LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Essays in Empirical Asset Pricing

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Dedicated to my loving wife, Maliheh,
whose unwavering support and encouragement
have made this accomplishment possible.

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe the rights of any third party.

Statement of Conjoint Work I confirm that Chapter 2 is jointly co-authored with Thummim Cho, and I contributed 50% of this work.

I declare that my thesis consists of approximately 18,600 words.

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Abstract

The first chapter 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 active fund managers hedge local income shocks by tilting their portfolios away from high local income beta stocks. I also show that the trade-off between income hedging and local bias can help explain the local bias puzzle.

In the second chapter, we study which asset pricing model firm managers use. Since firms time the stock market through equity net issuance, the direction of net issuance reveals the firm's net present value calculation and an asset pricing model most likely to be used in the calculation. Based on this insight, we develop a test that infers an asset pricing model most likely used by firms from the net issuance decision. We find that the CAPM explains the decision better than other factor models or market multiples. Our results are not driven by issuance due to external financing needs and are true even for firms with an extreme size or value characteristic.

The third chapter, I present a novel approach for estimating the intrinsic value of stocks. Specifically, I construct an exponentially affine stochastic discount factor (SDF) model that captures the term structure of interest rates. This method enables me to systematically integrate macroeconomic data on sources of risk into the valuation model. By comparing the performance of the estimated value-to-price ratio to traditional market multiples, I demonstrate its superior predictive power for short-term market returns in both in-sample and out-of-sample tests.

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Chapter 1

Income Risk and Flow Hedging by Mutual Funds

1.1 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]

[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.

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, 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

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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.

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 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.

1.2 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

[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.

[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."

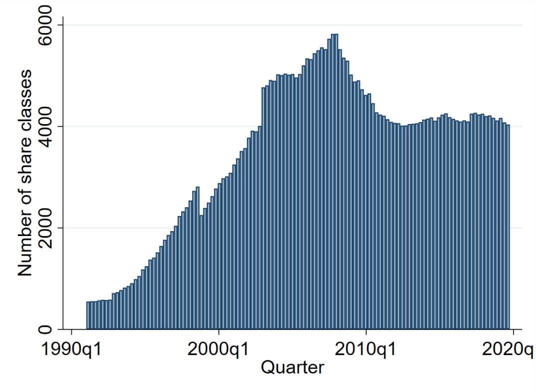
[6]The trade-off between income hedging and local bias has previously been studied in the literature. Massa and Simonov (2006) examine the portfolio holdings of Swedish households and find that they do not hedge their income risk but rather invest in assets that are closely related to their non-financial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

managed U.S. equity mutual funds based on their investment objectives, asset composition, and fund name. Appendix A.1 explains the details of the sample selection. I also obtain firms' headquarters addresses from Compustat and use Google Maps services to translate addresses to geographical coordinates.

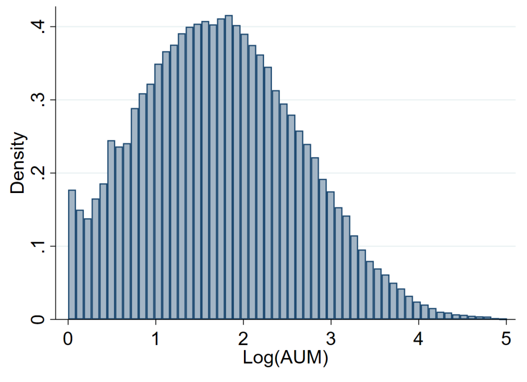
The portfolio holdings of mutual funds are collected from the Thomson Reuters mutual fund holdings data (S12) and CRSP mutual fund holdings data. To reduce data quality problems, and consistent with the recommendations of previous studies (e.g., Shive and Yun, 2013; Zhu, 2020), I use Thomson's portfolio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

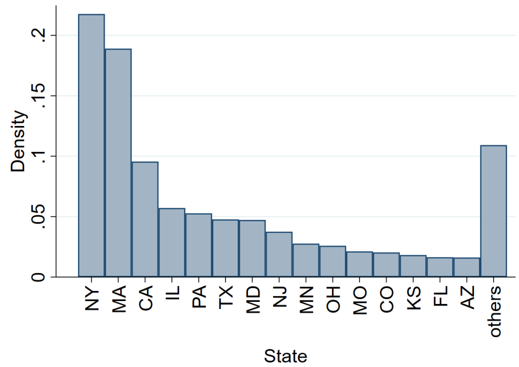
There are two reasons why I look at states as my geographical units. First, quarterly personal income, as my direct measure of income fluctuation, is reported only at the state level. The unemployment rate is reported monthly and with more geographical granularity. In unreported robustness checks, I 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 1.1: 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.1. 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.

1.2.1 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 1.1a shows the number of share classes identified as belonging

Table 1.1: Summary statistics

	Number of Obs.	Mean	S.D.	Median	1^{st} percentile	99^{th} 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.

to active retail equity mutual funds. Details of the sample selection are explained in Appendix A.1.

Figure 1.1b 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 1.1c. 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 1.1 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.

1.3 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]

$$flow_{f,t} = \frac{TNA_{f,t} - TNA_{f,t-1} * (1 + ret_{f,t}) - MGN_{f,t}}{TNA_{f,t-1}} \tag{1.1}$$

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:

$$\begin{aligned} flow_{f,t} =& \mu_t + \sum_{j=1}^{4} \alpha_j flow_{f,t-j} + \sum_{j=0}^{4} \beta_j ret_{f,t-j} \\ &+ \delta_0 size_{f,t-1} + \delta_1 age_{f,t} + \beta_0 g_{s,t} + \beta_1 g_{s,t-1} + error \end{aligned} \tag{1.2}$$

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

[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.

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 1.2 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 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

[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.

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 1.2: Fund flows and local income shocks

Sample	(1) All obs.	(2) All obs.	(3) All obs.	(4) All obs.	(5) Ex NY & MA	(6) Pre-2008	(7) Post-2008	(8) All obs.	(9) All obs.	(10) 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 (1.2)). 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.

1.4 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 $\frac{1}{2} f Q_t$. 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:

$$\max_{\phi_t} \frac{Q_t^{1-\gamma}}{1-\gamma} + E_t\left[\frac{Q_{t+1}^{1-\gamma}}{1-\gamma}\right] \tag{1.3}$$

subject to:

$$Q_{t+1} = Q_t(1 + R_{p,t+1}) + F_{t+1} \tag{1.4}$$

$$R_{p,t+1} = R_{f,t+1} + \boldsymbol{\phi}_t' \mathbf{R}^e_{t+1} \tag{1.5}$$

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 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

[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.

function of unexpected performance and income shocks:[11]

$$f_{t+1} = \theta_0 + \theta_r(r_{p,t+1} - E_t[r_{p,t+1}]) + \theta_y y_{t+1} + \varepsilon_{t+1} \tag{1.6}$$

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:*

$$\boldsymbol{\phi}_t^* = \kappa\left(\Sigma_t^{-1}\boldsymbol{\mu}_t - \psi\theta_y\Sigma_t^{-1}\mathbf{B}_t\right) \tag{1.7}$$

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 A.2.

All proofs are presented in Appendix A.2. 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 by the parameter ψ. Appendix A.2 shows that:

$$\psi = \frac{1 + (1 - \theta_0 + \theta_r)(\gamma - 1)}{1 - \theta_0} \tag{1.8}$$

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

[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.

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:*

$$\boldsymbol{\phi}^{tilt} = -\psi\theta_y\Sigma_t^{-1}\mathbf{B}_t \tag{1.9}$$

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

$$Cov(\boldsymbol{\phi}_{tilt}, \mathbf{B}) < 0 \tag{1.10}$$

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 (1.10) 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.

1.5 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:

$$g_{s,t-\tau} = \delta_0 + \delta_1 g^{US}_{t-\tau} + \varepsilon_{s,t-\tau} \quad \forall\, 0 < \tau < T \tag{1.11}$$

where $g_{s,t}$ is the growth rate of personal income in state s at time t, g_t^{US} 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:

$$r_{i,t-\tau} = \beta_0 + \beta_{s,i,t}^{state}\varepsilon_{s,t-\tau}^{state} + \beta_{s,i,t}^{US}g_{t-\tau}^{US} + \beta_{s,i,t}^{mkt}r_{t-\tau}^{mkt} + error \quad \forall\, 0 < \tau < T \tag{1.12}$$

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 $\beta_{s,i,t}^{state}$, 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:

$$W_{f,i,t}^{tilt} = W_{f,i,t} - W_{i,t}^{mkt} \tag{1.13}$$

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

$$W_{f,i,t}^{tilt} = \nu_{f,t} + \gamma_1\beta_{s,i,t-1}^{state} + \gamma_2\beta_{s,i,t-1}^{US} + \gamma_3\beta_{s,i,t-1}^{mkt} + error \tag{1.14}$$

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 (1.10), 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 (1.12), 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 1.2 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 1.1c). 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.

Table 1.3 reports the estimation results of Equation (1.14). 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 (1.10)). 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 A.3 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

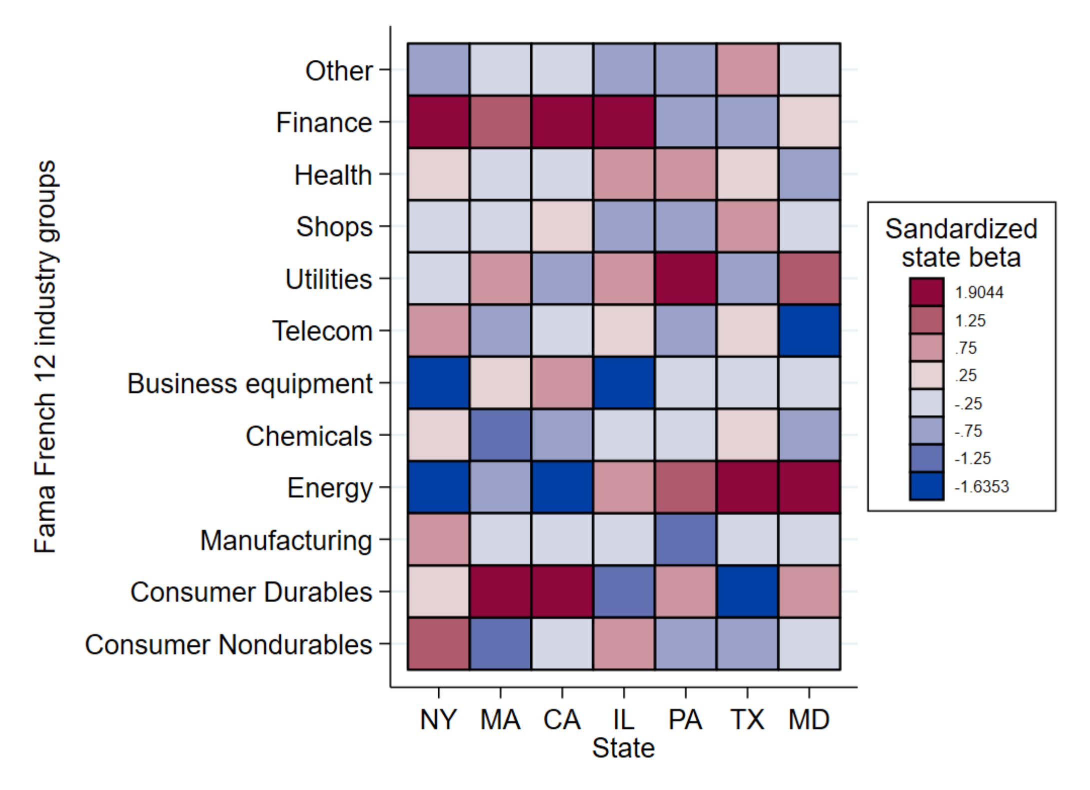


Figure 1.2: State-level local income betas

This figure shows standardized state-level local income betas (Equation (1.12)) 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 1.1a).

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 1.7, 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 1.3 shows the same results within the set of non-local

[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.

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.

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 A.4 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 (1.9). Column 7 of Table 1.3 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 1.4 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 1.3: 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
$\beta^{state}_{s,i,t}$	**-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)
$\beta^{US}_{s,i,t}$	**-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)
$\beta^{mkt}_{s,i,t}$	**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)
$\Sigma^{-1}\beta^{state}_{s,i,t}$							**-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 (1.14)). Income shocks are decomposed into an aggregate component and a state-level local component (Equation (1.11)). $\beta^{state}_{s,i,t}$ 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 A.4) with the vector of betas (Equation (1.9)). t-stats are reported in parentheses. All standard errors are calculated by three-way bootstrapping, as explained in Appendix A.3.

Table 1.4: 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.

1.6 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.

1.6.1 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:

$$flow_{f,t:t+1} = \sum_{j=1}^{4} \alpha_{k,j} flow_{f,t-j} + \sum_{j=0}^{4} \beta_{k,j} ret_{f,t-j} + \sum_{j=0}^{4} \gamma_{k,j} ret^2_{f,t-j} \\ + \delta_{k,0} size_{f,t-1} + \delta_{k,1} age_{f,t} + h_k(g_{s,t}) + error \qquad k = 1,2,3 \quad (1.15)$$

In this regression, all of the variables are demeaned in the cross-section. Since it was shown in Section 1.3 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:

$$
\begin{aligned}
\widehat{flow}_{f,t:t+1} = flow_{f,t:t+1} &- \sum_{j=1}^{4} \alpha_{k,j} flow_{f,t-j} - \sum_{j=0}^{4} \beta_{k,j} ret_{f,t-j} \\
&- \sum_{j=0}^{4} \gamma_{k,j} ret^2_{f,t-j} - \delta_{k,0} size_{f,t-1} - \delta_{k,1} age_{f,t}
\end{aligned} \tag{1.16}
$$

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 1.3a shows the flow-income relationship for the mutual funds with low performance, along with 90% confidence intervals. The graph is limited to the 2$^{\text{nd}}$ and 98$^{\text{th}}$ 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 1.3b 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 1.3c shows the flow-income relationship for top-performers, which has only a very moderate positive slope.

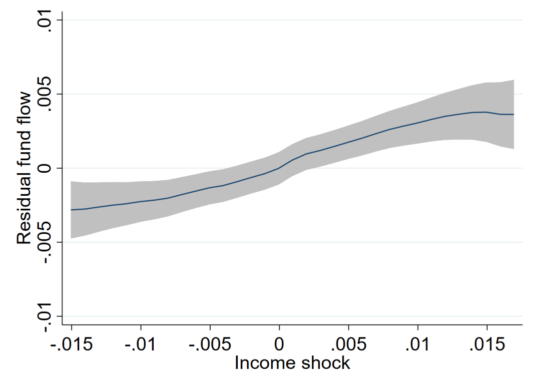
Since fund managers' incentive to hedge income risk, as predicted by the theoretical model, depends on the slope of the flow-income relationship, here I formally test the statistical significance of the difference in the slope of the flow-income relationship for funds with different past performance.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

$$
\widehat{flow}_{f,t:t+1} = \mu_t + \nu_f + (\theta_1 + (\theta_2 - \theta_1)D_2 + (\theta_3 - \theta_1)D_3) \times g_{s,t} + error \tag{1.17}
$$

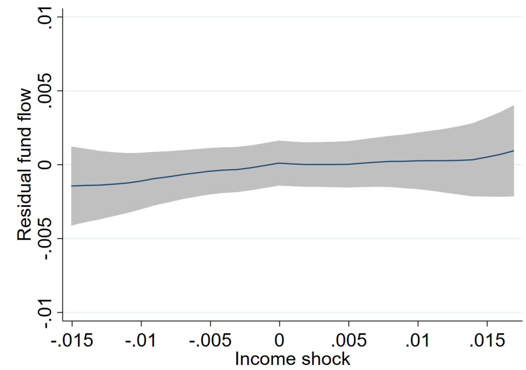
where D_k is a dummy variable that determines group assignment based on the last three-quarters' performance, μ_t and ν_f capture the time and fund fixed effects, and θ_k is the slope of the flow-income relationship for the mutual funds of group k.

Table 1.5 reports the results of the estimation of Equation (1.17). The table shows that the top-performing mutual funds are less sensitive to local income shocks com-

(a) Low performer funds



(b) Middle performer funds



(c) Top performer funds

Figure 1.3: 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.

pared 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.

1.6.2 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 1.6.1 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

Table 1.5: 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 (1.17)). 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.

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:

$$\Delta W^{tilt}_{f,i,t} = W^{tilt}_{f,i,t} - W^{tilt}_{f,i,t-1} \tag{1.18}$$

Substituting from Equation (1.13), a change in the portfolio tilts can be written as the change in the portfolio weights minus the change in the market weights:

$$\Delta W^{tilt}_{f,i,t} = \Delta W_{f,i,t} - \Delta W^{mkt}_{f,i,t} \tag{1.19}$$

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:

$$\Delta W^{tilt}_{f,i,t} = \nu_{f,t} + \gamma_1 \beta^{state}_{s,i,t-1} + \gamma_2 \beta^{US}_{s,i,t-1} + \gamma_3 \beta^{mkt}_{s,i,t-1} + error \tag{1.20}$$

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

Table 1.6: 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
$\beta^{state}_{s,i,t}$	**-0.004****	**-0.004****	-0.000	-0.001	**0.003****	**0.003***
	(-2.42)	(-2.55)	(-0.41)	(-0.75)	(2.30)	(1.84)
$\beta^{US}_{s,i,t}$	0.003	0.002	-0.000	-0.000	0.002	0.002
	(1.50)	(1.38)	(-0.08)	(-0.09)	(0.96)	(0.99)
$\beta^{mkt}_{s,i,t}$	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 (1.20)) for mutual funds with recent low, middle, or top performance. $\beta^{state}_{s,i,t}$ 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.

on their three-quarter performance at time $t - 1$ into three groups of top, middle, and low performers.

Table 1.6 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.

1.7 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 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 1.7 reports the average local income beta for

Table 1.7: 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.

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 1.2, 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 (1.9), 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).

1.8 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.

Chapter 2

Which Asset Pricing Model Do Firms Use? A Revealed Preference Approach

2.1 Introduction

Identifying an asset pricing model that firms use is important. How firms perceive risk affects their decision under uncertainty and equilibrium output in different states of nature. Our goal in this paper is to infer an asset pricing model, from a set of candidate models, closest to that of firms from the rich data on firms' trading of their own shares through issuance, repurchase, and dividend payouts ("net issuance").

We take the revealed preference approach developed in Berk and Van Binsbergen (2016) (BVB) and Barber, Huang, and Odean (2016) (BHO). Since economic agents react to positive net present value (NPV) opportunities, their actions reveal which model of risk they are likely to be using to compute the NPV. Based on this insight, BVB and BHO develop different techniques to infer the risk model investors use to evaluate actively managed mutual funds. We adapt BVB and BHO's techniques to a setting that reveals firms' net present value calculations: market timing through equity issuance. The resulting test identifies firm managers' risk model based on the ability of model-implied NPV estimates to explain the sign of equity net issuance.

Our approach builds on the extensive body of evidence that equity market timing—issuing when shares are overvalued and repurchasing when shares are undervalued—is a primary factor in equity issuance decisions.[1] In a survey of CFOs, Brav et al. (2005)

[1] A large behavioral corporate finance literature on this topic is surveyed by Baker, Ruback, and Wurgler (2007).

identify misvaluation to be the most important driver of share *repurchase*: "The most popular response for all repurchase questions on the entire survey is that firms repurchase when their stock is a good value, relative to its true value: 86.4% of all firms agree or strongly agree" (p.514). Similarly, Graham and Harvey (2001) identify the magnitude of equity undervaluation/overvaluation to be the second (out of ten) most important factor that influences CFOs' decision to *issue* common equity.[2] Complementing the survey evidence is that equity issuance is positively related to ex-ante measures of mispricing and predicts subsequent underperformance in stock returns.[3]

We face two main challenges in applying the revealed preference approach to equity net issuance. First, a firm's equity net issuance could be driven by variables other than market timing. In this case, an asset pricing model that generates NPV estimates more correlated with the omitted variables will have an artificial advantage over the competing models. We address this concern in various ways. We provide a theoretical framework for incorporating control variables into the test developed by BVB and apply it to control for proxies of investment opportunities. We also repeat our analysis using only the repurchase decision and not the issuance decision, as survey evidence identifies market timing as the primary motivation for share repurchase. In addition, we find consistent results using the BHO test method, which allows us to directly control for various proxies for investment opportunities including firm fixed effects. Finally, we repeat our analysis using firms that are unlikely to be financially constrained and therefore are less likely to rely on equity issuance to raise financing if they follow the pecking order.

The second issue is that the firm's *pre*-issuance mispricing that triggers net issuance can be difficult to estimate. While *post*-issuance mispricing can be easier to estimate, one could worry that the equity net issuance could eliminate or change the sign of mispricing, making post-issuance mispricing a poor indicator of pre-issuance mispricing. However, a simple model based on Gilchrist, Himmelberg, and Huberman (2005) justifies proxying pre-issuance mispricing with post-issuance mispricing. Since a firm is a monopolist in the supply of its own shares, the optimal corporate arbitrage pushes the price towards but not all the way to the intrinsic value. Thus, equity market mispricing

[2]67% of the responses state that misvaluation is a very important or important factor in the decision on issuance. This is a close second to the factor identified to be the most important, namely the availability of investment projects (measured by the earnings-per-share dilution post issuance), which 69% of the responses identify as very important or important.

[3]See for example Loughran, Ritter, and Rydqvist (1994); Ikenberry, Lakonishok, and Vermaelen (1995); Ikenberry, Lakonishok, and Vermaelen (1995); Spiess and Affleck-Graves (1995); Hovakimian, Opler, and Titman (2001); and Ritter (2003) among others.

persists even after share issuance and has the same sign as the issuance, allowing us to use post-issuance mispricing in our tests.

Our theory model shows that the magnitude of post-issuance mispricing can predict the direction of equity net issuance. However, it also shows that the optimal size of equity net issuance depends on the elasticity of demand for the firm's equity. Therefore, even though we expect the asset pricing model closest to that of firm managers to generate post-issuance mispricing that best explains the direction of the equity net issuance, we cannot make any conclusions about the size of equity net issuance. Because of this, and consistent with the previous studies that apply the revealed preference approach to the fund flows, we only focus on the sign of equity net issuances in our empirical tests.

To proceed, we measure post-net-issuance mispricing from the perspective of firm managers as the long-horizon (up to 10 years) cumulative alphas implied by a factor model. In each quarter, we sort firms based on the estimated mispricing and test which factor model generates a mispricing sort that best aligns with the direction of net issuance.[4] Across cumulative alphas over different horizons, we find that a longer time horizon better explains the direction of equity issuance, consistent with firm managers acting in the interest of long-term shareholders. We find our results to be robust to an alternative measure of mispricing.

The extant approach based on fund flows assumes fund investors who update their beliefs about the fund manager's skill based on the *past* realized alpha.[5] As a result, they relate the past realized alpha with respect to an asset pricing model to the direction of fund flows. In contrast, we assume firm managers who maximize the value of the firm for the existing long-term shareholders and relate firms' net issuance decision to *subsequent* long-horizon alphas. For instance, if firms repurchase shares because they perceive the shares to be underpriced relative to the CAPM, share repurchases would be more likely to be followed by positive long-horizon CAPM alphas than positive long-horizon three-factor alphas. [6]

[4]By the logic of previous paragraph, direction of net issuance proxies for the true post-issuance mispricing perceived by the firm.

[5]E.g., Berk and Van Binsbergen (2016), Barber, Huang, and Odean (2016), Agarwal, Green, and Ren (2018), and Blocher and Molyboga (2017))

[6]A common argument for why mispricing today is revealed by subsequent long-horizon alphas is that mispricing gets corrected over a long horizon. However, this does not need to be true for our mispricing measure to be valid. Even when mispricing does not disappear, today's overpricing (underpricing) leads to future dividend yield realizations that are too low (high) on a risk-adjusted basis, which then translate into alphas (Cho and Polk (2019)).

We run a horse race between several well-known single and multifactor models of risk, controlling for firm characteristics such as size, book-to-market, and a proxy for average Q that could proxy for investment opportunity, a potential driver of net issuance among financially constrained firms. We find that the CAPM consistently wins the race; that is, firms managers appear to use the CAPM to value the firm and make the issuance decision. Our results complement the survey evidence that the CAPM is by far the most popular risk model used by the firm managers (Bruner et al. (1998); Graham and Harvey (2001)), but our test has the advantage of using actual firm decisions, which avoids the potential issues of misreporting and selection bias in surveys.

The rich cross-section offered by the data allows us to see how the results change, if any, depending on the type of firms we look at. We zoom into the firms that strongly load on the size or value risk factors, since these firms would be making the largest mistake by using the CAPM if the true model of risk includes the size and value factors. Interestingly, CAPM mispricing better explains the direction of equity issuance even for these firms in the highest or lowest size or value quintiles, with the Fama French three factor model being a close contender.

As is standard in the revealed preference literature, when interpreting the results, one should be careful that the differences in the estimation errors factor into the comparison among asset pricing models.[7] If, for example, CAPM mispricing has smaller estimation errors, the test is more likely to identify the CAPM as the best model. Therefore, the correct way to interpret our results is that estimated CAPM mispricing best proxies for the firm's true perceived mispricing compared to mispricing estimated using other models.

Ben-David et al. (2021) find that the test for the asset pricing model used by mutual fund investors can be sensitive to how the test weighs the observations in different periods and point to the time variation in flow-performance sensitivity as the reason. Since our test is not based on investor flows, the same concern does not apply to our results. Still, we take two precautions in response. First, we follow Ben-David et al.'s suggestion to include time fixed effects in all regressions and use weighted least squares to ensure that our test coefficient is a time-series average of the cross-sectional coefficients.[8] Second, we examine if firms follow a simple rule based on market mul-

[7] "Consequently, our tests cannot differentiate whether these models underperform because they rely on variables that are difficult to measure, or because the underlying assumptions of these models are flawed" (Berk and Van Binsbergen (2016), p.2)

[8] We verify that our results are identical when using a Fama-MacBeth regression, which Ben-David et al. use to draw a different finding from previous studies.

tiples to make the net issuance decision and find that CAPM mispricing outperforms the market multiples in explaining net issuance decisions.

Our finding is also not implied by the notion that anomaly characteristics typically generate the largest spread in abnormal returns with respect to the CAPM. To compare different asset pricing models in their ability to rationalize the net equity issuance decisions, we rely on the cross-sectional *sorting* of firms into high vs. low estimated mispricing groups instead of the *level* of estimated mispricing.[9]

Studies on fund flows rely on the equilibrating mechanism that fund investors trade on positive NPV opportunities. In our setting, however, both firm managers and investors can correct mispricing through net issuance and trading, respectively. Our test is valid in the presence of these two equilibrating mechanisms. If the investors had already corrected mispricing, there would be no need for the firm manager's action. However, if investors have not corrected mispricing from the perspective of firm managers—who may have superior information about the firm—they would take advantage of the positive NPV opportunity through net issuance. And since mispricing would not be completely eliminated by net issuance (Gilchrist, Himmelberg, and Huberman (2005)), it generates subsequent alphas over a short or a long horizon, depending on how intensely the other investors also trade on the opportunity.

One may also worry that the net issuance itself could change the firm's risk exposures and that this could influence our findings based on post-net-issuance mispricing. However, an optimizing firm would internalize such a change in factor exposures to ensure that, with respect to their asset pricing model, the shares after net issuance remain mispriced in the same direction as before the net issuance.

Additional analyses point to the robustness of our findings. Although we control for firm characteristics that may be correlated with investment opportunities—another determinant of net issuance—, we further address this concern by following the literature (Lamont, Polk, and Saaá-Requejo (2001); Baker, Stein, and Wurgler (2003); Polk and Sapienza (2008)) to limit our sample to the firms that are not equity dependent based on the financial constraint measure of Whited and Wu (2006). We find consistent results using alternative measures of financial constraint provided by Kaplan and Zingales (1997), Hadlock and Pierce (2010), and Campello and Graham (2013). We also compare the performance of factor models to the simple market multiples

[9] Indeed, repeating the main analysis with the high vs. low split based on each of the return-predicting signals provided by Chen and Zimmerman (2020) (around 200 signals) as the left-hand side shows that the placebo test selects the CAPM only around 1 out of 4 times.

and find that mispricing with respect to the CAPM performs significantly better than market multiples in predicting the direction of equity issuance. Finally, our results are robust to using an alternative measure of mispricing that is arguably closer to the actual mispricing firms use to make net issuance decisions.

Our work contributes to the growing literature that uses revealed preferences to infer a risk model used by economic agents. Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) use different empirical methodologies to infer the risk model that investors use to evaluate mutual funds' performance. Agarwal, Green, and Ren (2018) and Blocher and Molyboga (2017) adapt the same methods to hedge funds. All of these studies reach the same conclusion that fund flows are best explained by CAPM alpha.

Ben-David et al. (2021) find, however, that mutual fund investors seem to use a simpler rule based on either raw returns or fund ratings. Gormsen and Huber (2023) uses firms' own perceived cost of capital to show that firms in the post-2000 sample appear to also account for the exposure to size and value factors.[10] Dessaint et al. (2021) explore the real implications of using the CAPM based on M&A data, and Baker, Hoeyer, and Wurgler (2019) study the effect on financing decisions. Hommel, Landier, and Thesmar (2021) find that the implied cost of capital imputed from comparable firms works better than discount rates inferred from factor models in justifying the actual equity prices. Whereas the paper asks how firms *should* discount cash flows, we ask how firms *do* in fact discount cash flows, especially in the context of net issuance.

Our work is also related to the literature on stock prices and net issuance, although our paper is unique in inferring firms' asset pricing model from the interaction between share prices and net issuance. Jung, Kim, and Stulz (1996) and Hovakimian, Opler, and Titman (2001) find a strong relation between stock prices and seasoned equity offerings. Ritter (1991), Spiess and Affleck-Graves (1995), Loughran and Ritter (1995), and Ritter (2003) use different sample periods and find that IPO firms and equity issuers earn lower average returns over the next five years and high market to book issuers earn even lower returns. Ikenberry, Lakonishok, and Vermaelen (1995) and Ikenberry, Lakonishok, and Vermaelen (2000) show that repurchasers have higher subsequent average returns and that low market-to-book repurchasers earn even higher returns. Pagano, Panetta, and Zingales (1998), Lerner (1994), Loughran, Ritter, and

[10]Restricting our sample to the most recent period shows that the CAPM and the three-factor model that includes size and value perform similarly in explaining net issuance, which could explain the result in Gormsen, whose sample also tends to have larger firms than a typical firm in our broad sample.

Rydqvist (1994) show that aggregate stock market indexes are positively related to IPO volume.

The rest of the paper is organized as follows. Section 2.2 presents the theoretical framework. Section 2.3 describes the data and variable construction. Section 2.4 conducts the horse race of asset pricing models of risk. Section 2.5 presents robustness checks and additional analysis. Section 2.6 concludes.

2.2 Theoretical framework

Our test in subsequent sections builds on two theoretical results highlighted in this section. First, a financially unconstrained firm issues equity shares to exploit stock market mispricing but does not fully eliminate the mispricing, since the firm is a monopolist in the supply of its own shares. Second, the revealed preference test on asset pricing models can be done while controlling for other variables that could affect the choice variable. Combining the first two results allows us to infer an asset pricing model most likely to be used by firm managers.

2.2.1 Equity issuance and equilibrium mispricing

A stylized model of stock price bubble and equity issuance based on Gilchrist, Himmelberg, and Huberman (2005) shows that corporate arbitrage does not fully eliminate stock mispricing. This prediction implies that the sign of post-issuance mispricing perceived by firm managers matches the sign of net equity issuance. This result is important because while *pre*-issuance mispricing is difficult to observe in the data, *post*-issuance mispricing can be inferred from the long-run behavior of the stock after the net issuance.

In a two-period setting, a rational firm manager chooses the level of capital K, which determines the present value of installed capital $\Pi(K)$. The firm is financially unconstrained and finances the purchase of the capital good K by issuing risk-free debt of L or selling a fraction n of the firm's market value of equity P.[11] Then, the intrinsic value of the firm's equity, perfectly observed by the firm manager, is

$$V(K, L) = \Pi(K) - L \tag{2.1}$$

[11] $n > 0$ implies net issuance and $n < 0$ implies equity repurchase.

where

$$K = L + nP. \tag{2.2}$$

The fraction n has an upper bound of one, $n < 1$, so long as the market value of equity before net issuance is positive.

The market value of equity P could deviate from the intrinsic value V and this "bubble" component of the market value, denoted B, can be corrected by the firm's equity net issuance:

$$P = (1 + B(n))V(K, L), \tag{2.3}$$

where $B'(n) < 0$ so that the demand curve for the firm's shares slopes downward.[12] All cash flows to shareholders occur in the second period so that the existing shareholders are prevented from raising external equity for the purpose of paying dividends to themselves in the concurrent period.

The firm manager chooses K and n to maximize the present value of cash flows to the existing shareholders:

$$\max_{K,n} (1 - n)(\Pi(K) - L), \tag{2.4}$$

subject to the resource constraint in Equation (2.2) restated as

$$L = \frac{K - n(1 + B(n))\Pi(K)}{1 - n(1 + B(n))}. \tag{2.5}$$

We focus on the firm's equity net issuance decision.

The first order condition with respect to the equity net issuance decision n implies that the sign of equilibrium post-net-issuance mispricing matches the sign of net equity issuance:

$$B(n) = \underbrace{-B'(n)}_{+} \underbrace{(1 - n)}_{+} n, \tag{2.6}$$

where $-B'(n) > 0$ because demand curve slopes downward and $(1 - n) > 0$ because n is bounded above at one.

Mispricing triggers equity issuance. However, since the firm is a monopolist in the supply of its own shares facing a downward-sloping demand curve, the usual monopoly

[12] See Gilchrist, Himmelberg, and Huberman (2005) for the microfoundation for this assumption based on investor belief heterogeneity and short-sale constraints.

pricing logic implies that the optimal equity issuance does not eliminate mispricing. Instead, stock bubble $B(n)$ persists in equilibrium even after net issuance n in the same direction. Firm arbitrage pushes the prices towards but not all the way down to the intrinsic value.

In this simple model, determining the exact magnitude of optimal equity issuance requires specifying the elasticity of demand further. However, it shows that the sign of post-issuance mispricing matches the sign of equity net issuance. Define mispricing as a monotonic transformation of the bubble term: $\delta = 1 - V/P = 1 - 1/(1+B)$. Also, define $\phi(.)$ as the sign function taking a value of 1 if the argument is positive and 0 if the argument is negative. Then, the model implies that the sign of optimal equity net issuance, n, and post-issuance mispricing, δ, must be the same:

$$\phi(n) = \phi(\delta). \tag{2.7}$$

In reality, the benefit of the corporate arbitrage would increase with the magnitude of the price bubble, and therefore, in the presence of transaction costs, firms would be more likely to issue equity the larger is the magnitude of the mispricing. A larger magnitude of pre-issuance mispricing would also mean, holding all else fixed, a larger post-issuance mispricing. Furthermore, equity net issuance could be driven by stock characteristics other than mispricing, such as investment opportunities. As a result, we express the ideas from our stylized theoretical model as the following assumption in our empirical implementation.[13]

Assumption 1. *Conditional on stock characteristics X, the probability of positive net issuance increases with the magnitude of the post-issuance mispricing.*

$$\frac{\partial Pr[\phi(n) = 1|\delta, X]}{\partial \delta} > 0 \tag{2.8}$$

Under this assumption, we show how to employ the revealed preference approach to infer the firm manager's model of risk. We then explain our empirical estimator of δ.

[13]Since the observations with zero net issuance contain less information about the firm's asset pricing model, we do not define ϕ for when $x = 0$ and drop such observations in the empirical analysis.

2.2.2 Inferring firms' asset pricing model from net issuance decisions

Our goal is to use equity issuance decisions and estimated mispricing with respect to different asset pricing models to infer the model of risk closest to the one used by the firm managers. When evaluating asset pricing models, we aim to make minimal assumptions about the distribution of estimation errors. Therefore, we compare models based on their ability to accurately rank firms by their level of mispricing, rather than using the estimated level of mispricing itself. This approach makes our analysis robust to potential shifts in the distribution of estimated mispricing.

Let subscript (i, t) denote the value for firm i at time t. Within each characteristic group X_{it}, sort all firms based on their mispricing into two groups:

$$\Delta_{it} = \begin{cases} 1 & \text{Top half of the firms based on } \delta_{it} \text{ at time } t \\ 0 & \text{Bottom half of the firms based on } \delta_{it} \text{ at time } t \end{cases} \tag{2.9}$$

The following propositions adapts the BvB framework in a way that applies to the rank of misprincing and controls for the observable characteristics.

Proposition 3. *Probability of positive issuance increases with the rank of mispricing:*

$$Pr[\phi(n_{it}) = 1|\Delta_{it} = 1, X_{it}] > Pr[\phi(n_{it}) = 1|\Delta_{it} = 0, X_{it}],$$

Proof of all propositions will come in the appendix.

Proposition 4. *The regression coefficient of the sign of equity issuance on the rank of mispricing is positive.*

$$\beta = \frac{Cov(\phi(n_{it}), \Delta_{it})}{Var(\Delta_{it})} > 0 \tag{2.10}$$

Equation (B.3) in the appendix shows that β has a clear interpretation as the difference in the probability of a positive issuance between the firms in the top versus bottom half of the mispricing:

$$\beta = Pr[\phi(n_{it}) = 1|\Delta_{it} = 1] - Pr[\phi(n_{it}) = 1|\Delta_{it} = 0] \tag{2.11}$$

Proposition 4 provides a simple test for asset pricing models: mispricing with respect to the candidate asset pricing model must predict the direction of equity issuance.

However, as we will see in the next section, all asset pricing models that we consider satisfy this condition. Therefore, we need a test to directly compare the performance of two asset pricing models. The next three propositions establish the foundations for this test. Before we do so, we make the following assumption made in BVB.

Assumption 2. *In the presence of a true asset pricing model, a false risk model has no additional explanatory power for the direction of equity issuance.*

$$Pr[\phi(n_{it}) = 1|\Delta_{it}^{T}, \Delta_{it}^{F}, X_{it}] = Pr[\phi(n_{it}) = 1|\Delta_{it}^{T}, X_{it}] \tag{2.12}$$

Proposition 5. *The regression coefficient of the sign of equity issuance on the rank of mispricing is maximized under the true risk model; i.e.,* $\beta^{T} > \beta^{F}$.

Definition 1. *Define model* c *as a better approximation of the true asset pricing model than model* d *if and only if:*

$$\begin{aligned} &Pr[\Delta_{it} = 1|\Delta_{it}^{c} = 1] + Pr[\Delta_{it} = 0|\Delta_{it}^{c} = 0] > \\ &\qquad Pr[\Delta_{it} = 1|\Delta_{it}^{d} = 1] + Pr[\Delta_{it} = 0|\Delta_{it}^{d} = 0] \end{aligned} \tag{2.13}$$

Proposition 6. *Model c is a better approximation of the true asset pricing model than model d if and only if* $\beta^{c} > \beta^{d}$.

Proposition 7 gives us a straightforward way to empirically test competing asset pricing models.

Proposition 7. *Consider an OLS regression of* $\phi(n_{it})$ *on the* $\Delta_{it}^{c} - \Delta_{it}^{d}$*:*

$$\phi(n_{it}) = \gamma_0 + \gamma_1(\Delta_{it}^{c} - \Delta_{it}^{d}) + \xi_{it} \tag{2.14}$$

Model c is a better approximation of the true asset pricing model than model d if and only if $\gamma_1 > 0$

2.3 Data and variable construction

We use stock price data from the Center for Research in Security Prices (CRSP) and annual accounting data from Compustat. We take one month treasury bill and factor returns data from Kenneth French's data library.

We construct our data in quarterly frequency. At the end of each quarter, we estimate issuance over the past quarter. We also use accounting data from the past calendar year to construct financial constraint measures. Next, we use future monthly returns to estimate post-issuance mispricing. In all of our main tests we drop observations with zero issuance.

2.3.1 Post-issuance mispricing

We proxy for post-issuance mispricing with long-horizon abnormal returns with respect to a candidate asset pricing model. Since the exact horizon relevant for the net issuance decision is unknown, we repeat the analysis using different horizons to look for consistent results.

For each stock i and time t, we use past 3 years of monthly returns to estimate stock-level factor betas associated with the candidate asset pricing model. We then use the estimated factor betas $\hat{\mathbf{b}}^c$ and realized factor returns $\mathbf{F}^c$ to estimate the benchmark return implied by model c:[14]

$$R^c_{i,t} = (\hat{\mathbf{b}}^c_{i,t})'\mathbf{F}^c_t. \tag{2.15}$$

We then estimate the time-and-firm-specific post-issuance mispricing based on a T-period horizon (up to 10 years) from the following equation:

$$\hat{\delta}^T_{i,t} = -\left(\prod_{s=t+1}^{t+T}(1 + R_{i,s} - R^c_{i,s}) - 1\right) \tag{2.16}$$

When the firm delists, we set the abnormal return to be zero so that delisting does not bias the mispricing measure.

We prefer our proxy for mispricing because it is simple and transparent. In robustness checks, we use a different estimator derived from a precise definition of mispricing, as we explain in Appendix B. We also consider a naive asset pricing model that simply uses the market return as the benchmark return and subtracts it from the stock return regardless of the stock's market beta. We call this model "excess market."

We limit the beginning of the sample to the earliest time that we have data for all models, which is 1969. Also, since we need a long horizon of 120 month (10 years) ex-post returns to estimate mispricing, the last year for which we can construct our 10-year mispricing measure is 2009.

[14]We express all vectors as column vectors.

2.3.2 Asset pricing models

We run horse race among some of the popular asset pricing models in the finance literature: the Capital Asset Pricing Model (CAPM) (Sharpe (1964); Lintner (1965)), the three-factor model of Fama and French (1993), the Carhart (1997) four-factor model, the five factor model of Fama and French (2015), the q-factor model of Hou, Xue, and Zhang (2015), and the intertemporal CAPM (ICAPM) model of Campbell et al. (2018).

We also consider simple alternatives to the factor models. This includes naively using expected stock market returns or expected industry returns as the cost of equity capital as well as inferring mispricing by comparing the firm's valuation multiples to industry peers.

2.3.3 Equity net issuance

Our left-hand side variable is the sign of the equity net issuance. Consistent with the literature on fund flows and following Daniel and Titman (2006), we construct our measure of equity net issuance as the percentage of firm's growth that is not attributable to the stock returns:

$$n_{i,t} = \frac{ME_{i,t}}{ME_{i,t-1}} - (1 + R_{i,t}). \tag{2.17}$$

Corporate actions such as splits and stock dividends leave this measure unchanged. However, any action that trades firm ownership for cash or services, like actual equity issues or employee stock option plans increases n. In contrast, any cash payout from the firm, like actual share repurchase or dividends decreases n. We find the results to be similar when using an alternative measure of equity net issuance that excludes dividend payments: $n_{i,t} = N_{i,t}/N_{i,t-1} - 1$, where N is the adjusted number of shares outstanding.

2.3.4 Financial constraint

Section 2.5 uses a measure of financial constraint to limit our sample to the firms that are not equity dependent. Whited and Wu (2006) measure the degree of financial constraint based on firm accounting characteristics as follows:

$$\begin{aligned} WW_{it} = &- 0.091 \times CF_{it} + 0.021 \times TLTD_{it} - 0.062 \times DIVPOS_{it} \\ &- 0.044 \times LNTA_{it} + 0.102 \times ISG_{it} - 0.035 \times SG_{it}, \end{aligned} \tag{2.18}$$

where CF_{it} stands for cash flow, $TLTD_{it}$ is the debt to equity ratio, $DIVPOS_{it}$ is a dummy variable that is equal to one if the firm has paid any dividends in the previous fiscal year, $LNTA_{it}$ is the logarithm of the total assets, ISG_{it} is the three digit SIC industry sales growth, and SG_{it} is the firm's sales growth. Intuitively, large firms with high cash flows and low leverage ratio that tend to pay dividends and do not have too many investment opportunities are less likely to be financially constrained.[15]

2.3.5 Summary statistics

Table 2.1 reports summary statistics of our sample of 599,415 firm×quarter observations between 1969 to 2009 (2009 is the last year in which the 10-year mispricing measure available). [16]

The quarterly issuance has a mean of 1.04 percent and standard deviation of 6.40 percent. The logarithm of total assets for the average firm is equal to 5.38 and age of 12.79 years. Estimated mispricing with respect to different factor models have different distributional properties. As we can see, the mean and the standard deviation have substantial variations across different models. However, we have defined our tests based on the rank of mispricing rather than its level. Therefore, our tests are robust to arbitrary shifts in the distribution.[17] Pearson and Spearman pairwise correlation

[15]Sales growth proxies for investment opportunities, thus firms with low sales growth in the industries with high sales growth are likely to have more investment opportunities. In unreported robustness checks, we have also used Kaplan-Zingales, size-age index, payout ratio, and size to measure financial constraint and we get similar results. As constructed by Lamont, Polk, and Saaá-Requejo (2001), the KZ index is given by:

$$\begin{aligned} KZ_{it} = &- 1.002 \times CF_{it} + 3.139 \times TLTD_{it} \\ &- 39.368 \times TDIV_{it} - 1.314 \times CASH_{it} + 0.283 \times Q_{it} \end{aligned} \tag{2.19}$$

Definition of new variables is as follows: $TDIV_{it}$ is the ratio of total dividends to assets, $CASH_{it}$ is the ratio of liquid assets to total assets, and Tobin's Q is defined as the market value of assets divided by the book value of assets. Hadlock and Pierce (2010) construct their measure of financial constraint by using only size and age:

$$SA_{it} = -0.737 \times SIZE_{it} + 0.043 \times SIZE^2_{it} - 0.040 \times AGE_{it} \tag{2.20}$$

[16]Our sample also includes a total of 235,234 firm × quarter observations with zero equity net issuance. These observations are excluded from our main tests as they are less informative. However, results are robust if one aggregates zero issuances with either of repurchases (Table B.1) or positive net issuances.

[17]Suppose for example that there are more repurchases than positive equity issuances in the data. In this case, an asset pricing model with a negative bias in the estimation of mispricing will have an artificial advantage over the competing models. Using the relative rank of estimated mispricing Δ_{it} rather than the absolute value of mispricing δ_{it} makes our tests robust to the arbitrary change in the mean or standard deviation of estimation error.

Table 2.1: Summary statistics

Variables	N	Mean	SD	1^{st} pctile	99^{th} pctile
Issuance	599,415	1.04	6.40	-8.28	36.98
Size	538,308	5.38	2.18	0.83	10.73
Age	544,912	12.78	11.14	1	49
		Estimated mispricing over 120 month			
CAPM	505,801	-0.23	1.33	-6.69	1.00
FF3	505,801	-0.13	1.28	-6.80	1.00
Carhart	505,801	-0.23	1.43	-7.89	1.00
ICAPM	486,369	-1.49	3.69	-20.93	1.00
Excess market	592,579	-0.16	1.28	-6.59	1.00
FF5	505,801	-0.37	2.04	-12.35	1.00
Q-theory	505,801	-0.74	3.23	-20.10	1.00

This table presents summary statistics of variables. Data is quarterly between 1969 and 2009. Size is defined as the log of total assets. We use past three years of monthly data to estimate factor betas. For the purpose of this table, estimated mispricing is winsorized at 1 and 99 percent cutoffs. This winsorization does not affect any of our empirical results, which are based on the rank of mispricing.

between different mispricing measures are reported in Table 2.2. All measures of mispricing tend to be highly correlated, and the naive "excess market" model is the one closest to the CAPM. Despite these correlations, we show that mispricing with respect to the CAPM significantly outperforms all other models at predicting the direction of equity issuance.

2.4 Results

We begin our analysis by regressing the sign of equity issuance on the binary rank of estimated mispricing (Equation (2.10)). To control for the characteristics that might be correlated with the mispricing and drive equity issuance, such as the availability of investment projects, we rank mispricing within each characteristic group. We report the results for different choices of control characteristics likely to be correlated with investment opportunities: size and book-to-market (value), size and the Peters and Taylor (2017) measure of (average) Q, size and momentum, and value and Q. We use 25 groups for each choice of controls based on 5×5 quintiles so that the incentives to engage in net issuance other than mispricing (e.g., investment opportunities) are likely to be similar among firms in the same characteristic group.

If size and value characteristics *perfectly* proxy for future size and value factor

Table 2.2: Pairwise correlation of estimated mispricing with respect to different models

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
				Panel A: Pearson Correlations			
CAPM	1						
FF3	0.829	1					
Carhart	0.758	0.888	1				
ICAPM	0.828	0.721	0.674	1			
Excess Market	0.902	0.769	0.723	0.847	1		
FF5	0.600	0.769	0.721	0.574	0.589	1	
Q-theory	0.499	0.559	0.635	0.480	0.473	0.607	1
				Panel B: Spearman Correlations			
CAPM	1						
FF3	0.872	1					
Carhart	0.816	0.922	1				
ICAPM	0.857	0.754	0.717	1			
Excess Market	0.927	0.823	0.784	0.863	1		
FF5	0.725	0.851	0.805	0.642	0.700	1	
Q-theory	0.667	0.712	0.761	0.601	0.635	0.719	1

This table presents average cross sectional correlation between estimated mispricing over a 10-year horizon with respect to different risk models. Data is quarterly from 1969q1 to 2008q2. For the purpose of this table, estimated mispricing is winsorized at 1 and 99 percent cutoffs. This winsorization does not affect any of our empirical results, which are based on the rank of mispricing.

exposures, respectively, controlling for these characteristics makes the comparison between the CAPM and the three-factor model of Fama and French moot. However, there is substantial variation in the size and value factor exposures not associated with the characteristics and the other way around (Daniel and Titman (1997)), especially when the comparison is between the characteristic at the time of net issuance and factor exposures in the following ten years. Note that these controls do not affect our ability to distinguish between the naive "excess market" method and the CAPM.

All of our tests include time fixed effects and weigh different time periods equally using weighted least squares, which makes the test coefficients identical to those based on Fama-MacBeth regressions. This is in response to Ben-David et al. (2021)'s finding that weighing different time periods equally in a revealed preference test generates results that survive a falsification test.

Table 2.3 reports the estimates of β (from Proposition 4) for different control groups. The numbers in the table report the percentage difference in the probability of positive equity net issuance when comparing the top versus the bottom rank of mispricing

(Equation (2.11)) . We expect this measure to be equal to zero if equity net issuance is unrelated to mispricing. Each column of the table corresponds to a different time horizon over which mispricing (Equation (2.16)) is estimated. The table shows that none of asset pricing models can be rejected in their ability to explain the direction of net issuance; i.e., all of estimated betas are significantly positive. Also, estimating mispricing over longer horizons improves its performance. For all time horizons and within all control groups, we see that CAPM mispricing best matches the direction of equity net issuance. Importantly, the CAPM also outperforms the naive model that simply subtracts the market return from the stock return to measure abnormal returns that feed our mispricing measure. Among other models, the Fama-French three-factor model also tends to provide a good proxy for actual mispricing used by firms.

To formally test whether the difference in the regression coefficients is statistically significant, we run a pairwise horse race among different asset pricing models (Equation (2.14)). Table 2.4 reports the *t*-statistics of the estimated γ_1 (in Proposition 7). A positive number means that the model in the row is closer to the asset pricing model of firm managers than the model in the column. Across all choices of control groups, the CAPM significantly outperforms other asset pricing models in rationalizing the equity net issuance decision. The t-statistics tend to be higher than typically found in asset pricing studies because we use the rank of estimated mispricing instead of its level as our right-hand side variable, which limits the variance of the errors in the regressions.

In all of our main tests we exclude observations with zero net issuance. Since survey evidence identifies market timing as the primary motivation for share repurchase, we repeat the horse race between asset pricing models using repurchase decisions only, not excluding the firms with zero net issuance this time. The results reported in Table B.1 confirm our previous finding that CAPM outperforms other asset pricing models in rationalizing firms' decision to repurchase equity.

It is interesting to compare the performance of the CAPM to that of other factor models for the firms in the highest or lowest size or value groups. These are the firms that strongly load on size or value factors that the CAPM fails to take into account. Table 2.5 shows that even for these extreme cases, CAPM outperforms all other factor models. Table 2.6 shows the *t*-statistics for γ_1 from the comparison of the CAPM against other factor models for all of the 25 size and value groups. The results collectively support that CAPM mispricing best explains firms' equity net issuance decisions.

Table 2.3: Single model regressions

	3	12	36	60	120
	Panel A: 25 Size and value groups				
CAPM	**0.029**	**0.053**	**0.070**	**0.078**	**0.087**
	(7.540)	(12.005)	(13.692)	(15.543)	(17.237)
FF3	0.025	0.045	0.060	0.068	0.076
	(9.052)	(14.004)	(14.784)	(16.016)	(16.408)
Carhart	0.023	0.041	0.054	0.062	0.067
	(8.322)	(13.299)	(14.715)	(15.787)	(15.166)
ICAPM	0.019	0.034	0.045	0.054	0.063
	(5.108)	(7.811)	(9.471)	(11.182)	(12.431)
Excess market	0.021	0.039	0.050	0.054	0.055
	(4.121)	(7.250)	(10.184)	(11.414)	(11.642)
FF5	0.015	0.028	0.030	0.035	0.041
	(6.237)	(10.412)	(9.226)	(9.862)	(10.062)
Q-theory	0.015	0.029	0.034	0.037	0.042
	(5.451)	(9.325)	(10.126)	(9.842)	(10.213)
	Panel B: 25 size and Q groups				
CAPM	**0.027**	**0.056**	**0.075**	**0.086**	**0.094**
	(6.947)	(12.295)	(14.879)	(16.103)	(17.371)
FF3	0.020	0.041	0.059	0.068	0.075
	(7.372)	(13.417)	(14.935)	(15.427)	(15.541)
Carhart	0.018	0.039	0.055	0.063	0.068
	(6.771)	(12.548)	(14.776)	(14.929)	(14.303)
ICAPM	0.017	0.038	0.052	0.063	0.074
	(4.290)	(8.194)	(10.772)	(12.679)	(13.408)
Excess market	0.020	0.042	0.057	0.063	0.065
	(4.163)	(8.128)	(11.761)	(12.762)	(12.918)
FF5	0.011	0.022	0.026	0.033	0.037
	(4.596)	(7.743)	(7.831)	(9.049)	(8.879)
Q-theory	0.012	0.027	0.036	0.040	0.044
	(4.208)	(7.831)	(9.705)	(9.871)	(9.904)

Single model regressions, continued

	3	12	36	60	120
	Panel C: 25 Size and momentum groups				
CAPM	**0.033**	**0.061**	**0.080**	**0.091**	**0.102**
	(8.396)	(12.268)	(13.788)	(15.827)	(18.318)
FF3	0.025	0.046	0.065	0.075	0.083
	(9.176)	(13.597)	(15.277)	(16.819)	(17.858)
Carhart	0.024	0.044	0.060	0.068	0.073
	(9.215)	(12.987)	(15.637)	(16.733)	(16.967)
ICAPM	0.022	0.042	0.057	0.067	0.077
	(5.693)	(8.809)	(10.536)	(12.438)	(14.316)
Excess market	0.027	0.051	0.066	0.074	0.075
	(5.114)	(9.149)	(12.280)	(14.491)	(15.188)
FF5	0.015	0.030	0.037	0.042	0.047
	(6.293)	(10.833)	(10.728)	(11.416)	(11.802)
Q-theory	0.017	0.033	0.041	0.046	0.050
	(5.810)	(8.824)	(10.577)	(11.273)	(11.966)
	Panel D: 25 Value and Q groups				
CAPM	**0.036**	**0.065**	**0.086**	**0.097**	**0.107**
	(7.328)	(12.847)	(15.440)	(16.957)	(18.273)
FF3	0.031	0.054	0.072	0.080	0.087
	(9.127)	(15.098)	(16.677)	(17.063)	(16.801)
Carhart	0.027	0.050	0.068	0.077	0.081
	(8.608)	(14.333)	(17.013)	(17.172)	(16.316)
ICAPM	0.028	0.050	0.069	0.081	0.097
	(5.810)	(9.655)	(12.529)	(14.437)	(14.874)
Excess market	0.031	0.056	0.073	0.080	0.083
	(5.557)	(9.676)	(13.681)	(15.005)	(15.552)
FF5	0.018	0.032	0.035	0.039	0.043
	(6.482)	(10.473)	(9.690)	(10.216)	(9.868)
Q-theory	0.016	0.031	0.039	0.042	0.045
	(5.052)	(8.314)	(10.454)	(10.331)	(9.666)

This table reports the results of the regression of the sign of equity issuance $\phi(n)$ on the binary rank of post-issuance mispricing Δ^c with respect to a candidate asset pricing model c.

$$\phi(n_{it}) = \mu_t + \gamma^c \Delta^c_{i,t} + \epsilon_{it}$$

The sign of equity net issuance is either zero (repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the binary, cross-sectional rank of mispricing Δ with respect to model c measured by post-issuance cumulative abnormal return over the horizon specified in the column (in months). Each panel specifies the characteristic groups within which the rank of mispricing is computed. Each cell represents a separate regression pertaining to a particular choice of model and the estimation window of mispricing. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The t-statistics are calculated using double clustered standard errors by firm and quarter. Largest β across different models in each horizon is bolded.

Table 2.4: Pairwise model comparisons

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Panel A: 25 Size and value groups				
CAPM	0.00	4.13	6.03	8.74	11.31	12.26	11.60
FF3	-4.13	0.00	4.67	3.34	6.29	13.65	9.32
Carhart	-6.03	-4.67	0.00	0.62	3.76	8.92	7.70
ICAPM	-8.74	-3.34	-0.62	0.00	2.69	5.74	5.24
Excess market	-11.31	-6.29	-3.76	-2.69	0.00	3.27	2.97
FF5	-12.26	-13.65	-8.92	-5.74	-3.27	0.00	-0.30
Q-theory	-11.60	-9.32	-7.70	-5.24	-2.97	0.30	0.00
			Panel B: 25 Size and Q groups				
CAPM	0.00	6.81	7.55	7.13	9.36	13.50	11.24
FF3	-6.81	0.00	3.43	-0.09	2.77	13.35	8.14
Carhart	-7.55	-3.43	0.00	-1.84	0.75	9.45	6.89
ICAPM	-7.13	0.09	1.84	0.00	2.39	7.73	6.14
Excess market	-9.36	-2.77	-0.75	-2.39	0.00	6.42	4.64
FF5	-13.50	-13.35	-9.45	-7.73	-6.42	0.00	-2.16
Q-theory	-11.24	-8.14	-6.89	-6.14	-4.64	2.16	0.00
			Panel C: 25 Size and momentum groups				
CAPM	0.00	6.12	7.67	9.33	11.91	13.81	12.74
FF3	-6.12	0.00	5.31	1.83	4.57	14.95	9.74
Carhart	-7.67	-5.31	0.00	-1.03	1.42	9.53	7.67
ICAPM	-9.33	-1.83	1.03	0.00	2.04	7.13	6.30
Excess market	-11.91	-4.57	-1.42	-2.04	0.00	5.77	4.98
FF5	-13.81	-14.95	-9.53	-7.13	-5.77	0.00	-0.76
Q-theory	-12.74	-9.74	-7.67	-6.30	-4.98	0.76	0.00
			Panel D: 25 Value and Q groups				
CAPM	0.00	6.67	7.21	3.63	8.35	13.52	11.85
FF3	-6.67	0.00	2.70	-2.71	1.08	14.35	10.04
Carhart	-7.21	-2.70	0.00	-3.59	-0.41	11.64	9.86
ICAPM	-3.63	2.71	3.59	0.00	3.75	9.34	8.66
Excess market	-8.35	-1.08	0.41	-3.75	0.00	8.82	7.43
FF5	-13.52	-14.35	-11.64	-9.34	-8.82	0.00	-0.71
Q-theory	-11.85	-10.04	-9.86	-8.66	-7.43	0.71	0.00

This table reports the *t*-statistics associated with γ_1 from the BvB test (Equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta_{it}^c - \Delta_{it}^d) + \xi_{it}.$$

The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to asset pricing model c vs. d. The models are compared on mispricing estimated by post-issuance cumulative abnormal return over 10 years. Each panel determines the control sub-groups. In each quarter and within each control sub-group, firms are ranked by estimated mispricing relative to a candidate model of risk. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 2.5: Pairwise model comparisons, extreme quintiles within 25 size and value groups

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
				Panel A: Low market equity			
CAPM	0.00	2.13	4.07	6.56	8.80	6.45	5.67
FF3	-2.13	0.00	3.27	3.72	5.32	6.54	4.65
Carhart	-4.07	-3.27	0.00	1.32	2.81	3.56	3.21
ICAPM	-6.56	-3.72	-1.32	0.00	0.91	1.32	1.26
Excess market	-8.80	-5.32	-2.81	-0.91	0.00	0.38	0.27
FF5	-6.45	-6.54	-3.56	-1.32	-0.38	0.00	-0.07
Q-theory	-5.67	-4.65	-3.21	-1.26	-0.27	0.07	0.00
				Panel B: High market equity			
CAPM	0.00	1.86	2.43	2.98	5.33	8.55	7.14
FF3	-1.86	0.00	1.33	1.05	3.00	9.34	6.40
Carhart	-2.43	-1.33	0.00	0.20	2.06	7.61	5.70
ICAPM	-2.98	-1.05	-0.20	0.00	1.69	6.15	4.77
Excess market	-5.33	-3.00	-2.06	-1.69	0.00	4.97	3.65
FF5	-8.55	-9.34	-7.61	-6.15	-4.97	0.00	-1.72
Q-theory	-7.14	-6.40	-5.70	-4.77	-3.65	1.72	0.00
				Panel C: Low market to book ratio			
CAPM	0.00	0.88	4.08	2.89	5.72	6.36	7.00
FF3	-0.88	0.00	5.12	1.77	4.31	7.62	7.11
Carhart	-4.08	-5.12	0.00	-1.38	1.06	2.80	4.50
ICAPM	-2.89	-1.77	1.38	0.00	2.31	3.49	4.56
Excess market	-5.72	-4.31	-1.06	-2.31	0.00	1.29	2.76
FF5	-6.36	-7.62	-2.80	-3.49	-1.29	0.00	1.35
Q-theory	-7.00	-7.11	-4.50	-4.56	-2.76	-1.35	0.00
				Panel D: High market to book ratio			
CAPM	0.00	6.21	5.86	7.56	8.01	11.44	8.44
FF3	-6.21	0.00	0.99	1.06	1.22	9.86	4.98
Carhart	-5.86	-0.99	0.00	0.47	0.51	8.19	4.87
ICAPM	-7.56	-1.06	-0.47	0.00	-0.39	5.93	3.68
Excess market	-8.01	-1.22	-0.51	0.39	0.00	6.72	3.97
FF5	-11.44	-9.86	-8.19	-5.93	-6.72	0.00	-2.22
Q-theory	-8.44	-4.98	-4.87	-3.68	-3.97	2.22	0.00

This table reports the *t*-statistics associated with γ_1 from the BvB test (Equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta^c_{it} - \Delta^d_{it}) + \xi_{it}.$$

among the firms in the highest or lowest size or value group. The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to asset pricing model c vs. d. The models are compared on mispricing estimated by post-issuance cumulative abnormal return over 10 years. In each quarter and within each of the 25 size and value sub-groups, firms are ranked by estimated mispricing relative to a candidate model of risk. Each panel determines the set of firms among which the horse race is run. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 2.6: Pairwise model comparisons against CAPM, extreme quintiles within 25 size and value groups

ME	PB	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
1	1	0.45	2.01	3.17	2.94	2.67	2.64
1	2	0.19	1.28	2.70	6.41	3.30	3.61
1	3	-0.13	2.91	4.76	7.57	3.31	4.38
1	4	3.25	4.82	5.15	6.93	6.11	5.05
1	5	2.02	1.89	3.42	3.37	4.20	2.12
2	1	1.42	4.12	1.80	3.98	4.23	5.50
2	2	0.57	2.35	4.76	6.40	3.23	4.76
2	3	1.49	2.22	3.99	7.98	4.27	4.45
2	4	2.76	2.48	5.30	6.77	3.85	5.74
2	5	3.29	2.48	4.92	3.99	5.72	5.61
3	1	0.41	2.14	1.98	3.17	2.96	4.90
3	2	1.60	2.28	3.63	6.14	3.55	5.04
3	3	0.85	2.42	4.64	6.81	4.14	4.93
3	4	2.35	3.80	4.17	6.61	5.48	6.03
3	5	3.99	5.04	4.84	5.12	6.48	4.73
4	1	0.49	2.80	2.10	5.56	4.54	4.73
4	2	1.18	2.27	1.95	3.71	4.90	3.59
4	3	1.54	2.04	1.92	5.52	6.05	3.82
4	4	1.55	1.68	2.66	4.33	6.00	4.96
4	5	4.73	5.04	3.49	5.18	8.22	6.55
5	1	-0.19	1.74	-0.86	2.34	3.61	3.05
5	2	-1.62	-1.26	-0.48	1.19	3.44	1.87
5	3	1.18	1.35	2.79	3.16	4.65	3.23
5	4	1.09	1.75	1.55	2.73	5.39	5.03
5	5	3.55	2.96	4.74	5.94	8.86	6.69

This table reports the *t*-statistics associated with γ_1 from the BvB test (Equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta_{it}^c - \Delta_{it}^d) + \xi_{it}.$$

among the firms in each of the 25 size and value groups. The first two columns determine the size and value group. The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to the CAPM (model c) vs. another asset pricing model d. The models are compared on mispricing estimated by post-issuance cumulative abnormal return over 10 years. In each quarter and within each of the 25 size and value groups, firms are ranked by estimated mispricing relative to a candidate model of risk. Each cell reports the *t*-statistics from a different regression. A positive number means that the CAPM wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

2.5 Additional Analysis

2.5.1 The BHO method

Barber, Huang, and Odean (2016) (BHO) develop a similar technique to run horse races among asset pricing models. The advantage of the BHO method is that we can easily control for other characteristics in a linear regression, although the added complexity makes the regression coefficients more challenging to interpret.

Following the BHO method, we first sort firms into deciles based on their estimated 10 year post-issuance mispricing.[18] Next, for each pairwise comparison of asset pricing models, we construct 100 dummy variables based on the decile ranking of estimated mispricing as defined by the two models:

$$D_{jkit} = \begin{cases} 1 & \Delta_{it}^{c} = j, \Delta_{it}^{d} = k \qquad \forall j, k = 1, ..., 10 \\ 0 & otherwise \end{cases} \tag{2.21}$$

Figure B.1 in the appendix shows all decile rankings and dummy variables for the comparison of CAPM and the three factor model. Gray cells correspond to firm-quarter observations that have similar mispricing rank based on both models and the black cell is the omitted dummy variable. We regress the sign of equity issuance on the full set of dummy variables, as well as time and industry fixed effects and controls. We then compare off-diagonal coefficients of dummy variables. For example, we compare estimated coefficients on the dummy variable corresponding to decile 4 based on the CAPM and decile 1 based on the three factor model (red cell, b_{41}) to the coefficient of the dummy corresponding to decile 1 based on the CAPM and decile 4 based on the three factor model(green cell, b_{14}). If a firm manager uses the CAPM rather than the three factor model, we expect $b_{41} > b_{14}$. Thus, similar to the BHO, we test the null hypothesis that the sum of the difference between off-diagonal coefficients is equal to zero. We also calculate a binomial test statistic which tests the null hypothesis that the proportion of differences equals 50%.

Table 2.7 collects the results from pairwise model comparisons. Panel A reports the sum of the differences and the corresponding p-values. A positive (negative) number means that the model on the row (column) of the table wins the race. Panel B reports the percentage of cases in which the first model (row) beats the second model (column)

[18]This ranking is unconditional, as opposed to the ranking in previous parts which was within the control groups

out of the 45 comparisons and the p-value of the binomial test. It shows that the CAPM is favored by an overwhelming majority and that it significantly outperforms the other models. This again supports that the CAPM is the closest asset pricing model to what firm managers use to estimate the intrinsic value of the firm.

Ben-David et al. (2021) find that the test for the asset pricing model used by mutual fund investors can be sensitive to how the test weighs the observations in different periods. The appendix shows that, since we include time fixed effects and use weighted least squares to give equal weights to all years, our univariate regression coefficients coincide with the Fama-MacBeth coefficients. Although our multivariate regression coefficients may not be identical to those from Fama-MacBeth regressions, we repeat the BHO analysis above using Fama-Macbeth regressions to find similar results. Table B.2 presents the time-series average of the cross-sectional coefficients.

2.5.2 Financial constraint

Despite our effort to control for them, one may still worry that equity issuance can happen for reasons unrelated to market timing, such as the financing of investment projects. We address this concern by limiting our sample to the firms that are not equity dependent, as previously done in Lamont, Polk, and Saaá-Requejo (2001), Baker, Stein, and Wurgler (2003), and Polk and Sapienza (2008).

Each quarter, we sort firms based on a measure of financial constraint and drop top half (most constrained firms). Table 2.8 presents the results of pairwise model comparison among unconstrained firms identified by the Whited and Wu (2006) measure. The results are close to the previous estimates in Table 2.4 and the CAPM outperforms all other models at explaining the direction of equity net issuance. The results are similar when an alternative measure of financial constraint is used (Kaplan and Zingales (1997); Hadlock and Pierce (2010); Campello and Graham (2013)).

2.5.3 Comparison to market multiples

Although not directly related to our research question on factor models, it is interesting to compare the performance of different risk models to that of simple market multiples. We consider price-to-book, price-to-earnings, and price-to-sales ratio as our test market multiples. In each quarter, we estimate mispricing with respect to the market multiples as the difference of the logarithm of the firm's lagged market multiple from the industry average for each of the 49 industry groups. Firms are considered overpriced (underpriced) if their lagged multiple is higher (lower) than the industry average. Table 2.9 shows that the CAPM significantly outperforms all market multiples in the race. The table also includes the horse race between factor models and mispricing with respect to the average industry returns.

2.5.4 An alternative measure of mispricing

Our main analysis measures mispricing as the compounded alpha over the post-issuance time horizon. While this measure is easy to understand and compute, it is not an expression derived from an exact definition of mispricing. As a robustness check, we define mispricing as the NPV of the buy-and-hold strategy on the firm and show that the ratio of NPV to price can be inferred from the long-run behavior of stock returns (see Appendix B). Repeating the analysis with this alternative measure of mispricing does not affect our findings (Table B.3).

2.6 Conclusion

Which asset pricing model do firm managers use to compare payoffs across time and state under uncertainty? In this paper, we use a revealed preference approach similar to Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) but adopted to net issuance decisions to answer this question. We find that firm managers are most likely to be using discount rates implied by the CAPM to discount future cash flows and make net issuance decisions. Our results deepen our understanding of how firms make decisions under uncertainty and shed further light on the asset pricing model most likely used by actual economic agents.

Table 2.7: Pairwise model comparison, BHO method

	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Sum of differences			
CAPM	1.393	2.936	3.450	5.788	3.742	3.775
	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FF3		3.224	1.016	1.310	4.118	2.766
		(0.000)	(0.008)	(0.016)	(0.000)	(0.000)
Carhart			-0.499	-0.396	1.580	1.803
			(0.123)	(0.359)	(0.000)	(0.000)
ICAPM				-1.445	1.826	1.941
				(0.052)	(0.000)	(0.000)
Excess market					1.556	1.651
					(0.000)	(0.000)
FF5						0.307
						(0.322)
			% of differences > 0			
CAPM	86.667	95.556	93.333	92.857	100.000	100.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FF3		93.333	73.333	80.000	97.778	100.000
		(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Carhart			37.778	48.889	88.889	95.556
			(0.135)	(1.000)	(0.000)	(0.000)
ICAPM				51.111	88.889	97.778
				(1.000)	(0.000)	(0.000)
Excess market					84.444	80.000
					(0.000)	(0.000)
FF5						68.889
						(0.016)

This table presents the results of pairwise horse race between competing risk models using BHO method. We estimate the relation between the sign of equity issuance and dummy variables denoting the decile ranks of post-issuance mispricing with respect to two competing asset pricing models:

$$\phi(n_{it}) = \mu_t + \nu_i + \sum_j \sum_k b_{jk} D_{jkit} + \kappa X_{i,t} \epsilon_{it}$$

The sign of equity net issuance is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. Controls include time and firm fixed effects, lagged equity issuance, lagged logarithm of total assets, lagged market to book ratio, age, profitability, investment, and asset growth. All mispricings are estimated over a 10-year time horizon. We compare off diagonal coefficients of dummy variables as in Figure B.1. Panel A presents sum of the differences of off-diagonal coefficient estimates and their p-values. A positive number indicates that the model in the row wins the race against the model in the column. Panel B shows the percentage of cases in which the first model (row) beats the second model (column) out of the 45 comparisons and the p-value of the binomial test. Data is quarterly from 1969 to 2009. All observations are deflated by the number of firms in each quarter and t-statistics are calculated using double clustered standard errors by firm and quarter.

Table 2.8: Pairwise model comparisons among financially unconstrained firms

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Panel A: 25 Size and value groups				
CAPM	0.00	3.48	5.08	6.25	9.39	10.55	10.36
FF3	-3.48	0.00	3.54	2.45	6.05	10.98	8.46
Carhart	-5.08	-3.54	0.00	0.43	4.09	7.81	7.28
ICAPM	-6.25	-2.45	-0.43	0.00	3.27	5.72	5.58
Excess market	-9.39	-6.05	-4.09	-3.27	0.00	2.56	2.68
FF5	-10.55	-10.98	-7.81	-5.72	-2.56	0.00	0.08
Q-theory	-10.36	-8.46	-7.28	-5.58	-2.68	-0.08	0.00
			Panel B: 25 Size and Q groups				
CAPM	0.00	5.26	6.11	4.95	8.39	11.65	10.34
FF3	-5.26	0.00	2.97	0.34	3.86	10.69	7.97
Carhart	-6.11	-2.97	0.00	-1.29	2.26	8.07	6.97
ICAPM	-4.95	-0.34	1.29	0.00	3.10	7.10	6.39
Excess market	-8.39	-3.86	-2.26	-3.10	0.00	4.49	3.92
FF5	-11.65	-10.69	-8.07	-7.10	-4.49	0.00	-0.71
Q-theory	-10.34	-7.97	-6.97	-6.39	-3.92	0.71	0.00
			Panel C: 25 Size and momentum groups				
CAPM	0.00	4.52	5.97	5.69	9.02	11.00	10.04
FF3	-4.52	0.00	3.76	1.15	4.43	10.22	7.97
Carhart	-5.97	-3.76	0.00	-0.87	2.31	7.07	6.40
ICAPM	-5.69	-1.15	0.87	0.00	2.85	6.15	5.85
Excess market	-9.02	-4.43	-2.31	-2.85	0.00	3.44	3.23
FF5	-11.00	-10.22	-7.07	-6.15	-3.44	0.00	-0.03
Q-theory	-10.04	-7.97	-6.40	-5.85	-3.23	0.03	0.00
			Panel D: 25 Value and Q groups				
CAPM	0.00	4.43	5.25	4.28	8.65	11.26	10.43
FF3	-4.43	0.00	2.40	0.04	3.95	11.01	8.31
Carhart	-5.25	-2.40	0.00	-1.11	2.46	8.70	7.59
ICAPM	-4.28	-0.04	1.11	0.00	3.62	7.27	6.79
Excess market	-8.65	-3.95	-2.46	-3.62	0.00	4.85	4.51
FF5	-11.26	-11.01	-8.70	-7.27	-4.85	0.00	-0.35
Q-theory	-10.43	-8.31	-7.59	-6.79	-4.51	0.35	0.00

This table reports the *t*-statistics associated with γ_1 from the BvB test (Equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta^c_{it} - \Delta^d_{it}) + \xi_{it}.$$

among the financially unconstrained firms. Each quarter, we first drop half of the observations that are more likely to be financially constrained based on the Whited and Wu index. The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to asset pricing model c vs. d. The models are compared on mispricing estimated by post-issuance cumulative abnormal return over 10 years. Each panel determines the control sub-groups. In each quarter and within each control sub-group, firms are ranked by estimated mispricing relative to a candidate model of risk. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table 2.9: Pairwise model comparison against market multiples

	PB	PE	PS	Excess industry
	Panel A: 25 Size and value groups			
CAPM	16.92	11.40	16.38	9.44
FF3	15.46	10.34	14.94	6.28
Carhart	14.43	9.18	13.70	3.10
ICAPM	12.79	7.17	12.48	1.52
Excess market	13.14	5.72	11.02	-1.73
FF5	11.64	5.10	10.30	-4.75
Q-theory	12.13	5.73	10.71	-3.97
	Panel B: 25 Size and Q groups			
CAPM	5.36	5.39	12.22	10.86
FF3	2.39	2.56	9.47	4.33
Carhart	1.30	1.60	8.31	2.08
ICAPM	1.94	1.68	9.21	3.79
Excess market	0.56	-0.17	7.11	1.30
FF5	-3.33	-2.84	3.99	-5.85
Q-theory	-2.14	-1.58	5.04	-3.72
	Panel C: 25 Size and momentum groups			
CAPM	3.18	5.15	9.67	9.38
FF3	0.30	2.39	6.84	4.24
Carhart	-1.05	1.08	5.39	0.89
ICAPM	-1.04	0.49	5.54	1.19
Excess market	-2.70	-1.32	3.76	-1.11
FF5	-5.59	-3.33	1.20	-7.26
Q-theory	-4.91	-2.61	1.55	-5.78
	Panel D: 25 Value and Q groups			
CAPM	19.25	12.07	19.17	7.41
FF3	17.88	9.77	17.59	0.82
Carhart	17.68	9.25	17.02	-0.45
ICAPM	16.23	10.34	17.04	3.61
Excess market	17.08	8.37	16.08	-0.46
FF5	13.81	3.62	12.23	-8.75
Q-theory	13.83	4.35	12.43	-7.19

This table reports the *t*-statistics associated with γ_1 from the BvB test (Equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta_{it}^c - \Delta_{it}^d) + \xi_{it}.$$

in comparison of the factor models against the simple market multiples. The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to asset pricing model c vs. rank of mispricing with respect to a market multiple d. The mispricing with respect to the factor models are estimated based on the post-issuance cumulative abnormal return over 10 years. The mispricing with respect to a market multiple is estimated as the log difference of the firm's market multiple from the average market multiple in the same industry. The last column compares factor models against mispricing inferred from average industry returns. Each panel determines the control sub-groups. In each quarter and within each control sub-group, firms are ranked by estimated mispricing relative to the candidate models. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Chapter 3

The Value-to-Price Ratio of US Stocks

3.1 Introduction

The majority of financial economists believe that the intrinsic value of a stock is equivalent to the present value of its expected future dividends, based on all the currently available information. For many years, the efficient markets theory shaped the standard academic view, which suggests that a security's price represents the best estimate of its intrinsic value at any given time. According to this theory, smart investors or traders can offset the irrational behaviour of other investors, making the markets more efficient. However, a substantial body of research has shown that the aggregate stock market can be highly inefficient. For example, Robert Schiller's research indicates that changes in market prices often occur for no fundamental reason but rather due to factors such as investor sentiments or "animal spirits" (e.g., Shiller, 1980, 1990). These findings challenge the traditional view that stock prices always reflect all available information and suggest that there may be opportunities for savvy investors to profit from market inefficiencies.

Acknowledging the potential for prices to deviate from intrinsic value, accurately measuring intrinsic value becomes of utmost importance. This study utilizes a VAR model and an advanced stochastic discount factor model to systematically estimate the intrinsic value of the US equity market while accounting for macroeconomic risk factors. The estimated value-to-price ratio is a real-time measure of aggregate mispricing. The performance of the constructed value-to-price ratio is compared to alternative measures of intrinsic value, revealing its superior ability to predict future market returns in both in-sample and out-of-sample tests.

To provide a more formal analysis, Vuolteenaho (2002) version of the Campbell and Shiller (1988) decomposition can be utilized to break down the variation in the book-to-market ratio of stocks into three distinct components:

$$log\left(\frac{B_t}{M_t}\right) = \mu - \sum_{j=1}^{\infty} \rho^j E_t[roe_{t+j}] + \sum_{j=1}^{\infty} \rho^j E_t[r^f_{t+j} + rp_{t+j}] + \sum_{j=1}^{\infty} \rho^j E_t[\alpha_{t+j}] \tag{3.1}$$

The equation can be expressed as follows: roe_t represents the logarithmic return on equity, r^f_t represents the risk-free interest rate, rp_t represents the explained risk premium, and α_t represents the abnormal returns. Equation (3.1) reveals that the logarithmic book-to-market ratio can be decomposed into three components: a projected cash-flow component, a rational component of the discount rate that can be explained by exposure to risk factors, and a residual mispricing component that equals the expected future abnormal returns. The last term is equal to the log of the buy-and-hold value-to-price ratio.

In this study, I construct a reduced-form stochastic discount factor (SDF) model to capture rational risk premium. In the context of Merton's Intertemporal Capital Asset Pricing Model (ICAPM), I use state variables that describe time variation in the investment opportunity set. Prior research has emphasized the significance of macroeconomic sources of risk for understanding changes in financial investment opportunities (e.g., Lettau and Ludvigson, 2001; Vassalou, 2003). For instance, Petkova (2006) finds that an asset pricing model centred on macroeconomic risk factors outperforms the Fama and French three-factor model in explaining the cross-section of average stock returns. I select inflation, consumption growth, short-term T-bill rate, and the term spread as the macroeconomic risk factors. The model parameters are calibrated to match the term structure of treasury bond yields with different maturities, assuming no mispricing in the treasury yields. Once the market prices of risk related to the aggregate sources of risk are derived, the model is employed to estimate the intrinsic value of the equity market.

I show that my constructed value-to-price ratio is driven by mispricing shocks that are washed away in more persistent measures like book-to-market or dividend-to-price ratios. As a consequence, the value-to-book ratio exhibits a stronger predictive power for short-term returns, while the difference diminishes and loses significance in the long run.

This paper is related to different streams in the finance and accounting literature. Firstly, I build upon prior research in finance that examines the time-series relation between market return and market multiples such as book-to-market and dividend-to-price ratios (e.g., Fama and French, 1988, 1989; Campbell and Shiller, 1988; Kothari and Shanken, 1997). I extend this literature by developing a method to systematically incorporate macroeconomic variables into a valuation model. I construct a value-to-price ratio measure that has superior forecasting power for market returns relative to simple market multiples.

My research is also related to the extensive literature in accounting that utilizes the residual-income formula to estimate the intrinsic value of stocks and investigates the efficacy of these models in explaining cross-sectional or time-series patterns in stock returns (e.g., Frankel and Lee, 1998; Lee, Myers, and Swaminathan, 1999; Ali, Hwang, and Trombley, 2003). However, unlike these studies, which often have a simplistic treatment of the risk premium, I propose a method to incorporate macroeconomic risk factors into an advanced SDF model.

Finally, my study is also related to the literature on modelling the stochastic discount factor. Specifically, I use an exponentially affine no-arbitrage model for the SDF, which is similar to the ones used in prior works such as Duffie and Kan (1996), Dai and Singleton (2000), and Ang and Piazzesi (2003). This model has been previously used to price claims to aggregate consumption (Lustig, Van Nieuwerburgh, and Verdelhan, 2013), evaluate the performance of private equity funds (Gupta and Van Nieuwerburgh, 2021), and price claims to government revenues and spending (Jiang et al., 2019). I demonstrate how this model can be utilized to estimate the intrinsic value of the equity market.

The rest of the paper is organized as follows. Section 2 developes the Model. Section 3 presents data sources and model calibration. Section 4 analyzes the performance of the estimated value-to-price ratio. Section 5 concludes.

3.2 The Model

In this section, I present a systematic method to estimate the intrinsic value of the overall stock market. The intrinsic value of the stock market can be thought of as the present value of the expected future dividends of all stocks in the market. To estimate this value, I use a VAR model to capture the joint dynamics of dividends and the

Stochastic Discount Factor. However, since dividend policy is difficult to model (e.g., Vuolteenaho, 2002), I use the clean surplus identity to express dividends as net income minus the change in the book value of equity:

$$D_t = X_t - \Delta B_t \tag{3.2}$$

Here, D_t represents total market dividends, X_t represents total net income, and ΔB_t is the change in the book value of equity for all firms in the market.

Using this equation, we can rewrite the intrinsic value-to-book ratio for the overall market as:

$$\begin{aligned} \frac{V_t}{P_t} &= \left(\frac{B_t}{P_t}\right) \times E_t\left[M_{t+1}\left(\frac{X_{t+1} - \Delta B_{t+1}}{B_t} + \frac{B_{t+1}}{B_t}\frac{V_{t+1}}{B_{t+1}}\right)\right] \\ &= \left(\frac{B_t}{P_t}\right) \times E_t\left[M_{t+1}ROE_{t+1} + M_{t+1}INV_{t+1}\left(\frac{V_{t+1}}{B_{t+1}} - 1\right)\right] \end{aligned} \tag{3.3}$$

Here, $ROE_{t+1} = 1 + \frac{X_{t+1}}{B_t}$ is the gross profitability of the market and $INV_{t+1} = \frac{B_{t+1}}{B_t}$ is the gross investment rate of the market.

To better understand this equation, let's consider a scenario where there is positive news about expected profitability next year. This one-time positive shock affects expected profitability, not investment or capital gains. If there is no mispricing ($V_t = P_t$), this positive shock should be reflected in today's asset price, which can be observed by a change in the book-to-market ratio or by discounting next year's earnings at a higher rate.

To further elaborate on the second channel, let's assume that the SDF and return on equity are jointly conditionally log-normal. In this case, we can write:

$$\begin{aligned} E_t[M_{t+1}ROE_{t+1}] = exp\Bigg[&E_t[m_{t+1}] + E_t[roe_{t+1}] + \frac{1}{2}Var_t(m_{t+1}) \\ &+ \frac{1}{2}Var_t(roe_{t+1}) + Cov_t(m_{t+1}, roe_{t+1})\Bigg] \end{aligned} \tag{3.4}$$

This equation reveals that the discount rate has two components: risk-free discounting ($E_t[m_{t+1}]$) and a risk premium ($Cov_t(m_{t+1}, roe_{t+1})$). Therefore, the positive shock to profitability can be counterbalanced by a higher one-period risk-free rate or by a higher market price of risk. If the changes in the book-to-market ratio and discount rate are insufficient to offset the effect of this positive shock, it is an indication of stock mispricing, and the value deviates from the market price.

3.2.1 Stochastic Discount Factor

This section aims to develop a model that captures the time series dynamics of the stochastic discount factor. To achieve this, it is essential that the SDF possesses certain desirable properties. Firstly, the model should be linear in state variables or risk factors to allow for a linear representation of mispricing. Secondly, as discussed earlier, the research aims to generate a time-varying risk premium to capture the varying levels of mispricing over time.

To meet these requirements, I propose a multifactor affine model with a homoskedastic vector of state variables and a heteroskedastic SDF. This model is commonly used in the literature (e.g., Campbell, 2017; Jiang et al., 2019). Building on the Intertemporal Capital Asset Pricing Model (ICAPM), I identify the primary sources of aggregate macroeconomic risk that describe the variations in investment opportunities and assume that their dynamics follow a Vector Autoregression (VAR) model. Specifically, I assume that the vector of state variables z_t follows a first-order Gaussian VAR model:

$$z_{t+1} = \Psi z_t + \Sigma^{\frac{1}{2}} \varepsilon_{t+1} \tag{3.5}$$

where z_t is the demeaned vector of state variables, and ε_t is the vector of independent and identically distributed (i.i.d) normal shocks with an identity covariance matrix. The model is homoskedastic, and the covariance matrix of the shocks to state variables is Σ. To decompose Σ, I use a Cholesky decomposition, which results in a lower triangular matrix $\Sigma^{\frac{1}{2}}$. This structural decomposition assumes that each variable is only contemporaneously affected by the shocks to the variables that precede it in the VAR.

According to the ICAPM model, risk is sourced from time-varying investment opportunities, and assets are compensated for being exposed to them. Therefore, the state vector can include any variable that can forecast investment opportunities. Past research by Vassalou (2003) and Lettau and Ludvigson (2001) demonstrates that changes in investment opportunities are related to business cycle fluctuations and can be summarized by GDP or consumption growth. In addition, Petkova (2006) shows that a VAR model that includes aggregate dividend yield, term spread, default spread, and short-term interest rate (one-month T-bill) outperforms Fama and French's three-factor model in explaining the cross-section of stock returns. Therefore, my state vector contains two key macroeconomic sources of risk, inflation (π_t) and consumption growth (cg_t), as well as two interest rates, the nominal short-term rate (ty_t), and yield spread $(yspr_t)$. These state variables are chosen to model time-varying investment opportunities, as well as the yield curve:

$$z_t = \begin{bmatrix} inf_t - \overline{inf} \\ cg_t - \overline{cg} \\ ty_t - \overline{ty} \\ yspr_t - \overline{yspr} \end{bmatrix}$$

Here, variables with a bar denote unconditional averages.

Inspired by the no-arbitrage term structure literature, I define an exponentially affine stochastic model for the Stochastic Discount Factor. The logarithm of the nominal SDF follows a normal distribution and can be represented as follows:

$$m_{t+1} = -ty_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1} \tag{3.6}$$

where ty_t represents the one period risk-free rate and ε_{t+1} is the same shock that affects state variables. The second term on the right-hand side of the above equation serves as an adjustment for Jensen's inequality that eliminates second-order effects. The market price of risk Λ_t takes on the following affine form:

$$\Lambda_t = \Sigma^{-\frac{1}{2}}(\Lambda_0 + \Lambda_1 z_t)$$

The vector Λ_0 comprises the average market prices of risk, while the matrix Λ_1 governs time-varying risk premiums. I will calibrate the market prices of risk in Λ_0 and Λ_1 such that the model aligns with the prices of bonds with varying maturities.

3.2.2 Dynamics of Mispricing

To incorporate this model into our framework, I use a first-order Gaussian Vector Autoregressive (VAR) model to capture the dynamics of market-wide profitability and investment. Specifically, I represent the model as follows:

$$w_{t+1} = \Gamma w_t + \Omega^{\frac{1}{2}} u_{t+1} \tag{3.7}$$

Here, w_t is the vector of market profitability and investment, defined as:

$$w_t = \begin{bmatrix} roe_t - \overline{roe} \\ inv_t - \overline{inv} \end{bmatrix}$$

The vector of iid shocks u_{t+1} follows a standard normal distribution, and Γ and Ω are the parameters of the VAR model.

To obtain a first-order linear approximation, I use a linear guess for the value-to-price ratio in terms of small changes in state variables: $\frac{V_t}{P_t} \approx \left(\frac{B_t}{P_t}\right)(1 + \kappa' z_t + \xi' w_t)$. I substitute the dynamics of m_{t+1} from Equation (3.6) and w_{t+1} from Equation (3.7) into Equation (3.3) to obtain:

$$\begin{aligned} E_t[M_{t+1} ROE_{t+1}] &= E_t[e^{-ty_t - \frac{1}{2}\Lambda_t'\Lambda_t - \Lambda_t'\varepsilon_{t+1} + \overline{roe} + \mathbb{1}_{roe}'(\Gamma w_t + \Omega^{\frac{1}{2}} u_{t+1})}] \\ &= e^{-\overline{ty} - \mathbb{1}_{ty}' z_t + \overline{roe} + \mathbb{1}_{roe}'\Gamma w_t + \frac{1}{2}\Omega_{1,1} - \mathbb{1}_{roe}'\beta(\Lambda_0 + \Lambda_1 z_t)} \\ &\approx 1 + \mathbb{1}_{roe}'\Gamma w_t - (\mathbb{1}_{ty}' + \mathbb{1}_{roe}'\beta\Lambda_1) z_t \end{aligned} \tag{3.8}$$

Here, $\beta = \Omega^{\frac{1}{2}} Cov(u_{t+1}, \varepsilon_{t+1})\Sigma^{-\frac{1}{2}}$ is the matrix of loadings on the risk factors and $\mathbb{1}_{roe}$ denotes $[1, 0]'$ vector which picks out the row of profitability from w_t. The covariance of the innovations of characteristics and risk factors $Cov(\varepsilon_{t+1}, u_{i,t+1})$ determines the factor loadings (betas), which are compensated by the time-varying risk premium Λ_t. I assume that both sides of the equation have equal zero-order terms and that the value-to-book ratio fluctuates around an average of one, which implies that:

$$e^{-\overline{ty} + \overline{roe} + \frac{1}{2}\Omega_{1,1} - \mathbb{1}'roe\beta\Lambda_0} = 1 \tag{3.9}$$

The second part of valuation equation (3.3) can be expanded as follows:

$$E_t\left[M_{t+1} INV_{t+1}\left(\frac{V_{t+1}}{B_{t+1}} - 1\right)\right] \approx E_t[M_{t+1} INV_{t+1}] E_t\left[\frac{V_{t+1}}{B_{t+1}} - 1\right] = c(\kappa'\Psi z_t + \xi'\Gamma w_t) \tag{3.10}$$

Here, $c = e^{\overline{inv}-\overline{roe}}$ is a constant. The first equality holds because $\left(\frac{V_t}{B_t} - 1\right)$ is only of the first order, and hence, the covariance of this with $M_{t+1}INV_{t+1}$ will be of the second order and can be neglected. The constant c comes from the fact that up to a zero-order approximation:

$$E_t[M_{t+1}INV_{t+1}] = e^{-\overline{ty}+\overline{inv}+\frac{1}{2}\Omega_{1,1}-\mathbb{1}'roe\beta\Lambda_0} = e^{\overline{inv}-\overline{roe}} \tag{3.11}$$

The second equality follows from Equation (3.9).

After substituting both parts (3.8) and (3.10) in the valuation equation (3.3), we obtain:

$$\frac{V_t}{B_t} \approx 1 + \kappa' z_t + \xi' w_t = 1 + \mathbb{1}'_{roe}\Gamma w_t - (\mathbb{1}'_{ty} + \mathbb{1}'_{roe}\beta\Lambda_1)z_t + c(\kappa'\Psi z_t + \xi'\Gamma w_t) \tag{3.12}$$

Matching the coefficients of z_t and w_t on both sides of the equation, we obtain:

$$\xi' = \mathbb{1}'_{roe}\Gamma(\mathbf{I} - c\Gamma)^{-1} \tag{3.13}$$

$$\kappa' = -(\mathbf{I} - c\Psi)^{-1}(\mathbb{1}'_{ty} + \mathbb{1}'_{roe}\beta\Lambda_1) \tag{3.14}$$

I use the above two equations to estimate κ and ξ and estimate a real-time value-to-price ratio.

3.3 Data and Calibration

I get macroeconomic data from the Federal Reserve Economic Database (FRED), while equity prices are obtained from the Center for Research in Equity Prices (CRSP) and accounting data is sourced from Compustat. The data is available on a quarterly basis, spanning from the first quarter of 1961 to the last quarter of 2019.

I calibrate the model parameters, specifically the market prices of risk, to match the model-implied treasury yields of different maturities with the term structure of interest rates. As (Campbell, 2017, chap. 8) and Jiang et al. (2019) show, using a multivariate exponentially affine SDF, the prices of bonds follow a simple linear form:

$$ty_t(h) = -\frac{A(h)}{h} - \frac{B(h)'}{h} z_t \tag{3.15}$$

where $ty_t(h)$ is the time t treasury yield of maturity h. The scalar $A(h)$ and vector $B(h)$ follow the following ordinary difference equations that depend on the VAR model parameters and market prices of risk:

$$A(h+1) = -\overline{ty} + A(h) + \frac{1}{2}B(h)'\Sigma B(h) - B(h)'\Sigma^{\frac{1}{2}}(\Lambda_0 - \Sigma^{\frac{1}{2}\prime}\mathbb{1}_{inf}) \tag{3.16}$$

$$B(h+1)' = -\mathbb{1}_{ty}' + (\mathbb{1}_{inf} + B(h))'(\Psi - \Sigma^{\frac{1}{2}}\Lambda_1) \tag{3.17}$$

This equation can be solved recursively using $A(0) = 0$ and $B(0) = \vec{0}$. I estimate the VAR system and calibrate the market prices of risk to best fit the model-implied bond prices of different maturities with the market rates. Appendix C.1 presents the estimation results.

In order to calibrate the model, I compare the nominal bond yields with maturities in three, five, seven, and ten years that are implied by the model to the actual bond yields in the data. The comparison is based on the difference between the two yields, and the results are presented in Figure 3.1. The figure illustrates that the model closely approximates the time-series of bond yields observed in the data.

3.4 Results

After calibrating model parameters, I use Equation (3.13) and (3.14) to estimate ξ and κ. A real-time measure of the value-to-price ratio is then estimated by using the following equation:

$$\frac{V_t}{P_t} \approx \left(\frac{B_t}{P_t}\right)(1 + \kappa' z_t + \xi' w_t) \tag{3.18}$$

In Figure 3.2, we can observe the time series of the value-to-price and book-to-market ratios. The value-to-price ratio is closely linked to the book-to-market ratio by construction. Nonetheless, their values can diverge substantially from one another at different points in time. Additionally, we can see that the value-to-price ratio has a lower standard deviation than the book-to-market ratio because the change in the risk factor adjusts a portion of the variation in market prices.

In this section, I examine whether the estimated value-to-price ratio has a superior ability to predict future market returns compared to traditional market multiples, which

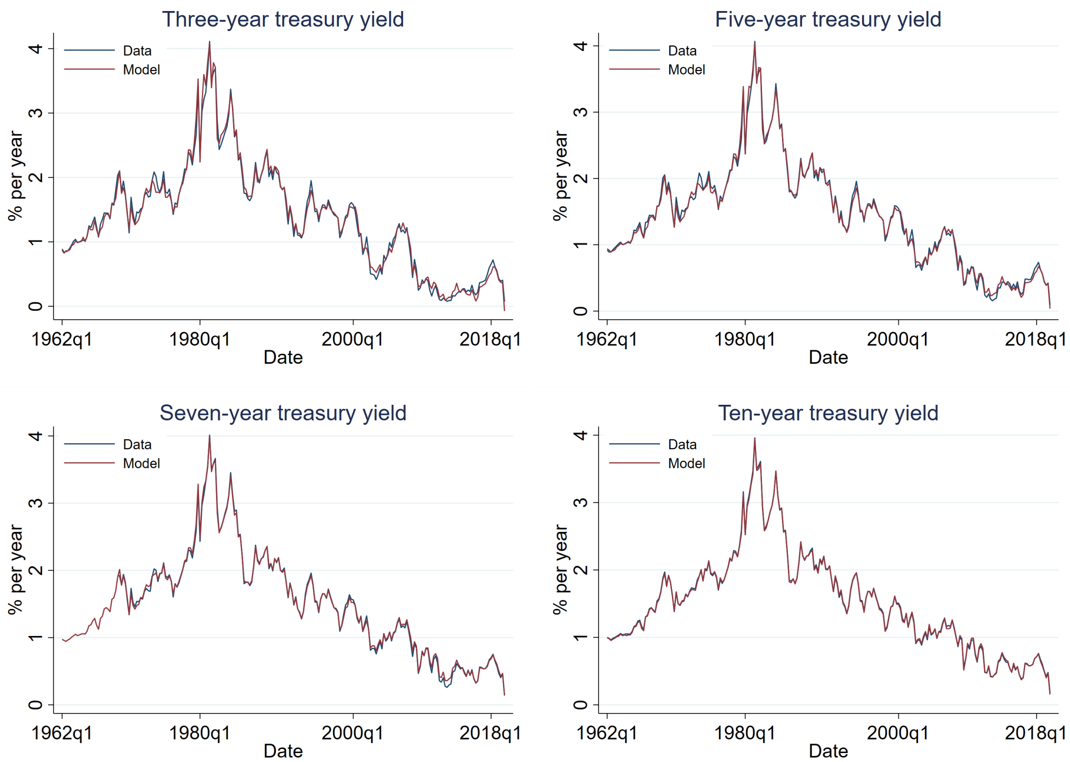


Figure 3.1: Model-implied and the time-series of nominal bond yields

This figure shows the Model-implied and time-series of nominal bond yields with three, five, seven, and ten years to maturity. The figure shows that the model closesly matches with the observed data.

would suggest that it captures the mispricing component. To evaluate this, I perform in-sample tests of the return forecasting ability of various market multiples. Specifically, I estimate the following regression:

$$r_{t,t+k} = \theta' X_t + error \tag{3.19}$$

where $r_{t,t+k}$ is the market return k periods ahead and X_t is the vector of explanatory variables. I estimate these forecasting regressions using overlapping observations, which may result in serial correlation in the error terms. To correct for this, I use the Newey-West correction with the appropriate number of lags. I conduct univariate and multivariate forecasting regressions for 1, 2, and 5-year horizons.

The univariate regression results are presented in Table 3.1. The first column shows that the estimated value-to-price ratio exhibits significant predictive power for future market returns across all horizons. Comparing the adjusted R-squared values across

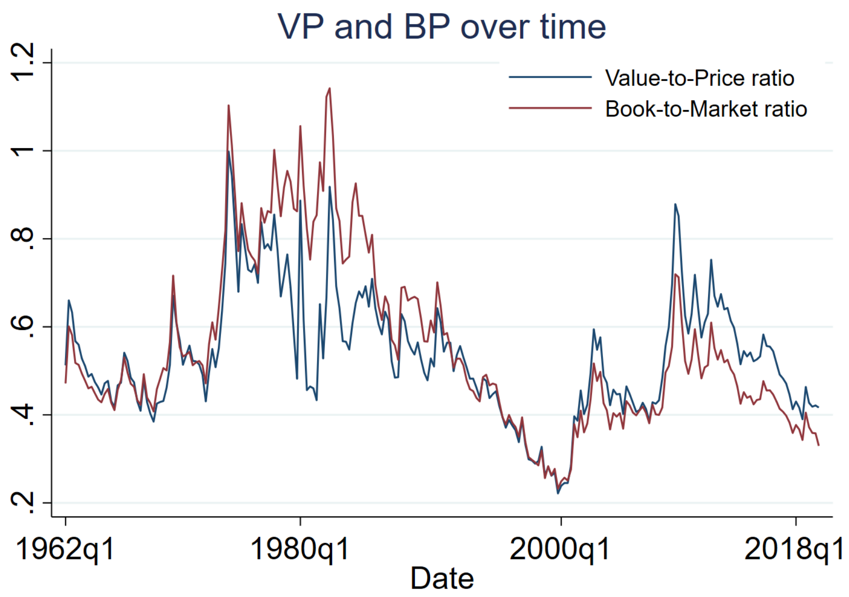


Figure 3.2: Time series of value-to-price ratio and book-to-market ratio

This figure shows the time series of the estimated value-to-price ratio and book-to-market ratio over time. The value-to-price ratio is a real-time measure estimated by Equation (3.18).

different regressions, we observe that the estimated value-to-price ratio has a stronger forecasting ability for future market returns at shorter horizons of 1 and 2 years. However, the predictive power decreases as the forecasting horizon increases to 5 years.

I conduct multivariate forecasting regressions to directly compare the performance of the value-to-price ratio with other market multiples. The results are presented in Table 3.2. Panels A and B indicate that when the value-to-price ratio is included as an explanatory variable, the forecasting power of other market multiples diminishes. Apart from the dividend-to-price ratio, all other market multiples lose statistical significance. However, the dividend-to-price ratio can complement the value-to-price ratio to provide more accurate short-term forecasts. At the five-year-long horizon of 5 years, the value-to-price ratio does not dominate other market multiples but can still significantly complement their forecasting power.

Taken together, the findings validate that the estimated value-to-price ratio is more effective in capturing short-term variations in market mispricing compared to more enduring measures such as the book-to-market ratio.

3.4.1 Out-of-sample tests

According to Welch and Goyal (2008), predictors of equity premium usually do not provide reliable out-of-sample predictions, making it difficult for investors with only available information to time the market for profit. In this section, I assess the performance of the estimated value-to-price ratio and compare it to traditional market multiples in out-of-sample tests.

At each quarter τ, I use the latest ten years of data available between $\tau - 40, ..., \tau - 1$ to re-estimate the VAR model parameters and re-calibrate market prices to match the term structure of interest rates in that time period. I estimate the value-to-price ratio during this period using these parameters, namely xi_τ and κ_τ. Then, I estimate the following regression to determine the relationship between future market returns and the value-to-price ratio or any of the traditional market multiples during this time period:

$$r_{t+4} = \theta'_\tau X_t + error \qquad \forall \tau - 40 \leq t \leq \tau - 4 \tag{3.20}$$

Here, X_t represents the value-to-price ratio or any other market multiples. Next, I use θ_τ to predict one-year future market return at time τ:

$$r^*_{\tau,\tau+4} = \theta'_\tau X_\tau \tag{3.21}$$

Here, $r^*_{\tau,\tau+4}$ represents an out-of-sample prediction of 1-year market return at time τ. Finally, I run the following regression to assess the performance of these out-of-sample forecasts in predicting market returns:

$$r_{t,t+4} = \gamma' r^*_{t,t+4} + error \tag{3.22}$$

Here, $r_{t,t+4}$ represents the actual market return over the 1-year period from time t to $t + 4$, and γ' represents the estimated coefficients from the regression.

Similar to the previous section, I conduct univariate and multivariate forecasting regressions at the 1-year horizon. Table 3.3 presents the results of these regressions. As noted by Welch and Goyal (2008), predictors of equity premium typically have poor out-of-sample performance and other statistics, and this is also observed in our results, where the performance of all market multiples significantly drops in out-of-sample tests.

However, the estimated value-to-price ratio remains a significant predictor of 1-year market returns, consistent with the in-sample tests. In multivariate regressions, with the estimated value-to-price ratio included as a predictor, all other market multiples lose statistical significance. These results suggest that the estimated value-to-price ratio is a dominant predictor of future market returns, outperforming other traditional market multiples in predicting 1-year future market returns.

3.5 Conclusion

This paper presents a novel method for estimating the intrinsic value of the equity market, which involves incorporating aggregate sources of macroeconomic risk into an advanced SDF model and calculating the present value of future cash flows through a VAR model. The estimated value-to-price ratio obtained using this method is then analyzed for its forecasting power of future market returns and compared with traditional market multiples, such as the book-to-market and dividend-to-price ratios. The findings reveal that the estimated value-to-price ratio significantly outperforms other market multiples in predicting short-term market returns, particularly at the one and two-year horizons. This finding suggests that the estimated value-to-price ratio better captures short-term fluctuations in market mispricing that are washed away in more persistent measures such as the book-to-market ratio. The in-sample and out-of-sample tests consistently validate the results.

Table 3.1: In-sample test, Univariate forecasting regressions

	(1)	(2)	(3)	(4)	(5)
	Panel A: Forecasting one-year market return				
VP_t	**0.427*****				
	(3.42)				
BP_t		**0.258*****			
		(3.09)			
DP_t			**9.046*****		
			(3.17)		
SP_t				**0.086*****	
				(2.96)	
EP_t					**1.214****
					(2.15)
Adj R-squared	0.129	0.088	0.056	0.074	0.040
	Panel B: Forecasting two-year market return				
VP_t	**0.674*****				
	(2.84)				
BP_t		**0.449*****			
		(3.03)			
DP_t			**14.611*****		
			(4.42)		
SP_t				**0.149*****	
				(3.16)	
EP_t					**1.984****
					(2.41)
Adj R-squared	0.176	0.146	0.081	0.123	0.060
	Panel C: Forecasting five-year market return				
VP_t	**1.377*****				
	(4.87)				
BP_t		**1.014*****			
		(5.36)			
DP_t			**27.786*****		
			(3.52)		
SP_t				**0.373*****	
				(5.76)	
EP_t					**4.221*****
					(2.60)
Adj R-squared	0.353	0.352	0.141	0.356	0.132

This table presents the results of the univariate forecasting regressions based on Equation (3.19). The standard errors are computed using Newey-West correction with the number of lags appropriate for each horizon (4, 8, and 20 for 1, 2, and 5-year forecasting regressions, respectively). The t-statistics are displayed in parentheses.

Table 3.2: In-sample test, Multivariate forecasting regressions

	(1)	(2)	(3)	(4)	(5)
	Panel A: Forecasting one-year market return				
VP_t	**0.423****	**0.374*****	**0.384****	**0.446*****	**0.743****
	(2.27)	(2.91)	(2.38)	(3.13)	(2.39)
BP_t	0.003				-0.772
	(0.02)				(-1.06)
DP_t		**5.091****			**8.185****
		(2.25)			(2.24)
SP_t			0.017		0.185
			(0.48)		(1.13)
EP_t				-0.144	-0.245
				(-0.27)	(-0.22)
Adj R-squared	0.125	0.140	0.126	0.126	0.152
	Panel B: Forecasting two-year market return				
VP_t	**0.500***	**0.583****	**0.535***	**0.683****	0.687
	(1.82)	(2.32)	(1.90)	(2.51)	(1.55)
BP_t	0.155				-0.131
	(1.26)				(-0.10)
DP_t		**8.528*****			**9.539***
		(2.71)			(1.81)
SP_t			0.053		0.011
			(1.26)		(0.35)
EP_t				-0.080	-1.874
				(-0.12)	(-1.12)
Adj R-squared	0.177	0.197	0.179	0.171	0.203
	Panel C: Forecasting five-year market return				
VP_t	**0.727***	**1.211*****	**0.782***	**1.358*****	1.400
	(1.83)	(4.17)	(1.93)	(3.97)	(1.61)
BP_t	**0.580****				-1.276
	(2.29)				(-0.65)
DP_t		**15.240****			9.025
		(2.58)			(1.23)
SP_t			**0.227*****		0.783
			(3.00)		(1.39)
EP_t				0.093	**-5.512*****
				(0.04)	(-3.08)
Adj R-squared	0.382	0.382	0.412	0.343	0.507

This table presents the results of the Multivariate forecasting regressions based on Equation (3.19). The standard errors are computed using Newey-West correction with the number of lags appropriate for each horizon (4, 8, and 20 for 1, 2, and 5-year forecasting regressions, respectively). The t-statistics are displayed in parentheses.

Table 3.3: Out-of-sample test, Forecasting 1-year market returns

	(1)	(2)	(3)	(4)	(5)
	Panel A: Univariate Regressions				
VP_t	**0.273****				
	(2.14)				
BP_t		-0.027			
		(-0.18)			
DP_t			**0.212***		
			(1.90)		
SP_t				-0.082	
				(-0.53)	
EP_t					0.050
					(0.43)
Adj R-squared	0.019	-0.005	0.014	-0.004	-0.004
	Panel B: Multivariate Regressions				
VP_t	**0.762*****	0.216	**0.656*****	**0.276****	**0.752*****
	(3.78)	(1.60)	(3.69)	(2.09)	(3.57)
BP_t	**-0.721*****				-0.482
	(-3.09)				(-1.47)
DP_t		0.150			0.114
		(1.27)			(0.97)
SP_t			**-0.638*****		-0.365
			(-3.02)		(-1.25)
EP_t				-0.0128	0.083
				(-0.10)	(0.067)
Adj R-squared	0.063	0.022	0.060	0.014	0.064

This table presents the results of the univariate forecasting regressions based on Equation (3.22). The standard errors are computed using Newey-West correction with the number of lags appropriate for each horizon (4, 8, and 20 for 1, 2, and 5-year forecasting regressions, respectively). The t-statistics are displayed in parentheses.

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A Appendix to Income Risk and Flow Hedging by Mutual Funds

A.1 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.

A.2 Proofs

Proof of proposition 3. 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 (1.3) can be rewritten in terms of the logarithm of the TNA $q_{t+1} = log(Q_{t+1})$:

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

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

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

Next, divide both sides of the budget constraint (1.4) by Q_t:

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

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

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

Also, we can log-linearize the portfolio return (1.5) in terms of the holdings' returns up to the second order:

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

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 (1.6), and portfolio returns as a function of asset returns from (A.5) in the linear law of motion of the assets under management (A.4) to get:

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

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

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:

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

where

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

and

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

■

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:

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

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

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

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

Thus, it is sufficient to show that:

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

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:

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

where $H_y = \mathbf{y}(\mathbf{y}'\mathbf{y})^{-1}\mathbf{y}'$. The inequality (A.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:

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

■

A.3 Bootstrapping Procedure

To calculate standard errors, I conduct three-way bootstrapping across blocks of time, industries, and mutual funds. All three equations (1.11), (1.12), and (1.14) 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 (1.11) and (1.12) 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 (1.14) 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.

A.4 Inverse of Covariance Matrix of Returns

Assume stock returns follow a three-factor structure:

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

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:

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

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.

B Appendix to Which Asset Pricing Model Do Firms Use?

B.1 Proofs

Proof of equation (2.6). Substituting the financing constraint (2.5) in the objective function (2.4) gives:

$$\max_{K,n}(1-n)\left(\Pi(K)-\frac{K-n(1+B(n))\Pi(K)}{1-n(1+B(n))}\right)=(1-n)\left(\frac{\Pi(K)-K}{1-n(1+B(n))}\right) \tag{B.1}$$

First order condition with respect to n gives:

$$1-n(1+B(n))=(1-n)(1+B(n)+nB'(n))\Rightarrow B(n)=-B'(n)(1-n)n \tag{B.2}$$

■

Proof of proposition 1. This proposition directly follows from Assumption 1, considering that the cross-sectional rank of mispricing is increasing in the level of mispricing. ■

Proof of proposition 2. Note that Δ_{it} is equal to 1 for half of the observations and equal to 0 for the other half by construction. Hence, $E[\Delta_{it}]=\frac{1}{2}$ and $Var(\Delta_{it})=\frac{1}{4}$.

$$\begin{aligned}
\beta &= \frac{Cov(\phi(n_{it}),\Delta_{it})}{Var(\Delta_{it})}=4\times(E[\phi(n_{it})\Delta_{it}]-E[\phi(n_{it})]E[\Delta_{it}])\\
&=2\times(Pr[\phi(n_{it})=1,\Delta_{it}=1]-Pr[\phi(n_{it})=1,\Delta_{it}=0])\\
&=Pr[\phi(n_{it})=1|\Delta_{it}=1]-Pr[\phi(n_{it})=1|\Delta_{it}=0] \qquad \text{(B.3)}\\
&=\sum_{X_{it}}\Big(Pr[\phi(n_{it})=1|\Delta_{it}=1,X_{it}]\frac{Pr[\Delta_{it}=1|X_{it}]Pr[X_{it}]}{Pr[\Delta_{it}=1]}\\
&\qquad -Pr[\phi(n_{it})=1|\Delta_{it}=0,X_{it}]\frac{Pr[\Delta_{it}=0|X_{it}]Pr[X_{it}]}{Pr[\Delta_{it}=0]}\Big)\\
&=\sum_{X_{it}}Pr[X_{it}]\Big(Pr[\phi(n_{it})=1|\Delta_{it}=1,X_{it}]-Pr[\phi(n_{it})=1|\Delta_{it}=0,X_{it}]\Big) \qquad \text{(B.4)}
\end{aligned}$$

The last line comes from the fact that $Pr[\Delta_{it}=1|X_{it}]=Pr[\Delta_{it}=0|X_{it}]=$

$Pr[\Delta_{it}] = \frac{1}{2}$ by construction. Proposition 3 implies that the term in the parenthesis is positive for every X_{it}, hence $\beta > 0$. ■

In order to prove Proposition 5, we use the following lemma:

Lemma 1. *For any two asset pricing models and within each control group:*

$$Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] = Pr[\Delta_{it}^T = 0, \Delta_{it}^F = 1|X_{it}] \tag{B.5}$$

Proof of Lemma 1.

$$Pr[\Delta_{it}^T = 1|X_{it}] = \frac{1}{2} = Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 1|X_{it}] + Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] \tag{B.6}$$

$$Pr[\Delta_{it}^F = 1|X_{it}] = \frac{1}{2} = Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 1|X_{it}] + Pr[\Delta_{it}^T = 0, \Delta_{it}^F = 1|X_{it}] \tag{B.7}$$

Comparing above two equations proves the result. ■

Proof of proposition 3. In Proposition 4 we showed that:

$$\beta = 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it} = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it} = 0]) \tag{B.8}$$

We can write β^T and β^F as follows:

$$\begin{aligned}
\beta^T &= 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0]) \\
&= 2 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 1] + Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] \\
&- Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 0] \Big)
\end{aligned} \tag{B.9}$$

$$\begin{aligned}
\beta^F &= 2 \times (Pr[\phi(n_{it}) = 1, \Delta_{it}^F = 1] - Pr[\phi(n_{it}) = 1, \Delta_{it}^F = 0]) \\
&= 2 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 1] + Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] \\
&- Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 0] \Big)
\end{aligned} \tag{B.10}$$

Thus,

$$\begin{aligned}
\beta^T - \beta^F &= 4 \times \Big(Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 1, \Delta_{it}^F = 0] - Pr[\phi(n_{it}) = 1, \Delta_{it}^T = 0, \Delta_{it}^F = 1] \Big) \\
&= 4 \sum_{X_{it}} \Big(Pr[\phi(n_{it}) = 1|\Delta_{it}^T = 1, \Delta_{it}^F = 0, X_{it}] Pr[\Delta_{it}^T = 1, \Delta_{it}^F = 0|X_{it}] Pr[X_{it}] \\
&- Pr[\phi(n_{it}) = 1|\Delta_{it}^T = -1, \Delta_{it}^F = 1, X_{it}] Pr[\Delta_{it}^T = -1, \Delta_{it}^F = 1|X_{it}] Pr[X_{it}] \Big)
\end{aligned} \tag{B.11}$$

By using Lemma 1, we can simplify above equation:

$$\begin{aligned}\beta^T - \beta^F &= 4\sum_{X_{it}} Pr[\Delta^T_{it}=1,\Delta^F_{it}=0|X_{it}]Pr[X_{it}] \\ &\times \Big(Pr[\phi(n_{it})=1|\Delta^T_{it}=1,\Delta^F_{it}=0,X_{it}] - Pr[\phi(n_{it})=1|\Delta^T_{it}=0,\Delta^F_{it}=1,X_{it}]\Big) \\ &= 4\sum_{X_{it}} Pr[\Delta^T_{it}=1,\Delta^F_{it}=0|X_{it}]Pr[X_{it}] \\ &\times \Big(Pr[\phi(n_{it})=1|\Delta^T_{it}=1,X_{it}] - Pr[\phi(n_{it})=1|\Delta^T_{it}=0,X_{it}]\Big) \end{aligned} \tag{B.12}$$

The last line comes from the fact that $Pr[\phi(n_{it})|\Delta^T_{it},\Delta^F_{it},X_{it}] = Pr[\phi(n_{it})|\Delta^T_{it},X_{it}]$. Proposition 3 implies that the term in the parenthesis is positive for every X_{it}, hence $\beta^T > \beta^F$. ■

Proof of proposition 4. Define:

$$\pi^c = Pr[\Delta_{it}=1|\Delta^c_{it}=1] + Pr[\Delta_{it}=0|\Delta^c_{it}=0] \tag{B.13}$$

By using equation (B.3), we can write:

$$\beta^c = Pr[\phi(n_{it})=1|\Delta^c_{it}=1] - Pr[\phi(n_{it})=1|\Delta^c_{it}=0] \tag{B.14}$$

We can write this as:

$$\begin{aligned}\beta^c =& Pr[\phi(n_{it})=1|\Delta^c_{it}=1,\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=1] \\ &+ Pr[\phi(n_{it})=1|\Delta^c_{it}=1,\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=1] \\ &- Pr[\phi(n_{it})=1|\Delta^c_{it}=0,\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=0] \\ &- Pr[\phi(n_{it})=1|\Delta^c_{it}=0,\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=0] \\ =& Pr[\phi(n_{it})=1|\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=1] \\ &+ Pr[\phi(n_{it})=1|\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=1] \\ &- Pr[\phi(n_{it})=1|\Delta_{it}=1]Pr[\Delta_{it}=1|\Delta^c_{it}=0] \\ &- Pr[\phi(n_{it})=1|\Delta_{it}=0]Pr[\Delta_{it}=0|\Delta^c_{it}=0] \\ =& \Big(Pr[\phi(n_{it})=1|\Delta_{it}=1] - Pr[\phi(n_{it})=1|\Delta_{it}=0]\Big)(\pi^c-1) \end{aligned} \tag{B.15}$$

The term in the first parenthesis is positive by Proposition 3, so $\beta^c > \beta^d$ is equivalent to $\pi^c > \pi^d$. ■

Proof of proposition 5.

$$\gamma_1 = \frac{Cov(\phi(n_{it}), \Delta^c_{it} - \Delta^d_{it})}{Var(\Delta^c_{it} - \Delta^d_{it})} \tag{B.16}$$

and since $Var(\Delta^c_{it}) = Var(\Delta^d_{it}) = \frac{1}{4}$ by construction:

$$\gamma_1 = \frac{\beta^c - \beta^d}{4 \times Var(\Delta^c_{it} - \Delta^d_{it})} \tag{B.17}$$

Therefore, $\beta^c > \beta^d$ is equivalent to $\gamma_1 > 0$. ■

Proof that our results are identical to Fama-MacBeth. Let $\dot{\phi}_{i,t}$ and $\dot{\Delta}_{i,t}$ be the cross-sectionally demeaned variables for the direction of net issuance and the binary rank of mispricing. Then, the univariate coefficient from a panel regression with time fixed effects is

$$\frac{4}{TN} \sum_t \sum_i \dot{\phi}_{i,t} \dot{\Delta}_{i,t}, \tag{B.18}$$

where $1/4$ is the sample variance of $\dot{\Delta}_{i,t}$, which is either $-1/2$ or $1/2$. Here, we assume balanced panel. Although in reality our panel data are unbalanced, we use weighted least squares to ensure that different years have the same weight in the regression. Hence, it suffices to analyze the balanced panel case.[1] On the other hand, the Fama-MacBeth coefficient is

$$\frac{1}{T} \sum_t (\frac{4}{N} \sum_i \dot{\phi}_{i,t} \dot{\Delta}_{i,t}), \tag{B.19}$$

which can be rearranged to be identical to the panel coefficient above. ■

B.2 An alternative measure of mispricing

Our benchmark mispricing in this paper is the compounded alpha (equation (2.16)). Despite its transparency and simplicity, this estimator does not have a clear interpretation as the deviation of price from the intrinsic value relative to an asset pricing model. The next lemma shows how we can estimate mispricing more accurately by using future realized returns and capital gains.

Definition 2. *Firm i's time-t mispricing with respect to a candidate asset pricing*

[1]We also ignore the degrees of freedom adjustment in the sample covariance calculation for simplicity.

model c is

$$\delta_{i,t}^{c} = \frac{P_{i,t} - V_{i,t}^{c}}{P_{i,t}}, \tag{B.20}$$

where

$$V_{i,t}^{c} = \sum_{j=1}^{\infty} \frac{1}{\left(1 + R_{i,t}^{c}\right)^{j}} E_t \left[D_{i,t+j}\right] \tag{B.21}$$

is the intrinsic value of dividends $\{D_{i,t+j}\}$ computed using the firm's rate of return $R_{i,t}^{c}$ implied by an asset pricing model c based on information up to time t.

Next, under the mild assumption that the deviation of price from value does not explode, we can use a modified version of the mispricing identity of Cho and Polk (2019) to express $\delta_{i,t}^{c}$ in terms of subsequent returns and capital gains.

Lemma 2. ***(Cho and Polk 2020).*** *Let $V_{i,t}^{c} = \sum_{j=1}^{\infty} \frac{1}{\left(1+R_{i,t}^{c}\right)^{j}} E_t \left[D_{i,t+j}\right]$ be the intrinsic value of the asset defined as the present value of cash flows with respect to the firm's discount rate $R_{i,t}^{c}$ implied by the asset pricing model. Then,*

$$\delta_{i,t}^{c} \equiv \frac{P_{i,t} - V_{i,t}^{c}}{P_{i,t}} = -\sum_{j=1}^{\infty} \frac{1}{\left(1 + R_{i,t}^{c}\right)^{j}} E_t \left[\frac{P_{i,t+j-1}}{P_{i,t}} (R_{i,t+j} - R_{i,t}^{c})\right], \tag{B.22}$$

where P_{t+j-1}/P_t and R_{t+j}^{e} are, respectively, the cumulative capital gain and excess return on the asset. This identity holds regardless of whether or not c is the true asset pricing model.

Proof. Let $\delta_{i,t}^{c}$ and $V_{i,t}^{c}$ be mispricing and intrinsic value with respect to a model-implied rate of return R^c. By definition, $V_{i,t}^{c} = E_t \left[\frac{1}{1+R^c}\left(D_{i,t+1} + V_{i,t+1}^{c}\right)\right]$. Use $V_{i,t}^{c} = \left(1 - \delta_{i,t}^{c}\right) P_{i,t}$ to substitute the V's on both sides of the equation:

$$\left(1 - \delta_{i,t}^{c}\right) P_{i,t} = E_t \left[\frac{1}{1 + R^c}\left(D_{i,t+1} + \left(1 - \delta_{i,t+1}^{c}\right) P_{i,t+1}\right)\right]$$

Rearranging, $\delta_{i,t}^{c} = -E_t \left[\frac{1}{1+R^c}\left(R_{i,t+1} - R^c\right)\right] + E_t \left[\frac{1}{1+R^c} \frac{P_{i,t+1}}{P_{i,t}} \delta_{i,t+1}^{c}\right]$. Iterating this difference equation for $\delta_{i,t}^{c}$ forward and imposing

$$\lim_{J \to \infty} \left\{\frac{1}{\left(1 + R^c\right)^{J}} E_t \left[P_{i,t+J} - V_{i,t+J}^{c}\right]\right\} = 0$$

gives equation (B.22): $\delta_{i,t}^{c} = -\sum_{j=1}^{\infty} \frac{1}{(1+R^c)^j} E_t \left[\frac{P_{i,t+j-1}}{P_{i,t}} (R_{i,t+j} - R^c)\right]$. ∎

Equation (B.22) motivates the sample realization of the right-hand side as the natural estimator of mispricing with respect to model c:

$$\hat{\delta}^c_{i,t} = -\sum_{j=1}^{J} \frac{1}{\left(1 + R^c_{i,t}\right)^j} \frac{P_{i,t+j-1}}{P_{i,t}} (R_{i,t+j} - R^c_{i,t}), \tag{B.23}$$

where $J = 10$ to 15 years is typically long enough to serve as an accurate approximation of the infinite sum. The finite-sum expression in expectation has the interpretation as the net present value of buying and holding the stock and selling it after J periods with respect to the discount rate $R^c_{i,t}$. The result also implies that for short horizons J, a simple cumulation of abnormal returns could proxy for mispricing. This motivates our baseline predictor of mispricing.

B.3 Additional Figure and Tables

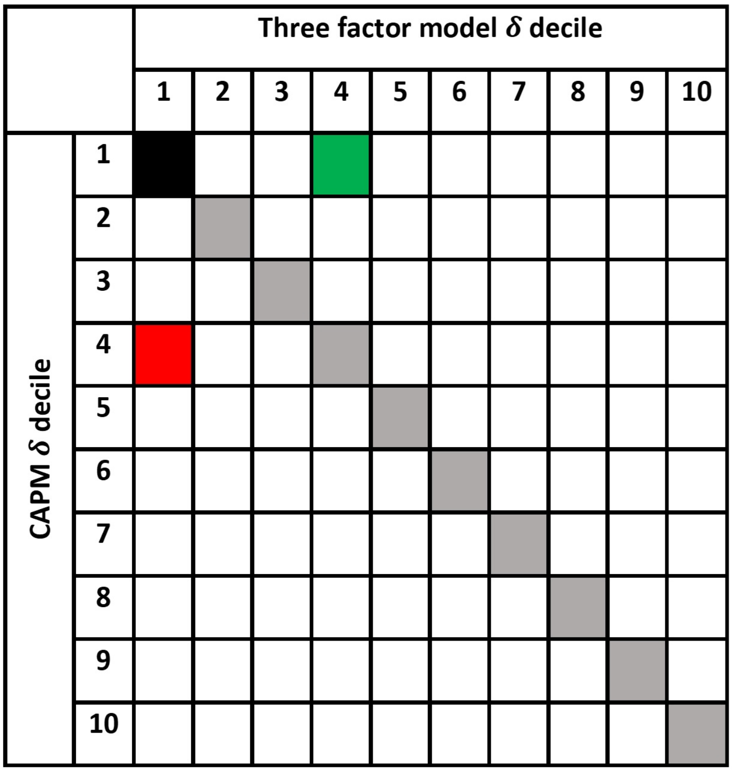

Figure B.1: Horse race dummy variables for pairwise comparison (BHO test)

This figure shows 100 possible dummy variables for the regression that compares mispricing with respect to the CAPM versus mispricing with respect to the Fama French three factor model. In the regression, omitted variable is the dummy with the first decile rank for both models. The gray cells represent firms with similar mispricing ranks from both models. The empirical tests compare the coefficients corresponding to 45 upper off-diagonal and 45 lower off-diagonal cells. For example, we compare the coefficient of dummy variable for firms with CAPM mispricing in the fourth decile and FF3 mispricing in the first decile (red) to the firms with CAPM mispricing in the first decile and FF3 mispricing in the fourth decile (green). CAPM wins the race if firm's issuance decision is more sensitive to the mispricing with respect to the CAPM, i.e. $b_{4,1} > b_{1,4}$.

Table B.1: Pairwise model comparisons, repurchases only

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Panel A: 25 Size and value groups				
CAPM	0.00	2.76	3.53	8.58	11.92	10.89	9.88
FF3	-2.76	0.00	1.99	4.48	6.45	12.80	8.29
Carhart	-3.53	-1.99	0.00	3.15	4.99	9.05	8.08
ICAPM	-8.58	-4.48	-3.15	0.00	0.31	2.33	2.38
Excess market	-11.92	-6.45	-4.99	-0.31	0.00	2.13	2.23
FF5	-10.89	-12.80	-9.05	-2.33	-2.13	0.00	0.25
Q-theory	-9.88	-8.29	-8.08	-2.38	-2.23	-0.25	0.00
			Panel B: 25 Size and Q groups				
CAPM	0.00	4.83	4.46	7.50	9.48	11.76	9.75
FF3	-4.83	0.00	0.88	2.41	3.31	12.02	7.09
Carhart	-4.46	-0.88	0.00	1.84	2.63	9.39	7.37
ICAPM	-7.50	-2.41	-1.84	0.00	-0.33	3.46	2.80
Excess market	-9.48	-3.31	-2.63	0.33	0.00	4.59	3.55
FF5	-11.76	-12.02	-9.39	-3.46	-4.59	0.00	-1.01
Q-theory	-9.75	-7.09	-7.37	-2.80	-3.55	1.01	0.00
			Panel C: 25 Size and momentum groups				
CAPM	0.00	5.04	5.21	9.20	11.38	13.33	11.25
FF3	-5.04	0.00	1.82	2.83	3.86	14.25	8.07
Carhart	-5.21	-1.82	0.00	1.75	2.63	10.15	7.97
ICAPM	-9.20	-2.83	-1.75	0.00	-0.22	4.32	3.42
Excess market	-11.38	-3.86	-2.63	0.22	0.00	4.93	3.98
FF5	-13.33	-14.25	-10.15	-4.32	-4.93	0.00	-0.83
Q-theory	-11.25	-8.07	-7.97	-3.42	-3.98	0.83	0.00
			Panel D: 25 Value and Q groups				
CAPM	0.00	2.39	1.15	2.76	6.45	9.59	7.26
FF3	-2.39	0.00	-1.72	-0.06	1.85	15.05	8.30
Carhart	-1.15	1.72	0.00	0.60	2.42	14.66	11.43
ICAPM	-2.76	0.06	-0.60	0.00	1.61	5.36	4.37
Excess market	-6.45	-1.85	-2.42	-1.61	0.00	6.12	4.55
FF5	-9.59	-15.05	-14.66	-5.36	-6.12	0.00	-1.04
Q-theory	-7.26	-8.30	-11.43	-4.37	-4.55	1.04	0.00

This table reports the *t*-statistics associated with γ_1 from the BvB test (equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta_{it}^c - \Delta_{it}^d) + \xi_{it}.$$

The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive or zero equity issuance). The right-hand variable is the difference in the binary rank of mispricing Δ with respect to a candidate asset pricing model c. with respect to asset pricing model c vs. d. The models are compared on mispricing estimated by post-issuance cumulative abnormal return over 10 years. Each panel determines the control sub-groups. In each quarter and within each control sub-group, firms are ranked by estimated mispricing relative to a candidate model of risk. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

Table B.2: Pairwise model comparison, BHO method, Fama Mcbeth regressions

	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Sum of differences			
CAPM	2.112	2.555	3.377	4.348	4.248	3.631
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FF3		1.694	0.789	1.879	3.779	2.756
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Carhart			-0.055	0.822	2.525	1.941
			(0.703)	(0.000)	(0.000)	(0.000)
ICAPM				0.156	1.965	1.188
				(0.293)	(0.000)	(0.000)
Excess market					1.014	0.683
					(0.000)	(0.000)
FF5						-0.261
						(0.051)
			% of differences >0			
CAPM	95.556	97.778	100.000	95.238	100.000	100.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FF3		95.556	77.778	88.889	100.000	100.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Carhart			51.111	77.778	100.000	95.556
			(1.000)	(0.000)	(0.000)	(0.000)
ICAPM				62.222	91.111	80.000
				(0.135)	(0.000)	(0.000)
Excess market					80.000	57.778
					(0.000)	(0.371)
FF5						37.778
						(0.135)

This table presents the results of pairwise horse race between competing risk models using BHO method. In this table, instead of running a panel regression, we estimate the relation between the sign of equity issuance and the decile rank of post-issuance mispricing using a Fama-Macbeth regression. The sign of equity net issuance is either zero (equity repurchase) or one (positive equity issuance). The sample excludes firm-quarter observations with zero net equity issuance. Controls include time and firm fixed effect, lagged equity issuance, lagged logarithm of total assets, lagged market to book ratio, age, profitability, investment, and asset growth. All mispricings are estimated over a 10-year time horizon. We compare off diagonal coefficients of dummy variables as in Figure B.1. Panel A presents the sum of the differences of off-diagonal coefficient estimates and their p-values. A positive number indicates that the model in the row wins the race against the model in the column. Panel B shows the percentage of cases in which the first model (row) beats the second model (column) out of the 45 comparisons and the p-value of the binomial test.. Data is quarterly from 1969 to 2009. All observations are deflated by the number of firms in each quarter and t-statistics are calculated using double clustered standard errors by firm and quarter.

Table B.3: Pairwise model comparisons, alternative measure of mispricing

	CAPM	FF3	Carhart	ICAPM	Excess market	FF5	Q-theory
			Panel A: 25 Size and value groups				
CAPM	0.00	7.66	9.14	9.75	15.04	11.34	10.36
FF3	-7.66	0.00	4.90	1.46	6.13	9.77	5.82
Carhart	-9.14	-4.90	0.00	-1.42	2.77	5.40	3.37
ICAPM	-9.75	-1.46	1.42	0.00	4.22	4.60	4.16
Excess market	-15.04	-6.13	-2.77	-4.22	0.00	1.84	0.96
FF5	-11.34	-9.77	-5.40	-4.60	-1.84	0.00	-1.22
Q-theory	-10.36	-5.82	-3.37	-4.16	-0.96	1.22	0.00
			Panel B: 25 Size and Q groups				
CAPM	0.00	7.91	7.94	8.68	13.89	11.49	9.88
FF3	-7.91	0.00	2.91	0.48	4.31	9.01	5.00
Carhart	-7.94	-2.91	0.00	-1.10	2.10	6.48	3.57
ICAPM	-8.68	-0.48	1.10	0.00	3.49	5.01	4.45
Excess market	-13.89	-4.31	-2.10	-3.49	0.00	3.90	2.73
FF5	-11.49	-9.01	-6.48	-5.01	-3.90	0.00	-1.43
Q-theory	-9.88	-5.00	-3.57	-4.45	-2.73	1.43	0.00
			Panel C: 25 Size and momentum groups				
CAPM	0.00	9.28	9.65	11.45	16.50	12.57	10.84
FF3	-9.28	0.00	3.49	1.10	4.95	9.17	4.67
Carhart	-9.65	-3.49	0.00	-0.95	2.31	6.41	3.05
ICAPM	-11.45	-1.10	0.95	0.00	3.08	4.69	3.58
Excess market	-16.50	-4.95	-2.31	-3.08	0.00	3.59	1.46
FF5	-12.57	-9.17	-6.41	-4.69	-3.59	0.00	-2.16
Q-theory	-10.84	-4.67	-3.05	-3.58	-1.46	2.16	0.00
			Panel D: 25 Value and Q groups				
CAPM	0.00	6.29	7.29	6.18	13.80	10.20	9.95
FF3	-6.29	0.00	3.53	-1.17	4.81	10.19	7.12
Carhart	-7.29	-3.53	0.00	-2.91	2.14	7.57	5.62
ICAPM	-6.18	1.17	2.91	0.00	6.13	6.63	6.88
Excess market	-13.80	-4.81	-2.14	-6.13	0.00	4.23	4.11
FF5	-10.20	-10.19	-7.57	-6.63	-4.23	0.00	-0.40
Q-theory	-9.95	-7.12	-5.62	-6.88	-4.11	0.40	0.00

This table reports the *t*-statistics associated with γ_1 from the BvB test (equation (2.14)):

$$\phi(n_{it}) = \gamma_{0t} + \gamma_1(\Delta_{it}^c - \Delta_{it}^d) + \xi_{it}.$$

The sign of equity net issuance $\phi(n)$ is either zero (equity repurchase) or one (positive equity issuance), and observations with zero net equity issuance are excluded. The right-hand variable is the difference in the binary rank of mispricing Δ with respect to asset pricing model c vs. d. The models are compared on mispricing estimated using equation (B.23) over 10 years. Each panel determines the control sub-groups. In each quarter and within each control sub-group, firms are ranked by estimated mispricing relative to a candidate model of risk. Each cell reports the *t*-statistics from a different regression. A positive number means that the model in the row wins the race against the model in the column and vice versa. All regressions include time fixed effects and the observations are deflated by the number of firms in each quarter. The *t*-statistics are calculated using double clustered standard errors by firm and quarter.

C Appendix to The Value-to-Price Ratio of US Stocks

C.1 Coefficient Estimates

C.1.1 The VAR system

$$z_{t+1} = \begin{bmatrix} inf_{t+1} - \overline{inf} \\ cg_{t+1} - \overline{cg} \\ ty_{t+1} - \overline{ty} \\ yspr_{t+1} - \overline{yspr} \end{bmatrix} = \Psi z_t + \Sigma^{\frac{1}{2}} \varepsilon_{t+1} \tag{C.1}$$

$$\Psi = \begin{bmatrix} 0.504 & 0.047 & 0.256 & -0.325 \\ -0.167 & 0.275 & 0.121 & 0.293 \\ 0.038 & 0.055 & 0.944 & 0.053 \\ -0.036 & -0.051 & 0.037 & 0.841 \end{bmatrix} \tag{C.2}$$

$$\Sigma^{\frac{1}{2}} = \begin{bmatrix} 0.558 & 0 & 00 & 0 \\ -0.098 & 0.616 & 0 & 0 \\ 0.031 & 0.064 & 0.211 & 0 \\ 0.011 & -0.017 & -0.120 & 0.111 \end{bmatrix} \tag{C.3}$$

$$w_{t+1} = \begin{bmatrix} roe_{t+1} - \overline{roe} \\ inv_{t+1} - \overline{inv} \end{bmatrix} = \Gamma w_t + \Omega^{\frac{1}{2}} u_{t+1} \tag{C.4}$$

$$\Gamma = \begin{bmatrix} 0.894 & -0.013 \\ -0.060 & 0.866 \end{bmatrix} \tag{C.5}$$

$$\Omega^{\frac{1}{2}} = \begin{bmatrix} 0.013 & 0 \\ 0.020 & 0.021 \end{bmatrix} \tag{C.6}$$

C.1.2 Market prices of risk

$$\Lambda_0 = \begin{bmatrix} -4.049 \\ -1.177 \\ 0.536 \\ -5.467 \end{bmatrix} \tag{C.7}$$

$$\Lambda_1 = \begin{bmatrix} 1.126 & -6.886 & -5.283 & -3.528 \\ 0.028 & 1.807 & -1.343 & -3.515 \\ 0.594 & -1.619 & -0.756 & 0.797 \\ -1.041 & 3.589 & 3.394 & 1.033 \end{bmatrix} \tag{C.8}$$