

Open-End Funds and Cross-Sectional Asset Returns

Minsoo Kim*

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Abstract

This paper studies how mutual funds- as the largest investor in stock market- matter for the equilibrium stock returns. Unlike direct household investors, fund managers face a distinct risk as an investment intermediary, namely fund flow risk: Fund flows are uncertain to managers, affect managers' income, and may force managers to liquidate their asset holdings. In an equilibrium model with fund managers, this paper shows that aggregate shocks to fund flows enter the stochastic discount factor (SDF) in addition to the aggregate market returns. Empirically, the implied SDF explains the average returns of 50 size, book-to-market, liquidity, and flow risk portfolios jointly and separately. In fact, the aggregate shocks to fund flows subsume explanatory power of the aggregate market returns across different model specifications. Moreover, the magnitude of the price of risk for the aggregate shocks to fund flows is very similar across the different sets of test assets, supporting the prediction that the aggregate shocks to fund flows are an important component of the SDF in stock market.

JEL classification: G12; G20; G23

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*University of Melbourne. E-mail: minsoo.kim@unimelb.edu.au. I am grateful to my advisor Ralph Koijen for his insightful advice and endless encouragement and to my committee members, Joao Cocco, Francisco Gomes, and Anna Pavlova, for detailed suggestions and support. I thank Adem Atmaz, Alexandru Barbu, Simcha Barkai, Svetlana Bryzgalova, Nuno Clara, James Dow, Alessandro Graniero, Nicholas Hirschey, Marcin Kacperczyk, Ryan Lewis, Dong Lou, Narayan Naik, Helene Rey, Arkodipta Sarkar, Stephen Schaefer, Henri Servaes, Varun Sharma, Taisiya Sikorskaya, Clemens Sialm (discussant), Vania Stavrakeva, Mikhail Tirsikh, and seminar participants at Chinese University of Hong Kong, Bank of Canada, Federal Reserve Bank Board of Governors, London Business School, University of Melbourne, University of Sydney, and 2019 Young Scholars Finance Consortium for helpful comments.

I. Introduction

Open-end mutual funds have become more important in financial markets over time.¹ French (2008) and Stambaugh (2014) document gradual capital shifts from direct investors to institutions, especially to open-end funds, in the U.S. common equity market. As a result, open-end mutual funds hold the largest share of the equity market, 28% in 2017, a marked increase from 4% in 1980, whereas direct investors hold 21% in 2017, a substantial decrease from 48% in 1980.² This paper attempts to study a new structure of equilibrium asset returns in the presence of open-end mutual fund managers in the asset market.

Open-end mutual funds face an inherent source of risk as an investment intermediary, namely fund flow risk. Fund flow is uncertain to fund managers because it is fund investors who decide when to buy/sell their fund shares. The uncertainty of fund flows matters to fund managers for at least two reasons. First, the fund flows directly affect the fund size and therefore part of the manager's income.³ Second, fund flows restrict managers from being able to time their purchases/liquidations of portfolio holdings at their discretion. In fact, open-end mutual funds allow daily redemptions and managers are required by law to pay back the fund investors within seven working days. The restriction on timing is the key difference between direct investors and fund managers as an investment intermediary.

Investors are also concerned about episodes where liquidity is low. Investors value securities based on their net returns after liquidating costs and require high compensations for holding securities with high levels of liquidating costs. In addition, traders also care about liquidity risk: they fear uncertainty and the variability of the liquidity level that liquidity may disappear when they need it. During market downturns, investors have high marginal utility and the ability to sell easily is especially valuable such that they are willing to accept a lower expected return for a security that is liquid during market downturns.

Fund managers care more about liquidity risk because they are subject to fund flow

¹As of 2017, \$50 trillion of assets are managed by open-end mutual funds worldwide based on the Investment Company Institute (ICI) Statistics released in 2018 Q2.

²For the time-series plot of the holdings and the full description of the data, see Appendix A.

³Ma, Tang, and Gomez (2018) analyze the compensation contracts of individual portfolio managers for 4,500 U.S. mutual funds. They find that the manager compensation is explicitly linked to the profitability of the investment advisor for 51% of the funds, which depends on the advisory fee rates and the total asset under management (AUM). For 20% of the sample funds, the manager compensation is directly linked to the fund's AUM.

risk and may have to liquidate their portfolio holdings when the fund investors want their money back. Mutual funds hold only 3-6% of cash relative to total net assets, distressed funds typically cannot borrow, and the Investment Company Act of 1940 prohibits some mutual funds from short selling (see Coval and Stafford (2007)), so redemptions often require selling securities. Constantinides (1986) makes the point that investors accommodate large transaction costs by drastically reducing the frequency and the volume of the trade. Fund managers, however, may not be able to time the transactions and require a high liquidity premium for a security that is illiquid when they may have to sell due to sudden and large fund outflows.⁴

This paper focuses on how fund flow risk and liquidity risk affect asset prices in equilibrium. To understand how they interact, I develop an equilibrium asset pricing model. I consider a pure exchange, overlapping generations economy that is populated by two classes of investors, fund managers and direct investors, both concerned about liquidating cost. The fund managers have CARA preferences over the end-of-period compensation that depends on the fund return and the fund flow at the end of the period. Managers receive the fund flow that depends on the fund performance and a flow shock, and the shock can be correlated across funds. The direct investors have CARA preferences over the end-of-period return of their own investment.

I solve the equilibrium asset pricing model and the result of the model implies that aggregate innovations in fund flows enter the stochastic discount factor (SDF) in addition to the aggregate market returns. Intuitively, during sudden and large aggregate fund outflows, an asset with high returns or low selling costs is particularly attractive to fund managers.

Specifically, expected returns are driven by two factors in equilibrium: 1) liquidity-adjusted market beta defined as the co-movement of net returns, i.e., returns net of liquidating costs of the security, with the net market returns, i.e., market returns net of aggregate market liquidity costs, and 2) fund flow beta defined as the co-movement of net returns with the aggregate unexpected fund flows. The fund flow beta is the main focus of this

⁴Recently, the U.S. Securities and Exchange Commission (SEC) has adopted new rules that will be effective as of December 2018 or June 2019 (depending on the requirement) to reduce the risk that funds will be unable to meet their redemption obligation. It will require open-end funds to establish a liquidity risk management program, disclose certain information on the fund's liquidity risk, and notify the SEC if illiquid asset exceeds 15 percent of holdings unless they qualify for an exemption from the SEC.

paper. It implies that a security with low returns (high liquidating costs) during the aggregate unexpected fund outflows must provide high compensation for investors in equilibrium. The model also implies that the fund flow beta becomes more important for predicting the equilibrium expected returns as the share of the aggregate fund size increases in the market. If there are no fund managers in the economy, my model collapses to one factor model of liquidity adjusted market beta, presented in Acharya and Pedersen (2005). Alternatively, if investors are not concerned about the liquidity cost and fund managers gain utility from the excess returns over the benchmark, it reduces to the two-factor model in Brennan (1993).

If aggregate fund flows are an important component of the SDF, then it should at least price the stocks that fund managers actively trade. Size and book-to-market are presumably two of the most well-established characteristics that differentiate the risk profiles of active mutual funds. For instance, Morningstar summarizes the holdings style of every equity mutual fund based on the two criteria of size and book-to-market. In addition, I also explore cross-sections that may have different attributes along the liquidity and fund flow risk that fund managers are concerned about. Namely, I construct 25 portfolios sorted by size and book-to-market and 25 portfolios by liquidity and fund flow beta to directly test the main economic mechanism of the asset pricing model in the data.⁵

I find that the model explains the cross-sectional average returns jointly when the 50 test portfolios are used simultaneously. The price of risk for fund flow beta is highly significant and positive across different model specifications: with/without liquidity-adjusted market beta and controlling for three Fama-French factors with a momentum factor. In contrast, the liquidity-adjusted market beta is subsumed by the fund flow beta: the price of risk for liquidity-adjusted market beta is insignificant when the fund flow beta is included in the model and the overall fit of the model, measured by cross-sectional R^2 , stays identical when only the fund flow beta remains in the model, removing the liquidity-adjusted market beta.

In asset pricing tests using the test portfolios separately, I highlight that the magnitude of the price of risk for fund flow beta is very similar across the different sets of test assets.

⁵For the sort purpose, I take into account the fact that the fund flow betas may change over time and are measured imprecisely, and model them as a function of characteristics that help to forecast fund flow risk going forward. In addition, I improve the measurement of the fund flows by cross-validating two independent mutual fund databases to filter out inconsistencies and to ensure complete coverage of share classes in each fund.

In contrast, the price of risk for liquidity-adjusted market beta fluctuates and even flips sign across the different portfolios. This supports the prediction that aggregate innovations in fund flows are an important component of the SDF.

The fund flow risk premium is estimated to be sizable, particularly for illiquid stocks. Conditional on the liquidity risk, the annual risk premium attributed to the fund flow risk is 5.28% for illiquid stocks and 2.90% for liquid stocks during the sample period of 1991-2013. After controlling for the three Fama-French factors with a momentum factor, the annual fund flow risk premium is 3.17% for illiquid stocks and 1.74% for liquid stocks. The large fund flow risk premium in illiquid stocks is consistent with the model in that fund flow risk is a bigger concern for illiquid stocks and that managers require higher compensation to hold the illiquid assets considering the fund flow risk.

My paper intersects several strands of literature including intermediary asset pricing, mutual fund flows, and liquidity. My paper is the first to explore aggregate shocks to fund flows as a pricing kernel in the U.S. equity market, motivated from a fact that mutual fund managers are the largest investor in the equity market. Also, while there is an extensive studies on mutual fund flows and liquidity separately, this paper is the first to look at the interaction of mutual fund flows and liquidity to explain cross-sectional average returns estimating flow risk premium conditional on liquidity from an asset pricing model with fund flow and liquidity components in it.

The empirical side of intermediary asset pricing is relatively new. Adrian, Etula, and Muir (2015) first test intermediary SDF in cross-sectional asset pricing and find that shocks to the leverage of security broker-dealers explain the average returns of 43 equity and bond portfolios. More recently, He, Kelly, and Manela (2017) show that shocks to the equity capital ratio of primary dealer price more sophisticated asset classes such as derivatives, commodities and currencies. Kojen and Yogo (2019) propose an asset pricing model with heterogenous asset demand to also match institutional and household stock holdings. In theoretical intermediary asset pricing, Brennan (1993), Cuoco and Kaniel (2011), He and Krishnamurthy (2012a), Kaniel and Kondor (2013), Basak and Pavlova (2013), and Vayanos and Woolley (2013) present equilibrium models to show how intermediaries may affect asset prices. In this paper, I bring in open-end mutual fund managers to the otherwise standard

liquidity-adjusted model of Acharya and Pedersen (2005) to understand how interaction of fund flow and liquidity risk affects asset prices.

Mutual fund flows have attracted extensive literature on the price impact of institutional flows. For instance, Warther (1995), Edelen and Warner (2001), Goetzmann and Massa (2003), Teo and Woo (2004), Coval and Stafford (2007), and Ben-Rephael, Kandel and Wohl (2011) find contemporaneous price pressure from mutual fund flows. Lou (2012) shows that expected flow-induce trading can predict the future returns of the mutual fund stocks. These papers corroborate the importance of the mutual fund managers to understand asset prices, however, none explores the aggregate fund flows as a pricing kernel or studies fund flow risk premium interacting with liquidity risk across a wide range of cross-sections.

Amihud and Mendelson (1986), Vayanos (1998), Chordia, Roll, and Subrahmanyam (2001a), Amihud (2002), Pastor and Stambaugh (2003), and Acharya and Pedersen (2005) among many others look at how average liquidity or liquidity risk is priced. Lynch and Tan (2011) present a partial equilibrium framework that the liquidity premium is large if the transaction costs co-vary negatively with wealth shocks. My model emphasizes that the liquidity risk is particularly important for the fund managers since the managers cannot time the transaction during sudden and large fund outflows. Empirical results also support this: the fund flow risk premium of illiquid stocks is almost twice that of liquid stocks.

The paper is organized as follows. Section II presents the equilibrium model. Section III describes data and empirical measures. Section IV discusses characteristics of portfolios sorted by liquidity and fund flow risk. Section V documents the main empirical results from the cross-sectional asset pricing test, and Section VI concludes. The proofs and detailed data works are in the Appendix.

II. Model

A. Economic Setup

Economy

I consider a pure exchange, overlapping generations economy that is populated by two classes of investors: fund managers and direct investors. Each generation at time t consists of I

homogeneous managers indexed by $i \in \{1, 2, \dots, I\}$ and J homogeneous direct investors indexed by $j \in \{1, 2, \dots, J\}$. Manager i starts off with an initial asset under management, $A_{i,t}$, and direct investor j has an initial asset $A_{j,t}$ at time t , and both classes of investors live for two periods from t to $t + 1$ and trade securities in period t and $t + 1$.

Liquidity is an elusive concept, which can refer to various costs associated with temporary price movement including brokerage fees and bid-ask spread. Broadly, it includes any trading-related frictions that make the actual transaction price deviate from the true underlying security value. Throughout the paper, I consider liquidity cost as a selling cost of a security per trade.

There are K risky securities in positive net supply indexed by $k \in \{1, 2, \dots, K\}$, as well as a risk-free asset in perfectly elastic zero net supply which pays an interest rate r_f . The risky security is a claim on its dividends and incurs a liquidating cost when selling at the end of the period. As in Acharya and Pedersen (2005), I assume investors sell all their securities at the end of the period $t + 1$. Dividends and liquidity cost vary over time following the AR(1) process to capture their persistence

$$D_t = \bar{D} + \rho^D(D_{t-1} - \bar{D}) + \eta_t^D, \quad (1)$$

$$C_t = \bar{C} + \rho^C(C_{t-1} - \bar{C}) + \eta_t^C, \quad (2)$$

where D_t and C_t are $K \times 1$ vectors of dividends and liquidity cost, respectively, $\rho^D, \rho^C \in [0, 1]$, $E[\eta_t^D] = E[\eta_t^C] = 0$, $Var[\eta_t^D] = \Sigma^D$, $Var[\eta_t^C] = \Sigma^C$, and $E[\eta_t^D(\eta_t^C)^T] = \Sigma^{CD}$.

I define $K \times 1$ gross return, r_{t+1} , $K \times 1$ relative liquidity cost, c_{t+1} , and $K \times 1$ net return after liquidity cost, r_{t+1}^c , with each security $k \in \{1, 2, \dots, K\}$ as

$$r_{k,t+1} = \frac{P_{k,t+1} + D_{k,t+1}}{P_{k,t}}, \quad c_{k,t+1} = \frac{C_{k,t+1}}{P_{k,t}}, \quad (3)$$

$$r_{k,t+1}^c = r_{k,t+1} - c_{k,t+1}, \quad (4)$$

where $P_{k,t}$ is the equilibrium stock price for security k at time t . In a competitive equilibrium, investors maximize the expected utility over their portfolio choice, taking the price as given. The equilibrium price is determined such that the asset market clears.

I model fund flows as a linear function of the fund performance and flow innovation⁶

$$f_{i,t+1} \equiv \frac{F_{i,t+1}}{A_{i,t}} = \alpha_0 + \alpha_1(r_{i,t+1}^c - r_{M,t+1}^c) + \eta_{i,t+1}, \quad (5)$$

where $F_{i,t+1}$ is the end-of-period fund flow in dollars to fund i , $A_{i,t}$ is the initial asset of the fund i , $r_{i,t+1}^c \equiv x_{i,t}^T(r_{t+1} - c_{t+1})$ is fund i 's return net of liquidity cost generated from $K \times 1$ beginning-of-period portfolio weight, $x_{i,t}$, $r_{M,t+1}^c \equiv x_{M,t}^T(r_{t+1} - c_{t+1})$ is the market return net of liquidity cost generated from $K \times 1$ beginning-of-period market portfolio weight $x_{M,t}$, α_1 is the common fund flow sensitivity to the fund performance, $\eta_{i,t+1}$ is the fund flow residual to the fund i at the end of the period. All managers use the market portfolio as the benchmark.

Fund Manager's Incentives

The fund managers have CARA preference over the end-of-period compensation. Fund manager i chooses a portfolio weight, $x_{i,t}$, at the beginning of the period and is constrained to invest all assets in the risky securities. The manager i 's portfolio choice problem is written as

$$\max_{x_{i,t}} E_t[Y_{i,t+1}] - \frac{b_I}{2} \text{Var}_t[Y_{i,t+1}] - \lambda(x_{i,t}^T \mathbf{1} - 1), \quad (6)$$

where b_I is the coefficient of constant absolute risk aversion common to all managers, λ is the Lagrange multiplier associated with the constraint that the managed portfolio is entirely invested in the risky securities, $\mathbf{1}$ is $K \times 1$ unit vector.

I model the manager i 's compensation, $Y_{i,t+1}$, as a function of two parts similar to Kojien (2014), a constant base salary and a variable component. The first part is a constant base salary proportional to its initial asset under management. The second part depends on its end-of-period fund value, which fluctuates due to the end-of-period fund returns and fund

⁶This is a reduced-form way of modelling various frictions that may constrain households from trading directly in the stock market, for instance high trading costs, time constraint, economies of scale. Consider another type of investors in the economy, indirect investors, who can only invest through the fund managers. The indirect investors receive an endowment at the beginning of the period, delegate part of the endowment to the fund managers based on fund performance and other reasons (residual term), and invest the rest in the risk-free asset. For tractability, I model fund flow as a function of contemporaneous return. This simplifying modelling assumption is relaxed during the empirical estimation of the flow innovation.

flows. This implies that the manager i 's maximization problem in (6) can be rewritten as

$$\max_{x_{i,t}} E_t [r_{i,t+1}^c + f_{i,t+1}] - \frac{b_I}{2} Var_t [r_{i,t+1}^c + f_{i,t+1}] - \lambda (x_{i,t}^T \mathbf{1} - 1). \quad (7)$$

The fund manager i chooses portfolio weight $x_{i,t}$ at the beginning of the period t that maximizes the conditional mean-variance utility of compensation in (7), which depends on the time-varying net return and fund flow at the end of the period.

Direct Investor's Incentives

Direct investors have CARA preference with constant absolute risk aversion and derive utility from the performance of their own investment at the end of the period, similar to the capital asset pricing model in Sharpe (1964) and Lintner (1965). The direct investor j 's portfolio strategy problem is written as

$$\max_{x_{j,t}} E_t [r_{j,t+1}^c - r_f] - \frac{b_J}{2} Var_t [r_{j,t+1}^c - r_f], \quad (8)$$

where $r_{j,t+1}^c \equiv x_{j,t}^T (r_{t+1} - c_{t+1})$ is direct investor j 's return net of liquidity cost generated from $K \times 1$ beginning-of-period portfolio weight, $x_{j,t}$, and b_J is the coefficient of absolute risk aversion.

B. Optimal Portfolio Strategies

All investors choose their optimal portfolios to maximize the utility in (7) or in (8). The full derivation is in Appendix B.

Fund Managers

The optimal portfolio choice of manager i at time t is written as

$$x_{i,t}^* = \underbrace{\frac{1}{b_I(1 + \alpha_1)} \Sigma_t^{-1} E_t \left[r_{t+1}^c - \frac{1}{1 + \alpha_1} \lambda \mathbf{1} \right]}_{\text{Mean-variance}} + \underbrace{\frac{\alpha_1}{1 + \alpha_1} x_{M,t}}_{\text{Benchmark}} - \underbrace{\frac{1}{1 + \alpha_1} \Sigma_t^{-1} Cov_t [r_{t+1}^c, \eta_{i,t+1}]}_{\text{Fund flow}}, \quad (9)$$

where $\Sigma_t \equiv Var_t [r_{t+1}^c]$.

The first term, $\frac{1}{b_I(1+\alpha_1)}\Sigma_t^{-1}E_t[r_{t+1}^c]$, resembles the standard portfolio choice of risk-return tradeoff but with return net of liquidity cost. The manager's demand is high for a security with a high expected net return relative to its variability, scaled by the risk aversion of the manager, b_I . The second term, $\frac{\alpha_1}{1+\alpha_1}x_{M,t}$, comes from the fund flows that depend on the relative performance over the market benchmark. The third component, $\Sigma_t^{-1}Cov_t[r_{t+1}^c, \eta_{i,t+1}]$, is the main distinguishing attribute of the manager's portfolio choice that plays a vital role in understanding economic mechanisms. Manager i 's demand for a security k depends on the covariance of its net returns with the unexpected fund flows to the fund i . If a security's returns decrease or liquidity costs increase during the negative states of the unexpected fund outflows, the manager has a low demand for the security.

When the risk aversion of the fund manager (b_I) goes to infinity and the flow sensitivity to the relative performance (α_1) goes to zero, the managers will still have a positive demand for stocks, in particular, those that provide a hedge against the aggregate fund flows. In contrast, if the flow sensitivity (a_1) goes to infinity, investors will hold exactly the market portfolio. When the volatility of the fund flow innovation and the flow sensitivity go to zero, then the demand collapses to Acharya and Pedersen (2005).

Direct Investors

Direct investor j 's optimal portfolio strategy equals the standard mean-variance portfolio choice that exploits the risk-return tradeoff but with return net of liquidity cost

$$x_{j,t}^* = \frac{1}{b_J}\Sigma_t^{-1}(E_t[r_{t+1}^c] - r_f\mathbf{1}). \quad (10)$$

C. Equilibrium Asset Prices

Equilibrium in the economy is defined in a standard way. Both fund managers and direct investors hold their optimal portfolios and the security market clears. To clear the market at each time t , the aggregate demand for each security $k \in \{1, 2, \dots, K\}$ from I fund managers

and J direct investors must equal supply

$$\sum_{i=1}^I A_{i,t} x_{i,t}^* + \sum_{j=1}^J A_{j,t} x_{j,t}^* = A_{M,t} x_{M,t}, \quad (11)$$

where $A_{M,t} \equiv \sum_{i=1}^I A_{i,t} + \sum_{j=1}^J A_{j,t}$ is the total asset of the aggregate market at time t , and $x_{i,t}^*$ and $x_{j,t}^*$ is the optimal portfolio choice of manager i and direct investor j in (9) and (10), respectively.

Proposition 1. (The Flow and Liquidity Asset Pricing Model) *The equilibrium expected net return of security k is given by*

$$E_t [r_{k,t+1}^c] = s_0 + s_1 \text{Cov}_t(r_{k,t+1}^c, r_{M,t+1}^c) + \text{Cov}_t(r_{k,t+1}^c, \bar{\eta}_{t+1}). \quad (12)$$

where $\bar{\eta}_{t+1}$ is the aggregate innovations in fund flows

$$\bar{\eta}_{t+1} = \sum_{i=1}^I \frac{A_{i,t}}{A_{I,t}} \eta_{i,t+1}, \quad (13)$$

and $A_{I,t} \equiv \sum_{i=1}^I A_{i,t}$ is the aggregate amount of asset under I managers.⁷

The expected return at the end of the period depends on two components in the flow and liquidity asset pricing model. The first component, covariation of net returns with net market returns, corresponds to the liquidity-adjusted market beta in Acharya and Pedersen (2005). It consists of the standard market beta and three liquidity betas: return sensitivity to market liquidity, liquidity sensitivity to market returns, and commonality in liquidity with the market liquidity.

The flow beta in the second term is the model's main contribution to explaining the cross-sectional expected returns. It is closely related to the managers' demand for security k in (9), but now it is the aggregate innovations in fund flows, $\bar{\eta}_{t+1}$, that matters to the equilibrium asset prices, instead of the individual flow innovation. If a security generates low returns or incurs high liquidity costs during large aggregate outflows, then the risk premium of the

⁷ s_0 is weighted average of the risk-free rate and the shadow price of full investment in risky assets, s_1 (s_2) is the share of direct investors (mutual funds) in the economy scaled by the risk aversion of managers, the risk aversion of direct investors, and the fund flow sensitivity to performance. The full derivation is in Appendix B.

security must be high in equilibrium.

When thinking of gross returns as the left-hand side variable in (12), the asset pricing model also includes the effect of liquidity on the average return (before liquidating cost). If the end-of-period trading cost of security k is expected to be high, then the compensation for holding the security k should be high in equilibrium. The expected liquidity cost affects the expected return by one to one because investors sell all their securities at the end of the period in the model.

Proposition 2. (Price of risk for the flow beta) *Suppose the risk aversion of the fund managers, b_I , the risk aversion of direct investors, b_J , and the flow performance sensitivity α_1 are positive. Then the price of risk of the flow beta increases with the size of the mutual funds in the economy while the price of risk of the market beta net of liquidity decreases with the size of the mutual funds in the economy*

$$\frac{\partial s_1}{\partial A_{I,t}} < 0, \quad \frac{\partial s_2}{\partial A_{I,t}} > 0. \quad (14)$$

The proposition states that the flow beta sensitivity to explain average returns increases as the share of the aggregate fund size increases in the market. The derivation is in Appendix B.

The flow and liquidity asset pricing model in (12) reduces to the models studied in the literature when I change part of the setup in the economy. If there is only one class of standard direct investor in the economy, it collapses to the liquidity-adjusted CAPM in Acharya and Pedersen (2005). Alternatively, if investors do not pay the liquidating cost and fund managers derive utility from excess returns over the benchmark, then the model reduces to the two factor model in Brennan (1993) with the two factors being covariance with the market returns and covariance with the benchmark returns.

An Unconditional Asset pricing model I derive an unconditional version of the flow and liquidity asset pricing model in (12) to explore the cross-sectional prediction of the model. An unconditional version can be derived under the assumption that the dividends and the liquidity costs in (1) and (2) are independent over time, that is $\rho^D = \rho^C = 0$. However, empirically illiquidity costs are highly persistent over time. Thus, I instead assume

that conditional covariances in the flow and liquidity asset pricing model are constant over time.⁸ The unconditional version of the equilibrium model for each stock k is written as

$$E[r_{k,t}^c] = s_0 + s_1 Cov(r_{k,t} - \varepsilon_{k,t}^c, \varepsilon_{M,t}^r - \varepsilon_{M,t}^c) + s_2 Cov(r_{k,t} - \varepsilon_{k,t}^c, \varepsilon_{k,t}^{\bar{\eta}}), \quad (15)$$

where ε^X is the shock to each variable X , specifically, $\varepsilon_{k,t}^c \equiv c_{k,t} - E_{t-1}[c_{k,t}]$, $\varepsilon_t^{\bar{\eta}} \equiv \bar{\eta}_t - E_{t-1}[\bar{\eta}_t]$, $\varepsilon_{M,t}^r \equiv r_{M,t} - E_{t-1}[r_{M,t}]$ and $\varepsilon_{M,t}^c \equiv c_{M,t} - E_{t-1}[c_{M,t}]$. To obtain less noisy estimates, I focus on the portfolio-level test of the flow and liquidity asset pricing model. For notational simplicity, I rewrite the unconditional asset pricing model in (15) for each portfolio p as

$$E[r_{p,t} - c_{p,t} - r_{f,t}] = \alpha + \lambda^{MKTc} \beta_p^{MKTc} + \lambda^{FLOW} \beta_p^{FLOW}, \quad (16)$$

where the market beta adjusted for liquidity is defined as $\beta_p^{MKTc} \equiv \beta_p^{rr} + \beta_p^{cc} - \beta_p^{rc} - \beta_p^{cr}$ with

$$\beta_p^{rr} = \frac{cov(r_t^p, \varepsilon_{M,t}^r)}{var(\varepsilon_{M,t}^r - \varepsilon_{M,t}^c)}, \quad \beta_p^{cc} = \frac{cov(\varepsilon_{p,t}^c, \varepsilon_{M,t}^c)}{var(\varepsilon_{M,t}^r - \varepsilon_{M,t}^c)}, \quad (17)$$

$$\beta_p^{rc} = \frac{cov(r_t^p, \varepsilon_{M,t}^c)}{var(\varepsilon_{M,t}^r - \varepsilon_{M,t}^c)}, \quad \beta_p^{cr} = \frac{cov(\varepsilon_{p,t}^c, \varepsilon_{M,t}^r)}{var(\varepsilon_{M,t}^r - \varepsilon_{M,t}^c)}, \quad (18)$$

and the flow beta is defined as $\beta_p^{FLOW} \equiv \beta_p^{rf} - \beta_p^{cf}$ with

$$\beta_p^{rf} = \frac{cov(r_{p,t}, \varepsilon_t^{\bar{\eta}})}{var(\varepsilon_t^{\bar{\eta}})}, \quad \beta_p^{cf} = \frac{cov(\varepsilon_{p,t}^c, \varepsilon_t^{\bar{\eta}})}{var(\varepsilon_t^{\bar{\eta}})}, \quad (19)$$

and λ^{MKTc} is the common price of risk for β_p^{rr} , β_p^{cc} , β_p^{rc} , and β_p^{cr} and λ^{FLOW} is the common price of risk for β_p^{rf} and β_p^{cf} . The unconditional flow and liquidity asset pricing model in (16) is the main focus of the empirical tests in the next sections.

III. Data and empirical measures

In this section, I estimate all empirical components needed to directly compute the six risk measures of each portfolio that underly the flow beta and the liquidity-adjusted market beta in (16). In Section IV.A, I compute the liquidity cost, i.e. the per-share selling cost,

⁸An alternative method that gives the same unconditional model is to assume the price of risks are constant over time and use the fact that for any random variable X and Y , $E[Cov_t(X, Y)] = Cov(X - E_t(X), Y - E_t(Y))$.

for each security k in each month t by the normalized Amihud (2002) illiquidity measure as employed in Acharya and Pedersen (2005). In Section IV.B, I estimate the monthly aggregate innovations in the mutual fund flows from flow-performance panel regression. In Section IV.C, I model the flow beta of each security as a function of its observable characteristics that help to predict the flow beta. In Section IV.D, I construct a set of 50 test portfolios: 25 portfolios sorted by illiquidity and predicted flow beta plus 25 size and book-to-market portfolios. For each portfolio, I compute the portfolio-level illiquidity and portfolio returns. In Section IV.E, I estimate the innovations in the portfolio illiquidity, the innovations in the market illiquidity, and the innovations in the market returns. These complete the necessary steps to estimate the two factors in the flow and liquidity asset pricing model for each of the 50 test portfolios.

A. Illiquidity cost

I employ the daily stock returns and volume data of ordinary common shares listed on the New York Stock Exchange (NYSE) and NYSE American (formerly AMEX) from the Center for Research in Security Prices (CRSP) to estimate the illiquidity cost of the stocks from 1991 to 2013 following the procedure in Acharya and Pedersen (2005). I do not include NASDAQ stocks because the volume data is overstated by including interdealer trades, unlike NYSE and NYSE American. My sample starts in 1991 to be consistent with the sample period of monthly mutual fund data that I will describe in detail in the next subsection. To avoid survivorship bias, I use the delisting return if the return on the delisting date is missing, as in Shumway (1997).⁹ The 30-day T-bill rate is also from CRSP.

I measure the illiquidity of stock k in month t as in Amihud (2002)

$$ILLIQ_{k,t} = \frac{1}{Days_{k,t}} \sum_{d=1}^{Days_{k,t}} \frac{|r_{k,t,d}|}{v_{k,t,d}}, \quad (20)$$

where $r_{k,t,d}$ is the return and $v_{k,t,d}$ is the dollar volume (in millions) of stock k in month t on day d . The intuition behind this measure is that a stock k is illiquid if its stock price

⁹I assign -30% to the stock return on the delisting date if the delisting code is 500 (reason unavailable), 520 (went to OTC), 551-573 and 580 (various reasons), 574 (bankruptcy), and 584 (does not meet exchange financial guidelines).

changes a great deal in response to the trading volume. That is, stock k is illiquid in month t if $ILLIQ_{k,t}$ is high.

I normalize the Amihud illiquidity measure to take into account that 1) the illiquidity measure has a strong downward trend as the value of the dollar price decreases over time and 2) the illiquidity measure is the ratio of return over dollar price, not dollar cost over dollar price as specified in the asset pricing model in (4). To accommodate these issues, I normalize the illiquidity measure by

$$c_{k,t} = \min(0.25 + 0.30 \times ILLIQ_{k,t} \times P_{M,t-1}, 30). \quad (21)$$

I multiply by the ratio of market portfolio capitalization, $P_{M,t-1}$, to make the series stationary over time. The coefficients of 0.25 and 0.3 are chosen to make the cross-sectional distribution of size portfolios of $c_{k,t}$ match the level and variance of the effective half spread, i.e., the difference between the transaction price and the midpoint of the prevailing bid-ask quote, reported by Chalmers and Kadlec (1998).¹⁰

Finally, the illiquidity cost is capped from the minimum of 0.25% to the maximum of 30%. During the period of 1991 to 2013 in my sample, the average illiquidity cost of 10 size portfolios ranges from 0.25% to 2.19% with a mean of 0.52% and a standard deviation of 0.57%.¹¹

B. Mutual fund flows

Sample criteria

I obtain the mutual funds' monthly returns, total net assets (TNA), and other fund characteristics from CRSP and Morningstar Direct from January 1991 to December 2013. My sample starts from January 1991 as the CRSP database records monthly total net assets from January 1991. The monthly inflation index is also from CRSP. I fully describe the

¹⁰For the market portfolio, I use all stocks with a beginning-of-month price between \$5 and \$1000 and with at least 15 days of both returns and dollar volumes in the month. To make sure that my results are not driven by using different normalizations of the illiquidity cost, I use the same definition of $P_{M,t-1}$ and the same coefficients of 0.25 and 0.30 from Acharya and Pedersen (2005).

¹¹Chalmers and Kadlec (1998) report the effective half spreads of 10 size portfolios ranging from 0.29% to 3.41% with a mean of 1.11% from 1962-1991. Similarly in Acharya and Pedersen (2005), the effective half spreads of 10 size portfolios are on average 1.24% with a standard deviation of 0.37%.

detailed procedure for merging the two mutual fund databases and the construction of the final mutual fund dataset in Appendix E.

There are a few notable advantages in utilizing the CRSP and Morningstar mutual fund databases together. First, I increase the accuracy of the fund returns and total net assets, which are essential to estimate the mutual fund flows, by cross-checking between CRSP and Morningstar. Second, the fund-level aggregate TNA is readily available in Morningstar, with which I can confirm that a fund is not missing a share class with significant size by comparing the sum of TNA across share classes in CRSP and the fund-level aggregate TNA.

To select my sample, I keep funds that are completely matched between CRSP and Morningstar following Pastor, Stambaugh, and Taylor (2015).¹² I use the fund net returns, TNA, and expense ratio from CRSP. In case of a missing expense ratio, I substitute it with the median during the sample period within the share class following Kojen (2014).¹³ For mutual funds acquiring other funds, I deduct the amount of acquiring TNA in the acquisition month following Lou (2012). For mutual funds that are merged with other funds, I drop the fund-months if CRSP keeps the data of the merged funds even after the merger date.

I aggregate across share classes to construct a fund-level dataset.¹⁴ For each month, I take the sum of TNA across subclasses and I take the TNA-weighted average of fund net returns and annual expense ratios. I compute the monthly gross fund return as the sum of the monthly net fund return plus 1/12 of the annual expense ratio. I exclude the fund-month if the maximum expense ratio across share classes during the month is larger than 4%.

In order to avoid fluctuations in fund-level TNA over time due to a missing share class in the middle of the time-series, I change fund-month TNA to missing if any share class is missing TNA in the month. Also I cross-check if the CRSP database is missing any share class of significant size: if the aggregate sum of TNA across share classes in CRSP differs by more than 50% of the fund-level aggregate TNA provided by Morningstar, I drop the fund.

I use only actively managed domestic equity mutual funds to be consistent with the

¹²I define a fund as completely matched if all share classes belonging to the fund are well matched. Each share class is well matched if and only if 1) the 60th percentile (over the available sample period) of the absolute value of the difference between the CRSP and Morningstar monthly fund returns is less than 5 basis points and 2) the 60th percentile of the absolute value of the difference between the CRSP and Morningstar monthly total net assets is less than \$100,000.

¹³If the expense ratio is negative, I keep it as missing.

¹⁴This is to avoid biased results by counting the returns of subclasses multiple times: among subclasses, the fee structures are different, however, the gross returns are identical.

Table 1: Summary statistics of mutual funds and aggregate innovations

The table shows the summary statistics of the final sample from the CRSP stocks and CRSP and Morningstar mutual funds from 1991-2013. In Panel B, innovations in fund flows is the sum of the time-fixed effect and the idiosyncratic residual of fund flows, η , from the flow performance regression in (23). In Panel C, aggregate innovations in fund flows is the AR(1) residual of the TNA-weighted average of innovations in fund flows in Panel B in (24). Innovations in market returns is AR(2) residual of value-weighted market returns with additional predictors of market returns described in subsection E. Innovations in market illiquidity is the residual of the normalized value-weighted illiquidity in AR(2) as specified in (29).

	Mean	Std. dev.	p10	p25	p50	p75	p90
Panel A: Mutual funds							
TNA (in mil \$)	1493	4987	39	87	264	914	2795
Monthly gross fund returns (%)	0.75	5.02	-5.48	-1.7	1.18	3.62	6.26
Monthly expense ratios (%)	0.1	0.04	0.05	0.08	0.09	0.12	0.14
Monthly fund flows (%)	-0.07	2.81	-2.85	-1.43	-0.4	0.87	3.19
Panel B: Fund flow innovations							
Innovations in fund flows (%)	-0.06	2.3	-2.33	-0.96	-0.18	0.73	2.37
Time-fixed effect (%)	-0.06	0.41	-0.57	-0.26	-0.09	0.16	0.46
Idiosyncratic residual of fund flows (%)	0.00	2.26	-2.21	-0.89	-0.1	0.77	2.35
Panel C: Aggregate innovations							
Aggregate innovations in fund flows (%)	0.00	0.46	-0.47	-0.26	-0.03	0.22	0.5
Innovations in market returns (%)	0.00	3.96	-5.07	-2.22	0.43	2.67	4.54
Innovations in market illiquidity (%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00

compensation function of fund managers in the model whose variable salary depends on the relative performance over their benchmarks in the US common equity market. I keep the active domestic equity funds by excluding index funds, bond funds, international funds, sector funds, target funds, real estate funds, and other non-equity funds using the Morningstar category, Primary prospectus benchmark, and Enhanced index from Morningstar.

I require lagged total net assets to be bigger than \$15 million in 2011 dollars following for instance Elton, Gruber, and Blake (2001). This alleviates concerns about having a too large fund flow mainly due to a small TNA in the denominator of the fund flow, which I define in (22). I require a fund to have at least 36 months of non-missing fund flows and fund returns to estimate innovations in fund flows with reasonable precision in the flow-performance regression in (23).

Finally, I have 1,511 distinct mutual funds and 151,736 fund-month observations in my final sample to estimate innovations in fund flows. The summary statistics of the final mutual fund sample are in Table 1 Panel A.

Innovations in mutual fund flows

I estimate the aggregate innovations in fund flows as follows. First, I compute the mutual fund flow for each fund i in month t , $f_{i,t}$, as in Chevalier and Ellison (1997), Sirri and Tufano (1998) and others as

$$f_{i,t+1} = \frac{A_{i,t+1} - A_{i,t} \times r_{i,t+1}}{A_{i,t}}, \quad (22)$$

where $r_{i,t+1}$ is fund i 's gross return. The fund flow, $f_{i,t+1}$, measures the new external flow for fund i from month t to month $t + 1$, relative to its initial fund size, excluding the increase or decrease due to the fund return from its asset investment in the previous month.

Second, I run a flow-performance regression using all panels of the qualified mutual funds with time-fixed effects

$$f_{i,t+1} = a_0 + a_1 (r_{i,t} - r_{M,t}) + a_2 f_{i,t} + \underbrace{\delta_{t+1} + \varepsilon_{i,t+1}}_{\eta_{i,t+1}} \quad (23)$$

where $r_{i,t}$ and $r_{M,t}$ is the lagged return of fund i and market, respectively.¹⁵ The time-fixed effects capture the common components of the fund flows across mutual funds that are not captured by the flow predictors in the flow-performance regression. This is consistent with the flow and liquidity asset pricing model in (12) in that it is the aggregate component of the fund flow innovations that matter for the asset prices.

In my sample from 1992-2013, a_1 is estimated to be 0.098 (t-stat: 32.62), and a_2 to be 0.557 (t-stat: 265.89), and a_0 to be -0.80 (t-stat: -10.17). R^2 is 33% when I include the time-fixed effect as the residual term, $R^2 = 1 - \text{var}[\delta_{t+1} + \varepsilon_{i,t+1}] / \text{var}[f_{i,t+1}]$. I estimate the fund flow innovations by the sum of the estimated time-fixed effects and the estimated idiosyncratic errors, $\hat{\eta}_{i,t+1} = \hat{\delta}_{t+1} + \hat{\varepsilon}_{i,t+1}$, for each fund i , and then take the TNA-weighted average to get the aggregate innovations in fund flows, $\bar{\eta}_{t+1}$, as the flow and liquidity asset pricing model suggests. To make sure there is no expected component in the aggregate innovations in fund flows, I take AR(1) residual of the aggregate innovations, $\varepsilon_t^{\bar{\eta}} \equiv \bar{\eta}_t - E_{t-1}[\bar{\eta}_t]$, from the

¹⁵For the purpose of the portfolio sort, which I describe in detail in the following subsection, I run the flow-performance panel regression using only information available at the time of the portfolio sort each year using mutual funds with at least 36 months of the flows and returns data. I assume liquidating costs of mutual fund portfolio i and its benchmark portfolio are close enough to cancel each other out.

following equation

$$\bar{\eta}_t = z_0 + z_1 \bar{\eta}_{t-1} + \varepsilon_t^{\bar{\eta}}. \quad (24)$$

Figure 1 plots the aggregate innovations in fund flows, $\varepsilon_t^{\bar{\eta}}$, from 1992-2013. Anecdotal evidence aligns with the movements of the aggregate innovations in the time-series plot. In particular, there are several drops in the aggregate fund flows in Figure 1 during the burst of the dot-com bubble lasting from March 2000 to October 2002. The decline from the burst peaked in July 2002, accompanied by the Enron scandal, and this coincides with the sharpest unexpected drop in the aggregate fund flows in Figure 1 in July 2002. During the 2008 financial crisis, there are series of aggregate outflows throughout 2008 until March 2009, with the peak outflows in September and October 2008 in the figure. The next largest drops appear in late 1998 when the Russian financial crisis and the collapse of Long-Term Capital Management occurred.

I use $\varepsilon_t^{\bar{\eta}}$ in (24) as the pricing kernel of the aggregate mutual fund managers throughout the paper and test if flow beta, computed by return and liquidity sensitivities with $\varepsilon_t^{\bar{\eta}}$, can price the cross-sections of average returns. In what follows, I explain how to compute the flow beta in detail.

C. Predicted flow beta

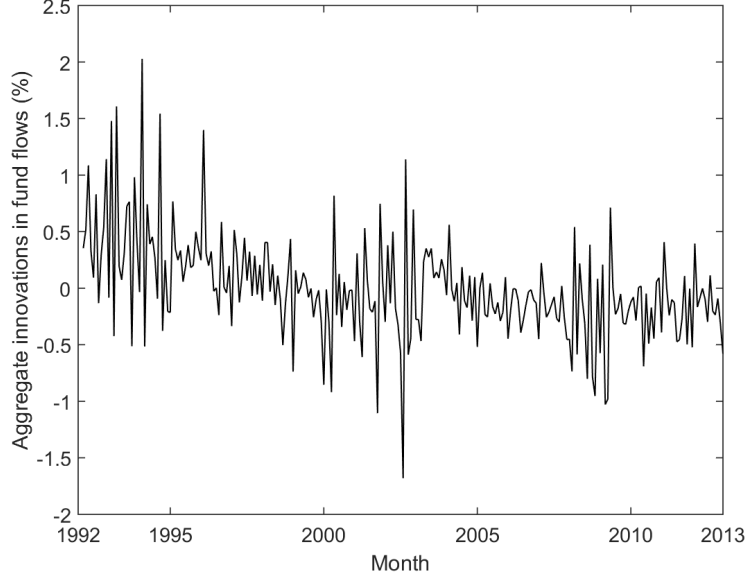
I model the flow beta of a security as a function of its observable characteristics that help to predict the flow beta similar to Pastor and Stambaugh (2003)

$$\beta_{k,t-1}^{rf} = \psi_1 + \psi_2' \mathbf{Z}_{k,t-1}, \quad (25)$$

where $\beta_{k,t-1}^{rf}$ is the return sensitivity of security k with the aggregate innovations in fund flows. $\mathbf{Z}_{k,t-1}$ includes four characteristics of security k computed using information available up to month $t - 1$: (1) the historical flow beta estimated from $t - 60$ to $t - 1$ if at least 36 months of returns are available, (2) the cumulative return from month $t - 6$ to $t - 1$, (3) the standard deviation of the stock's monthly returns from month $t - 6$ to $t - 1$, (4) the proportion of the stock's shares outstanding held by mutual fund managers on aggregate in the preceding

Figure 1: Aggregate innovations in fund flows

I compute the monthly aggregate innovations in fund flows using the qualified active domestic equity funds from the CRSP and Morningstar mutual fund database during 1992-2013. I describe the criteria of the qualified funds in detail in Section IV.B. I run a panel regression with time-fixed effects to estimate the innovations in fund flows for each fund. I compute the fund flow innovation by the sum of the estimated time-fixed effects and the estimated idiosyncratic error for each fund, and then take the TNA-weighted average to obtain the aggregate innovations in fund flows, consistent with the flow and liquidity asset pricing model. To make sure there is no expected component in the aggregate innovations in fund flows, I take AR(1) residual of the aggregate innovations.



quarter.¹⁶ The intuition behind these characteristics is that stocks with different short-term return dynamics (past cumulative return and volatility) and different mutual fund ownership could have different flow betas. For the purpose of portfolio construction, I rewrite the return of stock k as

$$r_{k,t} = \text{const} + \beta_{k,t-1}^{rf} \varepsilon_t^{\bar{\eta}} + \xi_{k,t}, \quad (26)$$

and substitute the flow beta $\beta_{k,t-1}^{rf}$ to obtain

$$r_{k,t} = \text{const} + (\psi_1 + \psi_2' \mathbf{Z}_{k,t-1}) \varepsilon_t^{\bar{\eta}} + \xi_{k,t}. \quad (27)$$

I run the OLS pooled time-series and cross-sectional regression using the full panel of qualified stocks and mutual funds to reduce the estimation error for common ψ_1 and ψ_2 . I compute

¹⁶I use holdings data of mutual fund from Thomson Reuters S12 (formerly CDA/Spectrum). I appreciate Doshi, Elkamhi, and Simutin for sharing the code to merge S12 with CRSP mutual funds and stock returns databases.

the predicted flow beta for each security k by

$$\hat{\beta}_{k,t}^{rf} = \hat{\psi}_1 + \hat{\psi}_2' \mathbf{Z}_{k,t}. \quad (28)$$

To avoid any biases that might come from using information that was not readily available to investors, I update the estimation of ψ_1 and ψ_2 at the time of each portfolio sort at year-end, exploiting information only available at the time of the sort. This includes re-estimation of the aggregate innovations in fund flows using the fund flows and fund returns available up to month t of the end of each year. I then re-estimate the rolling-window characteristics $\mathbf{Z}_{k,t-1}$ and update the estimation of ψ_1 and ψ_2 . Using the year-end characteristics, $\mathbf{Z}_{k,t}$, I compute the predicted flow beta by which the security k is sorted at year-end month t . A more detailed description of the re-estimation procedure is in Appendix C.

Table 2 presents three different sets of the estimated coefficients, $\hat{\psi}_1$ and $\hat{\psi}_2$, using data available up to the year-end in 2004, 2008, and 2012. Historical beta is highly significant with positive coefficients throughout the different year-ends. However, the coefficient estimates are smaller than 1, which points to a measurement error of the historical sort beta as commonly documented in the literature and confirms the importance of modelling the flow beta as a function of observable characteristics that help to predict fund flow risk going forward. In fact, sorting stocks by the predicted flow beta helps to create a wider monotonic spread of postranking flow beta across the test portfolios compared to sorting stocks by the historical flow beta alone. In most year-ends, stocks with high return volatility and low cumulative return in the past 6 months have high flow beta going forward. Also, stocks held more by mutual fund managers on aggregate as of the preceding quarter tend to have high flow beta as in the table.

D. Portfolios

In order to study how the interaction between liquidity and flow risk affects asset prices, I construct portfolios that may have different attributes across the two dimensions of liquidity and flow risk by sorting on the level of illiquidity and then by predicted flow beta. To raise the bar of my empirical test, I consider another set of test portfolios, namely 25 size and

Table 2: Characteristics coefficients for predicted flow beta

This table reports the estimated coefficients of the five characteristics for the predicted flow beta. I run OLS pooled regressions using all qualified panels of stocks from CRSP and mutual funds from CRSP and Morningstar from 1992 to 2013. The ending year of the sample varies depending on the year of the portfolio sort. In this table, I document three different end-years, 2004, 2008, and 2012, all starting from January 1992. The OLS t -statistics is in parenthesis.

Sample ending in	Intercept	Historical flow beta	Return volatility	Cumulative return	Ownership by funds
December 2004	2.32 (14.00)	0.11 (7.11)	0.10 (8.80)	-0.02 (-9.86)	0.10 (10.37)
December 2008	1.88 (12.76)	0.08 (6.19)	0.13 (12.53)	-0.03 (-14.36)	0.10 (13.27)
December 2012	1.80 (13.63)	0.04 (3.56)	0.16 (17.12)	-0.01 (-5.54)	0.07 (12.91)

book-to-market portfolios. If the aggregate fund flows are an important component of SDF, it should price cross-sections that the managers trade actively. Size and book-to-market are presumably two of the most well-established characteristics that the active mutual funds have invested in.

25 illiquidity and flow beta portfolios

I form 25 illiquidity and flow beta portfolios at the end of each year using all NYSE and NYSE American stocks with a beginning-of-year price between \$5 and \$1000 and with at least 100 days of both returns and dollar volume in the preceding year. I sort the qualified stocks to five portfolios based on the illiquidity in the preceding year, $ILLIQ_{k,y-1}$. I compute the annual illiquidity, $ILLIQ_{k,y-1}$, as the ratio of daily absolute returns over dollar volume of security k averaged over the previous year $y - 1$.¹⁷ In each of the five illiquidity portfolios, I then sort the stocks by the predicted flow beta, $\hat{\beta}_{k,t}^{rf}$, as estimated in (28). I exclude stocks if the annual liquidity measure in the preceding year or the predicted flow beta is missing.

After sorting at the end of each year, I hold the stocks in each portfolio over the next 12 months and take the value-weighted average across stocks within each portfolio to compute the monthly portfolio returns. I then rebalance at the end of the year and repeat this to link the time-series of the monthly returns in each portfolio from 1995 to 2013. The year starts

¹⁷The annual illiquidity measure is analogous to the monthly illiquidity measure, $ILLIQ_{k,t-1}$, as defined in (20). The only difference is that it is averaged over the year instead of the month. A sort by the normalized illiquidity instead of $ILLIQ_{k,y-1}$ results in the same portfolio construction since it adds/multiplies the identical coefficients to $ILLIQ_{k,t-1}$ for all stocks to compute the normalized illiquidity.

from 1995 because I need to have at least 36 months of returns to estimate the innovations in fund flows.

25 size and book-to-market portfolios

I construct 25 size and book-to-market portfolios at the end of each year using the same qualified stocks as in the 25 illiquidity and flow beta portfolios. I compute the size and book-to-market ratio following Fama and French (1993).¹⁸ If the book value is negative, I keep it as missing. I exclude stocks from the sort if the size or the book-to-market ratio is missing.

E. Innovations in portfolio illiquidity and market returns

Following Acharya and Pedersen (2005), I compute the innovations in portfolio illiquidity in month t , $\varepsilon_{p,t}^c = c_{p,t} - E_{t-1}[c_{p,t}]$, in the following AR(2) equation. Note that the same date, $t - 1$, is used for the market index, $P_{M,t-1}$, in the right hand side lags to ensure that AR(2) measures the innovations only in illiquidity, not changes in P_M

$$\begin{aligned} (0.25 + 0.3ILLIQ_{p,t}P_{M,t-1}) &= w_0 + w_1 (0.25 + 0.3ILLIQ_{p,t-1}P_{M,t-1}) \\ &+ w_2(0.25 + 0.3ILLIQ_{p,t-2}P_{M,t-1}) + \varepsilon_{p,t}^c, \end{aligned} \quad (29)$$

where $ILLIQ_{p,t}$ is the value-weighted average of truncated illiquidity¹⁹

$$ILLIQ_{p,t} = \sum_{k \in p} w_{k,p,t-1} \min \left(ILLIQ_{k,t}, \frac{30 - 0.25}{0.3P_{M,t-1}} \right), \quad (30)$$

and $w_{k,p,t-1}$ is the weight of market capitalization in month $t - 1$. Similarly, I compute the innovations in market illiquidity by $\varepsilon_{M,t}^c \equiv c_{M,t} - E_{t-1}[c_{M,t}]$ from an AR(2) equation that is analogous to (29) but using $ILLIQ_{M,t}$ instead of $ILLIQ_{p,t}$. I compute $ILLIQ_{M,t}$ by the value-weighted average of truncated illiquidity as in (30) but taking the average over all

¹⁸The size of a security is the market capitalization of the stock in December of the preceding year. For a company with non-missing total asset and total liability in Compustat, I compute the book value of a security as total asset minus total liability plus investment tax credit (if available) plus deferred taxes (if available) minus preferred stock (redemption value). If preferred stock (redemption value) is missing, I use preferred stock (liquidating value) or preferred/preference stock (capital), in order.

¹⁹The truncated illiquidity ensures that the normalized illiquidity for portfolio p , $c_{p,t} = 0.25 + 0.3ILLIQ_{p,t}P_{M,t-1}$, ranges between the minimum of 0.25% and the maximum of 30%.

stocks in the market instead of within each portfolio.

I construct the market portfolio returns by the value-weighted average of all stock returns with a beginning-of-month price between \$5 and \$1000 and with at least 15 days of both returns and dollar volume in the month. I compute the innovations in market returns by $\varepsilon_{M,t}^r \equiv r_{M,t} - E_{t-1}[r_{M,t}]$ from the AR(2) equation with additional control variables: volatility of the market returns, average market illiquidity, log of the average dollar volume, and log of the average turnover, all measured over the past 6-month rolling period (from month $t - 6$ to $t - 1$), and log of the market capitalization in month $t - 1$. All the market-level predictors are computed by value-weighted average.

IV. Portfolio characteristics

Flow and liquidity risk

For each portfolio p of the 25 illiquidity and flow beta portfolios, I utilize all empirical measures that I computed in the previous section to compute the two risk factors, β_p^{FLOW} and β_p^{MKTc} as derived in the asset pricing model in (16) using all the data from 1995 to 2013.

Table 3 reports the cross-sectional distributions of the β^{FLOW} and β^{MKTc} across the 25 illiquidity and flow beta portfolios. β^{FLOW} has a wide spread across the portfolios ranging from 3.43 to 6.11, with t -statistics significant at the 1% level in all 25 portfolios. This alleviates concerns about unreliable estimates of risk premia when covariances with the portfolio returns are small (see Bryzgalova (2016)). β^{FLOW} tends to increase across the flow beta sort, although the pattern in the middle is not as strong as in the low/high flow beta portfolios.

For portfolio characteristics, I take the value-weighted average across the stocks in each portfolio $p \in \{1, 2, 3, \dots, 25\}$ of monthly excess returns, normalized illiquidity cost ($c_{k,t}$), monthly turnovers, volatility of daily returns during month t , and the equal-weighted average of size at month t . The monthly turnover of a stock k in month t is the total number of shares traded during the month t over the average shares outstanding during the month t using the daily CRSP trade volume and the shares outstanding.

Monthly excess returns over the risk-free rate are higher for high flow beta stocks com-

Table 3: 25 illiquidity and flow beta portfolios

This table shows the characteristics of 25 illiquidity and predicted flow beta portfolios formed at the end of each year by the preceding year's illiquidity and predicted flow beta using CRSP stocks and CRSP and Morningstar mutual funds data from 1995-2013. β^{FLOW} is the flow risk net of liquidity cost and β^{MKTc} is the market risk net of liquidity cost. Monthly excess return is the time-series average of the value-weighted portfolio returns over the monthly 30d T-bill rate.

β^{FLOW}							$t(\beta^{FLOW})$						
	Flow beta							Flow beta					
	Low	2	3	4	High	5-1		Low	2	3	4	High	5-1
Liquid	3.43	3.92	4.51	4.12	4.37	0.94	Liquid	4.19	4.9	5.4	4.05	3.74	1.77
2	4.09	4.77	5.41	4.87	5.57	1.48	2	5.33	5.2	5.02	4.09	4.71	2.02
3	3.89	5.26	5.45	5.86	5.8	1.91	3	4.94	5.31	5.19	4.87	4.19	1.97
4	3.53	5.14	5.55	6.11	6.09	2.56	4	4.01	4.83	4.65	4.83	4.38	2.86
Illiquid	4.09	5.05	5.4	5.42	5.93	1.84	Illiquid	4.67	4.27	4.1	3.83	3.85	1.38

β^{MKTc}							$t(\beta^{MKTc})$						
	Flow beta							Flow beta					
	Low	2	3	4	High	5-1		Low	2	3	4	High	5-1
Liquid	0.71	0.74	0.85	0.97	1.16	0.45	Liquid	18.93	23.68	31.09	31.19	23.27	6.81
2	0.78	1.01	1.1	1.21	1.35	0.56	2	17.83	24.95	24.88	24.26	21.19	7.52
3	0.75	1.03	1.15	1.19	1.4	0.65	3	18.13	21.52	21.84	20.64	18.88	9.12
4	0.77	1.01	1.15	1.24	1.27	0.49	4	15.92	17.38	18.33	18.35	15.22	6.43
Illiquid	0.79	0.98	1.12	1.15	1.36	0.58	Illiquid	14.38	12.68	15.63	14.04	14.22	6.41

Monthly excess returns (%)							$t(\text{excess returns})$						
	Flow beta							Flow beta					
	Low	2	3	4	High	5-1		Low	2	3	4	High	5-1
Liquid	0.33	0.37	0.52	0.49	0.51	0.18	Liquid	1.2	1.23	1.63	1.3	1.03	0.46
2	0.63	0.66	0.76	0.79	0.67	0.04	2	2.07	1.85	1.8	1.73	1.33	0.12
3	0.6	0.79	0.87	0.69	0.73	0.13	3	1.93	2.01	2.12	1.46	1.35	0.35
4	0.65	0.84	0.95	1.13	1.24	0.59	4	2.06	2.03	2.07	2.28	2.33	1.64
Illiquid	0.6	0.94	1.24	0.92	1.47	0.87	Illiquid	1.71	2.07	2.52	1.72	2.57	2.06

pared to low flow beta stocks. The difference is particularly notable for illiquid stocks. For the most illiquid stocks, high flow beta stocks on average have 0.87% (10.44% annually) higher excess monthly returns than low flow beta stocks.

Consistent with the liquidity literature, the illiquidity cost increases exponentially for the most illiquid stocks. More interestingly, for the most illiquid stocks, the illiquidity cost reduces from 1.77% to 1.19% as flow beta increases while its average monthly excess return increases from 0.6% to 1.47%. This implies that, for illiquid stocks, the spread of the average returns across flow beta cannot be explained by the illiquidity cost alone. In Section IV, I formally test if the differences in β^{FLOW} explain the spread of the average excess returns across 25 illiquidity and flow beta portfolios.

Table 3: continued

I take time-series averages of the value-weighted normalized illiquidity cost ($c_{k,t}$), value-weighted monthly turnovers, value-weighted volatility of daily returns, and equal-weighted size. The monthly turnover is the total number of shares traded during the month over the average shares outstanding during the month using the daily CRSP trade volume and shares outstanding.

Normalized illiquidity cost (%)						Monthly turnovers (%)					
	Flow beta						Flow beta				
	Low	2	3	4	High		Low	2	3	4	High
Liquid	0.25	0.25	0.25	0.25	0.25	Liquid	11.26	9.58	11.16	11.9	17.9
2	0.26	0.26	0.26	0.26	0.26	2	13.07	16.07	19.13	21.98	25.84
3	0.28	0.28	0.29	0.28	0.29	3	11.48	13.19	16.68	19.6	24.21
4	0.39	0.39	0.39	0.38	0.37	4	9.64	11.53	14.37	16.12	18.34
Illiquid	1.77	1.6	1.6	1.41	1.19	Illiquid	4.92	8.12	8.88	9.58	12.62

Monthly volatility of daily returns (%)						Size (bil\$)					
	Flow beta						Flow beta				
	Low	2	3	4	High		Low	2	3	4	High
Liquid	1.6	1.62	1.74	1.91	2.29	Liquid	48.02	32.29	25.19	17.86	15.62
2	1.63	1.89	2.14	2.37	2.75	2	3.67	3.7	3.48	3.3	3.02
3	1.74	2	2.26	2.52	2.91	3	1.86	1.59	1.51	1.45	1.38
4	1.93	2.27	2.43	2.67	2.99	4	0.84	0.8	0.71	0.69	0.7
Illiquid	2	2.49	2.66	2.82	3.16	Illiquid	0.24	0.23	0.24	0.24	0.26

The turnover provides economically useful information on liquidating costs. Note that the normalized liquidating cost, $c_{p,t}$, is the average per-trade selling cost that investors pay only when they actually trade. If the actual security holding period is longer than the monthly estimation period of my empirical works, investors should not incur the full liquidating cost every month. In order to proxy the unknown security holding period, I use the inverse of the average turnover. The turnover reveals the percentage of shares outstanding traded during the month. In my sample, the average turnover is 0.14 using all qualified stocks in the portfolio formation. This implies that it takes on average $7.14 = 1/0.14$ months to trade the shares outstanding once. The asset pricing model assumes the security holding period is one month for all investors in (16). In order to adjust the liquidating cost proportionately to the holding period, I divide the liquidating cost by the average holding period in the asset pricing model

$$E[r_{p,t} - r_{f,t}] = \alpha + \frac{1}{7.14} E[c_{p,t}] + \lambda^{FLOW} \beta_p^{FLOW} + \lambda^{MKT} \beta_p^{MKTc}. \quad (31)$$

When I formally test the asset pricing model in Section V, I also model the unknown holding

period as a free parameter, τ , and have it estimated in the data

$$E[r_{p,t} - r_{f,t}] = \alpha + \tau E[c_{p,t}] + \lambda^{FLOW} \beta_p^{FLOW} + \lambda^{MKT} \beta_p^{MKTc}. \quad (32)$$

Additional characteristics in the 25 illiquidity and flow beta portfolios reveal that high flow beta stocks are in general more volatile than low flow beta stocks. The size distribution across the flow beta does not have a very clear pattern in all levels of illiquidity.

V. Main Empirical Results

In this section, I formally test if the differential sensitivities of return and liquidity cost with the aggregate fund flow explain the average returns cross-sectionally. The main focus is on the price of risk for the flow beta. In Section V.A, I estimate the price of risks in the flow and liquidity asset pricing model using the 50 test portfolios simultaneously: 25 size and book-to-market portfolios and 25 illiquidity and flow beta portfolios. In Section V.B, I estimate the price of risks for the 25 size and book-to-market portfolios and the 25 illiquidity and flow beta portfolios separately.

A. Cross-sectional analysis: joint test with 50 portfolios

Table 4 documents the results of the baseline case of the flow and liquidity model as derived in Section II (Model 1, Model 2), other specifications of the baseline model (Model 3 - Model 6), the baseline model controlling for the Fama-French three factors with a momentum²⁰ (Model 7).

Model 1 and Model 2 are the direct test of the flow and liquidity asset pricing model derived in Section II. In Model 1, I calibrate the parameter τ to be $0.14 \approx 1/7.14$ using the sample average turnover (0.14) to approximate the security holding period (7.14 months) as discussed in the previous section. The price of risk for the β^{FLOW} is estimated to be 0.2 and statistically significant at the 1% level while the risk price for the β^{MKTc} is 0.01 with t -statistics close to zero. In Model 2, I test the asset pricing model with a free parameter τ in front of the per-trading selling cost, $E[c_{p,t}]$, and have it estimated in the data. The

²⁰The market returns (MKT), size mimicking portfolio returns (SIZE), book-to-market mimicking portfolio returns (HML), and momentum mimicking returns (MOM) come from Kenneth French's data library.

Table 4: Joint test, 50 portfolios on size, book-to-market, illiquidity and flow beta

Using 50 monthly test portfolios, this table reports the estimated price of risks of various specifications from the following baseline cross-sectional asset pricing model

$$E[r_{p,t} - r_t^f - \tau c_{p,t}] = \alpha + \lambda^{FLOW} \beta_p^{FLOW} + \lambda^{MKT} \beta_p^{MKTc},$$

where β_p^{FLOW} is the co-movement of returns net of liquidity costs with aggregate innovations in fund flows and β_p^{MKTc} is the co-movement of returns net of liquidity costs with the market returns net of market liquidity costs of portfolio $p \in \{1, 2, \dots, 50\}$. To adjust the liquidating cost proportionately to the monthly estimation period, I use the calibrated value of $\tau=0.14$ or I estimate τ as a free parameter. The market returns (MKT), size mimicking portfolio returns (SMB), book-to-market mimicking portfolio returns (HML), and momentum mimicking returns (MOM) come from Kenneth French's data library. The sample period is from 1995 to 2013. The cross-sectional t -statistics or adjusted R^2 is in parentheses.

Model	Intercept	$E[c_t]$	β^{FLOW}	β^{MKTc}	MKT	SMB	HML	MOM	R^2
1	-0.29 (-1.68)	0.14 (-)	0.2*** (4.33)	0.01 (-0.02)					0.55 (0.53)
2	-0.27 (-1.61)	0.22*** (4.82)	0.18*** (3.8)	0.04 (0.18)					0.69 (0.66)
3	-0.29 (-1.77)	0.14 (-)	0.2*** (7.68)						0.55 (0.54)
4	-0.26 (-1.78)	0.22*** (4.88)	0.18*** (6.93)						0.69 (0.67)
5	-0.22 (-1.25)	0.14 (-)		0.86*** (5.33)					0.37 (0.36)
6	-0.21 (-1.24)	0.27*** (5.34)		0.79*** (5.04)					0.59 (0.57)
7	0.06 (0.32)	0.14 (-)	0.12** (2.03)		-0.06 (-0.25)	0.26** (2.07)	0.16 (1.1)	0.71 (1.79)	0.69 (0.66)

free parameter τ is estimated to be 0.22 (security holding period of about 5 months) in the cross-sectional regression in Model 2 and is statistically significant at the 1% level. The price of risk for the β^{FLOW} is estimated to be similar between Model 1 (0.2) and Model 2 (0.18) and are both statistically significant at the 1% level. The price of risk for the β^{MKTc} is positive but insignificant in both models.

In Model 3 and 4, I estimate an one-factor model with only β^{FLOW} with calibrated τ and with τ as a free parameter, respectively. The estimation results indicate that the model fits in Model 1 and Model 2 are fully captured by the β^{FLOW} : The R^2 of the one-factor model with β^{FLOW} alone is identical to that of the two-factor model. Both the price of risk of β^{FLOW} and τ are estimated precisely with very small standard errors and the price of risks are almost identical through Model 1 to Model 4. Model 5 and Model 6 present a case of an one-factor model with only β^{MKTc} . Although the price of risk is significant for β^{MKTc} , the difference between the estimated τ and the calibrated τ widens and the overall fit declines

from 54% in the β^{FLOW} -only model in Model 3 to 39% in the β^{MKTc} -only model in Model 5.

I control for the three Fama-French three factors and a momentum factor in Model 7. Since β^{MKTc} and MKT are highly correlated I include either one of the market factors in the test. The estimation results remain almost identical regardless of which market factor I include.²¹ I use the calibrated value for τ to alleviate concerns about overfitting with too many factors in the test. The price of risk for the β^{FLOW} is 0.12 and is statistically significant at the 5% level.

The flow risk premium is estimated to be sizable. From Table 3, β^{FLOW} ranges from 3.43 to 6.11 in the 25 illiquidity and flow beta portfolios. Using the price of risk of 0.20 in Model 1, this implies that, conditional on the liquidity risk, the monthly risk premium attributed to the flow risk is on average 0.44% (5.28% annually) for the two most illiquid portfolios and on average 0.24% (2.90% annually) for the two most liquid portfolios. After controlling for the Fama-French three factors and a momentum factor, the annual flow risk premium is 3.17% for the two most illiquid portfolios and 1.74% for the two most liquid portfolios.

Figure 2 confirms the overall performance of the flow and liquidity asset pricing model. It shows that the realized monthly excess returns of the 50 test portfolios and the fitted monthly excess returns from the asset pricing model line up well along the 45 degree line. The fitted returns are predicted using the price of risk estimated from the joint cross-sectional asset pricing test in Table 4 Model 2. The label $IiFj$ refers to the portfolio of stocks with illiquidity in i quintile and flow beta in j quintile for $i, j \in \{1, 2, \dots, 5\}$. Similarly, $SiBj$ indicates the portfolio of stocks with size in i quintile and book-to-market in j quintile for $i, j \in \{1, 2, \dots, 5\}$. The flow and liquidity asset pricing model prices most of the 50 portfolio returns reasonably well, however, with varying degrees of pricing errors across the 50 portfolios.

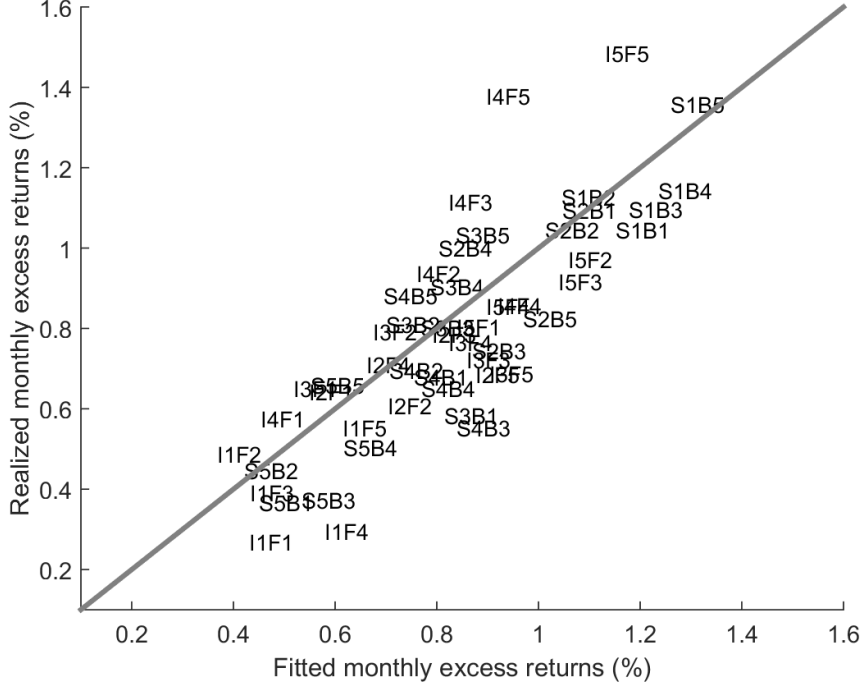
B. Cross-sectional analysis: 25 portfolios separately

Following the joint test, I examine the flow and liquidity model using the 25 size and book-to-market portfolios and the 25 illiquidity and flow beta portfolios separately in Table 6. I find that not only the price of risk for the flow beta is significantly positive, but also the magnitude

²¹The results are not reported, but available upon request.

Figure 2: Cross-sectional fit using 50 portfolios

The plot shows the cross-sectional fit of the flow and liquidity asset pricing model using 50 test portfolios simultaneously from 1995-2013. In each portfolio $p \in \{1, 2, \dots, 50\}$, I take the value-weighted average of excess stock returns over the 30d T-bill rate across stocks and then take the time-series average of the portfolio returns. I compute the fitted monthly excess returns using the estimated price of risks in the two-factor asset pricing model with the free parameter τ estimated in the data. The label $I_i F_j$ refers to the portfolio of stocks with illiquidity in i quintile and flow beta in j quintile for $i, j \in \{1, 2, \dots, 5\}$. Similarly, $S_i B_j$ indicates the portfolio of stocks with size in i quintile and book-to-market in j quintile for $i, j \in \{1, 2, \dots, 5\}$.



is very similar across the different portfolios and across different model specifications. This is empirically a hurdle to show that one stochastic discount factor prices across different assets. My model shows the consistent result, which further lends support to the prediction that the aggregate innovations in fund flows are an important component of the stochastic discount factor in the U.S. equity market in the recent sample period. In contrast, the price of risk for the market beta is statistically insignificant and flips sign across the different portfolios.

For the 25 size and book-to-market portfolios in Panel A, the price of risk for β^{FLOW} is estimated to be 0.19, compared to 0.2 in the joint test and 0.21 in 25 illiquidity and flow beta portfolios, with the calibrated value of 0.14 for τ in Model 1. Having τ as a free parameter changes the estimated value of the price of risk for β^{FLOW} to 0.16 in Model 2, with τ estimated to be 0.23. In Model 3 and Model 4, when I drop β^{MKTc} and keep only β^{FLOW} in the asset pricing model, the overall fit, price of risk, intercept and τ remain in

Table 5: Separate asset pricing tests

Using 25 monthly test portfolios separately, this table reports the estimated price of risks of various specifications from the following baseline cross-sectional asset pricing model

$$E \left[r_{p,t} - r_t^f - \tau c_{p,t} \right] = \alpha + \lambda^{FLOW} \beta_p^{FLOW} + \lambda^{MKT} \beta_p^{MKTc},$$

where β_p^{FLOW} is the co-movement of returns net of liquidity costs with aggregate innovations in fund flows and β_p^{MKTc} is the co-movement of returns net of liquidity costs with the market returns net of market liquidity costs of portfolio $p \in \{1, 2, \dots, 25\}$. To adjust the liquidating cost proportionately to the monthly estimation period, I use the calibrated value of $\tau=0.14$ or I estimate τ as a free parameter. The market returns (MKT), size mimicking portfolio returns (SMB), book-to-market mimicking portfolio returns (HML), and momentum mimicking returns (MOM) come from Kenneth French's data library. The sample period is from 1995 to 2013. The cross-sectional t -statistics or adjusted R^2 is in parentheses.

Panel A: 25 size and book-to-market portfolios

Model	Intercept	$E[c_t^p]$	β^{FLOW}	β^{MKTc}	MKT	SMB	HML	MOM	R^2
1	-0.24 (-1.37)	0.14 (-)	0.19*** (5.63)						0.58 (0.56)
2	-0.16 (-0.91)	0.23*** (3.99)	0.16*** (4.51)						0.75 (0.72)
3	-0.39 (-1.31)	0.14 (-)	0.16** (2.56)	0.28 (0.61)					0.59 (0.55)
4	-0.27 (-0.89)	0.22*** (3.83)	0.14** (2.35)	0.2 (0.43)					0.75 (0.71)
5	0.24 (0.6)		0.04 (0.59)		0.04 (0.09)	0.14 (0.66)	0.33 (1.68)	-0.15 (-0.21)	0.7 (0.62)

Panel B: 25 illiquidity and flow beta portfolios

Model	Intercept	$E[c_t^p]$	β^{FLOW}	β^{MKTc}	MKT	SMB	HML	MOM	R^2
1	-0.35 (-1.69)	0.14 (-)	0.21*** (5.13)						0.53 (0.51)
2	-0.37 (-1.76)	0.22*** (3.00)	0.21*** (4.95)						0.64 (0.6)
3	-0.34 (-1.59)	0.14 (-)	0.27*** (3.07)	-0.26 (-0.71)					0.54 (0.5)
4	-0.35 (-1.66)	0.22*** (2.83)	0.25*** (2.8)	-0.2 (-0.54)					0.64 (0.59)
5	-0.03 (-0.12)		0.21** (2.24)		-0.05 (-1.13)	0.3 (1.51)	0.04 (0.16)	1.44** (2.18)	0.67 (0.6)

similar range, which resembles the results in the joint test. In the 25 illiquidity and flow beta portfolios in Panel B, I observe very similar results. Across the different model specifications from Model 1 to Model 4, the estimated value of the price of risk for β^{FLOW} , τ , and intercept remain similar with the results in the 25 size and book-to-market portfolios.

In Model 5 with 25 size and book-to-market portfolios, I control for the Fama-French three factors and a momentum factor. SMB and HML factors are designed to explain size

and book-to-market portfolio returns. If flow beta explains 25 size and book-to-market portfolios because mutual fund managers actively trade with the risk profiles then flow beta should be correlated with SMB and HML. That is what happens in Model 5. When I have flow beta and SMB and HML together in the model, they are multicollinear each other, and none of the factors turn out to be statistically significant even though the overall fit of the model is quite high at 0.67. However, in 25 illiquidity and flow beta portfolios, when I control for the Fama-French three factors and a momentum factor in Model 5, price of risk of β^{FLOW} is statistically significant at 5% level.

VI. Conclusion

I propose and test an equilibrium asset pricing model that provides a framework to understand how mutual fund managers and direct investors affect asset prices when both are concerned about the liquidating cost. Fund managers, in particular, care about the liquidating cost because unexpected large outflows may force them to liquidate their asset holdings. The model implies that expected returns are driven by two factors: 1) flow beta, i.e., co-movement of net returns (net of liquidity costs) with the aggregate unexpected fund flows and 2) liquidity-adjusted market beta, i.e., co-movement of net returns with the net market returns. I find the flow beta prices 50 size, book-to-market, liquidity, flow beta simultaneously and separately. I find the price of risk of the flow beta is positively significant and the magnitude is similar across the portfolios and the overall fit is purely captured by a single-factor model of flow beta. This lends further support to the prediction that the aggregate innovations in fund flows are an important component of the stochastic discount factor. For illiquid stocks, I find that the flow beta risk premium is about twice that for liquid stocks.

The framework tested in this paper suggests that other illiquid asset classes in which delegating managers actively trade could be similarly explored. High yield bond funds and emerging market sovereign bond funds are a few examples that are subject to fund flow risk and liquidity risk. What is more interesting in bond asset class is that the ownership is more concentrated in the financial intermediaries compared to equity. It would be important to understand at how heterogeneous intermediaries interact each other especially when a group of intermediaries face an unexpected and large funding shock.

More broadly, it would be interesting to explore how the interaction of capital flow risk and liquidity risk affect asset prices and real economy in particular in the emerging market economy. Sudden outflows of foreign debt have repeatedly figured in active discussions among economists, policy makers and money managers in the past decades in attempt to understand its mechanism during negative liquidity episodes. Foreign capital flows have increased at an unprecedented rate in the past two decades and the high level of foreign debt outstanding across countries once again raises concerns over potential pain from the foreign debt outflows.

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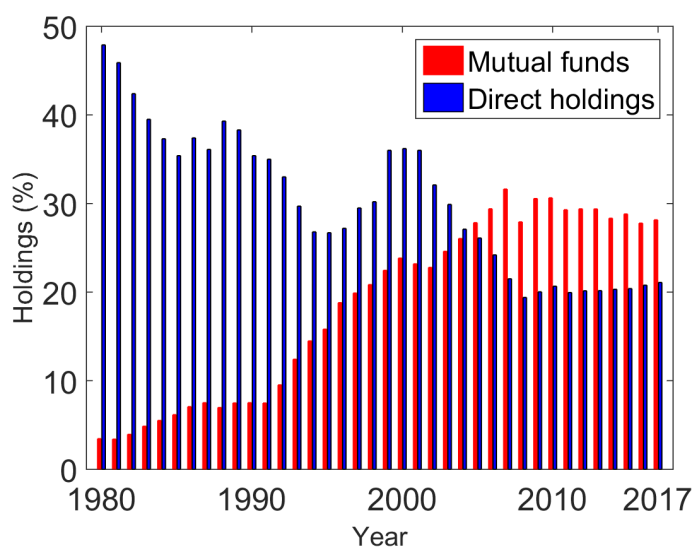
Appendix A. Flow of Funds Account

In this Appendix, I plot the share of the U.S. common equity market held by open-end mutual funds from 1980 to 2017. The data is from the Federal Reserve Board Flow of Funds Accounts L.223 (A) Corporate Equities from the Z.1 statistical release on 20 September 2018. Table L.223 reports the dollar value of the corporate equity held by various type of investors, including households and nonprofits, mutual funds, banks, and insurance companies.

In the Flow of Funds, household and nonprofit holdings is computed as a residual. Household and nonprofit holdings includes not only the common equity held by the nonprofit sector, but also preferred stocks and closely held corporations.

Similar to Stambaugh (2014), I estimate the value of the direct household holdings of common equity by using the ratio of direct household holdings to the total household and nonprofit holdings in 2007 from French (2008). I extrapolate the ratio to extend the estimate of the direct household holdings to 2017.

Figure A1: Holdings of the U.S. common equity market



Appendix B. Proofs

1. Proof of proposition 1

I start from fund manager i 's portfolio choice problem

$$\max_{x_{i,t}} E_t [x_{i,t}^T r_{t+1}^c + f_{i,t+1}] - \frac{b_I}{2} \text{Var}_t [x_{i,t}^T r_{t+1}^c + f_{i,t+1}] - \lambda (x_{i,t}^T \mathbf{1} - 1). \quad (\text{A.1})$$

Substituting the fund flows in (5) to (A.1), manager i 's maximization problem becomes

$$\begin{aligned} & \max_{x_{i,t}} E_t \left[\alpha_0 + \{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\}^T r_{t+1}^c + \eta_{i,t+1} \right] \\ & - \frac{b_I}{2} \text{Var}_t \left[\{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\}^T r_{t+1}^c + \eta_{i,t+1} \right] - \lambda (x_{i,t}^T \mathbf{1} - 1). \end{aligned} \quad (\text{A.2})$$

For notational simplicity, I denote

$$E_t \equiv E_t [r_{t+1}^c]_{K \times 1}, \quad (\text{A.3})$$

$$\Sigma_t \equiv \text{Var}_t [r_{t+1}^c]_{K \times K}, \quad (\text{A.4})$$

$$C_{i,t} \equiv \text{Cov}_t [r_{t+1}^c, \eta_{i,t+1}]_{K \times 1}. \quad (\text{A.5})$$

I rewrite manager i 's problem in a shorter expression after expanding the variance term

$$\begin{aligned} & \max_{x_{i,t}} \{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\}^T E_t - \frac{b_I}{2} \{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\}^T \Sigma_t \{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\} \\ & - b_I \{(1 + \alpha_1)x_{i,t} - \alpha_1 x_{M,t}\}^T C_{i,t} - \frac{b_I}{2} \text{Var}_t [\eta_{i,t+1}] - \lambda (x_{i,t}^T \mathbf{1} - 1). \end{aligned} \quad (\text{A.6})$$

The first order condition with respect to $x_{i,t}$ reads

$$(1 + \alpha_1)E - b_I(1 + \alpha_1)^2 \Sigma_t x_{i,t} + b_I \Sigma_t (1 + \alpha_1) \alpha_1 x_{M,t} - b_I(1 + \alpha_1) C_{i,t} - \lambda \mathbf{1} = 0. \quad (\text{A.7})$$

After arranging the terms, the optimal portfolio weight of fund manager i becomes

$$x_{i,t}^* = \frac{\alpha_1}{1 + \alpha_1} x_{M,t} + \frac{1}{b_I(1 + \alpha_1)} \Sigma_t^{-1} \left(E_t - \frac{1}{1 + \alpha_1} \lambda \mathbf{1} \right) - \frac{1}{1 + \alpha_1} \Sigma_t^{-1} C_{i,t}. \quad (\text{A.8})$$

For direct investor j with the portfolio choice problem

$$\max_{x_{j,t}} E_t [x_{j,t}^T (r_{t+1}^c - r_f \mathbf{1})] - \frac{b_J}{2} \text{Var}_t [x_{j,t}^T (r_{t+1}^c - r_f \mathbf{1})], \quad (\text{A.9})$$

I take the first order condition and rearrange the terms to get

$$x_{j,t}^* = \frac{1}{b_J} \Sigma_t^{-1} (E_t - r_f \mathbf{1}). \quad (\text{A.10})$$

I replace $x_{i,t}^*$ and $x_{j,t}^*$ in the market clearing condition

$$\sum_{i=1}^I A_{i,t} x_{i,t}^* + \sum_{j=1}^J A_{j,t} x_{j,t}^* = A_{M,t} x_{M,t}, \quad (\text{A.11})$$

to have

$$\begin{aligned} & \sum_{i=1}^I A_{i,t} \left\{ \frac{\alpha_1}{1 + \alpha_1} x_{M,t} + \frac{1}{b_I(1 + \alpha_1)} \Sigma_t^{-1} \left(E_t - \frac{1}{1 + \alpha_1} \lambda \mathbf{1} \right) - \frac{1}{1 + \alpha_1} \Sigma_t^{-1} C_{i,t} \right\} \\ & + \sum_{j=1}^J A_{j,t} \left\{ \frac{1}{b_J} \Sigma_t^{-1} (E_t - r_f \mathbf{1}) \right\} = A_{M,t} x_{M,t}, \end{aligned} \quad (\text{A.12})$$

I pre-multiply by Σ_t on both sides of the equation

$$\begin{aligned} & \sum_{i=1}^I \frac{\alpha_1 A_{i,t}}{1 + \alpha_1} \Sigma_t x_{M,t} + \sum_{i=1}^I \frac{A_{i,t}}{b_I(1 + \alpha_1)} \left(E_t - \frac{1}{1 + \alpha_1} \lambda \mathbf{1} \right) - \sum_{i=1}^I \frac{A_{i,t}}{1 + \alpha_1} C_{i,t} + \sum_{j=1}^J \frac{A_{j,t}}{b_J} (E_t - r_f \mathbf{1}) \\ & = A_{M,t} \Sigma_t x_{M,t}, \end{aligned} \quad (\text{A.13})$$

and rearrange using $\sum_{i=1}^I A_{i,t} \equiv A_{I,t}$, $\sum_{j=1}^J A_{j,t} \equiv A_{J,t}$, and $A_{M,t} \equiv A_{I,t} + A_{J,t}$

$$\begin{aligned} & \left(\frac{1}{b_I(1 + \alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right) E_t \\ & = \frac{1}{b_I(1 + \alpha_1)^2} A_{I,t} \lambda \mathbf{1} + \frac{1}{b_J} A_{J,t} r_f \mathbf{1} + A_{M,t} \Sigma_t x_{M,t} - \frac{\alpha_1}{1 + \alpha_1} A_{I,t} \Sigma_t x_{M,t} + \frac{1}{1 + \alpha_1} \sum_{i=1}^I A_{i,t} C_{i,t}. \end{aligned} \quad (\text{A.14})$$

I divide both sides by $\left(\frac{1}{b_I(1 + \alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right)$ and restore the original expressions for E_t , Σ_t ,

and $C_{i,t}$ to get

$$E_t [r_{t+1}^c] = s_0 \mathbf{1} + s_1 \text{Cov}_t [r_{t+1}^c, \bar{\eta}_{t+1}] + s_2 \text{Var}_t [r_{t+1}^c] x_{M,t}, \quad (\text{A.15})$$

and I rewrite for each stock $k \in \{1, 2, 3, \dots, K\}$

$$E_t [r_{k,t+1}^c] = s_0 + s_1 \text{Cov}_t (r_{k,t+1}^c, r_{M,t+1}^c) + s_2 \text{Cov}_t (r_{k,t+1}^c, \bar{\eta}_{t+1}), \quad (\text{A.16})$$

where

$$\bar{\eta}_{t+1} = \sum_{i=1}^I \frac{A_{i,t}}{A_{I,t}} \eta_{i,t+1}, \quad (\text{A.17})$$

$$s_0 = r_f \frac{\frac{1}{b_J} A_{J,t}}{\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t}} + \lambda \frac{\frac{1}{b_I(1+\alpha_1)^2} A_{I,t}}{\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t}}, \quad (\text{A.18})$$

$$s_1 = \frac{A_{M,t} - \frac{\alpha_1}{1+\alpha_1} A_{I,t}}{\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t}}, \quad s_2 = \frac{\frac{1}{1+\alpha_1} A_{I,t}}{\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t}}. \quad (\text{A.19})$$

2. Proof of proposition 2

The partial derivative of s_1 in (A.19) with respect to $A_{I,t}$ is

$$\frac{\partial s_1}{\partial A_{I,t}} = \frac{-\frac{\alpha_1}{1+\alpha_1} \left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right) - \left(A_{M,t} - \frac{\alpha_1}{1+\alpha_1} A_{I,t} \right) \frac{1}{b_I(1+\alpha_1)}}{\left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right)^2} \quad (\text{A.20})$$

$$= \frac{-\frac{\alpha_1}{b_J(1+\alpha_1)} A_{J,t} - \frac{1}{b_I(1+\alpha_1)} A_{M,t}}{\left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right)^2}. \quad (\text{A.21})$$

and the partial derivative of s_2 in (A.19) with respect to $A_{I,t}$ is

$$\frac{\partial s_2}{\partial A_{I,t}} = \frac{\frac{1}{1+\alpha_1} \left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right) - \frac{1}{1+\alpha_1} A_{I,t} \frac{1}{b_I(1+\alpha_1)}}{\left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right)^2} \quad (\text{A.22})$$

$$= \frac{\frac{1}{b_J} A_{J,t}}{\left(\frac{1}{b_I(1+\alpha_1)} A_{I,t} + \frac{1}{b_J} A_{J,t} \right)^2}, \quad (\text{A.23})$$

Under the assumptions that the risk aversion of the fund managers, b_I , the risk aversion of direct investors, b_J , and the flow sensitivity to fund performance are positive, $\frac{\partial s_1}{\partial A_{I,t}} < 0$

and $\frac{\partial s_2}{\partial A_{I,t}} > 0$.

Appendix C. Procedure for computing predicted flow beta

- (i) I re-estimate the aggregate innovations in fund flows using all fund flows and fund returns available up to month t of the end of each year.
- (ii) Using the aggregate innovations in fund flows, I compute the 60-month historical flow beta at month t using data from $t - 60$ to $t - 1$ if at least 36 months of returns are available. I repeat this for all the past 60-month rolling windows in the earlier part of the sample as long as a minimum of 36 monthly returns are available. This creates a monthly time-series of the historical flow betas up to month $t - 1$ for each security k .
- (iii) I construct the 6-month cumulative returns and standard deviation of the monthly returns at month t using data from month $t - 6$ to $t - 1$ for each security k . I repeat this for all the past 6-month rolling windows in the earlier part of the sample. This creates a monthly time-series of the historical cumulative returns and return volailities up to month $t - 1$ for each security k .
- (iv) I keep the time-series of the most recent preceding quarter's mutual fund ownership for each security k at month t . This creates a monthly time-series of the lagged mutual fund ownership up to month $t - 1$ for each security k .
- (iv) I construct \mathbf{Z}_{t-1}^k by joining the times-series of characteristics constructed in steps (ii)-(iv) and estimate the flow beta coefficients, ψ_1 and ψ_2 , in (27) by running the OLS pooled time-series cross-sectional regression.
- (iv) For the portfolio sort, I use year-end characteristics computed using all data available up to time t , \mathbf{Z}_t^k , and use $\hat{\psi}_1$ and $\hat{\psi}_2$ from (iv) to compute the predicted flow beta for security k as in (28).

Appendix D. Supplementary empirical results

Table 6: 25 illiquidity and flow beta portfolios

This table shows the characteristics of 25 illiquidity and predicted flow beta portfolios formed at the end of each year by the preceding year's illiquidity and predicted flow beta using CRSP stocks and CRSP and Morningstar mutual funds data from 1995-2013. The data on the three Fama-French factors and momentum are from Kenneth French's website.

Fama-French SMB β						$t(\beta)$					
Flow beta						Flow beta					
	Low	2	3	4	High		Low	2	3	4	High
Liquid	-0.07	-0.28	-0.25	-0.28	0.02	Liquid	-1.6	-6.44	-6.87	-7.32	0.42
2	-0.05	0.09	0.11	0.22	0.41	2	-0.97	1.84	2.05	3.75	6.23
3	0.23	0.28	0.37	0.35	0.52	3	4.69	5.18	6.53	5.37	6.4
4	0.34	0.52	0.53	0.54	0.79	4	6.55	9.44	8.93	8.44	10.45
Illiquid	0.32	0.69	0.63	0.84	0.86	Illiquid	5.39	9.67	9.72	11.64	9.17

Fama-French HML β						$t(\beta)$					
Flow beta						Flow beta					
	Low	2	3	4	High		Low	2	3	4	High
Liquid	0.01	0.12	0.1	0.1	0.11	Liquid	0.28	2.73	2.51	2.51	1.76
2	0.39	0.5	0.51	0.52	0.46	2	6.61	9.53	8.91	8.32	6.58
3	0.26	0.62	0.61	0.52	0.65	3	5.07	10.94	10.11	7.41	7.58
4	0.45	0.65	0.8	0.84	0.53	4	8.16	10.96	12.77	12.36	6.62
Illiquid	0.51	0.78	0.82	0.78	0.8	Illiquid	8.13	10.25	12.04	10.21	8.01

MOM β						$t(\beta)$					
Flow beta						Flow beta					
	Low	2	3	4	High		Low	2	3	4	High
Liquid	-0.01	0.03	-0.03	-0.02	0.01	Liquid	-0.18	0.93	-1.13	-0.66	0.24
2	-0.08	-0.08	-0.02	0.01	-0.07	2	-2.38	-2.45	-0.65	0.31	-1.61
3	0.02	-0.08	-0.04	-0.03	-0.09	3	0.67	-2.28	-0.97	-0.74	-1.85
4	0.08	-0.03	-0.08	-0.06	0	4	2.45	-0.92	-2.17	-1.4	-0.1
Illiquid	-0.1	-0.16	-0.06	-0.01	0.02	Illiquid	-2.83	-3.71	-1.39	-0.17	0.35

ILLIQ β						$t(\beta)$					
Flow beta						Flow beta					
	Low	2	3	4	High		Low	2	3	4	High
Liquid	0.08	0.03	0.04	0.02	0.24	Liquid	1.37	0.48	0.6	0.23	2.56
2	0.22	0.38	0.42	0.52	0.62	2	3.22	4.94	4.97	5.7	5.91
3	0.3	0.49	0.58	0.59	0.78	3	4.78	6.12	6.78	6.42	7.12
4	0.45	0.62	0.71	0.76	0.85	4	6.99	7.72	8.12	8.1	8.22
Illiquid	0.5	0.84	0.86	0.97	1.07	Illiquid	7.49	10.41	10.35	11	9.92

Appendix E. Merging CRSP and Morningstar mutual fund datasets

1. Raw CRSP database clean-up

The CRSP Mutual Fund data comes directly from the WRDS server in SAS data format. I use *monthly_tna_ret_nav* as the main base file of the CRSP database that contains monthly fund returns, total net assets, and other fund characteristics from January 1991 to December 2013, and merge in other CRSP data files to prepare for merging with the Morningstar database. I delete observations when both monthly fund returns and total net assets are missing. Then, *crsp_fundno* uniquely identifies each share class, and a pair of *crsp_fundno* and *month* uniquely identifies each observation in the CRSP database. The number of observations is 5,191,473 and there are 54,158 unique fund share classes, i.e., 54,158 unique *crsp_fundno*. I clean up the raw CRSP database in the order presented below:

Merge and check tickers

I merge in historical tickers from *fund_hdr_hist* and forward- and backward-fill the tickers within each *crsp_fundno*. If a ticker is missing, I then merge in another file, *fund_hdr*, which keeps the most recent ticker for each *crsp_fundno*, and I replace the missing tickers by the most recent ticker.

1. I check if a *crsp_fundno* has multiple tickers in a given month. There is no combination of *crsp_fundno* and *month* that has different tickers in the CRSP database.
2. I check if a *crsp_fundno* has multiple tickers over the entire sample period. There are 2,387 *crsp_fundnos* that have time-varying tickers over the sample period. In this case, I use the last (latest) ticker per *crsp_fundno* following Pastor, Stambaugh, Taylor (2015), PST(2015) hereafter.
3. Conversely, I check if a ticker has multiple *crsp_fundnos* in a given month. There are 35,051 combinations of ticker and month that correspond to more than one *crsp_fundno*. In this case, as in PST (2015), I replace the tickers with missing.
4. I check if a ticker has multiple *crsp_fundnos* over the entire sample period. There are

2,430 tickers that have multiple `crsp_fundnos`. I take care of these tickers later in the merging algorithm.

Merge and check CUSIPs

Similary, I merge in historical CUSIPs from *fund_hdr_hist* and forward- and backward-fill the CUSIPs within each `crsp_fundno`. If a CUSIP is missing, I then merge in another file, *fund_hdr*, which keeps the most recent CUSIP for each `crsp_fundno`, and I replace the missing CUSIPs with the most recent CUSIP.

1. I check if a `crsp_fundno` has multiple CUSIPs in a given month. There is no combination of `crsp_fundno` and month that has different CUSIPs in the CRSP database.
2. I check if a `crsp_fundno` has multiple CUSIPs over the entire sample period. There are 8,802 `crsp_fundnos` that have time-varying CUSIPs over the sample period. In this case, I use the last (latest) CUSIP per `crsp_fundno` following PST (2015).
3. Conversely, I check if a CUSIP has multiple `crsp_fundnos` in a given month. There are 12,554 combinations of CUSIP and month that correspond to more than one `crsp_fundno`. In this case, as in PST (2015), I change the CUSIPs to missing.
4. I check if a CUSIP has multiple `crsp_fundnos` over the entire sample period. There are 49 CUSIPs that have multiple `crsp_fundnos`. I take care of these CUSIPs later in the merging algorithm.

After merging tickers and CUSIPs, 89% of the observations have tickers and 95% of the observations have CUSIPs out of the total 5,191,473 observations in the CRSP dataset.

Check reversal

In order to prevent possible decimal-place mistakes, I check for extreme reversal patterns in the monthly total net assets following PST (2015). I first compute the proportional changes in total net assets, $dtna = (mtna - lag_tna) / lag_tna$, and create a reversal variable, $rev = (lead_tna - tna) / (tna - lag_tna)$. The reversal variable would be -1 if there is a decimal mistake, e.g., 20m, 2m, 20m. If $abs(dtna) \geq 0.5$, $-1.25 \leq rev \leq -0.75$, and $lag_tna \geq 10mil$, I change

total net assets to missing. This changes 2,457 observations in the CRSP dataset to have missing total net assets due to the reversal in the total net assets.

2. Raw Morningstar database clean-up

I download monthly fund returns, total net assets, and other fund characteristics that span from January 1991 to December 2013 from Morningstar Direct. I delete observations when both fund returns and total net assets are missing. I exclude observations with share class type “Load Waived” because this share class type is open to only certain investors; they never have a CUSIP; tickers always end with “.lw”, which do not match with CRSP; and total net assets are all missing. Then, secid uniquely identifies each share class, and a pair of secid and month uniquely identifies each observation in the Morningstar database. The number of observations is 5,547,782 and there are 46,351 unique fund share classes, i.e., 46,351 unique secid. I clean up the raw CRSP database in the order presented below:

Check tickers

1. I check if a secid has multiple tickers in a given month. There is no combination of secid and month that has different tickers in the Morningstar database.
2. I check if a secid has multiple tickers over the entire sample period. There is no secid that has time-varying tickers over the sample period: either a secid never has a ticker over the entire sample period or a secid has the same ticker over the entire sample period without any missing tickers. Therefore, there is no need to forward- and backward-fill the tickers as I did for the CRSP data.
3. I check if a ticker has multiple secids in a given month. There are 2,152 combinations of ticker and month (30 unique tickers) that correspond to more than one secid. In this case, as in PST (2015), I change the tickers to missing.
4. I check if a ticker has multiple secids over the entire sample period. There are 32 tickers that correspond to multiple secids over the entire sample period. I take care of these tickers later in the merging algorithm.

Check CUSIPs

1. I check if a secid has multiple CUSIPs in a given month. There is no combination of secid and month that has different CUSIPs in the Morningstar database.
2. I check if a secid has multiple CUSIPs over the entire sample period. There is no secid that has time-varying CUSIPs over the sample period: either a secid never has a CUSIP over the entire sample period or a secid has the same CUSIP over the entire sample period without any missing CUSIPs. Therefore, there is no need to forward- and backward-fill the CUSIPs as I did for the CRSP data.
3. Conversely, I check if a CUSIP has multiple secids in a given month. There are 4,039 combinations of CUSIP and month (63 unique CUSIPs) that correspond to more than one secid. In this case, as in PST (2015), I change the CUSIPs to missing.
4. I check if a CUSIP has multiple secids over the entire sample period. There are 3 CUSIPs that have multiple secids. I take care of these CUSIPs later in the merging algorithm.

After merging tickers and CUSIPs, 84% of the observations have tickers and 98% of the observations have CUSIPs out of the total 5,547,782 observations in the Morningstar dataset.

Check reversal

In order to prevent possible decimal-place mistakes, I check for extreme reversal patterns in the monthly total net assets following PST (2015). I first compute the proportional changes in total net assets, $dtna = (mtna - lag_tna) / lag_tna$, and create a reversal variable, $rev = (lead_tna - tna) / (tna - lag_tna)$. The reversal variable would be -1 if there is a decimal mistake, e.g., 20m, 2m, 20m. If $abs(dtna) \geq 0.5$, $-1.25 \leq rev \leq -0.75$, and $lag_tna \geq 10mil$, I change total net assets to missing. This changes 1,011 observations in the Morningstar dataset to have missing total net assets due to the reversal in the total net assets.

3. Complete match between CRSP and Morningstar

Following PST (2015), I define a fund as completely matched if all share classes belonging to the fund are well matched. I identify a fund by fundid in MS and a share class by secid and crsp_fundno. Each share class is well matched if and only if 1) the 60th percentile (over the available sample period) of the absolute value of the difference between the CRSP and MS monthly returns is less than 5 basis points and 2) the 60th percentile of the absolute value of the difference between the CRSP and MS monthly total net assets is less than \$100,000.

Well match in the merge by ticker

In order to find a mapping between secid and crsp_fundno whose share classes are well matched, I first merge CRSP and Morningstar by ticker and month. As a result, 3,341,636 observations have both crsp_fundno and secid, which makes up 65% of the 5,191,473 CRSP observations and 60% of the 5,547,782 MS observations. After the merge, I identify the well matched share classes based on the differences in returns and total net assets across two different databases. There are 28,871 well-matched share classes (3,211,356 observations), which amounts to 53% of the 54,158 CRSP share classes and 62% of the 46,351 MS share classes.

Well match in the merge by CUSIP

I then use CUSIP to merge CRSP and MS to supplement the mapping between secid and crsp_fundno whose share classes are well matched. After the merge by CUSIP, 3,802,794 observations have both crsp_fundno and secid, which makes up 73% of the 5,191,473 CRSP observations and 69% of the 5,547,782 MS observations. After the merge, I identify the well matched share classes based on the differences in returns and total net assets across two different databases. There are 34,447 well-matched share classes (3,564,345 observations), which amounts to 64% of the 54,158 CRSP share classes and 74% of the 46,351 MS share classes.

Complete match

I combine the two mappings of `secid` and `crsp_fundno` that I separately identified from the ticker merge and the CUSIP merge, and then I merge in the combined mapping to the MS database to identify completely matched funds. I find that 35,883 share classes are well matched (66% of the 54,158 CRSP share classes and 77% of the 46,351 MS share classes) and 9,521 funds (61% of the 15,504 MS funds) are completely matched. Among the remaining, 2,208 funds are partially matched observations (15% of the 15,504 MS funds): they have one or more share classes that are not well matched in a given fund. The remaining 3,775 funds (24% of the 15,504 MS funds) never have a well matched share class.

4. Merge CRSP and Morningstar

I keep only the completely matched funds in CRSP and in MS. Following PST (2015), I use CRSP as a base master file and merge in MS with only a complete match. As a result, it contains 2,865,094 observations (9,521 funds and 27,980 share classes) compared to 5,191,473 CRSP observations (54,158 share classes) before confining to the completely matched funds.

5. Expense ratios, returns, and total net assets

Expense ratios

I use expense ratios from CRSP because it provides exact the start and end day for each expense ratio observation whereas MS provides expense ratios over each fiscal year period. I change negative expense ratios to missing.

Returns

2,812,999 observations (98% of the 2,865,094 completely matched observations) have a returns difference between CRSP and MS of less than 10 basis points and 52,095 observations (1.8% of 2,865,094 completely matched observations) have a returns difference greater than a 10 basis points.

Total net assets

I change total net assets of a share class at a given month to missing if either CRSP or MS is missing the total net assets of the share class in the month. Also, if the absolute difference of the total net assets between CRSP and MS is greater than \$100,000 and the difference is bigger than 5% of the total net assets in CRSP, then I change the total net assets to missing. Other than these, I use the total net assets value from CRSP. 2,791,841 observations (97% of 2,865,094 completely matched observations) have a total net assets difference of less than \$100,000 and 73,253 observations (2.5% of 2,865,094 completely matched observations) have a total net assets difference greater than \$100,000.

6. Identify active equity funds

Index funds

I identify index funds by 1) indicator variables provided in CRSP and MS and 2) searching for a keyword in fund names. CRSP provides `index_fund_flag` and MS provides `enhanced_index` and `index_fund`. Index funds in CRSP have `index_fund_flag` values that are equal to B (index-based fund), D (pure index fund), or E (index fund enhanced). In MS, if the value of `enhanced_index` or `index_fund` is Yes, then the funds are identified as index funds. Lastly, I search for “index” in the CRSP fund names. Following this procedure, I create a variable `index_drop` and record 1 if it is an index fund.

Other funds

Morningstar provides two variables that classify funds into different categories: `morningstar_category` and `primary_prospectus_bchmk`. I first forward- and backward-fill `morningstar_category` and `primary_prospectus_bchmk` within each `crsp_fundno`. I then search for a set of keywords in the two variables to classify the category of the funds. The set of keywords are listed in each column of the following table. I first create indicator variables `bond_funds`, `international_funds`, `sector_funds`, `target_funds`, `real_estate_funds`, `other_non_equity` that records 1 if a fund contains any keywords listed in the column. I then create a variable `num_cat` that sums all the indicator variables.

Panel A: morningstar_category					
bond funds	international funds	sector funds	target funds	real estate funds	other non-equity
bank loan	china region	commodities broad basket	target date 2000-2010	global real estate	currency
convertibles	diversified emerging mkts	communications	target date 2011-2015	real estate	long/short equity
emerging markets bond	diversified pacific/asia	consumer cyclical	target date 2016-2020		managed futures
high yield bond	emerging markets bond	consumer defensive	target date 2021-2025		market neutral
high yield muni	europa stock	equity energy	target date 2026-2030		multialternative
inflation-protected bond	foreign large blend	equity precious metals	target date 2031-2035		trading-inverse commodities
intermediate government	foreign large growth	financial	target date 2036-2040		trading-inverse debt
intermediate-term bond	foreign large value	health	target date 2041-2045		trading-miscellaneous
long government	foreign small/mid blend	industrials	target date 2046-2050		
long-term bond	foreign small/mid growth	miscellaneous sector	target date 2051+		
multisector bond	foreign small/mid value	natural resources			
muni california intermediate	global real estate	technology			
muni california long	india equity	utilities			
muni massachusetts	japan stock				
muni minnesota	latin america stock				
muni national interm	pacific/asia ex-japan stk				
muni national long	world allocation				
muni national short	world bond				
muni new jersey	world stock				
muni new york intermediate					
muni new york long					
muni ohio					
muni pennsylvania					
muni single state interm					
muni single state long					
muni single state short					
nontraditional bond					
short government					
short-term bond					
ultrashort bond					
world bond					
Panel B: primary_prospectus_bchmk					
bond funds	international funds	sector funds	target funds	real estate funds	other non-equity
bond	ACWI	commodity	target	property	
treasury	world			reit	
govt	global				
barclay	emerging markets				
municipal	latin america				
convertible	eafe				
investment-grade	msci em				
consumer price index					
t-bill					
dollar (As in raw MS)					

7. Group subclasses

I aggregate share classes to have a fund-level dataset. At each month, I sum the CRSP total net assets and MS total net assets across subclasses; I take the tna-weighted average of CRSP returns, MS returns, CRSP expense ratios, CRSP turnover ratios; I take the maximum of index_drop and num_cat. If the maximum of the expense ratios is greater than 4%, I drop the fund-month.

8. Other screenings

I drop index funds (`index_drop=1`) and keep only domestic active equity funds (`num_cat=0`).

I keep only fund-month if lagged total net assets adjusted in 2011 dollars is greater than \$15,000,000. I require a fund to have at least 3 years of non-missing fund flows, lagged fund flows, and fund returns.