Business owner	0.159	0.250*
Homeowner	0.705	0.854*
Health index	2.792	2.998*
Log income	11.043	11.520*
Log networth	9.660	12.230*
Risk attitudes	1.862	2.106*
Employment status		
Employed	0.867	0.866
Unemployed	0.029	0.019*
Not in labour force	0.037	0.024*
Retired	0.067	0.091*
Marital status		
Single	0.187	0.141*
Married	0.599	0.731*
Divorced	0.186	0.108*
Widowed	0.029	0.020*
Education		
College degree	0.314	0.564*
High school and below	0.686	0.436*
Observations	15,650	2900

Note: A *t*-test was carried out between the active and inactive samples, where * indicates a statistically significant difference at the 99% level from the inactive sample.

TABLE A4 | Monetary policy shifts and household portfolios: OLS estimation, 1999–2007.

	Low-risk asset share		High-risk asset share	
Panel A: No macro controls				
FFR	0.253***		−0.204***	
	(0.023)		(0.018)	
RR shock		0.415***		−0.316***
		(0.038)		(0.032)
Panel B: GDP growth				
FFR	0.471***		−0.401***	
	(0.029)		(0.023)	
RR shock		0.453***		−0.353***
		(0.040)		(0.032)
GDP	−0.035***	−0.013***	0.032***	0.013***
	(0.003)	(0.002)	(0.002)	(0.002)
Panel C: CFNAI				
FFR	0.494***		−0.413***	
	(0.038)		(0.030)	
RR shock		0.413***		−0.316***
		(0.041)		(0.034)
CFNAI	−0.094***	0.001	0.082***	−0.000
	(0.012)	(0.008)	(0.009)	(0.006)
Observations	15,650	15,650	15,650	15,650

Note: This table presents estimates of Equation (1) for the low and high-risk portfolio shares. All regressions are based on OLS. Each regression includes the set of micro determinants as in Table 2 in the main paper. Standard errors are clustered at the household level and shown in parenthesis.

TABLE A5 | Summary statistics: 1999–2019.

	Mean	SD	Min	Max
Dependent variables				
Low-risk asset share	0.667	0.407	0	1
High-risk asset share	0.192	0.311	0	1
Macro variables				
2Y-Treasury yield	−0.003	0.011	−0.022	0.018
Real GDP growth	2.222	1.342	−0.425	4.687
Chicago Fed National Activity Index (CFNAI)	−0.185	0.461	−1.13	0.4
Independent variables				
Age	45.35	14.82	18	97
Female	0.246			
White	0.738			
Business owner	0.141			
Homeowner	0.667			
Log networth	8.813	7.918	−15.27	19.29
Risk attitudes	1.862	1.604	0	5
Health index	2.677	0.979	0	4
Income quartiles				
First quartile	9.602	0.699	0.280	10.264
Second quartile	10.607	0.184	10.264	10.908
Third quartile	11.201	0.170	10.908	11.499
Fourth quartile (omitted)	11.998	0.441	11.499	15.921
Employment status				
Employed (omitted)	0.797			
Unemployed	0.035			
Not in labour force	0.046			
Retired	0.121			
Marital status				
Single (omitted)	0.199			
Married	0.598			
Divorced	0.175			
Widowed	0.035			
Education				
High school and below (omitted)	0.638			
College degree	0.361			
Observations	40,178			