Income Risk and Flow Hedging by Mutual Funds*

Amirabas Salarkia

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Abstract

This paper investigates how household income risk influences mutual fund managers' portfolio decisions. I provide novel empirical evidence that state-level local income shocks affect capital flows to retail mutual funds. By analyzing portfolio holdings data, I find that, consistent with the predictions of a portfolio optimization model, active fund managers hedge local income shocks by tilting their portfolios away from high local income beta stocks. Furthermore, in expectation of a higher flow to income sensitivity, active fund managers change their portfolio tilts to hedge income shocks more strongly, and vice versa. This finding reveals that fund managers' incentive to hedge income shocks is partly driven by their flow-hedging motives. I also show that the trade-off between income hedging and local bias can help explain the local bias puzzle.

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1 Introduction

Income risk is one of the key sources of uncertainty that households face. Standard portfolio optimization shows that the welfare-maximizing portfolio includes a component to hedge household income risk (e.g., Campbell, 2017, chap. 10). Several empirical papers have studied how income risk affects the portfolio choices of U.S. and European households (e.g., Massa and Simonov, 2006; Angerer and Lam, 2009; Betermier et al., 2012). However, a substantial amount of household savings is invested indirectly through mutual funds. Surprisingly, empirical work has not yet examined the implications of household income risk for the portfolio decisions of active fund managers.

Why should fund managers care about household income risk? Fund managers' incentives are closely related to fund size. For example, Ibert et al. (2018) show that active fund managers' compensation is a monotonic function of the fund's assets under management (AUM). Therefore, active fund managers are incentivized to smooth their compensation by hedging the shocks that cause fluctuations in their AUM through fund flows (e.g., Dou, Kogan, and Wu, 2022). Since households' income shocks can affect capital flows to retail mutual funds, flow hedging can be one reason why mutual fund managers should care about household income shocks.[1]

In this paper, I use state-level local income shocks as a novel setting to investigate how household income risk influences mutual fund managers' portfolio decisions.[2] I show that state-level local income shocks significantly affect capital flows to local retail mutual funds. This finding suggests that mutual fund clients are more likely to invest in local funds, and therefore, their income shocks are transmitted to the local funds' flows.[3] Next, I show that, consistent with the predictions of a portfolio optimization model, fund managers hedge local income shocks by tilting their portfolios away from high local income beta stocks. Furthermore, after a period of poor performance,

[1]Mutual fund managers might have reasons other than flow hedging to care about household income risk. For example, fund managers might want to cater to their clients' income-hedging demands. Although I provide supportive evidence for the flow-hedging motive, I do not rule out other possible explanations.

[2]Ideally, one needs data on individual funds' clients and their income risk to study this question. Since these data are not readily available, I use state-level local income shocks as a convenience laboratory to explore this question.

[3]I do not claim causality between income shocks and fund flows; however, a correlation between these two is enough for the rest of the paper's results.

when fund flows are expected to be more sensitive to income shocks, fund managers change their portfolio tilts to hedge income shocks more strongly, and vice versa. This finding shows that flow hedging is one of the primary reasons why mutual fund managers care about household income shocks. Finally, I show that a strong trade-off exists between income hedging and local bias. Coval and Moskowitz (2001) show that mutual fund managers have an informational advantage with respect to their local stocks. However, considering this informational advantage, mutual fund managers' investment in local stocks is surprisingly small. Compared to the returns of non-local stocks, I show that those of local stocks are significantly more correlated with local income shocks, thereby making local stocks riskier from a flow-hedging perspective. This trade-off can help explain why mutual fund managers do not devote a greater fraction of their portfolios to local stocks.

The importance of these findings is twofold. First, from a household finance point of view, this paper shows that investing in local mutual funds is likely to increase household welfare. Households' incentive to hedge their income risk is aligned with mutual fund managers' incentive to hedge their own flow risk. Second, from a demand system asset pricing perspective, this paper shows that hedging clients' income risk can help explain mutual fund managers' demand for assets. Moreover, it confirms previous findings that flow hedging should be one of the core ingredients of any model that explains the portfolio decisions of mutual fund managers (e.g., Dou, Kogan, and Wu, 2022).

I begin the analysis by providing novel evidence that state-level local income shocks affect capital flows to retail mutual funds. Panel regression results show that mutual funds located in a state with a 1-percent higher quarterly income growth have, on average, a net flow of capital that is 0.32 percent higher compared to the funds in other states during the current quarter and next one. This evidence suggests that at least some mutual fund clients are likely to have a local bias in their asset allocation to mutual funds. Furthermore, the impact of income shocks on fund flows is considerably larger for small and young mutual funds, consistent with the intuition that these funds are more likely to have local clients. These findings are robust to using different proxies for income shocks, excluding states with a disproportionately high number of retail mutual funds from the sample and focusing on different sample subperiods.

Based on the empirical results regarding the flow-income relationship, I construct a stylized model to illustrate the portfolio optimization problem of mutual fund managers who care about their own welfare. The model assumes that mutual fund clients have a local bias in their asset allocation and takes the flow-income relationship as given. Overlapping generations of fund managers maximize their lifetime utility, and their management fee is a linear function of their AUM. The model shows that the optimal portfolio hedges the impact of income shocks on fund flows by tilting away from assets with high local income betas. The model also predicts that the magnitude of this income-hedging component increases with the flow-income sensitivity.

Next, using the portfolio holdings of retail mutual funds, I provide novel evidence of hedging state-level local income shocks. I estimate state-level local income betas at the industry level and find that mutual fund managers tilt their portfolios away from industries with high local income betas. These results are robust to different industry classifications, the exclusion of any single state or industry from the sample, and using different time horizons to estimate betas.

I focus on industry groups to test income hedging for two reasons. The first is a practical one: since the types of shocks that affect state-level income are more likely to affect stock returns at the industry level, I use industry groups to reduce the effect of stock-level idiosyncratic noise. The second reason is that previous studies find that industry selection plays an important role in explaining the performance of active mutual funds. For example, Kacperczyk, Sialm, and Zheng (2005) provide evidence of industry-level skills in mutual funds. Also, Busse and Tong (2012) show that industry selection accounts for one-third of mutual funds' performance.

One potential concern regarding these results might stem from the relation between income hedging and local bias. As I show, local stocks have significantly higher local income betas. On the other hand, the data show that the median local bias among all mutual funds is slightly negative. To ensure that the results are not driven only by mutual fund managers avoiding their local stocks, in a robustness check, I calculate the mutual funds' portfolio tilts within the set of non-local stocks. I find that even within the universe of each mutual fund's non-local stocks, mutual fund portfolios tilt away from industries with higher local income betas.

To uncover mutual fund managers' underlying motives in their hedging of local income shocks, I exploit the variation in the flow-income sensitivity across different mutual funds. If mutual fund managers' incentives to hedge household income shocks stem from their flow-hedging motives, we would expect income hedging to become stronger when fund flows are more sensitive to income shocks. As shown in previous studies (e.g., Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017), strategic complementarities can intensify the impact of fundamental shocks on investors' behaviour. In the case of mutual funds, substantial outflows force them to engage in costly and unprofitable trades that primarily hurt their remaining clients (e.g., Edelen, 1999; Coval and Stafford, 2007). As a result, the expectation that other clients will withdraw their money increases the incentive to withdraw and intensifies the impact of income shocks on fund flows. Based on this reasoning, we would expect mutual funds that expect outflows of capital due to their recent poor performance being more sensitive to income shocks. To test this hypothesis, I group mutual funds based on their recent performance and estimate the flow-income relationship using a semi-parametric kernel regression model. Although the shape of the flow-income relationship is very close to linear, the slope displays a sharp difference based on the funds' most recent performance. The flows of mutual funds with recent low performance, for whom strategic complementarities are more substantial, are significantly more sensitive to local income shocks.

Examining the trades of mutual funds reveals that hedging flow fluctuations is a primary concern for mutual fund managers' decision to hedge local income shocks. Following recent low performance, mutual fund managers tilt their portfolios more in the direction that hedges state-level local income shocks. Also, after recent good performance, fund managers trade in the opposite direction, reducing the magnitude of the income-hedging component in their portfolios.

Finally, this paper provides a new lens to study local bias—overinvestment in geographically proximate assets relative to their market weight—in the portfolio holdings of mutual funds.[4] Coval and Moskowitz (2001) find that the average fund manager generates an additional return of 2.67

[4]Extensive literature in finance shows that different types of investors are locally biased in their asset holdings. For example, Ivković and Weisbenner (2005) analyze brokerage data and find that the average household strongly prefers local stocks. Also, Hau (2001) finds a preference for local stocks in the portfolio holdings of professional traders in different European cities.

percent per year from local investment. However, the magnitude of the local bias is surprisingly small. The data show that the median local bias among all mutual funds is negative, and the average local bias is only moderately positive. Coval and Moskowitz (2001) call this the "local bias puzzle."[5] I show that the returns of local stocks are significantly more correlated with local income shocks. Therefore, a strong trade-off exists between income hedging and local bias.[6] Calibration of the optimal portfolio with the estimated parameters shows that the income-hedging motive can help explain the small magnitude of local bias for mutual funds.

The rest of the paper is organized as follows. Section 2 presents the data sources and describes the summary statistics. Section 3 analyzes the flow-income relationship. Section 4 solves the optimal portfolio problem of mutual funds in a stylized model. Section 5 investigates income hedging in the portfolio holdings of mutual funds. Section 6 shows that income hedging is partly driven by fund managers' incentive to hedge flow shocks. Section 7 discusses the implications of income hedging for local bias in the mutual funds industry. Section 8 concludes.

2 Data

The data in this paper are collected from multiple sources. Stock price data are from the Center for Research in Security Prices (CRSP). Also, mutual funds' monthly returns, total net assets (TNA), characteristics, investment objectives, and addresses are from the CRSP Survivorship-Bias-Free Mutual Fund database. Following previous studies (e.g., Chen, Goldstein, and Jiang, 2010), I rely on the CRSP's reported dummy variable *retail_fund* to identify retail mutual funds. Similar to previous studies (e.g., Kacperczyk, Sialm, and Zheng, 2008; Huang, Sialm, and Zhang, 2011), I filter actively managed U.S. equity mutual funds based on their investment objectives, asset composition, and fund name. Appendix A explains the details of the sample selection. I also obtain firms' headquarters addresses from COMPUSTAT and use Google Maps services to

[5] According to Coval and Moskowitz (2001): "Given the local performance findings, it remains a puzzle as to why fund managers do not devote a greater fraction of their assets toward local stocks."

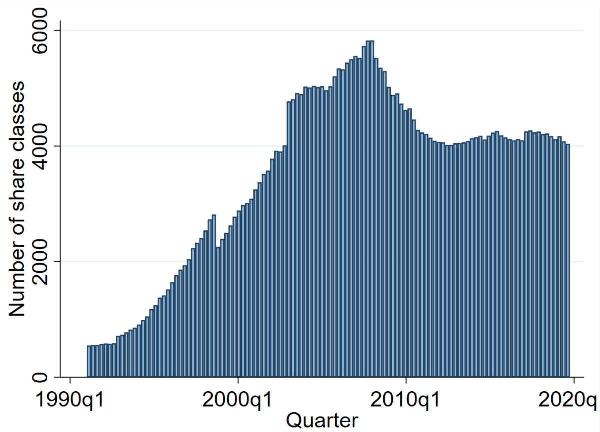
[6] The trade-off between income hedging and local bias has previously been studied in the literature. Massa and Simonov (2006) examine the portfolio holdings of Swedish households and find that they do not hedge their income risk but rather invest in assets that are closely related to their non-financial income. They explain this finding via investor familiarity, including through geographical proximity.

translate addresses to geographical coordinates.

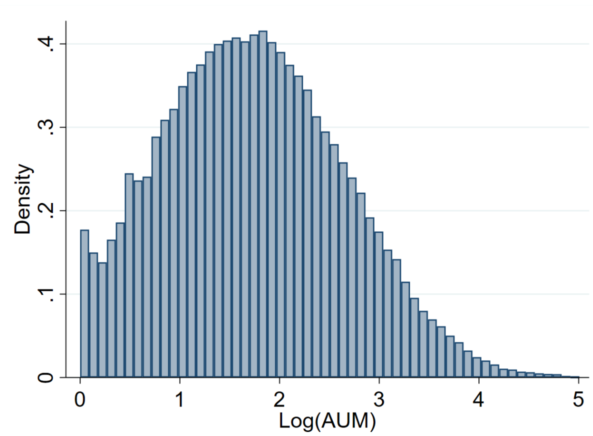
The portfolio holdings of mutual funds are collected from the Thomson Reuters mutual fund holdings data (S12) and CRSP mutual fund holdings data. To reduce data quality problems, and consistent with the recommendations of previous studies (e.g., Shive and Yun, 2013; Zhu, 2020), I use Thomson's portfolio holdings data until the second quarter of 2008 and CRSP portfolio holdings data after that.

State-level quarterly personal income and the Gross State Product (GSP) are from the Bureau of Economic Analysis (BEA). According to the BEA's data guide, personal income includes labor income in the form of wages and salaries, as well as income from owning a home or business, ownership of financial assets, and government transfers. It includes both domestic and international sources of income. However, it does not include realized or unrealized capital gains or losses. State-level personal income includes the income received by all residents in a state and adjusts for interstate commuters who work in a state different from their state of residence. In contrast to personal income, GSP does not include income from financial assets and is the state equivalent of the Gross Domestic Product (GDP) for the nation. The state-level quarterly unemployment rate is from the Bureau of Labor Statistics (BLS).

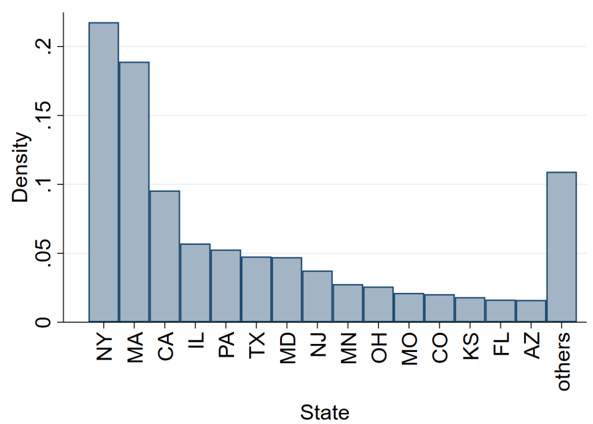
There are two reasons why I look at states as my geographical units. First, quarterly personal income, as my direct measure of income fluctuation, is reported only at the state level. The unemployment rate is reported monthly and with more geographical granularity. In unreported robustness checks, I define income shocks based on the unemployment rate volatility in all counties within 100km of a mutual fund's main office and find similar results. The second reason for using states as opposed to, for example, a constant radius around a mutual fund's office is that, depending on the location of the fund, a constant distance can have very different meanings. For example, a 100km distance from a mutual fund in New York City includes three states with a population of approximately 50 million. The same distance for a mutual fund in Arizona or Texas encompasses a much smaller population. To make a reasonable comparison, one needs to change the distance around the fund based on its location.



(a) Number of retail share classes in each quarter



(b) Distribution of the logarithm of AUM



(c) Distribution of observations in different states

Figure 1: Data Description

Panel (a) shows the number of share classes that are identified as belonging to the active retail equity mutual funds in each quarter. Details of the sample selection are explained in Appendix A. Panel (b) shows the distribution of the logarithm of Assets Under Management (AUM) among all observations. Zero corresponds to $1 million, and one corresponds to $10 million, etc. Panel (c) shows the distribution of observations across different states.

2.1 Summary of statistics

One mutual fund usually offers multiple share classes with different fees and minimum investment requirements to cater to different types of investors. Since these differences can affect household incentives to invest or withdraw, I focus on share classes to examine the impact of income shocks on the funds' flows. I limit the sample period from the first quarter of 1991 to the last quarter of

2019. I can identify very few retail share classes before 1991. The number of share classes ranges from almost 500 at the beginning of the sample to a maximum of close to 6,000 share classes before the 2008 financial crisis. Figure 1a shows the number of share classes identified as belonging to active retail equity mutual funds. Details of the sample selection are explained in Appendix A.

Figure 1b illustrates the distribution of the logarithm of assets under management (AUM) among the observations. Share classes with less than \$1 million AUM are excluded from the sample. The logarithm of AUM for the median share class is 1.70, corresponding to \$50.1 million. Also, the 90th percentile of the logarithm of AUM is 2.95, corresponding to \$891 million AUM.

The distribution of observations among different states is shown in Figure 1c. New York and Massachusetts are well known for having a high concentration of financial institutions. The graph shows that almost 40% of all observations belong to the share classes registered in these two states. The populous states of California, Illinois, Pennsylvania, and Texas follow these two states. To ensure that the results are not driven by the disproportionately high number of observations in a few states, I exclude New York and Massachusetts in the robustness checks.

Table 1 reports a summary of the main variable statistics. The sample includes 408,446 fund-quarter observations from 1991 until the end of 2019. Quarterly fund flows have a mean of 1.7 percent and a standard deviation of 17.9 percent. The average quarterly fund return is 1.9 percent. The average age in the sample is 10.8 years.

3 Income Shocks and Funds' Flow Fluctuations

In this section, I study the impact of state-level income shocks on the flows of retail mutual funds. Following prior literature (e.g., Lou, 2012), I construct quarterly fund flows as the increase in total net assets (TNA) not due to the fund's return or fund mergers $MGN_{f,t}$:[7]

$$flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} * (1 + ret_{f,t}) - MGN_{f,t}}{TNA_{f,t-1}} \tag{1}$$

[7]Throughout the paper, I use index f to refer to funds, i to refer to assets (industry groups), s to refer to states, and t to refer to periods of time.

Table 1: Summary statistics

	Number of Obs.	Mean	S.D.	Median	1st percentile	99th percentile
flow	408446	1.674	17.885	-1.551	-35.826	84.337
return	408446	1.927	9.869	2.732	-27.250	26.183
ΔAUM	408446	3.576	21.730	1.549	-43.609	94.118
size	408446	1.744	0.903	1.706	0.041	3.927
age	408446	10.809	10.240	8.000	1.250	57.750
income growth	408446	1.060	1.178	1.135	-2.875	4.391
ΔUnemployment	408234	-0.011	0.302	-0.067	-0.500	1.167
gsp growth	268154	0.933	1.105	1.028	-2.485	3.967

This table reports a summary of the main variables' statistics. Data is quarterly from 1991 until the end of 2019. Quarterly flow, return and change in Assets Under Management (AUM) are reported as a percent. Size is defined as the logarithm of the AUM. Age is in years, and observations less than one year are excluded. Summary statistics of quarterly state-level personal income growth and change in quarterly state-level unemployment rate associated with the fund observations are also reported. The time series of Gross State Product (GSP) starts from 2005, so the number of observations is lower.

Next, I construct a regression model to estimate the effect of state-level income shocks on the flows of retail mutual funds. Fund flows are highly persistent and strongly predictable by performance; therefore, I include four lags of fund flows and four lags of fund returns as control variables. I also control for the same period return, as it might be correlated with local income shocks and can explain fund flows. Specifically, I conduct the following regression:

$$\begin{aligned} flow_{f,t} =& \mu_t + \sum_{j=1}^{4} \alpha_j flow_{f,t-j} + \sum_{j=0}^{4} \beta_j ret_{f,t-j} \\ &+ \delta_0 size_{f,t-1} + \delta_1 age_{f,t} + \beta_0 g_{s,t} + \beta_1 g_{s,t-1} + error \end{aligned} \tag{2}$$

where $flow_{f,t}$ is the flow of fund f at time t. Other controls include the mutual fund size, defined as the logarithm of the assets under management, and the age of the fund. All of the regressions include time fixed effect. In robustness checks, I run the same regression with fund fixed effects as well.

The variable of interest is the state-level income shocks $g_{s,t}$ in the state where each mutual fund's main office is located. I use the growth rate of state-level personal income as the main variable to represent household income shocks. Quarterly income growth is highly unpredictable; therefore, it is reasonable to assume that raw income growth represents income shocks. Nevertheless, in robustness checks, I also predict the growth rate of personal income, $g_{s,t}$, by a VAR model and use the residuals as income shocks.

There are at least two reasons why income shocks might also affect fund flows with a lag. First, if income shocks happen toward the end of the quarter and fund clients respond to the shocks with some delay, we expect that the effect of the shocks will extend to the next period. Second, national accounts are based on accrual accounting, which means that shocks that happened and are recorded in one quarter might have an actual cash flow effect in the next quarter.[8] Because of these two reasons, I also include a lag of income growth in all my regressions. When interpreting the results, I calculate the sum of the two coefficients as the total effect of income shocks on the fund flows.

Table 2 reports the regression results. Column 1 shows that mutual funds located in a state with a 1-percent higher income growth have, on average, a 0.162-percent higher inflow of capital in that quarter and a 0.164-percent higher inflow in the next quarter, giving a total of 0.326 percent. The regression includes time fixed effects to absorb the aggregate shocks affecting all mutual funds across the United States. The fact that fund flows respond to local income shocks suggests that at least some mutual fund clients have a local bias in their asset allocation to mutual funds. Therefore, their income shocks are transmitted to local mutual funds. Although this finding is intuitive, it has not been previously documented in the literature.

There are multiple channels through which shocks can affect both state-level income and local fund flows; this paper does not emphasise any particular channel. Although shocks might have a pure income effect, there might also be a wealth or human capital effect. In this sense, these results only show a correlation between income shocks and flow fluctuations.

The rest of the table shows some robustness checks. Column 2 shows that the results are robust

[8] When firms make sales or purchases based on credit, each quarter they pay and receive the cash flows related to the transactions in previous quarters.

in the more conservative regression that also controls for the fund fixed effect. Column 3 adds the interaction of income growth with the size and age of the mutual fund. The results demonstrate that income shocks have a much stronger effect on small and young mutual funds. The total effect of a 1-percent income shock on the flows of mutual funds with zero size (i.e., 1 million dollars AUM) and zero age (i.e., newborn funds) is 0.682 percent. This evidence is consistent with small and young mutual funds being more likely to have local clients. In contrast, older mutual funds with a large amount of AUM are more likely to have clients dispersed in several states. Column 4 shows that this last result is also robust to the inclusion of fund fixed effect. As described in the summary statistics, many of the mutual funds are located in the two states of New York and Massachusetts. Column 5 shows that the results are robust to excluding mutual funds in these two states from the sample. Columns 6 and 7 report the regression results for the sample before and after the first quarter of 2008. I choose 2008 because it marks the midpoint of the sample with an equal number of observations beforehand and afterward. The results are mostly the same, although the magnitude is slightly smaller in the more recent sample.

In columns 8 to 10, I use other proxies for the income shocks. Column 8 reports the regression results that proxy for income shocks with the growth rate of the quarterly gross state product. Even though the quarterly gross state product time series start from 2005 and almost half of the sample is lost, I find similar results. In column 9, I use the quarterly change in the state-level unemployment rate. The results show that small and young mutual funds located in a state with a 1-percent jump in its quarterly unemployment rate have, on average, a 1.36-percent outflow of capital. Again, this effect becomes smaller with the fund size and age. Finally, in column 10, I use residuals from a pooled VAR model that predict the growth rate of personal income. The VAR model includes two lags of the state's income growth and two lags of the aggregate United States income growth. I find that the VAR regression has a very low R-squared, meaning that income growth is mainly unpredictable, and using a VAR model is more likely to introduce noise to the data. Despite this fact, the regression results show similar results.

Table 2: Fund flows and local income shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample	All obs.	All obs.	All obs.	All obs.	Ex NY & MA	Pre-2008	Post-2008	All obs.	All obs.	All obs.
$g_{s,t}$	**0.162*****	**0.105****	**0.439*****	**0.352*****	**0.377*****	**0.550*****	**0.233****	**0.226****	**-1.361****	**0.407*****
	(3.100)	(2.145)	(4.707)	(4.077)	(3.493)	(3.147)	(2.112)	(2.180)	(-2.268)	(4.241)
$g_{s,t-1}$	**0.164*****	**0.133****	**0.243*****	**0.214****	**0.369*****	**0.300***	0.060	**0.229****	0.159	**0.248****
	(2.933)	(2.402)	(2.575)	(2.407)	(3.480)	(1.896)	(0.508)	(2.004)	(0.256)	(2.512)
$g_{s,t} \times size_{f,t-1}$			**-0.121*****	**-0.079***	**-0.106****	**-0.165***	-0.034	-0.010	0.381	**-0.103****
			(-2.871)	(-1.916)	(-2.020)	(-1.837)	(-0.787)	(-0.207)	(1.411)	(-2.408)
$g_{s,t} \times age_{f,t-1}$			**-0.002*****	**-0.003*****	**-0.003*****	**-0.003*****	-0.000	-0.002	**0.012*****	**-0.002*****
			(-2.583)	(-3.749)	(-3.701)	(-2.824)	(-0.450)	(-1.578)	(3.113)	(-2.569)
Time fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fund fixed effect	NO	YES	NO	YES	NO	NO	NO	NO	NO	NO
No. obs.	401,846	401,386	401,846	401,386	237,887	196,075	205,771	260,024	401,638	401,846
Adj. R-squared	0.231	0.280	0.231	0.280	0.258	0.271	0.159	0.186	0.231	0.231

This table reports the results of the regression of fund flows on state-level local income shocks (Equation (2)). Controls include four lags of the flow, four lags of the return and same period return, fund size defined as the logarithm of the TNA, and fund age. The variable of interest is state-level quarterly income shocks $g_{s,t}$ in the state of each mutual funds' main office and its lag $g_{s,t-1}$. I use different proxies for income shocks. Columns (1) to (7) use the raw growth rate in state-level quarterly personal income. Column (8) proxies income shocks by the quarterly Gross State Product growth rate. Column (9) uses the change in the quarterly state-level unemployment rate. Column (10) uses the residual from a VAR model that predicts quarterly income growth. Columns (3) to (10) also include the interaction of income shock with fund size and age. t-stats are reported in parantheses. All standard errors are clustered by state $\times$ quarter.

4 The Model

I model delegated investment management in a discrete-time model with overlapping generations of fund managers. The exchange economy includes multiple risky assets and one riskless asset. I assume that some mutual fund clients have a local bias in their asset allocation, and therefore, I take the flow-income relationship estimated in the previous section as given.[9] Following Dou, Kogan, and Wu (2022) and consistent with the findings of Ibert et al. (2018), I assume that fund managers' pay is a fixed fraction f of the fund's AUM. [10] Overlapping generations of fund managers live for two periods. In each period, all of the AUM in each state, denoted by Q_t, is equally divided among young and old mutual funds. Young and old fund managers collect a compensation of $\frac{1}{2}fQ_t$. Also, following previous literature (for example Berk and Green, 2004; Kaniel and Kondor, 2013), I assume that fund managers must consume their compensation in each period. Fund managers have Constant Relative Risk Aversion (CRRA) utility functions with parameter γ.

Young fund managers solve the following two-period optimization problem:

$$\max_{\phi_t} \frac{Q_t^{1-\gamma}}{1-\gamma} + E_t\left[\frac{Q_{t+1}^{1-\gamma}}{1-\gamma}\right] \tag{3}$$

subject to:

$$Q_{t+1} = Q_t(1 + R_{p,t+1}) + F_{t+1} \tag{4}$$

$$R_{p,t+1} = R_{f,t+1} + \boldsymbol{\phi}_t'\mathbf{R}^e_{t+1} \tag{5}$$

where $R_{p,t+1}$ is the portfolio return of the fund, $\boldsymbol{\phi}_t$ is the vector of the portfolio weights, $\mathbf{R}^e_{t+1}$ is the vector of the risky asset excess returns at time $t+1$, and F_{t+1} is the dollar amount of new capital that flows to the fund. There is new literature in empirical asset pricing that analyzes fund flows to infer how mutual fund clients evaluate fund manager performance. Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) use different methods to show that mutual fund

[9]The income-flow relationship could be micro-founded, assuming that mutual funds have some monopoly power due to geographical proximity to their clients.

[10]Ibert et al. (2018) provide evidence that fund managers' pay concavely depends on the mutual funds' assets under management. Although I assume a linear pay model for simplicity, all of the conclusions are robust to alternative pay schemes that are increasing in fund size.

investors are most likely using the Capital Asset Pricing Model (CAPM) to assess fund managers' skills. Consistent with these findings, I assume that the fund flow rate $f_{t+1} = log\left(1 + \frac{F_{t+1}}{Q_t}\right)$ is a linear function of unexpected performance and income shocks:[11]

$$f_{t+1} = \theta_0 + \theta_r(r_{p,t+1} - E_t[r_{p,t+1}]) + \theta_y y_{t+1} + \varepsilon_{t+1} \tag{6}$$

where θ_0 is a constant, $r_{p,t+1} = log(1 + R_{p,t+1})$ is the logarithm of the portfolio return, y_{t+1} is the income shock, ε_{t+1} is the unexplained residuals orthogonal to the portfolio return and income shock, and θ_r and θ_y measure the sensitivity of flows to the performance and income shock, respectively.

Proposition 1. *The optimal mutual fund's portfolio is:*

$$\boldsymbol{\phi}_t^* = \kappa\left(\Sigma_t^{-1}\boldsymbol{\mu}_t - \psi\theta_y\Sigma_t^{-1}\mathbf{B}_t\right) \tag{7}$$

where Σ_t is the covariance matrix of risky asset returns, $\boldsymbol{\mu}_t$ is the vector of expected asset returns, $\mathbf{B}_t = Cov_t(\mathbf{r}_{t+1}, y_{t+1})$ is the covariance vector of asset returns with income shocks, and ψ and κ are parameters defined in Appendix B.

All proofs are presented in Appendix B. Proposition 1 shows that the optimal portfolio has two components. First, there is the standard mean-variance optimal portfolio $\Sigma_t^{-1}\boldsymbol{\mu}_t$. Second, there is an extra component to hedge the effect of income shocks on the fund's flow $\Sigma_t^{-1}\mathbf{B}_t$. The income-hedging component tilts the optimal portfolio away from assets that are positively correlated with local income shocks. Importantly, the magnitude of income hedging is directly related to the sensitivity of the flow-income relationship, θ_y. The magnitude of income hedging is also determined

[11] I am also assuming that fund managers use the same model of risk as their clients to estimate expected asset returns. The literature shows that even for sophisticated market agents, the CAPM is the best model to explain their behavior. For example, Agarwal, Green, and Ren (2018) find that hedge fund investors are likely to use the CAPM. Also, Cho and Salarkia (2021) analyze firms' market timing decisions and find that the CAPM is the closest risk model to that of firm managers. Nevertheless, the results are not dependent on this simplifying assumption.

by the parameter ψ. Appendix B shows that:

$$\psi = \frac{1 + (1 - \theta_0 + \theta_r)(\gamma - 1)}{1 - \theta_0} \tag{8}$$

A mutual fund's portfolio return not only directly affects the AUM but also indirectly affects through the fund's flow. Therefore, the magnitude of the income-hedging component, ψ, also depends on the sensitivity of the funds' flows to the performance, θ_r. Parameter κ, which also depends on the coefficient of the relative risk aversion, determines the total combination of the risky assets with the riskless asset. However, even though risk aversion scales back the demand for risky assets, fund managers should hold a riskless asset in combination with the above optimal portfolio of risky assets.

Testing Proposition 1 is empirically problematic because it requires estimating the inverse of covariance matrix Σ^{-1}. When there are many risky assets and a limited sample, estimates of the covariance matrix are close to singular, and the inverse matrix does not exist. The following proposition proves that the portfolio tilts of active mutual funds relative to the mean-variance benchmark are, on average, higher when the covariance of the asset return with local income shocks is higher.

Proposition 2. *Define $\boldsymbol{\phi}^{tilt}$ as the optimal portfolio tilt of fund managers relative to the mean-variance benchmark:*

$$\boldsymbol{\phi}^{tilt} = -\psi\theta_y\Sigma_t^{-1}\mathbf{B}_t \tag{9}$$

The cross-sectional covariance of portfolio tilts and vector of the covariance of asset returns and income risk are negative:

$$Cov(\boldsymbol{\phi}_{tilt}, \mathbf{B}) < 0 \tag{10}$$

Proposition 2 has a straightforward intuition. Portfolio tilts are proportional to the projection of vector $\mathbf{B}$ on the space of Σ^{-1}. The projection vector $\boldsymbol{\phi}^{tilt}$ is larger in any dimension in which the original vector $\mathbf{B}$ is larger in that dimension. Although I mainly use Equation (10) to test income hedging by mutual funds, in robustness checks, I also estimate the inverse matrix of the covariance of asset returns Σ^{-1} by assuming a factor structure for returns.

5 Income Hedging in the Portfolio of Mutual Funds

In this section, I formally test income hedging in the portfolio holdings of retail mutual funds. First, income shocks are decomposed into a common component that co-moves with the shocks that affect all U.S. states and an idiosyncratic state-level component. Specifically, I regress the growth rate of state-level personal income on the growth rate of aggregate U.S. personal income using rolling regressions:

$$g_{s,t-\tau} = \delta_0 + \delta_1 g^{US}_{t-\tau} + \varepsilon_{s,t-\tau} \quad \forall\, 0 < \tau < T \tag{11}$$

where $g_{s,t}$ is the growth rate of personal income in state s at time t, g^{US}_t is the growth rate of aggregate personal income in the United States, δ_0 and δ_1 are estimated parameters, and $\varepsilon_{s,t}$ is the residual income shocks.

Next, for every asset, I run the following regression to estimate local income betas, i.e., covariance of the asset's excess return with the idiosyncratic state-level income shocks:

$$r_{i,t-\tau} = \beta_0 + \beta^{state}_{s,i,t}\varepsilon^{state}_{s,t-\tau} + \beta^{US}_{s,i,t} g^{US}_{t-\tau} + \beta^{mkt}_{s,i,t} r^{mkt}_{t-\tau} + error \quad \forall\, 0 < \tau < T \tag{12}$$

This regression includes the growth rate of aggregate personal income in the United States and the market excess return as controls. The parameter of interest is $\beta^{state}_{s,i,t}$, which measures how much asset i co-moves with the idiosyncratic income shocks of state s using the past T quarters of data until time t.

Consistent with the theory, portfolio tilts are defined as the difference of the portfolio weights from the optimal mean-variance benchmark. Following previous studies (e.g. Dou, Kogan, and Wu, 2022), I proxy the optimal mean-variance benchmark with market weights and define portfolio tilts as the difference between an asset's weight in a mutual fund's portfolio from that asset's market weight:

$$W^{tilt}_{f,i,t} = W_{f,i,t} - W^{mkt}_{i,t} \tag{13}$$

where $W_{f,i,t}$ is the weight of asset i in the portfolio of fund f at time t, and $W^{mkt}_{i,t}$ is the market weight of the asset at that time. Finally, Proposition 2 is formally tested by running the following regression:

$$W_{f,i,t}^{tilt} = \nu_{f,t} + \gamma_1 \beta_{s,i,t-1}^{state} + \gamma_2 \beta_{s,i,t-1}^{US} + \gamma_3 \beta_{s,i,t-1}^{mkt} + error \tag{14}$$

The parameter of interest is γ_1, which measures the average cross-sectional covariance of state-level local income betas with portfolio tilts. Based on Equation (10), γ_1 should be negative, meaning that retail mutual funds tilt their portfolios away from assets that co-move with local income shocks. To ensure that the regression does not suffer from a look-ahead bias, I employ estimated betas using the data up to time $t-1$ to explain portfolio tilts at time t.

I estimate income-hedging betas, Equation (12), at the industry level. With limited quarterly data, estimating betas at the stock level will be very noisy. In particular, estimated betas for small stocks with high volatility will be unreliable. Since the type of shocks that affect state-level income are likely to affect stock returns at the industry level, estimating betas at the industry level helps reduce idiosyncratic noise. Moreover, previous studies (e.g., Kacperczyk, Sialm, and Zheng, 2005; Busse and Tong, 2012) find that industry selection plays an important role in explaining the performance of active mutual funds. In my main regression analysis, I use 49 Fama and French industry groups and the rolling windows of 40 quarters to estimate the regressions. However, I show that the results are robust to alternative industry classifications and estimation windows.

Figure 2 shows a heat map of state-level local income betas. Estimated betas are standardized within each state. For a better illustration, I use a broader definition of 12 Fama and French industry groups, and the estimation window is the last 20 years. The figure shows estimated betas for the seven states with the highest number of mutual fund observations (Figure 1c). The figure shows that income-hedging betas are consistent with the industry concentration in different states. Energy sector stocks are more positively correlated with the idiosyncratic income shocks of the energy-producing states of Texas and Pennsylvania, while they are hedging the idiosyncratic income shocks of New York, California, and Massachusetts. In contrast, financial sector stocks are positively correlated with the income shocks of the financial hubs, i.e., New York, Massachusetts, California, and Illinois, while they are moderately hedging the income risk of Texas and Pennsylvania.

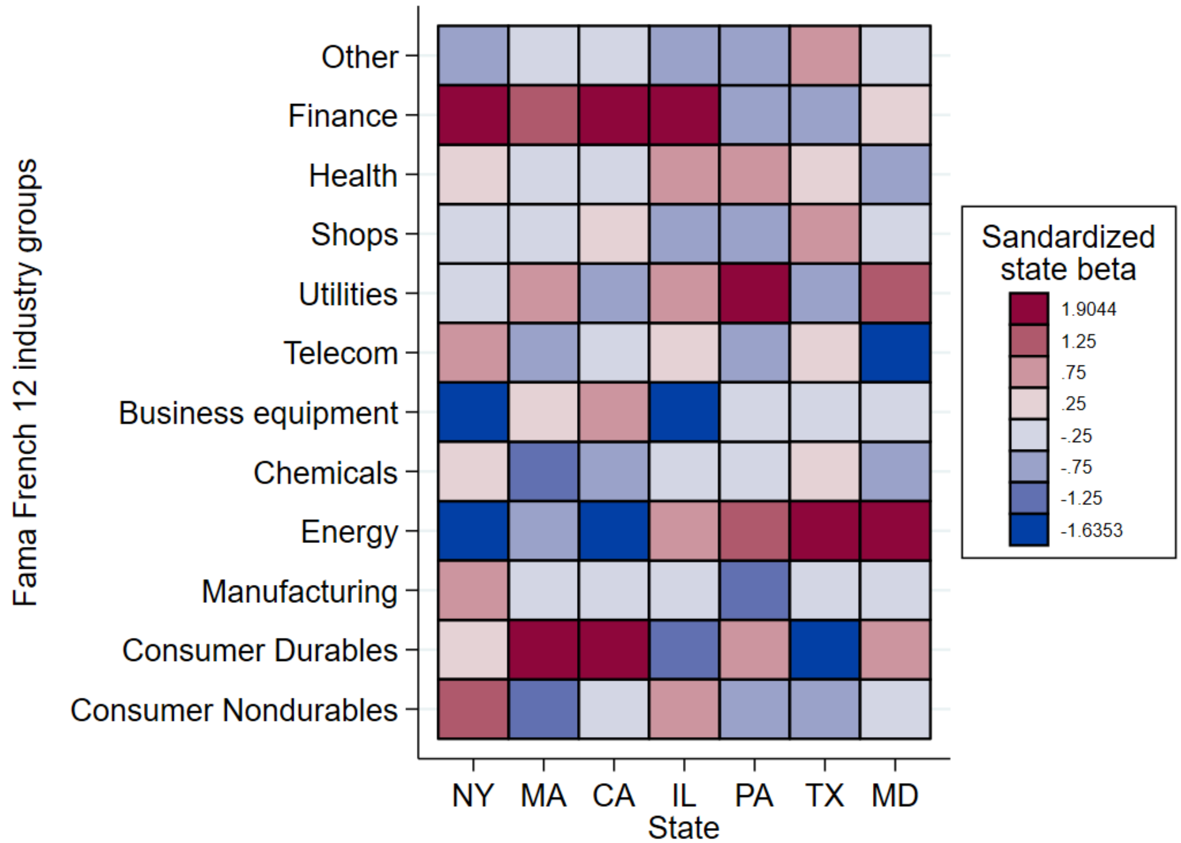


Figure 2: State-level local income betas

This figure shows standardized state-level local income betas (Equation (12)) for different pairs of state and industry. Stocks are categorized into 12 groups, and the estimation period is from 2000 to 2019. The figure only shows 7 states with the highest number of mutual funds (Figure 1a).

Table 3 reports the estimation results of Equation (14). All of the betas and portfolio tilts are standardized within each fund-quarter. In the baseline estimation model, stocks are categorized into 49 Fama-French groups, and betas are estimated using the rolling windows of 40 quarters. Column 1 shows the negative relationship between state-level local income betas and portfolio tilts, as the theory predicts (Equation (10)). A one standard deviation increase in the covariance of the asset's return with the state-level income shocks reduces the portfolio tilt by 0.011 standard deviations. The results also show that mutual funds tilt their portfolio away from industries that are more positively correlated with fluctuations in the aggregate U.S. personal income and tilt toward assets with a high market beta. All standard errors are calculated by three-way bootstrapping across time, industries, and funds. Appendix C explains the details of the bootstrapping procedure. The results reported in columns 2 and 3 show that this result is robust to alternative industry classifications. Column 2 uses a broader industry classification by Fama and French that groups stocks into 38 groups. Column 3 uses two-digit standard industry classification (SIC) codes to group stocks into 77 different groups. Also, columns 4 and 5 show that the results are robust to using alternative rolling window lengths of 30 or 60 quarters.

One potential concern regarding these results is their connection to local bias. As I show in Section 7, local stocks are more likely to co-move with local income shocks. On the other hand, the median mutual fund has a negative local bias, i.e., tilts away from local stocks.[12] To ensure that my findings are not merely a repackaging of the previous findings about local bias, in a robustness check, I limit the sample to the non-local stocks for each mutual fund. In particular, I exclude all local stocks from the investment universe of each mutual fund and look at portfolio tilts within the set of non-local stocks. Portfolio tilts measured in this way are independent of the degree of local bias. Column 6 of Table 3 shows the same results within the set of non-local stocks, although the magnitude is slightly smaller, as expected.

A second potential concern might be that the correlation between asset returns and local income shocks (i.e., local income betas) could be a consequence of mutual fund managers' portfolio choices. However, careful consideration of this argument shows that this channel would lead to opposite conclusions. Imagine that a fund manager, for whatever reason, prefers to hold more assets from one industry. Following a positive income shock, the fund has, on average, an inflow of capital, putting demand pressure on the assets it holds and pushing up their prices. Therefore, one would expect the returns of assets held by mutual funds to co-move more positively with the fund's state-level local income shocks. Nevertheless, I provide evidence that the opposite is true: mutual fund managers hold fewer assets that co-move with local income shocks.

[12] This is consistent with the findings of Coval and Moskowitz (2001), who show that the median mutual fund has a negative local bias. However, certain mutual funds have a very high local bias, such that the average local bias is moderately positive.

Proposition 2 proves that we can test the main predictions of the theoretical model without estimating the inverse matrix of the covariance of asset returns. Nevertheless, in a robustness check, I estimate the inverse matrix by assuming a three-factor structure for asset returns. Appendix D explains the details of covariance matrix inversion. Next, I estimate theoretical portfolio tilts by multiplying the inverse covariance matrix of returns with the state-level local income betas $\Sigma^{-1}B$, according to Equation (9). Column 7 of Table 3 shows the estimation results. Finally, columns 8 and 9 of the table show that the sign and magnitude of the regression coefficients remain the same in the pre- and post-2008 periods. Also, in unreported regressions, I find that the results are robust to the exclusion of any single state or industry from the sample.

In the above-mentioned regressions, portfolio tilts are calculated among all industry groups. If a mutual fund chooses not to hold any stocks from a particular industry, this is considered as a negative portfolio tilt toward that industry. Using the Fama and French 49 industry classifications, I find that the median mutual fund holds stocks from only 24 different industry groups; thus, they choose not to invest in 25 industries. Mutual funds' choice of whether to invest in an industry or not is informative about their intentions in general and hedging income risk in particular. However, one might be concerned that the set of industries in which a mutual fund can invest could be dictated through a mandate and conclude that income hedging is not an active choice of fund managers. To address this concern, in unreported robustness checks, I only look at the portfolio tilts within the set of industries with non-zero portfolio weights for each mutual fund. I find that even within the set of industries in which a mutual fund chooses to invest, portfolio tilts are consistent with income- hedging motives.

To estimate the magnitude of portfolio tilts, for every mutual fund and in each quarter, I sort all stocks based on their estimated local income betas into three groups. Table 4 reports the average market weight, average portfolio weight, and average portfolio tilt for each group of stocks. The table shows that the average mutual fund buys 1 percent more from stocks that hedge local income shocks, and 0.8 percent less from stocks that are risky with respect to local income shocks. The difference in the portfolio tilts among the two groups is 1.8 percent and statistically significant.

Table 3: Income hedging in the portfolio of mutual funds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Industry groups	49 FF	38 FF	77 SIC2	49 FF	49 FF	49 FF	49 FF	49 FF	49 FF
Time windows	$T = 40$	$T = 40$	$T = 40$	$T = 30$	$T = 60$	$T = 40$	$T = 40$	$T = 40$	$T = 40$
Sample	All obs.	All obs.	All obs.	All obs.	All obs.	Non-local	All obs.	Pre-2008	Post-2008
$\beta_{s,i,t}^{state}$	**-0.011*****	**-0.013*****	**-0.009*****	**-0.010****	**-0.010*****	**-0.009****		**-0.010***	-0.009
	(-2.971)	(-2.641)	(-2.999)	(-2.510)	(-2.789)	(-2.322)		(-1.944)	(-1.599)
$\beta_{s,i,t}^{US}$	**-0.045*****	**-0.022***	**-0.013***	**-0.041*****	**-0.039*****	**-0.043*****	**-0.045*****	**-0.070*****	-0.018
	(-3.516)	(-1.722)	(-1.670)	(-3.205)	(-2.849)	(-4.083)	(-3.52)	(-5.362)	(-1.046)
$\beta_{s,i,t}^{mkt}$	**0.081*****	**0.088*****	**0.068*****	**0.077*****	**0.080*****	**0.080*****	**0.081*****	**0.088*****	**0.074*****
	(4.175)	(3.454)	(3.692)	(4.835)	(3.935)	(4.274)	(4.12)	(3.588)	(3.720)
$\Sigma^{-1}\beta_{s,i,t}^{state}$							**-0.008****		
							(-2.07)		
Fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. obs.	12,404,252	8,990,932	17,107,727	12,404,252	12,404,252	12,404,252	12,404,252	6,427,673	5,976,579
Adj. R-squared	0.007	0.008	0.005	0.004	0.007	0.006	0.006	0.009	0.005

This table reports the results of the regression of portfolio tilts on state-level local income betas (Equation (14)). Income shocks are decomposed into an aggregate component and a state-level local component (Equation (11)). $\beta_{s,i,t}^{state}$ measures the covariance of industry returns with state-level local income shocks. All betas and portfolio tilts are standardized within each fund-quarter. All regressions include fund $\times$ quarter fixed effects. Columns (1) to (5) report the results of regressions based on different industry classifications and estimation windows to estimate betas. In column (6), the portfolio weights of every mutual fund are rescaled to sum up to 1 within the set of non-local stocks, and portfolio tilts are recalculated within this set. In column (7), hypothetical portfolio tilts are estimated by multiplying the inverse covariance matrix of asset returns (Appendix D) with the vector of betas (Equation (9)). t-stats are reported in parentheses. All standard errors are calculated by three-way bootstrapping, as explained in Appendix C.

Table 4: Magnitude of portfolio tilts

		Market weight	Portfolio weight	Portfolio tilt
Hedge	1	**32.99**	**33.96**	**0.97*****
				(8.61)
	2	**33.10**	**32.91**	**-0.19****
				(-2.53)
Risky	3	**33.91**	**33.13**	**-0.79*****
				(-6.97)
		Hedge - Risky		**1.76*****
				(8.24)

This table reports the magnitude of portfolio tilts for stocks sorted based on state-level local income betas. Every quarter and for each fund, all stocks are sorted based on their local income betas into three groups. This table reports the average market weight, average portfolio weight, and average portfolio tilt for each group of stocks. Standard errors are clustered by fund, and t-stats are reported in parentheses.

6 Income Risk and Flow Hedging

To investigate the underlying motives of fund managers in their hedging of local income shocks, I exploit the variation in the flow-income sensitivity over time and across different mutual funds. First, I show that flow-income sensitivity changes based on the mutual funds' recent performance. Next, I show that, consistent with the predictions of the theoretical model, in expectation of a higher flow to income sensitivity, managers of active funds change their portfolio tilts to hedge income shocks more strongly and vice versa. This reveals that fund managers' incentive to hedge income shocks is partly driven by their flow-hedging motives.

6.1 Flow-income sensitivity

Previous studies (e.g., Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017) show that strategic complementarities play a substantial role in explaining the flows of retail mutual funds. Mutual funds with substantial outflows must engage in costly and unprofitable trades that mainly damage their remaining clients (e.g., Edelen, 1999; Coval and Stafford, 2007). As a result, the expectation that other clients will withdraw their money increases the incentive to withdraw and intensifies the impact of income shocks on the fund flows. Since mutual funds with recent good performance have, on average, an inflow of capital due to their performance, they are less likely to be prone to strategic complementarities among fund clients. However, mutual funds with recent low performance have an expected outflow of capital. Therefore, if a negative income shock hits these mutual funds, they are more likely to sell their assets. This induces other fund clients to withdraw their money to avoid further losses and amplifies the impact of income shocks on the funds' flows. Based on this mechanism, the sensitivity of fund flows to income shocks must decrease in the funds' recent performance.

To test this hypothesis, I follow Chevalier and Ellison (1997) to estimate the flow-income relationship using a semi-parametric kernel regression model. In particular, I group mutual funds in each quarter based on their past three-quarter returns into three groups denoted by k: low, middle, and top-performers. Then, I estimate the following semi-parametric regression model separately for each group of mutual funds:

$$\begin{aligned} flow_{f,t:t+1} = &\sum_{j=1}^{4} \alpha_{k,j} flow_{f,t-j} + \sum_{j=0}^{4} \beta_{k,j} ret_{f,t-j} + \sum_{j=0}^{4} \gamma_{k,j} ret^2_{f,t-j} \\ &+ \delta_{k,0} size_{f,t-1} + \delta_{k,1} age_{f,t} + h_k(g_{s,t}) + error \qquad k = 1, 2, 3 \end{aligned} \tag{15}$$

In this regression, all of the variables are demeaned in the cross-section. Since it was shown in Section 3 that the impact of income shocks on the funds' flows extends over two quarters, the left-hand side variable in this regression, $flow_{f,s,t:t+1}$, is the sum of the flows of fund f in quarter t and $t+1$. The linear part of the equation includes four lags of fund flows, the same period return and four lags of return, as well as their squared terms. Consistent with the findings of Chevalier and Ellison (1997), I include the quadratic terms to capture the convexity in the flow-performance relationship. The impact of income shocks on the fund flows of each group is determined by the non-linear function h_k.

This equation is estimated in two steps. On the right-hand side, $ret_{f,t}$ and $ret^2_{f,t}$ could possibly be correlated with local income shocks. Using Robinson (1988)'s non-parametric method of partialling-out procedure, I perform kernel regression of the left-hand side variable $flow_{f,t:t+1}$, as well as $ret_{f,t}$ and $ret^2_{f,t}$ on $g_{s,t}$. Then, I regress the residuals on residuals and other control variables to obtain a consistent estimate of α's, β's, γ's, and δ's. Having estimated these parameters, I can subtract the linear explanatory part from the fund flows:

$$\begin{aligned}\widehat{flow}_{f,t:t+1} = flow_{f,t:t+1} - \sum_{j=1}^{4} \alpha_{k,j} flow_{f,t-j} - \sum_{j=0}^{4} \beta_{k,j} ret_{f,t-j} \\ - \sum_{j=0}^{4} \gamma_{k,j} ret^2_{f,t-j} - \delta_{k,0} size_{f,t-1} - \delta_{k,1} age_{f,t}\end{aligned} \quad (16)$$

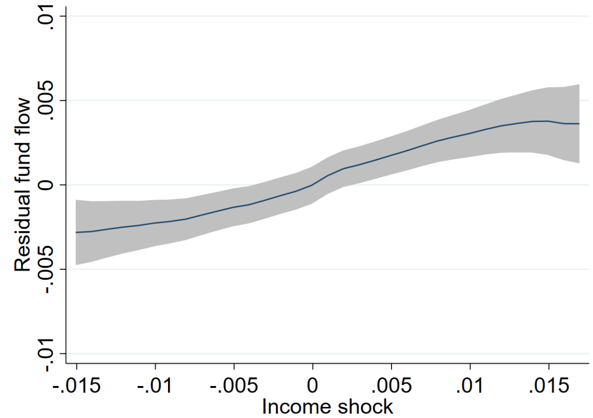
and fit a non-linear relation between the residual flows, $\widehat{flow}_{f,t:t+1}$, and local income shocks, $g_{s,t}$, for each group of funds. In these kernel regressions, I use the Epanechnikov kernel with varying window widths across the income shocks to do more smoothing around the edges.

Figure 3a shows the flow-income relationship for the mutual funds with low performance, along with 90% confidence intervals. The graph is limited to the 2nd and 98th percentile of income shocks since there are few and dispersed observations off these limits. The graph clearly shows the effect of income shocks on the fund flows and shows that the relationship is very close to linear. Figure 3b shows that mid-performers exhibit lower sensitivity of fund flows to income shocks compared to low-performers. There is some negative convexity in the positive income shock region, but it seems small, and the relationship is essentially linear. Finally, Figure 3c shows the flow-income relationship for top-performers, which has only a very moderate positive slope.

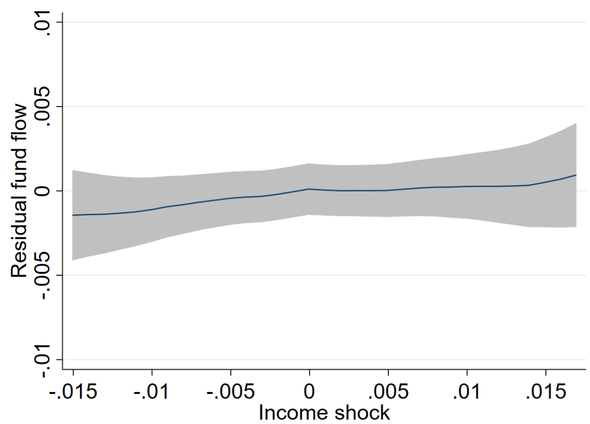
Since fund managers' incentive to hedge income risk, as predicted by the theoretical model, depends on the slope of the flow-income relationship, here I formally test the statistical significance of the difference in the slope of the flow-income relationship for funds with different past performance. In particular, I approximate the functions h_k with linear forms:

$$\widehat{flow}_{f,t:t+1} = \mu_t + \nu_f + (\theta_1 + (\theta_2 - \theta_1)D_2 + (\theta_3 - \theta_1)D_3) \times g_{s,t} + error \quad (17)$$

(a) Low performer funds



(b) Middle performer funds



(c) Top performer funds

Figure 3: Flow-income relationship

This Figure shows the flow-income relationship for mutual funds with different past performances. Each quarter, mutual funds are sorted based on their last three-quarter performance into three groups, and the income-flow relationship is separately estimated for each group.

where D_k is a dummy variable that determines group assignment based on the last three-quarters' performance, μ_t and ν_f capture the time and fund fixed effects, and θ_k is the slope of the flow-income relationship for the mutual funds of group k.

Table 5 reports the results of the estimation of Equation (17). The table shows that the top-performing mutual funds are less sensitive to local income shocks compared to the low-performers, and the difference in the slopes is statistically significant. Column (2) shows that this result is also robust to the inclusion of fund fixed effects.

Table 5: Slope of the flow-income relationship based on recent fund performance

	(1)	(2)
θ_1	**0.671*****	**0.545*****
	(3.842)	(3.454)
$\theta_2 - \theta_1$	-0.232	-0.274
	(-1.277)	(-1.495)
$\theta_3 - \theta_1$	**-0.524****	**-0.548****
	(-2.022)	(-2.144)
Time fixed effect	YES	YES
Fund fixed effect	NO	YES
No. obs.	368628	368201
Adj. R-squared	-0.000	0.075

This table reports the difference in the slope of the flow-income relationship for mutual funds with different past performances (Equation (17)). Mutual funds are grouped based on their last three-quarter returns into $k = 3$ groups. θ_k measures the sensitivity of flows of funds in group k to local income shocks. All standard errors are clustered by state $\times$ quarter.

6.2 Income hedging and mutual fund trades

In this section, I exploit the variation in flow-income sensitivity to investigate if mutual fund managers' income hedging is driven by their flow-hedging motives. Section 6.1 shows that the flow-income relationship is more vital for mutual funds with recent low performance compared to top-performers. Proposition 2 shows that if mutual fund managers' decision to hedge against local income shocks stems from their intention to hedge fund flow fluctuations, income hedging should become larger (smaller) when the flow-income sensitivity is higher (lower). However, if income hedging is only driven by the fund managers' intention to cater to their clients' hedging demands, there is no difference between top versus low performers. To test this hypothesis, I investigate the relation between the active trades of mutual funds and local income betas. In particular, I define portfolio tilt change as:

$$\Delta W^{tilt}_{f,i,t} = W^{tilt}_{f,i,t} - W^{tilt}_{f,i,t-1} \tag{18}$$

Substituting from Equation (13), a change in the portfolio tilts can be written as the change in the portfolio weights minus the change in the market weights:

$$\Delta W_{f,i,t}^{tilt} = \Delta W_{f,i,t} - \Delta W_{f,i,t}^{mkt} \tag{19}$$

I limit the sample to the active trades of mutual funds, i.e., $\Delta W_{f,i,t} \neq 0$, and test whether changes in the portfolio tilts are consistent with income-hedging motives. In particular, I run the following regression for the top- and low-performing mutual funds separately:

$$\Delta W_{f,i,t}^{tilt} = \nu_{f,t} + \gamma_1 \beta_{s,i,t-1}^{state} + \gamma_2 \beta_{s,i,t-1}^{US} + \gamma_3 \beta_{s,i,t-1}^{mkt} + error \tag{20}$$

Similar to the previous section, there is a lag difference between the estimated betas and fund trades to avoid any look-ahead bias. Also, mutual funds are classified based on their three-quarter performance at time $t-1$ into three groups of top, middle, and low performers.

Table 6 presents the results of the regression. Column 1 shows that after a period of poor performance, mutual funds, on average, increase their portfolio tilts toward industries that better hedge against their local income shocks. Column 2 shows the same result within the set of non-local stocks for each mutual fund, meaning that the results are not driven by mutual funds' trading of local stocks. Columns 3 and 4 show that trades of the middle-performing mutual funds, on average, do not have any particular direction with respect to income hedging. In contrast, column 5 shows that, following a period of top performance, mutual funds, on average, trade in a direction to decrease income hedging in their portfolios. Column 6 shows that this result is also robust if we limit the sample to the set of non-local stocks for each mutual fund. In unreported regressions, I find the same sign and magnitude of the regression coefficients using different industry classifications, estimation periods, and limiting the sample to before and after 2008.

7 Income Hedging and Local Bias

There is a vast literature in empirical asset pricing that investigates local bias for different types of investors. Coval and Moskowitz (1999) show that U.S. asset managers show a strong preference

Table 6: Income hedging and mutual funds' trades

	Low performers		Middle performers		Top performers	
	(1)	(2)	(3)	(4)	(5)	(6)
Industry groups	49 FF	49 FF	49 FF	49 FF	49 FF	49 FF
Time windows	$T = 40$	$T = 40$	$T = 40$	$T = 40$	$T = 40$	$T = 40$
Sample	All obs.	Non-local	All obs.	Non-local	All obs.	Non-local
$\beta_{s,i,t}^{state}$	**-0.004****	**-0.004****	-0.000	-0.001	**0.003****	**0.003***
	(-2.42)	(-2.55)	(-0.41)	(-0.75)	(2.30)	(1.84)
$\beta_{s,i,t}^{US}$	0.003	0.002	-0.000	-0.000	0.002	0.002
	(1.50)	(1.38)	(-0.08)	(-0.09)	(0.96)	(0.99)
$\beta_{s,i,t}^{mkt}$	0.000	0.000	**0.004*****	**0.005*****	-0.002	-0.001
	(0.22)	(0.04)	(4.44)	(4.49)	(-1.18)	(-0.89)
Fixed effect	YES	YES	YES	YES	YES	YES
No. obs.	1,594,995	1,594,973	1,808,997	1,808,997	1,632,872	1,632,872
Adj. R-squared	0.000	0.000	0.000	0.000	0.000	0.000

This table reports the results of the regression of change in portfolio tilts on state-level local income betas (Equation (20)) for mutual funds with recent low, middle, or top performance. $\beta_{s,i,t}^{state}$ measures the covariance of industry returns with state-level local income shocks. All betas and portfolio tilts are standardized. All regressions include fund $\times$ quarter fixed effects. Standard errors are clustered at the state $\times$ industry level. For each group of mutual funds, the left-hand side variable in the first column is the total portfolio tilts, whereas in the second column, portfolio tilts are calculated among the set of non-local stocks.

for locally headquartered firms. The average fund manager invests in companies that are 160 to 184 kilometers closer to her than the average stocks she could have held. Coval and Moskowitz (2001) study local bias in the portfolio of mutual funds and find that although median mutual funds' local bias is slightly negative, there are certain mutual funds with strong local bias such that the average mutual fund exhibits a moderate bias toward local stocks. They also show that mutual funds earn substantial abnormal returns in their nearby investments. Hau (2001) studies the portfolio holdings of professional traders in eight different European countries and finds that they earn higher returns in their geographically proximate investments. Ivković and Weisbenner (2005) study local bias in the portfolio holdings of households and find a strong preference for local investments. The average household generates higher risk-adjusted returns in their local investments as well.

All together, the evidence suggests that investors have an informational advantage with respect to their nearby stocks and generate higher abnormal returns in their local investments. Coval and Moskowitz (2001) find that the average mutual fund manager generates an additional 2.67 percent of annual returns on their local investments. If we take an average fund manager, the average quarterly excess return on the manager's local portfolio is 2.08%. The standard deviations of local and distant portfolios are 7.24% and 4.4%, respectively, and the correlation between these two is 0.65. Given these parameters, the optimal mean-variance portfolio places 15.7% on local stocks and 84.3% on the distant portfolio. However, in the data, the median local investment is only 5.0%, and the average local investment is 7.6%. Compared to the average market weight of local stocks, which is 7.1%, this magnitude of local bias is surprisingly small. Coval and Moskowitz (2001) state, "Given the local performance findings, it remains a puzzle as to why fund managers do not devote a greater fraction of their assets toward local stocks".

In this section, I show that local stocks are more positively correlated with local income shocks. Hence, there is a trade-off between income hedging and local bias. To demonstrate this, I split the portfolio holdings of mutual funds into two groups: local stocks that are headquartered in the same state as the mutual fund, and distant stocks that are headquartered elsewhere. Table 7 reports the average local income beta for local and distant portfolios. Column 1 calculates local income betas at the stock level, while column 2 calculates local income betas at the industry level. Both columns show that local portfolios have significantly higher betas compared to distant portfolios.

As a simple "back of the envelope" calculation and consistent with the estimates of Table 2, I take the sensitivity of fund flows to income shocks, θ_y, equal to 0.33, and the sensitivity of fund flows to performance, θ_r, equal to 1. By using Equation (9), I find that with a coefficient of risk aversion $\gamma = 160$, the optimal portfolio, including the income-hedging component, matches with the data. From previous literature on the equity premium puzzle, we know that CRRA utility functions require a very high coefficient of risk aversion to match with the data (e.g., Cochrane, 2009, chap. 1), and other papers in this literature accept these high parameters (e.g., Yogo, 2006).

Table 7: Difference in local income betas between the local and distant portfolio of mutual funds

	Stock level	Industry level
β_L^{state}	**29.4*****	**19.9*****
	(2.95)	(3.32)
β_D^{state}	4.1	0.4
	(1.26)	(0.34)
Difference	**25.3*****	**19.5*****
	(3.18)	(3.33)

This table reports the average local income betas for local and distant stocks of each mutual fund. Local stocks belong to companies headquartered in the same state as the mutual fund, and distant stocks belong to companies headquartered in any other state. Each cell of the table results from a different set of regressions. In column 1, local income betas are estimated at the stock level. In column 2, local income betas are estimated at the industry level, as in previous sections. The results of both columns show that the local portfolio of mutual funds has significantly higher local income betas compared to their distant portfolio.

8 Conclusion

This paper shows that household income risk influences the portfolio decisions of active retail fund managers. I show that state-level local income shocks significantly affect capital flows to local retail mutual funds. As a result, mutual fund managers, whose compensation depends increasingly on their assets under management, are incentivized to hedge local income shocks. Active fund managers hedge local income shocks by tilting their portfolios away from high local income beta stocks. To investigate the underlying motives of fund managers in their hedging of local income shocks, I exploit the variation in the flow-income sensitivity across mutual funds with different recent performances. I find that, in expectation of a higher flow to income sensitivity, managers of active funds change their portfolio tilts to hedge income shocks more strongly, and vice versa. This finding reveals that fund managers' incentive to hedge income shocks is partly driven by their intention to hedge fund flow fluctuations. Finally, I show that a strong trade-off exists between income hedging and local bias. Mutual fund managers potentially have an informational advantage with respect to local stocks. However, local stocks are more positively correlated with local income shocks. This trade-off can help explain why mutual fund managers' investment in local stocks, considering their informational advantage, is surprisingly small.

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A Appendix: Sample Selection

I follow previous studies on mutual funds (e.g., Kacperczyk, Sialm, and Zheng (2008); Dou, Kogan, and Wu (2022)) to filter the set of active equity mutual funds. In particular, I do the following steps to select equity mutual funds:

- I first select funds with the following Lipper objective codes: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT
- If the Lipper objective code is unavailable, I select funds with the following Strategic Insight objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE
- If none of the above is available, I select funds with the following Wiesenberger codes: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM
- Finally, since objective classes do not always correctly identify equity mutual funds, I include fund observations with at least 80 percent invested in common stocks.

Next, following previous studies (e.g., Busse and Tong (2012); Ferson and Lin (2014) I do the following steps to filter out index funds:

- I identify a fund as an index fund if its "index fund flag" in the CRSP data is B, D, or E.
- I also consider a fund as an index fund if its ETF flag is "F" or "N".
- Next, I also identify a fund as an index fund if its name includes any of the following strings: Index, Ind, Idx, Indx, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000, INDEX Passive

In the next step, I select retail mutual funds by using the retail fund flag and institutional fund flag in the CRSP database. These two indexes are not mutually exclusive, so I only select funds that are identified as being retail funds and notinstitutional. Following Kacperczyk, Sialm, and Zheng

(2005), I drop fund observations with less than \$1 million TNA in the previous quarter. I also drop newly born funds that were established less than 1 year ago. This consists of a small fraction of observations. Finally, fund flows and returns are winsorized at 0.5 and 99.5 percent to correct for data errors.

B Appendix: Proofs

Proof of proposition 1. I follow Campbell and Viceira (1999, 2001) to log-linearize the dynamic optimization problem up to the second order. Assuming that random variables are log-normal, the objective function (3) can be rewritten in terms of the logarithm of the TNA $q_{t+1} = log(Q_{t+1})$:

$$E_t\left[\frac{Q_{t+1}^{1-\gamma}}{1-\gamma}\right] = E_t\left[\frac{e^{(1-\gamma)q_{t+1}}}{1-\gamma}\right] = \frac{1}{1-\gamma}e^{(1-\gamma)E_t(q_{t+1})+\frac{(1-\gamma)^2}{2}Var_t(q_{t+1})} \tag{B.1}$$

Taking the logarithm and ignoring the constants, the objective function is:

$$\max_{\phi_t} E_t(q_{t+1}) + \left(\frac{1-\gamma}{2}\right)Var_t(q_{t+1}) \tag{B.2}$$

Next, divide both sides of the budget constraint (4) by Q_t:

$$\frac{Q_{t+1}}{Q_t} = (1+R_{p,t+1}) + \left(1+\frac{F_{t+1}}{Q_t}\right) - 1 \tag{B.3}$$

Define the logarithm of return $r_{p,t+1} = log(1+R_{p,t+1})$ and the rate of fund flows $f_{t+1} = log\left(1+\frac{F_{t+1}}{Q_{t+1}}\right)$:

$$\begin{aligned} q_{t+1} - q_t &= log\left(e^{r_{p,t+1}} + e^{f_{t+1}} - 1\right) \\ &= log(1 + r_{p,t+1} + \frac{1}{2}r_{p,t+1}^2 + f_{t+1} + \frac{1}{2}f_{t+1}^2) \\ &= r_{p,t+1} + f_{t+1} - r_{p,t+1}f_{t+1} \end{aligned} \tag{B.4}$$

Also, we can log-linearize the portfolio return (5) in terms of the holdings' returns up to the second order:

$$r_{p,t+1} = r_{f,t+1} + \phi_t' \mathbf{r}_{t+1}^e + \frac{1}{2}\boldsymbol{\phi}_t'(\mathbf{v}_t - \Sigma_t \boldsymbol{\phi}_t) \tag{B.5}$$

where $\mathbf{r}_{t+1}^e = log\left(\frac{1+\mathbf{R}_{t+1}}{1+R_{f,t+1}}\right)$ is the logarithm of excess returns, $\Sigma_t = Var_t(\mathbf{r}_{t+1}^e)$ is the covariance matrix of asset excess returns, and $\mathbf{v}_t = diag(\Sigma_t)$ is the vector of the diagonal elements of Σ_t. Substitute fund flows as a function of unexpected performance and income shocks from (6), and portfolio returns as a function of asset returns from (B.5) in the linear law of motion of the assets under management (B.4) to get:

$$E_t(q_{t+1}) = const. + (1-\theta_0)\boldsymbol{\phi}_t'\boldsymbol{\mu}_t - (1+2\theta_r-\theta_0)\frac{1}{2}\boldsymbol{\phi}_t'\Sigma_t\boldsymbol{\phi}_t - \theta_y\boldsymbol{\phi}_t'\mathbf{B}_t \tag{B.6}$$

$$Var_t(q_{t+1}) = const. + (1+\theta_r-\theta_0)^2\boldsymbol{\phi}_t'\Sigma\boldsymbol{\phi}_t + 2(1+\theta_r-\theta_0)\boldsymbol{\phi}_t'\mathbf{B}_t \tag{B.7}$$

where $\boldsymbol{\mu}_t = E_t(r_{t+1}^e) + \frac{\mathbf{v}_t}{2}$ is the vector of mean excess returns including the Jensen correction, $\mathbf{B}_t = Cov_t(\mathbf{r}_{t+1}, y_{t+1})$ is the vector of the covariance of asset returns with income shocks, and the constant terms are independent of portfolio choice $\boldsymbol{\phi}_t$. Next, substitute the above two equations in the objective function and take the first-order condition of the optimization problem to get:

$$\boldsymbol{\phi}_t^* = \kappa\left(\Sigma_t^{-1}\boldsymbol{\mu}_t - \psi\theta_y\Sigma_t^{-1}\mathbf{B}_t\right) \tag{B.8}$$

where

$$\kappa = \frac{1-\theta_0}{(1-\theta_0+2\theta_r)+(\gamma-1)(1-\theta_0+\theta_r)^2} \tag{B.9}$$

and

$$\psi = \frac{1+(1-\theta_0+\theta_r)(\gamma-1)}{1-\theta_0} \tag{B.10}$$

■

Proof of Proposition 2. The proof is similar to Corollary 2.2 in Dou, Kogan, and Wu (2022). The cross-sectional covariance of local income betas $\mathbf{B}_t$ and its projection $\Sigma_t^{-1}\mathbf{B}_t$ is positive. To see this, first rewrite the covariance as:

$$Cov(\mathbf{B}_t, \Sigma_t^{-1}\mathbf{B}_t) = n^{-1}\mathbf{B}_t'\Sigma_t^{-1}\mathbf{B}_t - n^{-2}(\mathbf{B}_t'\mathbf{1})(\mathbf{1}'\Sigma_t^{-1}\mathbf{B}_t) \tag{B.11}$$

Because Σ_t is a positive definite symmetric matrix, according to the Cauchy-Schwarz inequality:

$$n^{-1}\mathbf{B}_t'\mathbf{1}\mathbf{1}'\Sigma_t^{-1}\mathbf{B}_t = n^{-1}(\mathbf{B}_t'\mathbf{1}\mathbf{1}'\Sigma_t^{-\frac{1}{2}})(\Sigma_t^{-\frac{1}{2}}\mathbf{B_t}) \tag{B.12}$$

$$\leq n^{-1}(\mathbf{B}_t'\mathbf{1}\mathbf{1}'\Sigma_t^{-1}\mathbf{1}\mathbf{1}'\mathbf{B}_t)^{\frac{1}{2}}(\mathbf{B}_t'\Sigma_t^{-1}\mathbf{B}_t)^{\frac{1}{2}} \tag{B.13}$$

Thus, it is sufficient to show that:

$$n^{-1}\mathbf{B}_t'\mathbf{1}\mathbf{1}'\Sigma_t^{-1}\mathbf{1}\mathbf{1}'\mathbf{B}_t \leq n^{-1}\mathbf{B}_t'\Sigma_t^{-1}\mathbf{B}_t \tag{B.14}$$

Denote $\mathbf{x} = n^{-\frac{1}{2}}\Sigma_t^{-\frac{1}{2}}\mathbf{B_t}$ and $\mathbf{y} = n^{-1}\Sigma_t^{-\frac{1}{2}}\mathbf{1}$. The inequality is equivalent to showing that:

$$\mathbf{x}'H_y\mathbf{x} \leq \mathbf{x}'\mathbf{x} \tag{B.15}$$

where $H_y = \mathbf{y}(\mathbf{y}'\mathbf{y})^{-1}\mathbf{y}'$. The inequality (B.15) is true because H_y is an orthogonal projection matrix. By definition, the portfolio tilt is $\boldsymbol{\phi}_t^{tilt} = -\psi\theta_y\Sigma_t^{-1}\mathbf{B}_t$, where ψ and θ_y are positive parameters. Therefore:

$$Cov(\boldsymbol{\phi}_t^{tilt}, \mathbf{B}_t) = -\psi\theta_y Cov(\mathbf{B}_t, \Sigma_t^{-1}\mathbf{B}_t) \leq 0 \tag{B.16}$$

■

C Appendix: Bootstrapping Procedure

To calculate standard errors, I conduct three-way bootstrapping across blocks of time, industries, and mutual funds. All three equations (11), (12), and (14) are bootstrapped together. Each bootstrap is constructed by the following two stages. The numbers presented here refer to the main regression with 49 industry groups and 40 estimation windows of 40 quarters. Other regressions follow similar steps with different parameters.

- In the first stage, at each quarter t, I randomly select with replacement 10 blocks of 4 quarters from the last 40 quarters of income growth and industry return data and stitch them together to construct a time-series.Next, I estimate betas from Equation (11) and (12) using reconstructed time series.
- In the second stage, I randomly select with replacement
  - 49 industries from the set of 49 Fama and French industry groups
  - 40 blocks of 4 quarters in the period of 1980q1:2019q4
  - 8,717 funds from the set of 8,717 unique mutual funds in the data.

  Next, I match selected funds, industries, and time blocks together, and merge them with the estimated betas from the first stage.

Following these two stages does not generate an equal number of observations in each bootstrap. Finally, Equation (14) is estimated for each bootstrap, and the estimated coefficients are saved. The standard errors are calculated from repeating this procedure 100 times and calculating the standard deviations of the estimates.

D Appendix: Inverse of Covariance Matrix of Returns

Assume stock returns follow a three-factor structure:

$$r_t = K'\mathbf{F}_t + \varepsilon_t \tag{D.17}$$

where r_t is the vector of asset returns, F_t is the vector of factor returns, and K is the matrix of factor loadings. Use the Woodbury matrix identity to calculate the inverse sigma:

$$\begin{aligned}\Sigma^{-1} =& (K'\Sigma_F K + \sigma_\varepsilon^2 \mathcal{I}_n)^{-1} \\ =& \sigma_\varepsilon^{-2}\Big[\mathcal{I}_n - K'(\sigma_\varepsilon^2 \Sigma_F^{-1} + KK')^{-1}K\Big]\end{aligned} \tag{D.18}$$

At each date t, I use the past three years of monthly data to estimate the factor loadings, average idiosyncratic volatility, and covariance of factor returns.