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How Does Illiquidity Affect Delegated Portfolio Choice?

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Abstract

In response to how they are compensated, mutual fund managers who are underperforming by mid-year are likely to increase the risk of their portfolios toward the year-end. We argue that an increase in the liquidity of the stocks that managers use to shift risk can lead to an increase in the size of their risky bets. This in turn hurts fund investors by increasing the costs of misaligned incentives associated with delegated portfolio management. We provide both theoretical and empirical results that are consistent with this argument. We use decimalization as an exogenous shock to liquidity to identify causal effects.

I. Introduction

A large proportion of portfolios are managed on an agency basis by mutual fund managers on behalf of investors.[1] However, managers and investors do not

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[1] According to the Investment Company Institute Fact Book of 2015, households make up the largest group of investors in mutual funds. They held approximately 90% of the nearly $16 trillion in mutual fund assets at year-end 2014. Moreover, registered investment companies managed approximately 24% of household financial assets at year-end 2014.

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necessarily share the same objectives. Investors would like their fund managers to maximize risk-adjusted returns, but fund managers would instead like to maximize their own compensation. The compensation of these managers is primarily a function of the amount of assets under management, which gives them incentives to follow investment policies that attract investors' money even if these policies reduce risk-adjusted returns.

Investors tend to reward with additional money flows those funds that perform well relative to their benchmarks, but they do not penalize poor performance equivalently. This convex relation creates an implicit incentive for managers to increase the risk of their portfolios so as to increase the likelihood of future fund inflows.[2] To the extent that this distracts fund managers from maximizing risk-adjusted returns, it can be costly to fund investors.

The purpose of this article is to understand how stock liquidity and portfolio constraints affect the incentives of fund managers to engage in risk shifting and how that ultimately affects fund investors who choose to delegate instead of investing directly.

We focus on the effects of stock liquidity and portfolio constraints motivated by two empirical findings documented in prior research. First, Huang, Sialm, and Zhang (2011) show that risk shifters tend to hold more illiquid stocks in their portfolios compared with other funds. Second, Almazan, Brown, Carlson, and Chapman (2004) show that mutual fund policies often prohibit fund managers from taking short positions and from borrowing to finance their portfolios. In addition to borrowing and short-sale constraints, mutual funds are also often subject to style-drift restrictions imposed by the U.S. Securities and Exchange Commission (SEC), as well as limits on tracking errors and cash holdings. These additional constraints can be even more restrictive than the limits on borrowing and short selling.[3] For instance, SEC Rule 35d-1 requires that an investment company with a name that suggests that it focuses its portfolio holdings on a particular type of investment, or on investments in a particular industry, should invest at least 80% of its assets in the type of investment suggested by its name.

We begin our study by extending the model of Basak, Pavlova, and Shapiro (2007) to allow for portfolio constraints and changes in the liquidity of the stocks that fund managers use for risk-shifting purposes. We consider a risk-averse fund manager who is compensated based on the fund's value at the end of the year, which is determined by the portfolio choice of the manager during the year and money inflows or outflows that happen at the end of the year. We assume that the flow–performance relation is convex, which creates a local convexity in the fund manager's objective function.[4] This gives the manager an implicit incentive to take extra risks to increase the expected future fund inflows.

[2]If there are reasons to believe that the flow–performance relation is not convex, as argued by Spiegel and Zhang (2013), mutual fund managers have an alternative source of convexity in their incentives, which is due to the end-of-year bonus payments that are typical in their compensation contracts, as documented by Farnsworth and Taylor (2006) and Ma, Tang, and Gomez (2019).

[3]Typically, equity funds follow fully invested benchmarks and are not allowed to hold large cash reserves. Simutin (2014) reports that the average fund holds only 4% of its assets in cash.

[4]The assumption of a convex flow–performance relation is based on empirical evidence provided by Chevalier and Ellison (1997) and Sirri and Tufano (1998), among others.

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The manager can invest in a liquid risk-free bond and in a liquid stock. The fund's performance benchmark is composed of these two liquid securities. The manager can also invest in an illiquid stock that does not belong to the list of constituents of the benchmark.[5] The liquidity of this nonbenchmark stock is assumed to be time-varying. For tractability, time variation in liquidity is captured in a reduced form following the framework of Ang, Papanikolaou, and Westerfield (2014), according to which the stock can only be traded contingent on the arrival of randomly occurring trading opportunities.

In our baseline model, we assume that the illiquid nonbenchmark stock carries only idiosyncratic risk. The immediate implication of this assumption is that, if mutual funds are allowed to borrow and sell short, as in Basak et al. (2007), the equilibrium holding of the nonbenchmark stock is null, and the fund manager engages in risk shifting using only the liquid benchmark stock.[6]

However, as described previously, mutual funds are typically subject to various constraints, such as prohibitions against borrowing and short selling, limits on tracking errors and cash holdings, and style-drift restrictions such as SEC Rule 35d-1. These constraints limit the fund manager's ability to shift risk using the benchmark stock, which is a superior risk-shifting instrument given its greater liquidity. Therefore, portfolio constraints induce the fund manager to take on idiosyncratic risk using the illiquid nonbenchmark stock.[7]

We then examine how changes in the liquidity of the nonbenchmark stock affect the risk-shifting incentives of the fund manager. We show that the lower the liquidity of the nonbenchmark stock, the smaller the size of the bets taken by the manager. This is because shifting risk with the nonbenchmark stock exposes the fund manager to liquidity risk that cannot be hedged.[8] As a result, the fund manager reduces the size of his or her bets on the illiquid stock and chooses to follow an investment strategy that is more in line with what the fund investor would choose if investing directly. This suggests that stock illiquidity and the investor–manager agency problem are two different market frictions that can have

[5]The assumption that the nonbenchmark stock is more illiquid than the benchmark stock is motivated by empirical evidence. In Section V, we study a sample of 680 actively managed equity mutual funds in the United States over the period between 1999 and 2002. In our sample, approximately 34% of the funds use the Standard & Poor's (S&P) 500 index as their benchmark. Nearly 25% of the value of the portfolio holdings of this subset of funds is invested in stocks that do not belong to the list of constituents of the S&P 500. We find that the liquidity cost is 26% higher for portfolio stocks outside the S&P 500 compared with portfolio stocks inside the S&P 500. The liquidity cost of each stock is estimated according to the methodology proposed by Hasbrouck (2009).

[6]The assumption that the nonbenchmark stock is a pure idiosyncratic bet allows us to shut down other potential reasons for holding it that are not related to risk shifting, such as the diversification and risk-premium motives. We are grateful to an anonymous referee for suggesting this approach to separate risk shifting from other reasons for holding the nonbenchmark stock, and we highlight that our results would still hold under more general parameterizations of our model.

[7]In the empirical part of this paper (see Section V), we show that risk shifting in the mutual fund industry is mostly idiosyncratic in nature. This is consistent with the tight constraints mutual funds are subject to, such as tracking-error and cash-holding limits, as well as style-drift restrictions. In our model, if we impose a tight position limit on the risk-free bond, the position limit on the benchmark stock also tightens, forcing the fund manager to shift risk using the nonbenchmark stock.

[8]This is similar to the effect found by Kahl, Liu, and Longstaff (2003). They show that the need to hedge the temporarily irreversible positions in illiquid stocks can lead to a significant reduction in the portfolio allocations to those stocks.

offsetting effects. In other words, stock illiquidity can deter the misbehavior of fund managers, which in turn can be beneficial to fund investors. However, it is beyond the scope of this article to quantify the magnitude of the trade-off between the benefits of stock market liquidity and the costs of portfolio delegation.[9]

The main results of our model remain qualitatively unchanged when we include a style-drift restriction such as SEC Rule 35d-1. This restriction requires the fund manager to allocate at least 80% of the portfolio to the benchmark stock. In this model specification, the fund manager needs to use leverage (i.e., short the risk-free bond) to be able to shift risk using the illiquid nonbenchmark stock and, at the same time, satisfy the style-drift restriction.[10] This suggests that demand for leverage by mutual funds is positively associated with their idiosyncratic risk taking, which we test empirically.

The novel implications of our model are therefore twofold. First, the higher the liquidity of the stocks used by fund managers to shift portfolio risk, the larger the size of their risky bets. Second, in the presence of binding portfolio constraints, fund managers are more likely to take on idiosyncratic risk in response to beating their performance benchmarks.

We use a sample of U.S. domestic actively managed equity mutual funds to provide empirical support for these novel implications of our model. We first test the hypothesis that an improvement in stock liquidity encourages risk shifting in the mutual fund industry. It is, however, challenging to identify a causal relation between stock liquidity and risk shifting by fund managers because these two variables may be jointly determined by some unobservable characteristics, or the causality may run from risk shifting to the liquidity of the stocks used to shift risk. We overcome this challenge by taking advantage of an exogenous shock to liquidity. In 2001, stock markets in the United States reduced the minimum tick size from 1/16 to 1/100 of a dollar. This "decimalization" event had a greater positive effect on liquidity (i.e., lower bid–ask spreads and higher turnover) for stocks with lower prices. We exploit this differential effect in our identification strategy, following Edmans, Fang, and Zur (2013).[11]

We measure risk-shifting propensity using tracking-error volatilities calculated from daily fund and benchmark returns. In particular, we measure the extent to which tracking-error volatilities change from the first to the secondhalf of a

[9] We assume that the portfolio-delegation decision is exogenous in our model. Moreover, we do not allow the investor to choose the fund's benchmark. Basak, Pavlova, and Shapiro (2008) show how optimal benchmarking could be used to reduce the adverse effects of managerial incentives.

[10] Basak et al. (2007) do not explore the possibility that fund managers may engage in idiosyncratic risk taking when they are subject to portfolio constraints.

[11] We find that the stocks with the lowest prices experience the largest decrease in bid–ask spreads from 2000 to 2002. The magnitude of that decrease is 103 basis points (bps) (t-statistic $=-11.59$). The remaining stocks experience a decrease in bid–ask spreads from 2000 to 2002 of only 15 bps (t-statistic $=-3.85$). We also find that in the year 2000, the average turnover of low-priced stocks is approximately 50% of that for other stocks, whereas in 2002, it increases to 60%, which represents a 20% increase. This analysis is restricted to the stocks held by a sample of U.S. actively managed equity mutual funds, which we use to perform all of our empirical tests. We provide more details on the construction of this sample in Section V.

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calendar year in response to relative performance.[12] Next, we employ a difference-in-differences approach to examine the risk-shifting behavior of fund managers around the decimalization event. We find that fund managers are 10% more likely to increase their tracking-error volatilities from the first to the second half of the year in the post- compared with the pre-decimalization years. This result is statistically significant and economically large: It compares with a 37% unconditional probability of observing an increase in tracking errors from the first to the second half of an average year.

The results are stronger for funds that are underperforming by mid-year and funds that hold a larger fraction of their portfolios in low-priced stocks, which are the stocks that have experienced the greatest improvement in liquidity as a result of the decimalization. We find that mid-year loser funds that hold more low-priced stocks are 21% more likely to increase their tracking-error volatilities toward the year-end around the decimalization event. These results are consistent with the prediction of our model that an increase in stock liquidity encourages fund managers to take more risk.

We corroborate our findings by conducting a number of placebo tests. First, if we assign random benchmarks to the mutual funds, the effect disappears. This suggests that fund managers respond to relative performance only with respect to their declared benchmarks, not with respect to random benchmarks. Second, we conduct time-series placebo tests using the years 2004 and 2005 as pseudo-decimalization years. We do not find similar effects of mutual fund ownership of low-priced stocks on risk shifting during these placebo periods. Third, we perform a falsification analysis using closet-index funds. These funds hug their benchmarks very closely and are therefore less likely to change their tracking-error volatilities in response to an improvement in the liquidity of their portfolio holdings. We find that this is indeed the case: The decimalization event does not affect the tracking-error volatilities of closet indexers. Lastly, we test the tournament hypothesis of Brown et al. (1996) by measuring performance relative to the median fund in the same style category[13] instead of using their declared benchmarks, and we control for the effect of mean reversion in fund return volatilities, as suggested by Schwarz (2012). We find that the results are weaker under the tournament setting.[14] This suggests that self-designated benchmarks appear to encourage risk shifting to a larger extent than tournaments. This result is consistent with Reed and Wu (2005) and Lee, Trzcinka, and Venkatesan (2019), who also find that fund managers tend to shift risk in response to beating their benchmarks but not in response to beating their median peer funds.

[12] In our model, as in that of Basak et al. (2007), any deviation from the benchmark is inherently risky. We capture the risk-shifting behavior of fund managers by computing the tracking errors of their funds' returns with respect to the returns of their respective benchmarks. This is in contrast to Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997), who define risk-taking incentives as the sensitivity of a fund's value to its volatility.

[13] Del Guercio and Tkac (2002) show that investors chase funds that perform well relative to other funds following the same style.

[14] Busse (2001) shows that the tournament effect disappears when using daily data. We show that the tournament effect is still significant using daily data when we focus the analysis on the period around the decimalization event.

We control for several characteristics related to the risk-shifting incentives of fund managers as proposed in prior research. In particular, it has been shown that young funds (e.g., Chevalier and Ellison (1997)), funds with high expense ratios (e.g., Gil-Bazo and Ruiz-Verdu (2009)), and funds that belong to small families (e.g., Huang, Wei, and Yan (2007)) are more likely to take excessive risks in response to beating their benchmarks. Therefore, we control for funds' age, expense ratio, and family size. Huang et al. (2011) show that the poor performance of risk shifters is not due to trading costs associated with the risk-shifting activity itself. We control for the funds' turnover to account for such trading costs. Furthermore, we control for the level of tracking error in the first half of the year and the mid-year deviation of the funds' portfolios from the composition of their declared benchmarks (i.e., the active share measure from Cremers and Petajisto (2009)).

The second main implication of our theoretical model is that in the presence of binding portfolio constraints, fund managers are more likely to take on idiosyncratic risk in response to beating their benchmarks. Therefore, there should be a positive relation between the demand for leverage and the amount of idiosyncratic risk taken by fund managers. To provide evidence consistent with this implication, we start by decomposing the tracking-error volatilities of mutual funds into their idiosyncratic and systematic components. We argue that the idiosyncratic (systematic) component of the tracking error is more likely driven by risk shifting using nonbenchmark (benchmark) stocks, to be consistent with our theoretical model. We expect to find that the additional risk shifting we observe around the decimalization event is mostly idiosyncratic in nature, especially for the funds with more binding leverage constraints.[15]

To examine the effect of the tightness of leverage constraints on the relation between liquidity and risk shifting, we create a measure of demand for leverage by mutual funds similar to the one proposed by Boguth and Simutin (2018). We find that an increase in borrowing demand is indeed associated with higher idiosyncratic risk taking by mutual funds, and we find that the relation is stronger around the decimalization event, which is consistent with the implications of our theoretical model.[16]

To shed light on the costs of risk-shifting behavior, we study the performance implications of increasing tracking-error volatilities around the decimalization event. We find that mid-year losers who hold low-priced stocks and who increase their tracking errors from the first to the second half of the year are 16% less likely to beat their declared benchmarks by year-end in the post- versus the pre-decimalization years. This is relative to mid-year losers holding

[15] We do not find much systematic risk taking in the data, compared with our theoretical results, because in practice, mutual funds are subject to numerous portfolio constraints and are not allowed to hold large cash reserves (e.g., Simutin (2014)). If we were to include all these restrictions in our model, we would be able to reduce the gap between the empirical findings and our theoretical results.

[16] We focus on the effects of the tightness of leverage constraints because mutual funds are mainly long-only investment vehicles, which makes it a nontrivial task to propose an empirical proxy for their demand for short selling. Moreover, when we include a style-drift restriction like SEC Rule 35d-1 in our model, we are forced to relax the borrowing constraint so that the fund manager is able to take on idiosyncratic risk and at the same time satisfy the style-drift restriction. The implication is that there should be a positive relation between the demand for leverage and idiosyncratic risk taking by mutual funds. Our empirical analysis also provides support for this implication of our theoretical model.

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low-priced stocks that do not increase tracking errors toward the year-end. This result is economically meaningful, but we do not find it to be statistically significant. This suggests that an exogenous improvement in stock liquidity can be hurtful to investors who choose to delegate instead of investing directly because it encourages fund managers to take extra risks that are not necessarily compensated with higher returns. This is consistent with the idea that agency conflicts are the likely motivation behind the variation in tracking-error volatilities observed around the decimalization event.[17]

A potential alternative explanation for our empirical findings is that the relation between fund flows and performance varies over time and is more convex in the post- versus the pre-decimalization years. In that case, the observed increase in risk shifting by fund managers around the decimalization event would not be caused by the improvement in liquidity but by an increase in the convexity of the flow–performance relation. We rule out this alternative explanation by showing that the flow–performance relation in fact exhibits a significant decrease in convexity around the decimalization event.

The remainder of the article is organized as follows: In Section II, we review the related research. Section III describes the theoretical model, and Section IV lays out its main implications. In Section V, we empirically test the novel implications of our model, and we conclude in Section VI.

II. Related Literature

This study is related to the intersection of two strands of research, i) on the risk-shifting incentives of mutual fund managers, which result from a positive and convex flow–performance relation, and ii) on the implications of liquidity frictions for dynamic asset allocation. We provide a quick review of these two blocks of research.

There is a large number of empirical studies showing that fund managers appear to compete with one another for investors' money. For instance, Brown et al. (1996) and Chevalier and Ellison (1997) show that fund managers with mid-year performance below the peer-group median increase their portfolio risk toward the year-end, relative to mid-year winners. This tournament behavior is motivated by the tendency of fund investors to reward good performers with disproportionately large inflows compared with the small amount of redemptions observed for poor performers. However, a number of subsequent studies show that the tournament effect disappears when using different risk-shifting measures, different methodologies, or different data frequencies. For instance, Busse (2001) shows that the evidence on mutual fund tournaments disappears when using daily data. Kempf, Ruenzi, and Thiele (2009) show that the risk-shifting incentives of fund managers are contingent on the state of the economy and on employment risk.

[17]Huang et al. (2011) argue that funds change their portfolio risk significantly over time, either because fund managers are unskilled or because they are skilled to take advantage of time-varying investment opportunities. They look at the performance consequences of risk shifting to shed light on its underlying motivations. They use a sample of 2,979 U.S. equity funds over the period 1980–2009 and find inferior performance mainly for funds that increase idiosyncratic risk exposure and funds that increase their tracking errors relative to their benchmarks, which is consistent with our results.

Schwarz (2012) argues that mean reversion in the volatility of fund returns mechanically generates the tournament effect.[18]

We contribute to this literature by showing that an exogenous improvement in the liquidity of the stocks used as a risk-shifting tool can encourage fund managers to take extra risks, which can be costly to fund investors. Furthermore, we show that when we focus the analysis on the years around the decimalization and when we use changes in tracking-error volatilities to capture the propensity to shift risk, the tournament effect does not disappear using daily data, as suggested by Busse (2001).

The tracking-error measure that we use in our empirical tests is motivated by our theoretical model as well as prior work. Basak et al. (2007) and Chen and Pennacchi (2009) show that there is a tendency for mutual funds to increase the tracking-error volatilities of their portfolios, but not their return volatilities, as their performance declines relative to their benchmarks.

We extend the model of Basak et al. (2007) by including the effects of portfolio constraints and by allowing for changes in the liquidity of the stocks used by fund managers to shift portfolio risk. We model illiquidity as in Ang et al. (2014), according to which an illiquid stock can only be traded contingent on the arrival of randomly occurring trading opportunities. This captures the difficulty of finding a counterparty to trade with when the security is illiquid, which could be due to a small number of market participants or large bid–ask spreads, among other reasons.[19]

III. Theoretical Model

We build on the framework of Basak et al. (2007) and study the problem of a fund manager who needs to deal not only with investors' money flows but also with the position limits that are imposed in practice (e.g., borrowing and short-selling constraints and style-drift restrictions) and the illiquidity of the stocks he or she invests in.

We assume an investment horizon of $[0, T]$, and we assume that there are three securities in the economy: a liquid risk-free bond S_0 that offers a constant interest rate r, a liquid stock S_L, and an illiquid stock S_I. The price of S_L and the fundamental value of S_I evolve according to the following processes:

$$dS_{Lt} = \alpha_L S_{Lt} dt + \sigma_L S_{Lt} dB_{Lt} \tag{1}$$

and

$$dS_{It} = \alpha_I S_{It} dt + \sigma_I S_{It} dB_{It}, \tag{2}$$

[18] Other empirical articles that have studied the effects of the flow–performance relation include those by Goetzmann and Peles (1997), Sirri and Tufano (1998), Zheng (1999), Del Guercio and Tkac (2002), Lynch and Musto (2003), Nanda, Wang, and Zheng (2004), Huang et al. (2007), and Chaudhuri, Ivkovic, and Trzcinka (2018).

[19] This type of illiquidity differs from other types that have been proposed in prior research, such as the idea that assets can be traded subject to a transaction cost (e.g., Constantinides (1986)) or the idea that assets can be traded but only in limited amounts (e.g., Longstaff (2001)) or at deterministic times (e.g., Kahl et al. (2003), Longstaff (2009)).

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where B_L and B_I are two standard Brownian motions with the correlation coefficient $\rho \in [-1,1]$. Following Ang et al. (2014), we assume that S_I can only be traded contingent on the arrival of randomly occurring liquidity events, which coincides with the arrival of a Poisson process N_t with intensity $\lambda > 0$, for $0 < t < T$.

The performance of the fund manager is measured relative to that of a benchmark. We assume that the benchmark is a portfolio composed exclusively of liquid securities and can be replicated by trading its components continuously.[20] In particular, we assume that the benchmark consists of a proportion β invested in S_L and a proportion $1-\beta$ invested in S_0. Therefore, its value denoted by Z_t evolves according to the following process:

$$dZ_t = (r + \beta(\alpha_L - r))\, Z_t dt + \beta \sigma_L Z_t dB_{Lt}. \tag{3}$$

The manager's portfolio has two components: i) a liquid component that invests in S_L and in S_0 and ii) an illiquid component that invests in S_I. We denote by X_t the dollar amount invested in the liquid component, and by Y_t we denote the dollar amount invested in the illiquid component. The joint evolution of (X_t, Y_t), when the fund manager is waiting for the next opportunity to trade S_I (i.e., in-between liquidity events), is given by

$$dX_t = (r + \pi_t(\alpha_L - r))X_t dt + \pi_t \sigma_L X_t dB_{Lt}, \tag{4}$$

$$dY_t = \alpha_I Y_t dt + \sigma_I Y_t dB_{It}, \tag{5}$$

where π_t is the fraction of X_t invested in S_L. When a trading opportunity for S_I arrives at time τ, the fund manager can transfer some amount I_τ from the liquid portion of the portfolio to the illiquid portion, as follows:

$$X_\tau = X_{\tau-} - I_\tau, \tag{6}$$

$$Y_\tau = Y_{\tau-} + I_\tau, \tag{7}$$

where a positive (negative) value of I_τ represents a purchase (sale) of S_I.

We assume that the fund manager cannot short or buy stocks on margin. As a result, we require that $X_t \geq 0$, $Y_t \geq 0$, and $\pi_t \in [0,1]$, for all $t \in [0,T]$.[21] Following Basak et al. (2007), we assume that the mutual fund is open-ended, experiencing inflows or outflows at $t = T$. Therefore, the value of the fund at the terminal date, after experiencing money flows, is given by

$$W_T = \left(1 + f(R^f - R^b)\right)(X_{T-} + Y_{T-}), \tag{8}$$

where $f(R^f - R^b)$ represents the proportional flow rate function, which depends on the fund's performance relative to the benchmark, and

$$R^f = \ln \frac{X_{T-} + Y_{T-}}{X_0 + Y_0}, \quad R^b = \ln \frac{Z_{T-}}{Z_0} \tag{9}$$

[20] A large number of mutual funds use liquid equity indices as their benchmark portfolios. Sensoy (2009) documents that more than one-third of the U.S. actively managed mutual funds use the S&P 500 index as their benchmark.

[21] In order to ensure the solvency of the fund, $X_t \geq 0$ and $Y_t \geq 0$ are endogenously required, like in Ang et al. (2014). In reality, mutual funds' ability to short sell and purchase securities on margin is severely restricted by the Investment Company Act of 1940 (see Almazan et al. (2004)). Moreover, because most funds are evaluated against all-equity benchmarks, few maintain significant cash balances (see Simutin (2014)).

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are the continuously compounded returns of the fund (on a before-flow basis) and the benchmark in period $[0, T]$, respectively. Without loss of generality, we set the initial value of the benchmark to be equal to the initial value of the fund (i.e., $Z_0 = X_0 + Y_0$). As a result, the value of the fund after money flows is given by

$$W_T = \left(1 + f\left(\ln\left(\frac{X_{T-} + Y_{T-}}{Z_{T-}}\right)\right)\right)(X_{T-} + Y_{T-}). \tag{10}$$

The fund manager chooses the optimal policy $\Theta_t^* = (\pi_t^*, I_t^*)$ to maximize the expected constant relative risk aversion (CRRA) utility derived from the value of assets under management (after flows) at time T:

$$E\left[\frac{1}{1-\gamma} W_T^{1-\gamma}\right], \tag{11}$$

where $\gamma > 0$ and $\gamma \neq 1$ denote the risk-aversion coefficient of the fund manager.[22]

We follow Basak et al. (2007) and use a flow–performance function of the collar type, which draws on the estimations of Chevalier and Ellison (1997):

$$f(R^f - R^b) = \begin{cases} f_L & \text{if } R^f - R^b < \theta_L, \\ f_L + \psi(R^f - R^b - \theta_L) & \text{if } \theta_L \leq R^f - R^b < \theta_H, \\ f_H \equiv f_L + \psi(\theta_H - \theta_L) & \text{if } R^f - R^b \geq \theta_H, \end{cases} \tag{12}$$

where $\psi > 0$, and $\theta_L < \theta_H$. When the performance of the fund relative to its benchmark reaches the threshold θ_L, the flow function $f(\cdot)$ exhibits a local convexity until it reaches θ_H, above which it flattens out.[23]

For brevity, we relegate the definition of the fund manager's value function and the corresponding Hamilton–Jacobi–Bellman (HJB) equation to Section 1 of the Appendix. We offer a verification theorem that characterizes the fund manager's optimal investment policy in Section 2 of the Appendix. Taking advantage of the homogeneity of the CRRA utility representation, we can reduce the dimensionality of the HJB equation. We describe this reduction in dimensionality, and the numerical method used to solve it, in Sections 3 and 4 of the Appendix, respectively.

IV. Model Implications

There is no closed-form solution for the problem described in the previous section. Therefore, we conduct a numerical analysis. The baseline parameter values that we use are as follows. We set the fund manager's investment horizon to $T = 1$, which corresponds to 1 calendar year, and we set the fund manager's risk-aversion level to $\gamma = 2$. The risk-free rate is $r = 0.04$. The annualized expected return of the liquid stock S_L is set at $\alpha_L = 0.08$, and its annualized volatility is $\sigma_L = 0.15$. To separate the risk-shifting incentives from other reasons that would lead the fund manager to trade in the illiquid nonbenchmark stock S_I, such as

[22] In the mutual fund industry, fund advisors' compensation is typically a constant fraction of the value of assets under management (AUM). Therefore, in this model, maximizing the utility derived from the terminal value of AUM is equivalent to maximizing the utility derived from compensation.

[23] Our results are robust to the alternative flow–performance functions of Basak et al. (2007).

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diversification or the extraction of an illiquidity premium, we assume that S_I is a pure idiosyncratic bet that carries no risk premium by setting $\alpha_I = r = 0.04$, $\sigma_I = 0.50$, and $\rho = 0$. As a result, the capital asset pricing model (CAPM) relation $\alpha_I = r + (\rho\sigma_I/\sigma_L)(\alpha_L - r)$ holds in our baseline case. We assume an all-equity benchmark consisting entirely of the liquid stock S_L (i.e., $\beta = 1$).[24]

The parameters of the flow function are calibrated to the estimates of Chevalier and Ellison (1997). Specifically, when the performance of the fund relative to the benchmark (i.e., $R^f - R^b$) is below $\theta_L = -0.08$, the flow function is flat at the level of $f_L = -0.2$ (i.e., the fund experiences an outflow of 20% of AUM at year-end). When $R^f - R^b \geq \theta_L = -0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When $R^f - R^b \geq \theta_H = 0.08$, the flow–performance relation returns to the flat position at the level of $f_H = 0.5$ (i.e., inflow of 50% of AUM by year-end).

We consider various values of λ, the frequency of the liquidity events for S_I, to reflect different levels of liquidity. For example, the case in which the average time interval between liquidity events is a half year corresponds to $\lambda = 2$, and the case in which the average time interval between liquidity events is 1 week corresponds to $\lambda = 52$.

The parameter values for our baseline case have a number of immediate implications. First, because the risk premium for S_I is 0, an investor facing no money flows would choose a null exposure to S_I. Therefore, if the manager in our baseline model allocates a positive weight to S_I, he or she will be taking an idiosyncratic risk. Second, the money flows into and out of the fund respond asymmetrically to its performance relative to the benchmark. They reward outperformance with large inflows, whereas redemptions due to underperformance are more moderate. This convexity in the flow–performance relation generates an incentive to deviate from the benchmark (e.g., Basak et al. (2007)).

A. Optimal Investment Policies

In this section, we examine the fund manager's optimal investment policy. At each time $t \in [0, T)$, there is an optimal asset allocation rule ξ_t, which is a function of the performance of the fund relative to the benchmark, given by $R_t = (X_t + Y_t)/(Z_t)$. The fund manager rebalances his or her positions X_τ and Y_τ so that $Y_\tau/(X_\tau + Y_\tau) = \xi_\tau$ if a liquidity event occurs at time τ. We examine the properties of this rule ξ_t in more detail in the following subsection.

1. Portfolio Constraints and Idiosyncratic Risk Taking

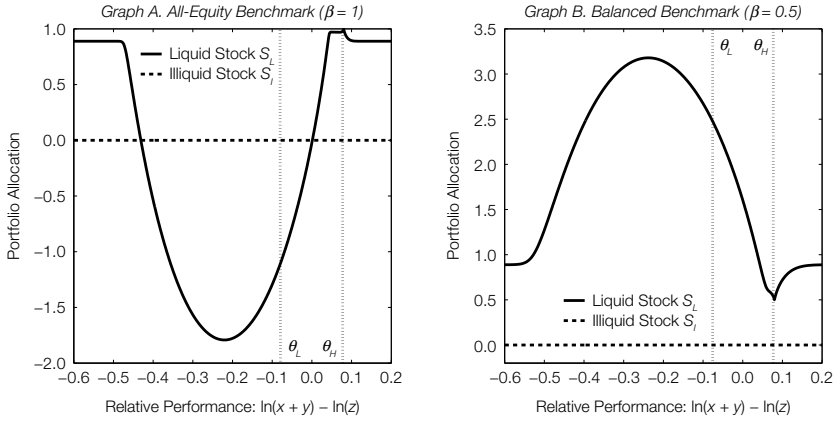
We start our analysis by examining the effects of portfolio constraints on the fund manager's incentive to take on idiosyncratic risk.

Figure 1 illustrates the allocation rule ξ and how it is associated with the relative performance $R = \ln(x + y) - \ln(z)$, in the absence of borrowing and short-selling constraints. This is the behavior of ξ at mid-year ($t = 0.5$) and for liquidity events with intensity $\lambda = 12$. In Graph A, we consider an all-equity benchmark for which we set $\beta = 1$ (our baseline case), and we allow the investment policy to vary within the interval $\pi_t \in [-4, 1]$. This corresponds to Economy (b) of

[24] This is motivated by the fact that mutual funds in practice typically follow benchmarks that are fully invested in equity, such as the S&P 500 index.

FIGURE 1
Risk Shifting with Liquid Benchmark Stock Only

Figure 1 illustrates the fund manager's optimal weight on the illiquid nonbenchmark stock S_I (i.e., the dotted line) and on the liquid benchmark stock S_L (i.e., the solid line) as a function of relative performance at mid-year (i.e., $t=0.5$) and conditional on the arrival of a liquidity event at that time. In Graph A the fund follows an all-equity benchmark (i.e., $\beta=1$), and in Graph B it follows a balanced benchmark (i.e., $\beta=0.5$). This figure does not impose leverage and short-selling constraints. The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The two vertical dashed lines indicate the performance thresholds that define the flow–performance function. For $\ln(x+y)-\ln(z)<\theta_L=-0.08$, the flow function is flat at the level of $f_L=-0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y)-\ln(z)\geq\theta_L=-0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When it reaches $\ln(x+y)-\ln(z)\geq\theta_H=0.08$, the flow–performance relation returns to flat at the level of $f_H=0.5$ (i.e., inflow of 50% of AUM by year-end). The remaining parameter values used to generate these plots are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, and intensity of the Poisson process $\lambda=12$ (i.e., liquidity events occur once a month, on average).



Basak et al. (2007), in which the manager takes short positions on the liquid benchmark stock when shifting portfolio risk, despite the positive risk premium offered by this stock.[25] In Graph B, we consider a balanced benchmark that is half invested in the liquid stock and half invested in the risk-free bond (i.e., $\beta=0.5$), and we allow the investment policy to vary within the interval $\pi_t\in[0,5]$. This corresponds to Economy (a) of Basak et al. (2007). In this case, the manager may invest more than 100% of the portfolio in the liquid benchmark stock when engaging in risk shifting. Figure 1 shows that the fund manager does not take any idiosyncratic risk when there are no restrictions on borrowing and short selling, which is consistent with the results of Basak et al. (2007).

However, the results in Figure 1 change significantly when we impose short-selling and borrowing constraints, as well as other (more restrictive) position limits. Figure 2 illustrates the changes. It shows the optimal investment policies chosen by the fund manager for both the illiquid nonbenchmark stock (Graph A) and the liquid benchmark stock (Graph B) at mid-year ($t=0.5$), conditional on the arrival of a liquidity event at this point in time. Graph B shows that, as the fund's performance deteriorates relative to that of its benchmark, the fund

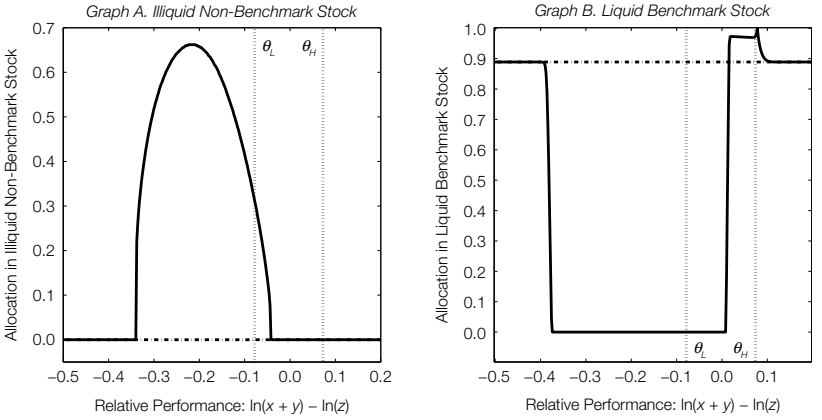
[25] This is because the normal Merton weight on that stock (in the absence of money flows) is 88.9% for the parameter values in our baseline case, which is smaller than $\beta=1$.

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FIGURE 2

Liquid and Illiquid Stock Allocations for All-Equity Benchmark

Figure 2 illustrates the fund manager's optimal weight on the illiquid nonbenchmark stock S_I (Graph A) and on the liquid benchmark stock S_L (Graph B) as a function of relative performance at mid-year (i.e., $t=0.5$) and conditional on the arrival of a liquidity event at that time. The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The two vertical dashed lines indicate the performance thresholds that define the flow–performance function. For $\ln(x+y)-\ln(z)<\theta_L=-0.08$, the flow function is flat at the level of $f_L=-0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y)-\ln(z)\geq\theta_L=-0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When it reaches $\ln(x+y)-\ln(z)\geq\theta_H=0.08$, the flow–performance relation returns to flat at the level of $f_H=0.5$ (i.e., inflow of 50% of AUM by year-end). The remaining parameter values used to generate these plots are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, intensity of the Poisson process $\lambda=12$ (i.e., liquidity events occur once a month, on average), and the weight of the benchmark on the liquid stock $\beta=1$ (i.e., all-equity liquid benchmark).



manager first engages in risk shifting using the liquid benchmark stock. In particular, the fund manager reduces the exposure to the liquid benchmark stock to 0% and increases the exposure to the risk-free bond to 100%.[26] This is consistent with the results for Economy (b) of Basak et al. (2007).[27] However, as the performance of the fund deteriorates further relative to the benchmark, and the short-selling constraint on the liquid benchmark stock is binding, the fund manager starts to engage in risk shifting using the illiquid nonbenchmark stock. In other words, when the short-sale constraint on the benchmark stock is binding, the manager starts taking on idiosyncratic risk. This is represented in Graph A.

The short-sale constraint that we include in our baseline model is motivated by the empirical evidence provided by Almazan et al. (2004). However, we do not need the short-sale constraint to bind for the fund manager to take on idiosyncratic risk. In practice, fund managers are subject to other portfolio constraints that are more restrictive than the short-sale restriction. For instance, fund managers may be subject to tracking-error constraints and style-drift restrictions, such as SEC

[26] In practice, mutual funds are subject to tracking-error limits and style-drift restrictions, which prevent them from deviating too much from their benchmarks. They are also not allowed to hold significant cash reserves. These more restrictive constraints are likely to force them to more readily substitute the liquid benchmark stock with the illiquid nonbenchmark stock.

[27] In our model there is also a case corresponding to Economy (a) of Basak et al. (2007). We briefly describe this case in Section 5 of the Appendix.

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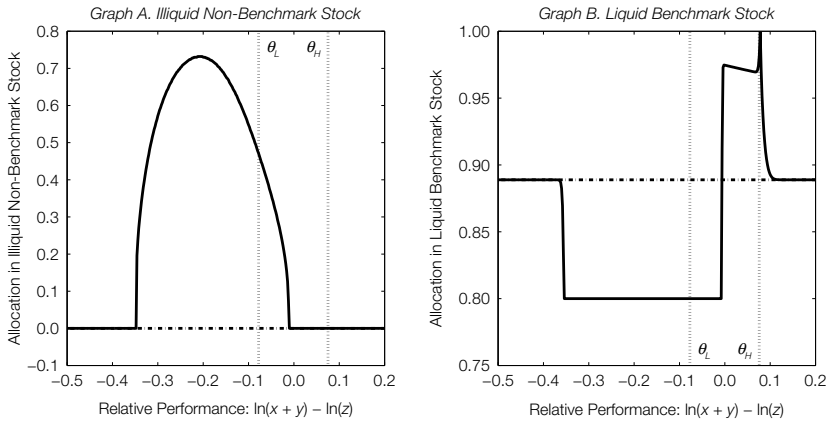
Rule 35d-1. This rule requires that an investment company with a name that suggests that it focuses its portfolio holdings in a particular type of investment, or in investments in a particular industry, should invest at least 80% of its assets in the type of investment suggested by its name.

Figure 3 shows the portfolio allocations that we obtain when we require that the fund manager invests at least 80% of the entire portfolio in the liquid benchmark stock, as required by SEC Rule 35d-1. This assumes that the benchmark represents the style of the mutual fund. Graph B shows that the portfolio allocation in the liquid benchmark stock can never be below 80%. As expected, the short-sale constraint never binds in this setting, and the manager shifts portfolio risk using the benchmark stock only until it hits the style-drifting constraint of 80%. If the relative performance deteriorates further, the manager takes on idiosyncratic risk using the illiquid nonbenchmark stock, as illustrated in Graph A. This suggests that the binding short-sale constraint is not the key driver of our main results.[28]

It is important to highlight that for the style-drift constraint to be feasible, we need to allow the fund manager to borrow. If borrowing is not allowed, the position limit of 80% on the benchmark stock cannot be satisfied because the manager cannot control the portfolio weight of the illiquid stock when it is not

FIGURE 3
Optimal Investment Policies and Style-Drift Restrictions

Figure 3 illustrates the fund manager's optimal weight on the illiquid nonbenchmark stock S_I (Graph A) and on the liquid benchmark stock S_L (Graph B) in the presence of a style-drift restriction such as U.S. Securities and Exchange Commission (SEC) Rule 35d-1. The optimal policies are a function of relative performance at mid-year (i.e., $t=0.5$) and conditional on the arrival of a liquidity event at that time. The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The two vertical dashed lines indicate the performance thresholds that define the flow–performance function. For $\ln(x+y)-\ln(z)<\theta_L=-0.08$, the flow function is flat at the level of $f_L=-0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y)-\ln(z)\geq\theta_L=-0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When it reaches $\ln(x+y)-\ln(z)\geq\theta_H=0.08$, the flow–performance relation returns to flat at the level of $f_H=0.5$ (i.e., inflow of 50% of AUM by year-end). The remaining parameter values used to generate these plots are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, intensity of the Poisson process $\lambda=12$ (i.e., liquidity events occur once a month, on average), and the weight of the benchmark on the liquid stock $\beta=1$ (i.e., all-equity liquid benchmark).



[28] We would like to thank an anonymous referee for this suggestion.

tradable (i.e., in between liquidity events). This is why the portfolio allocation in the illiquid nonbenchmark stock can take values above 20% in Graph A of Figure 3. The implication is that there should be a positive relation between the demand for leverage and idiosyncratic risk taking by mutual funds, which we test empirically in Section V.[29]

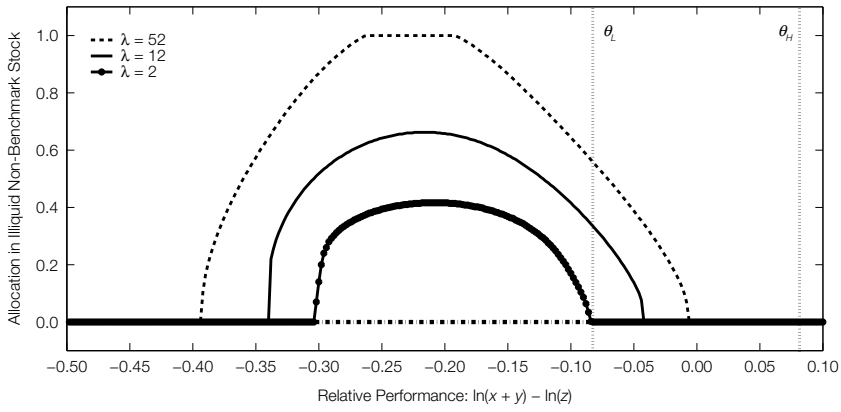
2. Implications of Stock Liquidity

We now focus on Graph A of Figure 2 and examine how it changes with the liquidity of the nonbenchmark stock (i.e., the intensity parameter λ). Intuitively, because shifting risk with the nonbenchmark stock exposes the fund manager to liquidity risk that cannot be hedged, the fund manager is expected to reduce the size of his or her idiosyncratic bets on the illiquid stock when the value of λ decreases.

Figure 4 shows how the optimal policy of the fund manager at mid-year ($t=0.5$) changes with the parameter λ. In general, the fund manager's risk-shifting incentives weaken as we decrease the liquidity of S_I. As λ decreases, not only does the risk-shifting range shrink, but also the maximum allocation in S_I decreases. For example, for $\lambda=2$ (semiannual liquidity events), the maximum allocation on S_I in the risk-shifting region is approximately 40%, whereas for $\lambda=52$ (weekly liquidity events), the maximum allocation in S_I is 100%, which is the maximum risk-shifting level in the presence of borrowing and short-selling constraints.

FIGURE 4
Risk-Shifting Incentives and (Stochastic) Stock Illiquidity

Figure 4 illustrates the fund manager's optimal weight on the illiquid stock S_I as a function of relative performance for different degrees of stochastic illiquidity $\lambda \in \{2, 12, 52\}$, corresponding to 2, 12, and 52 liquidity events on average in a year. This plot corresponds to snapshots of the fund manager's optimal policy at mid-year (i.e., $t=0.50$, for $T=1$). The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$. The two vertical dashed lines indicate the relative performance thresholds (θ_L and θ_H) that define the flow–performance function. The remaining parameter values used to generate this plot are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, and the weight of the benchmark on the liquid stock $\beta=1$ (i.e., all-equity liquid benchmark).



[29] In Section 5 of the Appendix, we describe additional results that we can derive from our model. We provide an analysis of the endogenous risk aversion induced by fund flows and the time dynamics of the optimal investment policy of the fund manager.

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This result suggests that the lack of stock liquidity can weaken the incentive of fund managers to take excessive risks in response to beating their performance benchmarks. It also holds in the presence of the style-drift restriction illustrated in Figure 3.[30]

B. Utility Costs of Portfolio Delegation

To the extent that lower risk shifting by fund managers translates into higher risk-adjusted returns, fund investors who choose to delegate instead of investing directly benefit from the illiquidity of the nonbenchmark stock. In this section, we measure the costs of portfolio delegation that accrue to fund investors.[31]

The preferences of investors and fund managers can differ along several dimensions. On the one hand, fund managers have explicit incentives to administer investors' money according to their own attitude toward risk. On the other hand, fund managers have implicit incentives to shift risk to increase the likelihood that they will outperform their benchmarks, which allows them to sell additional fund shares to the investors and increase the amount of assets under management. These differences in incentives, either explicit or implicit, can create significant utility costs to fund investors.

We measure the investor's utility costs through the certainty equivalent rate of return. For a particular investment policy Π, the certainty equivalent (CE) is the risk-free rate of return $\text{CE}(\Pi)$ that makes the investor indifferent between following Π over the investment horizon T or earning this risk-free rate on the same initial investment over the same period. For an investor with CRRA coefficient γ_I and initial wealth w_0, the variable $\text{CE}(\Pi)$ solves

$$\frac{[\text{CE}(\Pi)w_0]^{1-\gamma_I}}{1-\gamma_I} = E\left[\frac{(w_T^{\Pi})^{1-\gamma_I}}{1-\gamma_I}\right], \tag{13}$$

where the superscript Π denotes the final wealth w_T that is attained under policy Π, and the risk-aversion parameter γ_I shows that the certainty equivalent is generated using the value function of the investor.[32] We can then compute the cost to the investor of switching from investment policy Π_1 to Π_2 as $L(\Pi_1, \Pi_2) = \text{CE}(\Pi_2)/\text{CE}(\Pi_1) - 1$. A negative (positive) value of $L(\Pi_1, \Pi_2)$ represents a utility loss (gain) associated with moving from policy Π_1 to Π_2.[33]

[30] For brevity, we do not report the effects of liquidity on risk shifting in the presence of a style-drift restriction, but the results are available from the authors.

[31] We assume that the portfolio delegation decision is exogenous. The decision to delegate may be based on the assumption that in comparison with the individual investor, the manager is subject to lower opportunity costs of engaging in active portfolio management or better investing education, among others.

[32] In terms of notation, we use lowercase letters such as w_0 and w_T to denote the investor's wealth, and we use uppercase letters such as W_T in Section III to denote the fund manager's value of assets under management. In the presence of liquidity frictions, w_0 and w_T are replaced by $x_0 + y_0$ and $x_T + y_T$, respectively.

[33] In this article, we focus on the costs associated with portfolio delegation. However, we do not rule out the possibility that there are benefits associated with delegated portfolio management. In fact, the investor's decision to delegate (exogenous in our model) is very likely motivated by those perceived benefits that we are excluding from our analysis.

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We compute the certainty equivalent that the investor obtains when investing directly, and we compare it with the certainty equivalent that the investor's value function would generate if using the optimal investment policy of the fund manager. If we assume that Π_1 is the optimal investment policy of the investor if he or she were to invest directly and that Π_2 is the optimal policy of the fund manager, which includes the effects of the explicit (i.e., risk appetite) and implicit (i.e., convex flow–performance relation) incentives, then it always holds that $L(\Pi_1, \Pi_2) \leq 0$. The negative value of $L(\Pi_1, \Pi_2)$ represents the extra amount of wealth (as a fraction of the initial wealth) that the investor would require to be indifferent between delegating and investing directly. In what follows, we use the absolute value $l(\Pi_1, \Pi_2) = |L(\Pi_1, \Pi_2)|$ as our measure of the investor's utility costs of portfolio delegation.

Absent explicit incentives (i.e., $\gamma = \gamma_I$), Π_2 only differs from Π_1 because of the risk-shifting incentives of the fund manager. In the presence of explicit incentives (i.e. $\gamma \neq \gamma_I$), Π_2 can differ from Π_1 along two dimensions. First, the manager and the investor differ in terms of risk appetite. Second, the manager has risk-shifting incentives that the investor does not have. Therefore, in the presence of explicit incentives, we decompose the utility costs that accrue to the investor and distinguish the part that is attributable to the explicit incentives from the part that is due to the implicit incentives. We describe the detailed decomposition approach in Section 6 of the Appendix.

We report in Table 1 the utility costs that accrue to the investor from portfolio delegation. We present the split of such costs between the portions that are due to explicit and implicit incentives, respectively. We also present results for different levels of λ, which measures the liquidity of S_I. Panel A shows the case in which the effect of explicit incentives is absent ($\gamma = \gamma_I$). For $\lambda = 52$, the utility cost of portfolio delegation $l(\Pi_1, \Pi_2)$ is 1.59%, implying that the investor would need to be given an additional 1.59% of initial wealth to be indifferent between delegating and investing directly. As λ decreases (i.e., S_I becomes more illiquid), the cost of portfolio delegation decreases. For instance, when $\lambda = 2$ (i.e., S_I can only be traded twice a year on average), the utility cost of portfolio delegation is 0.46%. Therefore, the investor's cost of delegation when $\lambda = 2$ is less than one-third of the cost when $\lambda = 52$.

Panel B of Table 1 shows the utility cost of portfolio delegation when the investor has a risk-aversion coefficient of $\gamma_I = 4$, whereas the risk aversion of the fund manager remains the same ($\gamma = 2$). In this case, the utility cost of portfolio delegation has two components, one that is due to differences in risk aversion between the investor and the manager and the other that is due to the risk-shifting incentives of the fund manager.[34]

The higher the risk aversion of the investor, the higher are the costs of portfolio delegation. Indeed, the utility costs attributable to the implicit incentives of the fund manager are larger for $\gamma_I = 4$ compared with $\gamma_I = 2$ across all the

[34]The investor's utility from investing directly ($CE(\Pi_1)$) does not change much across the different levels of liquidity. This is the case in both Panels A and B of Table 1. In our model, the investor does not care about intertemporal consumption. Therefore, our result that illiquidity does not have a large impact on the utility of the investor is consistent with Ang et al. (2014). They show that the reduced ability to smooth consumption is the main driver of the utility costs of illiquidity.

TABLE 1
Utility Costs of Portfolio Delegation and Stock Illiquidity

Table 1 reports the utility costs that accrue to fund investors from delegating their investment decisions to mutual fund managers instead of investing directly. These costs are due to differences in risk appetite between investors and managers (explicit incentives), as well as the gambling incentives of fund managers that are created by the positive and convex flow–performance relation (implicit incentives). Panel A accounts only for the effect of implicit incentives (i.e., $\gamma = \gamma_I$), whereas Panel B considers the costs of both implicit and explicit incentives (i.e., $\gamma \neq \gamma_I$). The utility costs are measured at the level of the investor's centralized problem. The certainty equivalent rate of return $CE(\Pi)$ makes the investor indifferent between following policy Π and earning a risk-free rate on the same initial wealth over the same period of time. The policy Π_1 is the optimal policy of the investor if investing directly, whereas the policy Π_2 is the optimal policy of the fund manager. The total cost of portfolio delegation is given by $I(\Pi_1, \Pi_2) = |CE(\Pi_2)/CE(\Pi_1) - 1|$. The larger the values of $I(\Pi_1, \Pi_2)$, the costlier it is for the investor to delegate instead of investing directly. In Panel B, the total cost of portfolio delegation $I(\Pi_1, \Pi_2)$ is decomposed into two parts: one that is exclusively due to explicit incentives, and the other that is due to implicit incentives. Utility costs for different degrees of illiquidity ($\lambda \in \{2, 4, 12, 26, 52\}$) for stock S_I are reported. The flow–performance function is calibrated according to the empirical estimations of Chevalier and Ellison (1997): $f_L = -0.20$, $f_H = 0.50$, $\theta_L = -0.08$, and $\theta_H = 0.08$. The remaining parameter values used to compute these costs of delegation are as follows: investment horizon $T = 1$, risk-free rate $r = 0.04$, expected return of the liquid stock $\alpha_L = 0.08$, volatility of the liquid stock $\sigma_L = 0.15$, expected return of the illiquid stock $\alpha_I = 0.04$, volatility of the illiquid stock $\sigma_I = 0.50$, correlation between the returns of the two stocks $\rho = 0$, and the weight of the benchmark on the liquid stock $\beta = 1$ (i.e., all-equity liquid benchmark).

	Average Time between Liquidity Events ($1/\lambda$)				
	1/52	1/26	1/12	1/4	1/2
Panel A. $\gamma = \gamma_I = 2$					
$CE(\Pi_2)$	1.043	1.045	1.049	1.053	1.055
$CE(\Pi_1)$	1.060	1.060	1.060	1.060	1.060
$I(\Pi_1, \Pi_2)$ (%)	1.59	1.38	1.04	0.61	0.46
Panel B. $\gamma = 2$, $\gamma_I = 4$					
$CE(\Pi_2)$	1.013	1.018	1.025	1.033	1.035
$CE(\Pi_1)$	1.050	1.050	1.050	1.050	1.050
$I(\Pi_1, \Pi_2)$ (%)	3.52	3.09	2.39	1.63	1.40
Implicit $I(\Pi_1, \Pi_2)$ (%)	2.65	2.22	1.52	0.75	0.52
Explicit $I(\Pi_1, \Pi_2)$ (%)	0.87	0.87	0.87	0.88	0.88

liquidity levels. However, the deterrence effect that the illiquidity of the nonbenchmark stock imposes on the manager's risk-shifting incentives still substantially improves the investor's utility. For example, the utility cost of portfolio delegation decreases from 3.52% when $\lambda = 52$ to 1.40% when $\lambda = 2$, which represents a reduction of approximately 60%. This reduction in delegation costs is attributable entirely to the weakening of the manager's implicit incentives as the liquidity of the nonbenchmark stock decreases.

Next we generate some comparative statics on the costs of delegation. To focus on the effects associated with the fund manager's risk-shifting incentives, we do not change the parameters that determine the investor's optimal investment policy (i.e., we keep r, α_L, σ_L, α_I, σ_I, ρ, and γ_I unchanged). We examine how the managerial risk aversion γ, the riskiness of the benchmark β, and the parameters of the flow–performance relation, $f_H - f_L$ and $\theta_H - \theta_L$, affect the delegation costs. We also focus our comparative statics on the case in which the effects of explicit incentives are absent (i.e., $\gamma = \gamma_I = 2$), unless otherwise noted.[35]

Table 2 shows the results of our comparative statics analysis. In general, for each λ, we find that the costs of portfolio delegation (i.e., $I(\Pi_1, \Pi_2)$) exhibit the following patterns. First, the costs of delegation decrease with the fund manager's risk-aversion coefficient (i.e., γ). For example, for $\lambda = 12$ (i.e., monthly liquidity events), $I(\Pi_1, \Pi_2)$ decreases from 2.46% when $\gamma = 1.5$ to 0.32% when $\gamma = 2.5$.

[35] When we allow γ to vary around its baseline value of 2, γ_I remains equal to its baseline value of 2, and we only report the component of the total utility cost that is due to implicit incentives.

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TABLE 2
Utility Costs of Portfolio Delegation: Comparative Statics

Table 2 reports comparative statics on the utility costs of portfolio delegation (i.e., $I(\Pi_1, \Pi_2)$ in percentage points). These costs are computed as in Table 1, for different degrees of illiquidity of stock S_I ($\lambda \in \{2, 4, 12, 26, 52\}$). Table 2 presents the sensitivity of $I(\Pi_1, \Pi_2)$ to changes in the fund manager's risk aversion γ, the riskiness of the benchmark β, and the parameters that determine the shape of the flow–performance relation (i.e., the implicit reward for outperformance $f_H - f_L$ and the flow threshold differential $\theta_H - \theta_L$). For the cases in which $\gamma \neq \gamma_I$, we report only the component of $I(\Pi_1, \Pi_2)$ that is due to implicit incentives (as in Table 1, the component due to explicit incentives is negligible). The baseline parameter values we use to create this table are as in Table 1. To study the sensitivity of the utility costs of delegation, we change one parameter at a time while keeping all other parameters unchanged.

	Average Time between Liquidity Events ($1/\lambda$)				
	1/52	1/26	1/12	1/4	1/2
Baseline	1.59	1.38	1.04	0.61	0.46
$\gamma = 1.5$	3.71	3.21	2.46	1.32	0.89
$\gamma = 2.5$	0.52	0.44	0.32	0.25	0.13
$\beta = 0.8$	1.45	1.28	0.85	0.32	0.15
$\beta = 0.9$	1.51	1.33	0.96	0.50	0.34
$f_H - f_L = 0.5$	1.44	1.24	0.91	0.49	0.34
$f_H - f_L = 0.9$	1.65	1.44	1.11	0.71	0.56
$\theta_H - \theta_L = 0.12$	2.09	1.83	1.44	0.92	0.72
$\theta_H - \theta_L = 0.2$	0.93	0.78	0.52	0.22	0.13

This is because a more risk-averse fund manager is more likely to track the benchmark closely, which leads to less severe portfolio distortions. Second, $I(\Pi_1, \Pi_2)$ increases with β, the risk exposure of the benchmark. For example, when $\lambda = 12$, $I(\Pi_1, \Pi_2)$ increases from 0.85% when $\beta = 0.8$ to 0.96% when $\beta = 0.9$. This is because to outperform a benchmark portfolio that is more aggressive, the manager needs to take larger bets in the illiquid nonbenchmark stock, which provides unspanned volatility over the benchmark portfolio. Third, the delegation costs increase with the implicit reward for outperformance ($f_H - f_L$) and decrease with the flow threshold differential ($\theta_H - \theta_L$). For example, if $\lambda = 12$, $I(\Pi_1, \Pi_2)$ increases from 0.91% when $f_H - f_L = 0.5$ to 1.11% when $f_H - f_L = 0.9$, and it decreases from 1.44% when $\theta_H - \theta_L = 0.12$ to 0.52% when $\theta_H - \theta_L = 0.2$. This is because increasing $f_H - f_L$ or decreasing $\theta_H - \theta_L$ represents an increase in the convexity of the flow–performance relation, which leads to stronger risk-shifting incentives on the part of the fund manager.

We highlight that the delegation costs in Table 2 increase monotonically with the liquidity parameter λ. The lower the liquidity of S_I, the weaker are the risk-shifting incentives of the fund manager, which then translates into lower portfolio delegation costs to the fund investor.[36] We test this novel prediction of our model in the next section.

V. Empirical Analysis

In this section, we test the hypothesis that stock illiquidity can mitigate the incentive of mutual fund managers to engage in risk shifting. We also relate the degree of tightness of mutual funds' portfolio constraints to the type of risk taken by fund managers. To the best of our knowledge, the existing empirical evidence

[36] In Section 7 of the Appendix, we show that similar results can be obtained if we were to assume that the occurrence of liquidity events was deterministic instead of stochastic.

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has not yet verified these novel implications of our model. We use the decimalization event of 2001 as an exogenous shock to liquidity to identify causal effects.

A. Sample Statistics

We test the novel predictions of our model using a sample of U.S. actively managed mutual funds. We only include in our sample funds with complete information over the period 1999–2002 (i.e., the years around the decimalization event), to avoid composition biases. Our final sample consists of 680 distinct funds with 2,720 fund-year observations. In Section 8 of the Appendix, we provide a detailed description of the data sources, filters, and variables used in our analysis.

Table 3 provides descriptive statistics for the main variables. We measure changes in portfolio risk by taking the ratio of the tracking error in the second half of the year TE(7,12) to the first half of the year TE(1,6), and we denote it as TER = TE(7,12)/TE(1,6). The median fund in our final sample has a TE(1,6) of 0.006 and a TER of 0.95, suggesting a slight decrease in tracking error from the first to the second half of the year. The median fund outperforms its declared benchmark by 0.5% at mid-year. The value-weighted average price (VWPRC) of the stocks held by the funds in our sample is highly skewed, with an average of \$171 and a median of \$51. The average fund has \$1.9 billion in assets under management (total net assets (TNA)), whereas the median fund has \$373 million. We take the natural logarithm of TNA to adjust for skewness and use ln(TNA) in our analysis. The median fund charges 1.2% of TNA as its expense ratio, has a turnover ratio of 74%, and is 96 months (8 years) old. The median fund has a net outflow of 1.2% at mid-year and belongs to a family with four affiliated funds. The median fund exhibits an average active share in the first half of the year (i.e., AS(1,6)) of 81%.

TABLE 3
Summary Statistics

Table 3 provides summary statistics of our sample of U.S. actively managed mutual funds over the 4-year period 1999–2002 around the decimalization year. It includes 680 funds and 2,720 observations. It includes only funds with complete information for the whole period, to circumvent potential composition biases. TER is the tracking error of the fund with respect to the prospectus benchmark in the second half of the year, divided by its tracking-error volatility in the first half of the year. RS is an indicator that equals 1 if TER > 1, and 0 otherwise. EXRET(1,6) is the performance of the fund in excess of the benchmark at mid-year. VWPRC is the value-weighted average of the price of the fund's portfolio holdings in the prior year. TE(1,6) is the tracking error in the first half of the year. AS(1,6) is the average active share in the first half of the year. TNA is the total net assets of a mutual fund at the end of the prior year. EXP and TURN are the expense ratio and the turnover ratio, respectively, at the end of the prior year. AGE is the time in months since a fund's inception, measured at the end of the prior year. FLOW(1,6) is the growth rate of assets under management, after adjusting for the appreciation of the fund's assets, measured at mid-year. It is computed as follows: $\text{FLOW}(1,6) = [\text{TNA}(6) - (1 + \text{RET}(1,6)) \times \text{TNA}(-1)]/\text{TNA}(-1)$, where TNA(6) is the value of assets under management at month 6 of a given year, TNA(−1) is the value of assets at the end of the prior year, and RET(1,6) is the return of the fund for the first 6 months of a given year (compounded daily). NFUNDS is the number of funds affiliated with the same family.

Variable	*N*	Mean	Std. Dev.	Skew	P5	P25	Median	P75	P95
TER	2,720	0.951	0.324	2.941	0.544	0.743	0.911	1.109	1.446
RS	2,720	0.374	0.484	0.523	0.000	0.000	0.000	1.000	1.000
EXRET(1,6)	2,720	0.005	0.071	0.149	−0.118	−0.037	0.003	0.047	0.132
VWPRC	2,720	171.4	1,162.6	22.9	21.3	33.1	51.0	81.4	436.9
TE(1,6)	2,720	0.006	0.004	1.040	0.002	0.004	0.006	0.008	0.014
AS(1,6)	2,720	0.775	0.172	−0.687	0.462	0.654	0.805	0.927	0.985
TNA	2,720	1,933.3	6,851.5	10.9	30.1	129.3	373.1	1,183.6	8,287.0
EXP	2,720	0.013	0.004	0.378	0.007	0.010	0.012	0.015	0.020
TURN	2,720	0.902	0.726	1.829	0.129	0.400	0.740	1.170	2.380
AGE	2,720	141.2	125.4	2.5	38.0	70.0	96.0	165.0	407.0
FLOW(1,6)	2,720	0.039	0.293	3.826	−0.240	−0.079	−0.012	0.078	0.503
NFUNDS	2,720	14.4	44.4	5.2	1.0	1.0	4.0	11.0	29.0

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B. Effect of Stock Liquidity on Risk-Shifting Incentives

The risk-shifting hypothesis states that fund managers tend to exhibit TER values greater than 1 when they are underperforming their benchmarks by mid-year. To identify a causal effect from stock liquidity to the risk-shifting incentives of fund managers, we use the decimalization event of 2001 as an exogenous shock to liquidity. The change in tick size from 1/16 to 1/100 dollars led to an increase in liquidity, especially for stocks with low prices. We define a dummy variable DECIMAL, which equals 1 if a given year is 2001 or later, and 0 for years before 2001.[37] Thus, the indicator DECIMAL compares the activities of mutual funds pre- and post-decimalization. We retain only the years 1999–2002 in our analysis.[38] The advantage of retaining only the years surrounding the decimalization event is that it alleviates the effect of confounding events far from the decimalization year.

Our identification strategy focuses on stocks with low prices, which experienced the largest improvement in liquidity from pre- to post-decimalization. To show this, we sort the stocks in our sample into terciles based on their average prices during the year 2000 (the year before the decimalization event), compute the average bid–ask spread (as a percentage of the mid-quote) for the stocks in each of those terciles, and then compare these average values with their corresponding values in year 2002 (the year after the decimalization event). The stocks in the lowest tercile exhibit the largest decrease in bid–ask spreads from 2000 to 2002, with a magnitude of −103 bps, with a t-statistic of −11.59. The remaining stocks (the stocks that fall in the remaining two terciles) experience an average decrease in bid–ask spreads from 2000 to 2002 of approximately −15 bps (with a t-statistic of −3.85). We also examine the effect of decimalization on the average turnover (the ratio of monthly volume to the number of shares outstanding) of low-priced stocks versus other stocks. In the year 2000, the average turnover of low-priced stocks is approximately 50% of that for other stocks, whereas in 2002, it increases to 60%, which represents an economically large increase of approximately 20%. We thus create a dummy variable LOWPRC, which equals 1 when VWPRC falls in the lowest tercile of the distribution of VWPRC values across all funds in a given year, and 0 otherwise. We expect to find a stronger effect of decimalization on risk shifting for funds that hold more low-priced stocks.

We perform a difference-in-differences analysis using the following regression specification:

$$\begin{aligned} (14) \qquad \text{RS} \;=\; & \beta_0 + \beta_1 \text{UNDER} + \beta_2 \text{DECIMAL} + \beta_3 \text{LOWPRC} \\ & + \beta_4 \text{UNDER} \times \text{DECIMAL} + \beta_5 \text{UNDER} \times \text{LOWPRC} \\ & + \beta_6 \text{DECIMAL} \times \text{LOWPRC} \\ & + \beta_7 \text{UNDER} \times \text{DECIMAL} \times \text{LOWPRC} \\ & + \text{Controls} + \text{Effects} + \epsilon, \end{aligned}$$

[37] The decimalization event occurred on Jan. 31, 2001, for firms traded on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) and on Apr. 9, 2001, for firms traded on the National Association of Securities Dealers Automated Quotations (NASDAQ). However, given that we are interested in risk shifting from the first half to the second half of a given year, the exact month of the occurrence of the decimalization event is not relevant for our analysis.

[38] The length of the time series is constrained by the Center for Research in Security Prices (CRSP) daily data on mutual fund returns, which start in 1999.

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where the dependent variable risk shifting (RS) is equal to 1 if TER > 1, and 0 otherwise. This model captures the likelihood that a fund manager increases the tracking error from the first to the second half of the year. The variable UNDER is an indicator that equals 1 if a fund's compounded return is less than or equal to the compounded return of its benchmark in the first half of the year, and 0 otherwise.

Table 4 reports the results of this estimation. In column 1 we include only UNDER in the set of independent variables. This specification tests whether mid-year losers behave differently from mid-year winners. The coefficient estimate on the variable UNDER is not statistically different from 0,

TABLE 4

The Effect of Liquidity on the Risk-Shifting Incentives of Fund Managers

Table 4 presents estimates of 14 different regression specifications, 7 of which are reported in Panel A, and the remaining in Panel B. The main tests are presented in Panel A, and sensitivity analyses and placebo tests are presented in Panel B. The coefficient estimates for the main independent variables of interest are reported in Panels A and B, and the coefficient estimates for the remaining control variables are reported in Panel C. The dependent variable in columns 1–13 is risk shifting (RS), an indicator that equals 1 when a fund increases its tracking-error volatility in the second half of the year compared with the first half of the year (i.e., TER > 1), and 0 otherwise. In column 14 we test the tournament hypothesis, and the dependent variable is the ratio of the fund return volatility in the second half of the year relative to that in the first half of the year. The set of independent variables includes an indicator UNDER that equals 1 when the fund is not outperforming its benchmark by mid-year (EXRET(1,6) ≤ 0), and 0 otherwise. In column 14, UNDER indicates underperformance relative to peer funds in the same investment style. In all specifications, DECIMAL is an indicator variable for the decimalization event, which equals 1 if a given year is 2001 or later, and 0 otherwise. LOWPRC is an indicator that equals 1 when the value-weighted price (VWPRC) of a fund's portfolio holdings is in the bottom third of the distribution of VWPRC values across all the funds in a given year, and 0 otherwise. The remaining covariates, reported in Panel C, are the tracking error at mid-year (i.e., TE(1,6) in most of the specifications, except for columns 8 and 9, in which it is replaced with TE(1,5) and TE(1,7), respectively), the fund return volatility at mid-year (FVOL(1,6)), the natural log of assets under management (ln(TNA)), the expense ratio (EXP), an indicator for whether a fund offers more than one share class (MULTI), an indicator for whether a fund charges a front-end or back-end load (LOAD), the fund's turnover ratio (TURN), the natural log of the number of months since inception (ln(AGE)), the money flows in the first half of the year (FLOW(1,6)), and the natural log of the number of funds affiliated with the same family (ln(FAM)). All the specifications include investment-objective fixed effects to ensure that any variable that varies only by investment style is absorbed and cannot explain any of the regression findings. The sample period covers the years 1999–2002. Standard errors (in parentheses) are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the same fund. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Linear Probability Model

	RS (= 1 if TER > 1; 0 otherwise)						
	1	2	3	4	5	6	7
Intercept	0.198**	0.226**	0.195**	0.236**	0.201**	0.225**	0.236**
	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.100)
UNDER	0.006			−0.022	−0.014		−0.013
	(0.018)			(0.024)	(0.022)		(0.031)
DECIMAL		0.103***		0.074***		0.093***	0.099***
		(0.018)		(0.025)		(0.022)	(0.031)
LOWPRC			−0.069***		−0.093***	−0.078***	−0.066*
			(0.021)		(0.026)	(0.027)	(0.034)
UNDER × DECIMAL				0.059*			−0.009
				(0.035)			(0.043)
UNDER × LOWPRC					0.056		−0.025
					(0.036)		(0.048)
DECIMAL × LOWPRC						0.026	−0.060
						(0.037)	(0.048)
UNDER × DECIMAL × LOWPRC							0.211***
							(0.072)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,720	2,720	2,720	2,720	2,720	2,720	2,720
Adj. R^2	0.150	0.160	0.153	0.160	0.153	0.162	0.165

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TABLE 4 (continued)
The Effect of Liquidity on the Risk-Shifting Incentives of Fund Managers

Panel B. Sensitivity Analysis and Placebo Tests

	May	July	Random	2004	2005	Closet	Tournament
	8	9	10	11	12	13	14
Intercept	0.265***	0.307***	0.234**	0.650***	0.308***	0.308**	0.312***
	(0.101)	(0.103)	(0.096)	(0.095)	(0.091)	(0.120)	(0.090)
UNDER	0.024	−0.032	0.060**	−0.158***	−0.013	−0.037	0.000
	(0.031)	(0.031)	(0.029)	(0.028)	(0.027)	(0.036)	(0.024)
DECIMAL	0.023	0.040	−0.016	−0.227***	0.071**	0.134***	0.388***
	(0.030)	(0.031)	(0.031)	(0.031)	(0.029)	(0.035)	(0.029)
LOWPRC	−0.034	−0.063*	−0.026	−0.038	−0.038	−0.051	0.002
	(0.035)	(0.033)	(0.034)	(0.037)	(0.034)	(0.036)	(0.034)
UNDER × DECIMAL	−0.019	0.003	0.029	0.143***	−0.015	0.000	−0.044
	(0.043)	(0.044)	(0.042)	(0.040)	(0.037)	(0.050)	(0.039)
UNDER × LOWPRC	−0.067	−0.019	−0.076	0.213***	0.128***	0.002	0.050
	(0.049)	(0.050)	(0.049)	(0.048)	(0.044)	(0.051)	(0.047)
DECIMAL × LOWPRC	−0.057	−0.048	0.051	−0.077	0.002	−0.091*	−0.063
	(0.048)	(0.047)	(0.047)	(0.049)	(0.048)	(0.051)	(0.046)
UNDER × DECIMAL × LOWPRC	0.201***	0.240***	0.106	−0.148**	−0.152**	0.203***	0.117*
	(0.073)	(0.076)	(0.073)	(0.068)	(0.064)	(0.077)	(0.070)
CLOSET						0.003	
						(0.059)	
UNDER × CLOSET						0.074	
						(0.073)	
DECIMAL × CLOSET						−0.140*	
						(0.072)	
LOWPRC × CLOSET						−0.075	
						(0.167)	
UNDER × DECIMAL × CLOSET						−0.012	
						(0.100)	
UNDER × LOWPRC × CLOSET						−0.330*	
						(0.178)	
DECIMAL × LOWPRC × CLOSET						−0.038	
						(0.253)	
UNDER × DECIMAL × LOWPRC × CLOSET						0.156	
						(0.332)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,720	2,720	2,720	3,696	4,008	2,720	2,720
Adj. R^2	0.135	0.099	0.167	0.054	0.038	0.168	0.320

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TABLE 4 (continued)
The Effect of Liquidity on the Risk-Shifting Incentives of Fund Managers

Panel C. Regression Estimates of Control Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
TE(1,6)	−60.780***	−55.558***	−61.461***	−55.831***	−61.159***	−56.053***	−55.462***	−52.232***	−46.875***	−39.226***	−24.058***	−57.808***	−54.878***	
	(2.543)	(2.592)	(2.529)	(2.612)	(2.547)	(2.627)	(2.670)	(2.490)	(2.926)	(1.544)	(5.759)	(6.135)	(2.685)	
FVOL(1,6)														−32.859***
														(1.885)
AS(1,6)	0.402***	0.369***	0.466***	0.379***	0.462***	0.429***	0.424***	0.361***	0.281***	0.236***	0.024	0.063	0.329***	0.112*
	(0.072)	(0.071)	(0.075)	(0.072)	(0.075)	(0.074)	(0.075)	(0.075)	(0.078)	(0.065)	(0.079)	(0.078)	(0.104)	(0.059)
ln(TNA)	−0.003	−0.001	−0.004	−0.002	−0.004	−0.003	−0.003	−0.003	−0.005	−0.001	0.014**	−0.004	−0.004	0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
EXP	6.800**	6.070**	6.893***	5.821**	6.812**	6.132**	5.747**	4.495*	4.142	5.440**	6.471***	8.573***	5.747**	6.035**
	(2.670)	(2.643)	(2.663)	(2.650)	(2.668)	(2.639)	(2.650)	(2.658)	(2.716)	(2.585)	(2.349)	(2.135)	(2.652)	(2.454)
MULTI	−0.049*	−0.043*	−0.048*	−0.042*	−0.047*	−0.043*	−0.040	−0.039	−0.029	−0.023	−0.011	−0.017	−0.040	−0.049**
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)	(0.023)	(0.021)	(0.025)	(0.023)
LOAD	0.011	0.009	0.010	0.009	0.010	0.008	0.010	0.008	0.008	−0.011	−0.013	−0.010	0.010	0.000
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.019)	(0.021)	(0.019)
TURN	0.027**	0.020	0.022*	0.018	0.023*	0.016	0.013	0.020	0.017	0.013	0.006	0.020*	0.011	0.041***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.011)	(0.011)	(0.013)	(0.012)
ln(AGE)	0.045***	0.027*	0.046***	0.027*	0.046***	0.029*	0.028*	0.022	0.024	0.049***	0.001	0.026**	0.029*	0.046***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)
FLOW	0.039	0.025	0.037	0.026	0.040	0.022	0.024	0.025	0.013	0.004	0.047*	−0.008	0.013	0.089***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)	(0.026)	(0.027)	(0.030)	(0.026)
ln(FAM)	−0.015**	−0.013*	−0.015**	−0.013*	−0.015**	−0.013*	−0.013*	−0.006	−0.007	−0.011*	−0.014**	0.001	−0.013*	−0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)

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which suggests that there is no difference between losers and winners in their choices of tracking-error volatility from the first to the second half of the year. In column 2 we test whether funds are more likely to increase their tracking errors in the post-decimalization years compared with the pre-decimalization years. The coefficient estimate on DECIMAL is positive and statistically significant at the 1% level, suggesting that funds are 10% more likely to increase risk in the post-decimalization years compared with the pre-decimalization years. This result is also economically significant because it compares with a 37% (the average value of RS in Table 3) unconditional probability of observing an increase in tracking error from the first to the second half of the year. In column 3 we test whether funds that hold more low-priced stocks differ from the other funds in terms of their change in tracking errors over the calendar year. The coefficient on LOWPRC is negative and significant at the 1% level. This suggests that funds that hold low-priced stocks are 6.9% less likely than other funds to increase their tracking errors from the first to the second half of the year.

In columns 4–7 of Table 4, we consider several possible interactions between the indicators UNDER, DECIMAL, and LOWPRC. The specification in column 4 includes the indicators UNDER and DECIMAL, as well as their interaction UNDER $\times$ DECIMAL. The coefficient on UNDER is not significant, which means that loser funds are just as likely to increase their tracking errors as winner funds in the pre-decimalization years. The coefficient on DECIMAL is positive and significant at 1% level, which suggests that mid-year winner funds are 7.4% more likely to increase their tracking errors in the post- versus the pre-decimalization years. The coefficient on the interaction UNDER $\times$ DECIMAL is positive and significant at the 10% level. This difference-in-differences test reflects the extent to which the likelihood of an increase in tracking errors differs between losers and winners in the post- compared with the pre-decimalization years. A positive and significant coefficient of 5.9% is evidence of stronger risk-shifting incentives for loser funds in the post- versus the pre-decimalization years.

To be consistent with our argument that the decimalization event had a stronger effect on the liquidity of stocks with low prices, in column 7 of Table 4 we include the indicator LOWPRC together with UNDER and DECIMAL, as well as their multiple interactions. The main coefficient of interest in this specification is on the triple interaction UNDER $\times$ DECIMAL $\times$ LOWPRC. The coefficient estimate is positive and statistically significant at the 1% level. This is a difference-in-difference-in-differences estimate. It suggests that there is a 21% higher probability of observing an increase in tracking errors for loser versus winner funds in the post- versus the pre-decimalization years. This comparison is for funds holding low-priced stocks relative to other funds. This is causal evidence that an improvement in liquidity induces mid-year losers to take extra risks, which is consistent with the novel prediction of our model.

We corroborate our findings by conducting a number of placebo tests and sensitivity analyses, which we report in Panel B of Table 4. The specification that we use in columns 8–12 of Panel B is the same as that in column 7 of Panel A,

and the main coefficient estimate of interest is again on the triple interaction term UNDER × DECIMAL × LOWPRC.[39]

In columns 8 and 9 of Table 4, we show that our results are robust to changes in the definition of mid-year in the computation of tracking-error ratios and relative-performance measures. In our baseline specification, the threshold month that defines mid-year is June. However, columns 8 and 9 show that our results remain qualitatively unchanged if we choose either May or July as the threshold months to define mid-year, respectively.

In column 10 of Table 4, we show that if we assign random benchmarks to the mutual funds, the effect disappears. This suggests that fund managers respond to relative performance but only with respect to their declared benchmarks, not to random benchmarks.

In columns 11 and 12 of Table 4, we conduct time-series placebo tests using the years 2004 and 2005 as the pseudo-decimalization years, instead of the actual year of the event. We choose 2004 and 2005 as placebo years because they are sufficiently far from the actual event in 2001 (the windows of analysis of the placebo tests do not overlap with the window used in the main test) and do not include the period of the financial crisis. We do not find similar effects of mutual fund ownership of low-priced stocks on the risk shifting of fund managers during these placebo periods. The coefficient estimate for the interaction term UNDER × DECIMAL × LOWPRC is in fact negative and significant at the 5% level in each of the placebo periods, whereas it is positive and significant at the 1% level in the actual event year.

In column 13 of Table 4, we perform a falsification test using closet-index funds, which are considered to be passive funds that track their benchmarks very closely.[40] As a result, closet indexers are naturally less likely to shift risk in response to an exogenous shock to the liquidity of the stocks they hold. We then include a variable CLOSET to indicate whether a fund is a closet indexer according to the active-share measure developed by Cremers and Petajisto (2009).[41] We find that the decimalization event does not affect the tracking-error ratios of closet indexers.

Lastly, in column 14 of Table 4, we test the tournament hypothesis of Brown et al. (1996) by measuring a fund's performance relative to the median fund in the same style category instead of its declared benchmark.[42] In the specification in column 14, we control for the effect of mean reversion in fund return volatility, as suggested by Schwarz (2012). We compute the variable FVOL(1,6), which denotes the standard deviation of the daily fund returns in the first half of the year. The dependent variable in column 14 is the ratio of fund return volatility in the

[39] The sequential numbers that we use for the specifications in Panel B are a continuation of the sequence in Panel A. This is because in Panel C we report the coefficient estimates for all 14 different specifications of Table 4.

[40] If we use only index funds for this analysis, the sample is much smaller than the sample of closet indexers, which significantly decreases the power of the tests.

[41] Following Cremers and Petajisto (2009), we consider a fund to be a closet indexer when its active share is at most 60% across all the quarters in a given year.

[42] Del Guercio and Tkac (2002) show that investors chase funds that perform well relative to other funds following the same style.

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second half of the year to the fund return volatility in the first half of the year. We find that the results are weaker under the tournament setting (only significant at the 10% level). This suggests that self-designated benchmarks appear to encourage risk shifting to a larger extent than tournaments. This result is consistent with the findings of Reed and Wu (2005) and Lee et al. (2019).

In Panel C of Table 4, we report the coefficient estimates for all the control variables in the 14 specifications of Panels A and B. In all the specifications, we control for characteristics related to the risk-shifting incentives of fund managers that have been proposed in prior research. In particular, we control for the natural logarithm of the time since the inception of the fund (ln(AGE)), the expense ratio (EXP), the natural logarithm of the number of funds affiliated with the same family (ln(FAM)), the turnover ratio (TURN), and the fund flows in the first half of the year (FLOW(1,6)). We also control for the level of tracking error in the first half of the year (TE(1,6)),[43] as well as the mid-year deviation of the funds' portfolios from the compositions of their declared benchmarks (i.e., the average active share from Cremers and Petajisto (2009) for the first half of the year, denoted as AS(1,6)).

C. Decomposition of Risk Shifting and the Effect of Portfolio Constraints

In this section, we propose a decomposition of the TER variable into its idiosyncratic and systematic components, to provide a better mapping onto our theoretical model. We argue that the idiosyncratic component is more likely to be associated with risk shifting using nonbenchmark stocks, and the systematic component is more likely to be associated with portfolio distortions using benchmark stocks.

The tracking-error variance (which we denote as TEV) between fund returns and benchmark returns can be represented as $\text{TEV} = E[(r_F - r_B)^2]$, which is the expected value of the squared deviations of fund returns from benchmark returns. We decompose TEV by running the following regression:

$$R_F = \alpha + \eta R_B + \epsilon, \tag{15}$$

where R_F and R_B are the returns of the fund and its benchmark, in excess of the risk-free rate, respectively. This is a single-factor model where the factor is the fund's benchmark. TEV can then be represented as $\text{TEV} = (\eta - 1)^2\sigma_B^2 + \sigma_\epsilon^2$, where η is the estimate of the slope, σ_B is the standard deviation of the benchmark returns, and σ_ϵ is the standard deviation of the regression residuals. To match the methodology that we use to compute the TER variable, we denote the systematic component of the tracking-error volatility as $\text{TES} = |\eta - 1|\sigma_B$ (i.e., the square root of $(\eta - 1)^2\sigma_B^2$), and the idiosyncratic component is $\text{TEI} = \sigma_\epsilon$ (i.e., the square root of σ_ϵ^2). We perform these regressions separately for the first half and the second half of the year, for each fund–benchmark pair, using daily returns. We denote the systematic component of the tracking-error volatility in the first (second) half of the year as TES(1,6) (TES(7,12)), and we denote the idiosyncratic component as TEI(1,6) (TEI(7,12)). Next, we define an indicator variable RSS, which equals 1 if

[43] In columns 8 and 9 of Table 4, the tracking errors in the first half of the year are computed over 5 and 7 months (i.e., TE(1,5) and TE(1,7)), respectively.

TESR > 1, where TESR = TES(7,12)/TES(1,6), and 0 otherwise. RSS indicates whether there is an increase in the systematic component of the tracking-error volatility from the first to the second half of the year. We also define the indicator variable RSI, which equals 1 if TEIR > 1, where TEIR = TEI(7,12)/TEI(1,6), and 0 otherwise. RSI indicates whether there is an increase in the idiosyncratic component of the tracking-error volatility from the first to the second half of the year.

We implement linear probability models similar to those in Table 4 but separately for the idiosyncratic and the systematic components of the tracking-error volatility. We report the results of these estimations in columns 1 and 3 of Table 5. The results in column 1 show that fund managers are more likely to take idiosyncratic risks using nonbenchmark stocks around the decimalization event. There is no significant effect of the decimalization event on systematic risk taking by fund managers, as shown in column 3. This differs somewhat from our theoretical results in Figure 2 but is consistent with the existence of tighter constraints in practice, such as the style-drift restriction we illustrate in Figure 3. In addition to the style-drift restriction imposed by the SEC, it is also typical for equity funds to follow all-equity benchmarks and for investors to impose limits on tracking errors and limits on the cash reserves that funds can hold (Simutin (2014)). In our theoretical model, imposing a tight position limit on the risk-free bond also tightens the position limit on the benchmark stock and forces the fund manager to shift risk using the nonbenchmark stock (i.e., take on idiosyncratic risk). Overall, we expect our empirical estimates to be smaller in magnitude compared with what is predicted by our theory, due to the many constraints that are imposed on mutual funds in practice (see Almazan et al. (2004)), which are not accounted for in our model.

A crucial difference between our model and the model of Basak et al. (2007) is that we allow for portfolio constraints to be imposed on mutual funds. In the presence of these portfolio constraints, the fund manager is likely to take idiosyncratic risk for risk-shifting purposes. This is an additional implication of our model that has not yet been tested in the existing literature.

We test this prediction in columns 2 and 4 of Table 5. Specifically, we interact the indicator variables from the specifications in columns 1 and 3 with an additional indicator for leverage constraint tightness (LCT). This is a measure of demand for leverage by mutual funds similar to the measure proposed by Boguth and Simutin (2018), who suggest that one can capture the borrowing demand of mutual funds, and thus the tightness of their leverage constraints, by computing the extent to which they increase their holdings of high-market-beta stocks. We start by computing the market beta of each stock held by the funds in our sample, using the market model and rolling windows of 36 months of monthly returns. Next, we compute the value-weighted average of the market beta of the portfolio holdings of each fund for the second half of the prior year and the first half of the current year. The indicator LCT equals 1 if the average market beta of the holdings of the fund increased from the second half of the prior year to the first half of the current year, and 0 otherwise. Thus, LCT captures the funds that implicitly increase their borrowing demand by loading more on higher-beta stocks. In columns 2 and 4, we interact LCT with the other indicator variables.

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These interactions show that funds with an increase in borrowing demand are more likely to increase the idiosyncratic component of the tracking-error volatility of their portfolios as a result of the exogenous positive shock to liquidity due to the decimalization event.

TABLE 5

Decomposition of Risk Shifting and Leverage Constraint Tightness

Table 5 reports estimates of the effect of leverage constraint tightness (LCT) on risk shifting after decomposing the risk shifting into a systemic component and an idiosyncratic component. The dependent variable in columns 1 and 2 is RSI, an indicator that equals 1 when a fund increases the idiosyncratic component of the tracking-error volatility in the second half of the year compared with the first half of the year (i.e., TEIR > 1), and 0 otherwise. In columns 3 and 4 the dependent variable is RSS, an indicator that equals 1 when a fund increases the systematic component of the tracking-error volatility in the second half of the year compared with the first half of the year (i.e., TESR > 1), and 0 otherwise. The coefficient estimates for the main independent variables of interest are reported in Panel A, and the coefficient estimates for the remaining control variables are reported in Panel B. The indicator variables in Panel A are defined as in Table 4, except for the indicator LCT, which captures the borrowing demand by a mutual fund (i.e., equals 1 if a fund increases the average market beta of its portfolio holdings from the second half of the prior year to the first half of the current year, and 0 otherwise). The set of control variables is the same as in Table 4, except that when the dependent variable is RSI (RSS), we replace TE(1,6) that we used in Table 4 with the idiosyncratic (systematic) component of the tracking error at mid-year TEI(1,6) (TES(1,6)). All specifications include investment-objective dummies to ensure that any variable that varies only by investment style is absorbed and cannot explain any of the regression findings. The sample period covers the years 1999–2002. Standard errors (in parentheses) are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the same fund. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Decomposition of Risk Shifting and the Effect of Leverage Constraint Tightness

	RSI		RSS	
Dependent Variable	1	2	3	4
Intercept	0.148	0.147	0.458***	0.459***
	(0.100)	(0.100)	(0.103)	(0.103)
UNDER	0.012	−0.051	0.015	0.006
	(0.031)	(0.036)	(0.033)	(0.040)
DECIMAL	0.154***	0.165***	−0.020	−0.010
	(0.032)	(0.036)	(0.032)	(0.036)
LOWPRC	−0.046	−0.125***	−0.014	−0.035
	(0.036)	(0.043)	(0.039)	(0.048)
UNDER × DECIMAL	−0.091**	−0.056	0.006	0.002
	(0.044)	(0.052)	(0.045)	(0.056)
UNDER × LOWPRC	−0.073	0.063	−0.064	0.041
	(0.050)	(0.066)	(0.053)	(0.074)
DECIMAL × LOWPRC	−0.049	−0.030	−0.041	−0.078
	(0.050)	(0.061)	(0.050)	(0.062)
UNDER × DECIMAL × LOWPRC	0.276***	0.114	0.079	0.093
	(0.075)	(0.098)	(0.077)	(0.102)
LCT × UNDER		0.126***		0.019
		(0.044)		(0.048)
LCT × DECIMAL		−0.038		−0.029
		(0.045)		(0.046)
LCT × LOWPRC		0.162***		0.042
		(0.053)		(0.055)
LCT × UNDER × DECIMAL		−0.036		0.020
		(0.077)		(0.080)
LCT × UNDER × LOWPRC		−0.277***		−0.187*
		(0.090)		(0.097)
LCT × DECIMAL × LOWPRC		−0.004		0.107
		(0.090)		(0.091)
LCT × UNDER × DECIMAL × LOWPRC		0.298**		−0.100
		(0.143)		(0.149)
Controls	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes
No. of obs.	2,677	2,677	2,677	2,677
Adj. R^2	0.170	0.178	0.103	0.104

(continued on next page)

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TABLE 5 (continued)
Decomposition of Risk Shifting and Leverage Constraint Tightness

Panel B. Regression Estimates of Control Variables

	RSI		RSS	
	1	2	3	4
TEI(1,6)	−59.972***	−60.275***		
	(4.057)	(4.090)		
TES(1,6)		−50.612***	−50.756***	
		(2.968)	(3.010)	
AS(1,6)	0.441***	0.454***	−0.016	−0.015
	(0.076)	(0.076)	(0.072)	(0.072)
ln(TNA)	0.003	0.003	−0.006	−0.006
	(0.006)	(0.006)	(0.006)	(0.006)
EXP	6.761**	6.282**	4.950*	5.007*
	(2.723)	(2.720)	(2.740)	(2.737)
MULTI	−0.054**	−0.050**	−0.070***	−0.072***
	(0.025)	(0.025)	(0.026)	(0.026)
LOAD	0.007	0.009	0.006	0.004
	(0.021)	(0.021)	(0.022)	(0.022)
TURN	0.035***	0.033***	0.033**	0.032**
	(0.013)	(0.013)	(0.013)	(0.013)
ln(AGE)	0.023	0.021	0.031**	0.031**
	(0.015)	(0.015)	(0.015)	(0.015)
FLOW	0.055*	0.051	−0.018	−0.019
	(0.033)	(0.033)	(0.032)	(0.033)
ln(FAM)	−0.015**	−0.015**	−0.009	−0.009
	(0.007)	(0.007)	(0.007)	(0.007)

D. Risk Shifting and the Likelihood of Beating the Benchmark

In this section, we examine whether risk shifting is costly to fund investors. Following the argument of Huang et al. (2011), changes in TER can be driven by the gambling activities of unskilled managers, or by skilled fund managers taking advantage of time-varying investment opportunities. To distinguish skilled from unskilled managers, one can examine the performance consequences of the changes in TER. In this section, we study how changes in TER affect the likelihood that funds beat their benchmarks.

We implement linear probability models and report the results in Table 6. The dependent variable is the indicator OVER, which equals 1 if the daily compounded return of a fund during the 12 months of a given year, in excess of the compounded return of its declared benchmark, which we denote by EXRET(1,12), is positive, and 0 otherwise.

As independent variables, we use the same indicators as in our baseline specification in column 7 of Panel A in Table 4. Those indicators are UNDER, DECIMAL, and LOWPRC, as well as their multiple interactions. We also include in our set of independent variables the indicator RS, as defined in Section V.B. We then interact RS with all the other indicators to test whether a change in tracking errors around the decimalization event indeed helps fund managers beat their benchmarks by year-end.

In column 1 of Table 6, the coefficient estimate on RS is negative but not statistically significant. This suggests that increasing tracking errors from the first to the second half of the year does not improve the chances of beating the bench-

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TABLE 6

Risk Shifting and the Likelihood of Beating the Benchmark

Table 6 reports estimates from eight different regression specifications, in which the dependent variable is an indicator that equals 1 if a given fund beats the benchmark by year-end (EXRET(1,12) > 0), and 0 otherwise. We denote this indicator variable as OVER. In addition to the main variables of interest from Table 4, this table also includes risk shifting (RS) as a regressor as well as the interaction of RS with all other variables, UNDER, DECIMAL, and LOWPRC. The remaining covariates are the same as described in Table 4. We include investment-objective dummies to ensure that any variable that varies only by investment style is absorbed and cannot explain any of the regression findings. Standard errors (in parentheses) are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the same fund. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	OVER (= 1 if EXRET(1,12) > 0; 0 otherwise)							
	1	2	3	4	5	6	7	8
Intercept	0.708***	0.947***	0.639***	0.572***	0.776***	0.843***	0.536***	0.680***
	(0.088)	(0.075)	(0.087)	(0.089)	(0.073)	(0.076)	(0.088)	(0.075)
RS	−0.010	−0.031	0.137***	0.040*	0.039	−0.010	0.147***	0.055
	(0.020)	(0.023)	(0.029)	(0.024)	(0.035)	(0.030)	(0.035)	(0.045)
UNDER		−0.556***			−0.412***	−0.539***		−0.365***
		(0.020)			(0.029)	(0.025)		(0.037)
DECIMAL			−0.065***		0.092***		−0.124***	0.106***
			(0.025)		(0.026)		(0.030)	(0.037)
LOWPRC				0.220***		0.156***	0.133***	0.169***
				(0.027)		(0.026)	(0.034)	(0.036)
UNDER × DECIMAL					−0.350***			−0.391***
					(0.039)			(0.049)
UNDER × LOWPRC						−0.008		−0.124**
						(0.043)		(0.058)
DECIMAL × LOWPRC							0.192***	−0.057
							(0.049)	(0.048)
UNDER × DECIMAL × LOWPRC								0.208**
								(0.087)
RS × UNDER		0.074**			0.210***	0.090**		0.197***
		(0.034)			(0.056)	(0.042)		(0.068)
RS × DECIMAL			−0.208***		−0.145***		−0.135***	−0.145**
			(0.040)		(0.046)		(0.048)	(0.060)
RS × LOWPRC				−0.139***		−0.026	−0.024	−0.010
				(0.042)		(0.044)	(0.062)	(0.066)
RS × UNDER × DECIMAL					−0.079			−0.047
					(0.067)			(0.083)
RS × UNDER × LOWPRC						−0.105		−0.011
						(0.072)		(0.115)
RS × DECIMAL × LOWPRC							−0.225***	0.004
							(0.083)	(0.087)
RS × UNDER × DECIMAL × LOWPRC								−0.157
								(0.146)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2,720	2,720	2,720	2,720	2,720	2,720	2,720	2,720
Adj. R^2	0.021	0.296	0.047	0.044	0.355	0.308	0.073	0.364

mark by year-end for the average fund. In column 2 we compare mid-year losers and winners, using the indicator UNDER and its interaction with RS. The positive and significant coefficient on RS × UNDER suggests that mid-year losers can improve the chances of beating their benchmarks (but only slightly) by year-end if they increase their tracking errors in the second half of the year. This confirms that risk shifting can at times have a favorable outcome, which is why unskilled fund managers might engage in such a practice. In column 3, the negative loading on the interaction RS × DECIMAL suggests that it is 20.8% less likely for a fund

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to beat its benchmark if it increases its tracking error in the post-decimalization years.

In column 8 of Table 6, we include all the indicators and their multiple interactions. The coefficient estimate of interest is on the interaction term RS × UNDER × DECIMAL × LOWPRC, which is negative but not significantly different from 0. This suggests that risk shifting can be costly to fund investors because the risk-shifting activity does not seem to result in higher returns. It is also consistent with the notion expressed by Huang et al. (2011) that agency problems, rather than the ability to take advantage of changing investment opportunities, are the likely motivation behind the observed time variation in the risk levels of funds.

In conclusion, these findings suggest that the lack of stock liquidity can work as a deterrent of misbehavior by fund managers, which in turn can benefit fund investors. However, it is beyond the scope of this article to quantify the magnitude of the trade-off between the benefits of improved stock market liquidity and the costs of portfolio delegation.

E. Time Variation in the Convexity of the Flow–Performance Relation: Alternative Explanation?

According to the standard risk-shifting theory, the fund manager's incentive to take extra risks is particularly strong when investors' flows are a convex function of relative performance, meaning that flows are more sensitive to outperformance than to underperformance. The convexity of the response of flows to past performance is a well-established fact in existing literature (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)). We reestimate this relationship in Table 7, using the excess return of mutual funds with respect to their declared benchmarks as our measure of relative performance.

In columns 1 and 2 of Table 7, we present the results of panel regressions that fit a linear and a nonlinear flow–performance specification, respectively. In both specifications there is a strong relation between flows and performance. In column 1, a 1% increase in EXRET(1,12) in a given year is associated with a 0.73% increase in fund flows in the following year. In column 2, we allow for nonlinearity in the flow–performance relation. The regression coefficient associated with QUINTILE_5 suggests that top-performing funds in a given year receive flows in the following year that are 17.1% larger compared with the funds with a performance that falls in the middle (omitted) quintile. The nonlinearity in the flow–performance relation is pronounced among funds belonging to the top two quintiles. In post-estimation tests, we find that the difference between the top-two quintile performers (expressed as the difference QUINTILE_5 − 2 × QUINTILE_4) is 12.6% per year and significant at the 1% level.[44]

[44]The list of covariates that we use in Table 7 is similar to the list used in previous tables (i.e., ln(TNA), EXP, MULTI, LOAD, TURN, ln(AGE), ln(FAM)), except that we use a measure of fund flows for the entire year (FLOW(1,12)) instead of FLOW(1,6). We also add to the list of controls the liquidity of each fund's portfolio holdings, computed as the value-weighted liquidity cost of the stocks held by the fund. We use the liquidity cost estimates of Hasbrouck (2009), a data set that is available on Joel Hasbrouck's Web site (http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html). We use portfolio liquidity as an additional control because it has been shown in prior literature that the flow–performance relation is sensitive to the liquidity of the assets held by mutual funds (e.g., Chen, Goldstein, and Jiang (2010)).

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TABLE 7

Nonlinearity of the Flow–Performance Relation

Table 7 reports regression coefficient estimates of the flow–performance relation. The dependent variable is the flow in the following year (FLOW(13,24)), measured as the change in total net assets (TNA) from a given year to the following year, divided by the TNA at the end of a given year, as follows: FLOW(13,24) = [TNA(24) − (1 + RET(13,24)) × TNA(12)]/TNA(12). In column 1, we present a linear specification in which the main independent variable is the benchmark-adjusted return (compounded daily) for each fund in a given year. In column 2, we present a nonlinear specification in which the benchmark-adjusted performance of each fund at the end of a given year is captured through four indicator variables, where QUINTILE_k is set to 1 if the 1-year benchmark-adjusted return of a fund is in quintile *k* (5th quintile denotes the top 20% performers) of all fund returns during the year, and 0 otherwise. The middle quintile is omitted. In column 3 we add the indicator DECIMAL and its interactions with QUINTILE_k. The remaining covariates are the same as in Table 4, except that we use a measure of fund flows for the entire year (FLOW(1,12)) instead of FLOW(1,6). The list of controls also includes the liquidity of the portfolio holdings of each fund, computed as the value-weighted liquidity cost of each stock held. We use the stock-level liquidity cost estimates of Hasbrouck (2009). We include investment-objective fixed effects to ensure that any variable that varies only by investment style is absorbed and cannot explain any of the regression findings. Standard errors (in parentheses) are adjusted by clustering that accounts for heteroscedasticity and dependence of observations across the same fund. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	FLOW(13,24)		
	1	2	3
Intercept	0.241***	0.252***	0.195***
	(0.067)	(0.069)	(0.071)
EXRET(1,12)	0.730***		
	(0.062)		
QUINTILE_1 (bottom)		−0.093***	−0.096***
		(0.019)	(0.027)
QUINTILE_2		−0.061***	−0.054**
		(0.016)	(0.024)
QUINTILE_4		0.022	0.057**
		(0.019)	(0.028)
QUINTILE_ 5 (top)		0.171***	0.248***
		(0.024)	(0.038)
DECIMAL			−0.018
			(0.025)
QUINTILE_1 × DECIMAL			0.002
			(0.036)
QUINTILE_2 × DECIMAL			−0.013
			(0.033)
QUINTILE_4 × DECIMAL			−0.070*
			(0.037)
QUINTILE_5 × DECIMAL			−0.158***
			(0.048)
Controls	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes
No. of obs.	2,681	2,681	2,681
Adj. R^2	0.203	0.193	0.205

In Section V.B we have documented that an exogenous increase in liquidity, as a result of the decimalization event, can strengthen the incentive of mutual fund managers to take extra risks in response to beating their benchmarks. An alternative explanation for such a finding could be that the relation between fund flows and past performance became more convex around the time of the decimalization event. Under that alternative explanation, the reason for fund managers to take more risks around the decimalization could be the stronger convexity of the flow–performance relation instead of the improvement in stock liquidity. To rule out such alternative explanation, we run a specification in column 3 of Table 7 in which we include the indicator DECIMAL and its interactions with the QUINTILE dummies. This specification captures the potential change in the convexity of the flow–performance relation around the decimalization event.

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The negative and significant coefficients on the interactions QUINTILE_4 × DECIMAL and QUINTILE_5 × DECIMAL suggest that the flow–performance relation is actually less convex around the decimalization event.[45] This helps us rule out this potential alternative explanation.

VI. Conclusion

We argue that an improvement in stock liquidity can strengthen the risk-shifting incentives of mutual fund managers, which in turn can increase the costs that accrue to fund investors from portfolio delegation.

We first present a theoretical model that shows that i) in the presence of portfolio constraints, fund managers are likely to take on idiosyncratic risk in response to beating their performance benchmarks, and ii) an increase in the liquidity of the stocks they use to shift portfolio risk can increase the size of their risky bets.

We then provide empirical evidence consistent with these implications. We use the decimalization event of 2001 as a positive shock to liquidity to show that fund managers are more likely to increase the tracking errors of their portfolios with respect to their benchmarks when their holdings experience an exogenous improvement in liquidity. In particular, mutual funds are 10% more likely to increase their tracking-error volatilities from the first to the second half of the year around the decimalization event. Moreover, mutual funds holding a larger fraction of their portfolios in low-priced stocks are 21% more likely to shift portfolio risk around decimalization compared with other funds. The economic magnitude of these results is large; they compare with a 37% unconditional probability of observing an increase in tracking error from the first to the second half of the year in our sample.

After decomposing the risk shifting of mutual funds into its idiosyncratic and systematic components, we find that the risk shifting observed around the decimalization event is mostly idiosyncratic in nature. We show that the tightness of the leverage constraints of mutual funds is an important driver of their idiosyncratic risk taking. Lastly, we find that risk shifters are not necessarily more likely to beat their benchmarks around decimalization, suggesting that the observed changes in tracking errors are not the result of the trading skills of fund managers, which can therefore be costly to fund investors.

Overall, our results suggest that an improvement in stock market liquidity does not necessarily benefit all market participants. It can encourage additional risk taking by fund managers, which in turn can lead to extra costs for delegating investors.

[45] This effect is different from the one documented by Chen et al. (2010). They show that due to strategic complementarities and "fund run" effects, the generally convex shape of the flow–performance relation (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)) is less pronounced for funds holding illiquid stocks. In their case, the reduction in the convexity of the flow–performance relation is due to an increase in the sensitivity of flows to underperformance for illiquid funds. However, in our case, the reduction in convexity occurs in the outperformance region.

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Appendix. Technical Issues and Additional Results

The content of this Appendix is as follows. We define the value function of the fund manager, derive the HJB equation, and provide a verification theorem that characterizes the fund manager's optimal investment strategy. Next, we describe how the dimensionality of the value function can be reduced, as well as the numerical procedure we adopt to solve the fund manager's problem. We also provide some additional results derived from our model and describe how we decompose the total cost of portfolio delegation into a part that is due to differences in risk aversion between the manager and the investor (explicit incentives) and a part that is due to the risk-shifting incentives of the fund manager (implicit incentives). We also compare our results with the results we would have obtained if we were to assume that the occurrence of liquidity events was deterministic instead of stochastic in our model. Lastly, we describe the data sources, filters, and variables used to test the empirical implications of our theoretical model.

1. Indirect Utility Function of the Mutual Fund Manager

We assume that the fund manager derives CRRA utility from the terminal value of assets under management (i.e., $U(W_T)=1/(1-\gamma)W_T^{1-\gamma}$). The fund manager's value function from Section III is as follows:

$$V(t,x,y,z) = \sup_{\Theta_s:t\le s\le T} E\left[U(W_T)|(X_t,Y_t,Z_t)=(x,y,z)\right], \tag{A-1}$$

which is governed by the following HJB equation:

$$\frac{\partial V}{\partial t}+\sup_{\pi\in[0,1]}\mathcal{L}^{\pi}V+\lambda\left(\sup_{I\in[-y,x]}V(t,x-I,y+I,z)-V(t,x,y,z)\right) = 0 \tag{A-2}$$

in the solution region $\Omega=\{(t,x,y,z):0\le t\le T,x\ge 0,y\ge 0,x+y>0,z>0\}$, with terminal condition

$$V(T,x,y,z) = U\left[\left(1+f\left(\ln\frac{x+y}{z}\right)\right)(x+y)\right], \tag{A-3}$$

where

$$\begin{aligned}\mathcal{L}^{\pi}V = {} & rx\frac{\partial V}{\partial x}+\alpha_I y\frac{\partial V}{\partial y}+(r+\beta(\alpha_L-r))z\frac{\partial V}{\partial z}\\ & +\frac{1}{2}\sigma_I^2y^2\frac{\partial^2V}{\partial y^2}+\frac{1}{2}\sigma_L^2\beta^2z^2\frac{\partial^2V}{\partial z^2}+\beta\rho\sigma_L\sigma_I yz\frac{\partial^2V}{\partial y\partial z}\\ & +\left[(\alpha_L-r)x\frac{\partial V}{\partial x}+\beta\sigma_L^2xz\frac{\partial^2V}{\partial x\partial z}+\rho\sigma_L\sigma_I xy\frac{\partial^2V}{\partial x\partial y}\right]\pi\\ & +\frac{1}{2}\sigma_L^2x^2\pi^2\frac{\partial^2V}{\partial x^2}.\end{aligned} \tag{A-4}$$

To derive the HJB equation (A-2), we begin by considering an arbitrary set of admissible investment policies $\Theta_t=(\pi_t,I_t),0\le t\le T$. For notational convenience, we still denote by (X_t,Y_t,Z_t) the stochastic processes generated by policy Θ_t. Bellman's principle of optimality indicates that $V(t,X_t,Y_t,Z_t)$ is a super-martingale. Therefore, its infinitesimal increment has a nonpositive expected value:

$$E[dV(t,X_t,Y_t,Z_t)] \le 0. \tag{A-5}$$

The probability that the Poisson process N_t will not hit within an infinitesimal time step dt is $1-\lambda dt$. In this case, the value function evolves according to the following

diffusion:

$$dV(t,X_t,Y_t,Z_t) = \left(\frac{\partial V}{\partial t}+\mathcal{L}^{\pi_t}V\right)dt+\frac{\partial V}{\partial x}\pi_t\sigma_L X_t dB_{Lt} + \frac{\partial V}{\partial y}\sigma_I Y_t dB_{It}+\frac{\partial V}{\partial z}\beta\sigma_L Z_t dB_{Lt}. \tag{A-6}$$

The Poisson process N_t will hit within the time interval dt with probability λdt, and the value function will experience a jump:

$$dV(t,X_t,Y_t,Z_t) = V(t+,X_t-I_t,Y_t+I_t,Z_t)-V(t,X_t,Y_t,Z_t). \tag{A-7}$$

Therefore, the expected value of the infinitesimal increment in the value function can be represented as follows:

$$E[dV(t,X_t,Y_t,Z_t)] = (1-\lambda dt)\left[\frac{\partial V}{\partial t}+\mathcal{L}^{\pi_t}V\right]dt + \lambda dt\,[V(t+,X_t-I_t,Y_t+I_t,Z_t)-V(t,X_t,Y_t,Z_t)]. \tag{A-8}$$

If we combine equation (A-8) with equation (A-5) and take $dt\to 0$, we obtain

$$\frac{\partial V}{\partial t}+\mathcal{L}^{\pi_t}V+\lambda[V(t,X_t-I_t,Y_t+I_t,Z_t)-V(t,X_t,Y_t,Z_t)] \leq 0. \tag{A-9}$$

Bellman's principle of optimality suggests that equation (A-9) holds with equality under the optimal policy $\Theta_t^*=(\pi_t^*,I_t^*)$. Therefore, $V(t,x,y,z)$ satisfies equation (A-2).

2. Verification Theorem

We provide a verification theorem that helps characterize the fund manager's optimal investment policy described in Section III.

Verification Theorem. Let $v(t,x,y,z)$ be the solution to the HJB equation (A-2) with the boundary condition (A-3), and assume that v is $\mathcal{C}^1$ in t and $\mathcal{C}^2$ in (x,y,z). In addition, let

$$\pi^*(t,X_t,Y_t,Z_t) = \arg\max_{0\le\pi\le 1}\left\{\left[(\alpha_L-r)X_t\frac{\partial v}{\partial x} + \beta\sigma_L^2 X_t Z_t\frac{\partial^2 v}{\partial x\partial z}+\rho\sigma_L\sigma_I X_t Y_t\frac{\partial^2 v}{\partial x\partial y}\right]\pi+\frac{1}{2}\sigma_L^2 X_t^2\pi^2\frac{\partial^2 v}{\partial x^2}\right\}, \tag{A-10}$$

where all the partial derivatives are evaluated at (t,X_t,Y_t,Z_t), and

$$I^*(\tau,X_\tau,Y_\tau,Z_\tau) = \arg\max_{I\in[-Y_\tau,X_\tau]} v(\tau,X_\tau-I,Y_\tau+I,Z_\tau), \tag{A-11}$$

where τ is the arrival time of the Poisson process N_t. Then $v(t,x,y,z)$ coincides with the value function of equation (A-1), and (π^*,I^*) is the corresponding optimal investment policy.

The proof of this verification theorem is as follows.

For $t\in[0,T]$, let $t=s_0<s_1<\cdots<s_K=T$ be a uniform partition of the interval $[t,T]$, with $s_j-s_{j-1}=\Delta s$ for all j. Assume Δs is small enough so that $1-\lambda\Delta s>0$.

Given an arbitrary admissible policy (π,I), we consider a time interval $[s_j,s_{j+1}]$. Due to the time homogeneity of the Poisson process N_t, there is no arrival of a liquidity event in this interval with a probability $1-\lambda\Delta s$ (the higher-order terms are omitted because we

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let $\Delta s \to 0$). In this case, the value function of the fund manager is given by

$$\text{(A-12)}\quad v(s_{j+1}, X_{s_{j+1}}, Y_{s_{j+1}}, Z_{s_{j+1}}) = v(s_j, X_{s_j}, Y_{s_j}, Z_{s_j}) + \left(\frac{\partial v}{\partial t} + \mathcal{L}^{\pi} v\right)(s_j, X_{s_j}, Y_{s_j}, Z_{s_j})\Delta s + n_0 + \epsilon_0,$$

where ϵ_0 denotes the higher-order terms of Δs, and $n_0 = v_x \pi_t \sigma_L X_t \Delta B_{Lt} + v_y \sigma_I Y_t \Delta B_{It} + v_z \beta \sigma_L Z_t \Delta B_{Lt}$ represents the random shocks of the Brownian motions, which have zero mean. The probability that a liquidity event arrives in the time interval $[s_j, s_{j+1}]$ is given by $\lambda \Delta s$. We denote this arrival time as τ_j. At this arrival time, the value function of the fund manager experiences a shock, which can be described as follows:

$$\begin{aligned}\text{(A-13)}\quad & v(s_{j+1}, X_{s_{j+1}}, Y_{s_{j+1}}, Z_{s_{j+1}}) \\ &= v(s_j, X_{s_j}, Y_{s_j}, Z_{s_j}) + \left(\frac{\partial v}{\partial t} + \mathcal{L}^{\pi} v\right)(s_j, X_{s_j}, Y_{s_j}, Z_{s_j})(\tau_j - s_j) + n_1 + \epsilon_1 \\ &\quad + v(\tau_j, X_{\tau_j}, Y_{\tau_j}, Z_{\tau_j}) - v(\tau_j -, X_{\tau_j -}, Y_{\tau_j -}, Z_{\tau_j -}) \\ &\quad + \left(\frac{\partial v}{\partial t} + \mathcal{L}^{\pi} v\right)(\tau_j, X_{\tau_j}, Y_{\tau_j}, Z_{\tau_j})(s_{j+1} - \tau_j) + n_2 + \epsilon_2,\end{aligned}$$

where n_1 and n_2 are defined like n_0 previously, and ϵ_1 and ϵ_2 represent the higher-order terms.

If we take expectations, we obtain the following relation:

$$\begin{aligned}\text{(A-14)}\quad & E\left[v(s_{j+1}, X_{s_{j+1}}, Y_{s_{j+1}}, Z_{s_{j+1}}) - v(s_j, X_{s_j}, Y_{s_j}, Z_{s_j})\right] \\ &= E\left[\left(\frac{\partial v}{\partial t} + \mathcal{L}^{\pi} v\right)(s_j, X_{s_j}, Y_{s_j}, Z_{s_j})\Delta s + \lambda \Delta s\,(v(\tau_j, X_{\tau_j}, Y_{\tau_j}, Z_{\tau_j}) \right. \\ &\quad \left. - v(\tau_j -, X_{\tau_j -}, Y_{\tau_j -}, Z_{\tau_j -})) + \epsilon\right],\end{aligned}$$

where ϵ denotes the collection of all the higher-order terms. At the time of rebalancing, which occurs when the Poisson process N hits, there is a transfer between the liquid and the illiquid components of the fund manager's portfolio, whereas the benchmark portfolio remains unchanged. This can be represented as follows:

$$\text{(A-15)}\quad X_{\tau_j} = X_{\tau_j -} - I_{\tau_j},$$

$$\text{(A-16)}\quad Y_{\tau_j} = Y_{\tau_j -} + I_{\tau_j},$$

and

$$\text{(A-17)}\quad Z_{\tau_j} = Z_{\tau_j -}.$$

After adding across all j values, and for small enough $\Delta s \to 0$, the fund manager's value function takes the following form:

$$\begin{aligned}& E\left[v(s_K, X_{s_K}, Y_{s_K}, Z_{s_K}) - v(s_0, X_{s_0}, Y_{s_0}, Z_{s_0})\right] \\ &= E\left[\int_t^T \left(\frac{\partial v}{\partial t} + \mathcal{L}^{\pi} v\right)(s, X_s, Y_s, Z_s) + \lambda\,(v(s, X_s - I_s, Y_s + I_s, Z_s) - v(s, X_s, Y_s, Z_s))\,ds\right].\end{aligned}$$

Because the integrand is nonpositive, $v(t,x,y,z)$ is at least as large as the value function:

$$\text{(A-18)}\quad v(t, X_t, Y_t, Z_t) \geq E[v(T, X_T, Y_T, Z_T)] = E[U(W_T)],$$

which holds as an equality when (π, I) is chosen according to equations (A-10) and (A-11). In that case, v equals the value function V.

3. Reduction of the Dimensionality of the Value Function

Given the linearity of the dynamics of X_t, Y_t, and Z_t and the homotheticity of the CRRA utility function, the value function V is also homothetic in (x,y,z) with degree $1-\gamma$. Therefore, there exists a function $\phi(t,\zeta,\eta)$ such that

$$V(t,x,y,z) = \frac{(x+y)^{1-\gamma}}{1-\gamma} e^{(1-\gamma)\phi(t,\zeta,\eta)}, \tag{A-19}$$

where $\zeta = y/(x+y)$, and $\eta = \ln(z)/(x+y)$. By calculating the partial derivatives of V using the partial derivatives of ϕ, we can then verify that $\phi(t,\zeta,\eta)$ is governed by the following equation:

$$\phi_t + \mathcal{M}\phi + \frac{\lambda}{1-\gamma}\left(\sup_{I'\in[-\zeta,1-\zeta]} e^{(1-\gamma)\left(\phi(t,\zeta+I',\eta)-\phi(t,\zeta,\eta)\right)} - 1\right) = 0 \tag{A-20}$$

with the terminal condition

$$\phi(T,\zeta,\eta) = \ln(1+f(-\eta))$$

in $\Sigma = \{(t,\zeta,\eta): 0\le t\le T, 0\le\zeta\le 1, \eta\in R\}$, where $I' = I/(x+y)$, and

$$\begin{aligned}\mathcal{M}\phi = {} & a_0 + a_1\phi_\zeta + a_2\phi_\eta + a_3(\phi_{\zeta\zeta}+\gamma'\phi_\zeta^2) + a_4(\phi_{\eta\eta}+\gamma'\phi_\eta^2) + a_5(\phi_{\zeta\eta}+\gamma'\phi_\zeta\phi_\eta)\\ & + \sup_{0\le\pi\le 1}\Big\{\big[b_0 + b_1\phi_\zeta + b_2\phi_\eta + b_3(\phi_{\zeta\zeta}+\gamma'\phi_\zeta^2)\\ & + b_4(\phi_{\eta\eta}+\gamma'\phi_\eta^2) + b_5(\phi_{\zeta\eta}+\gamma'\phi_\zeta\phi_\eta)\big]\pi\\ & + \big[c_0 + c_1\phi_\zeta + c_2\phi_\eta + c_3(\phi_{\zeta\zeta}+\gamma'\phi_\zeta^2) + c_4(\phi_{\eta\eta}+\gamma'\phi_\eta^2) + c_5(\phi_{\zeta\eta}+\gamma'\phi_\zeta\phi_\eta)\big]\pi^2\Big\}\end{aligned}$$

with $\gamma' = 1-\gamma$, and the remaining coefficients are as follows:

$$\begin{aligned}
a_0 &= r + (\alpha_I - r)\zeta - \tfrac{1}{2}\gamma\sigma_I^2\zeta^2,\\
a_1 &= \zeta(1-\zeta)(\alpha_I - r - \gamma\sigma_I^2\zeta),\\
a_2 &= \beta(\alpha_L - r) + \zeta(r - \alpha_I + \sigma_I^2\gamma\zeta - \beta\rho\sigma_L\sigma_I\gamma) - \tfrac{1}{2}\left(\sigma_I^2\zeta^2 + \sigma_L^2\beta^2 - 2\beta\rho\sigma_L\sigma_I\zeta\right),\\
a_3 &= \tfrac{1}{2}\sigma_I^2\zeta^2(1-\zeta)^2,\\
a_4 &= \tfrac{1}{2}\left(\sigma_I^2\zeta^2 + \sigma_L^2\beta^2 - 2\beta\rho\sigma_L\sigma_I\zeta\right)\\
a_5 &= \zeta(1-\zeta)(\beta\rho\sigma_L\sigma_I - \sigma_I^2\zeta),\\
b_0 &= (\alpha_L - r - \rho\sigma_L\sigma_I\gamma\zeta)(1-\zeta),\\
b_1 &= -(\alpha_L - r)\zeta(1-\zeta) + \rho\sigma_L\sigma_I\gamma\zeta(1-\zeta)(2\zeta-1),\\
b_2 &= (1-\zeta)(r - \alpha_L - \gamma\beta\sigma_L^2 + 2\gamma\rho\sigma_L\sigma_I\zeta) - (1-\zeta)(\rho\sigma_L\sigma_I\zeta - \beta\sigma_L^2),\\
b_3 &= -\rho\sigma_L\sigma_I\zeta^2(1-\zeta)^2,\\
b_4 &= (1-\zeta)(\rho\sigma_L\sigma_I\zeta - \beta\sigma_L^2),\\
b_5 &= \zeta(1-\zeta)\left[\kappa\sigma_L\sigma_I(2\zeta-1) - \beta\sigma_L^2\right],\\
c_0 &= -\tfrac{1}{2}\sigma_L^2\gamma(1-\zeta)^2,\\
c_1 &= \sigma_L^2\gamma\zeta(1-\zeta)^2,\\
c_2 &= \sigma_L^2\gamma(1-\zeta)^2 - \tfrac{1}{2}\sigma_L^2(1-\zeta)^2,\\
c_3 &= \tfrac{1}{2}\sigma_L^2\zeta^2(1-\zeta)^2,\\
c_4 &= \tfrac{1}{2}\sigma_L^2(1-\zeta)^2,\\
c_5 &= \sigma_L^2\zeta(1-\zeta)^2.
\end{aligned}$$

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4. Numerical Procedure

We briefly explain the numerical technique that we use to solve equation (A-19). We apply a standard finite-differences scheme on Σ. In the main algorithm, we apply an iterative method with error tolerance $\mathrm{TOL} > 0$, with the following steps (assuming the function value at time $t + \Delta t$ is known):

Step 1. Let $i = 0$ and take the initial guess: $\phi^0(t, \zeta, \eta) = \phi(t + \Delta t, \zeta, \eta)$.

Step 2. Find $\pi_i^* = \arg\max_{0 \le \pi \le 1} f(\pi, \phi^i)$, where

$$f(\pi,\phi) = \left\{ \left[\frac{b_0}{\gamma'} + b_1\phi_\zeta + b_2\phi_\eta + b_3(\phi_{\zeta\zeta} + \gamma'\phi_\zeta^2) + b_4(\phi_{\eta\eta} + \gamma'\phi_\eta^2) + b_5(\phi_{\zeta\eta} + \gamma'\phi_\zeta\phi_\eta) \right] \pi \right.$$
$$\left. + \left[\frac{c_0}{\gamma'} + c_1\phi_\zeta + c_2\phi_\eta + c_3(\phi_{\zeta\zeta} + \gamma'\phi_\zeta^2) + c_4(\phi_{\eta\eta} + \gamma'\phi_\eta^2) + c_5(\phi_{\zeta\eta} + \gamma'\phi_\zeta\phi_\eta) \right] \pi^2 \right\}.$$

Step 3. Solve the discretized version of the following equation:

$$\phi_t^{i+1} + \mathcal{M}_0(\pi_i^*)\phi^{i+1} + \frac{\lambda}{1-\gamma}\left(e^{(1-\gamma)\sup_{I' \in [-\eta, 1-\eta]} \phi^i(t,\zeta+I',\eta) - (1-\gamma)\phi^{i+1}(t,\zeta,\eta)} - 1\right) = 0,$$

where the operator $\mathcal{M}_0(\pi)\phi$ is expanded as follows:

$$\mathcal{M}_0(\pi)\phi = \frac{a_0}{\gamma'} + a_1\phi_\zeta + a_2\phi_\eta + a_3(\phi_{\zeta\zeta} + \gamma'\phi_\zeta^2) + a_4(\phi_{\eta\eta} + \gamma'\phi_\eta^2) + a_5(\phi_{\zeta\eta} + \gamma'\phi_\zeta\phi_\eta)$$
$$\times \left\{ \left[\frac{b_0}{\gamma'} + b_1\phi_\zeta + b_2\phi_\eta + b_3(\phi_{\zeta\zeta} + \gamma'\phi_\zeta^2) + b_4(\phi_{\eta\eta} + \gamma'\phi_\eta^2) + b_5(\phi_{\zeta\eta} + \gamma'\phi_\zeta\phi_\eta) \right] \pi \right.$$
$$\left. + \left[\frac{c_0}{\gamma'} + c_1\phi_\zeta + c_2\phi_\eta + c_3(\phi_{\zeta\zeta} + \gamma'\phi_\zeta^2) + c_4(\phi_{\eta\eta} + \gamma'\phi_\eta^2) + c_5(\phi_{\zeta\eta} + \gamma'\phi_\zeta\phi_\eta) \right] \pi^2 \right\}.$$

Step 4. If $(|\phi^{i+1} - \phi^i|)/(\max\{1, |\phi^i|\}) < \mathrm{TOL}$, set $\phi(t, \zeta, \eta) = \phi^{i+1}(t, \zeta, \eta)$. Otherwise, set $i = i + 1$ and go back to Step 2.

5. Additional Results

a. Economy (a) of Basak et al. (2007)

In our model there is also a case corresponding to Economy (a) of Basak et al. (2007). We show in Figure A1 what happens when we assume a balanced benchmark (i.e., $\beta = 0.5$). Figure A1 shows that when underperforming the benchmark, the fund manager first engages in risk shifting by increasing the exposure to the liquid benchmark stock. However, as the fund's portfolio performance deteriorates further relative to the benchmark, the manager starts building up a large position on the illiquid nonbenchmark stock. This mechanically reduces the allocation on the liquid benchmark stock because the fund's portfolio is constrained to have no leverage.

b. Effective Risk Aversion

To understand what drives the risk-shifting behavior, we plot in Figure A2 the effective risk aversion of the fund manager in the underperformance region.[46] This graph does not include the effect of illiquidity ($\lambda = \infty$), only the effect associated with the implicit

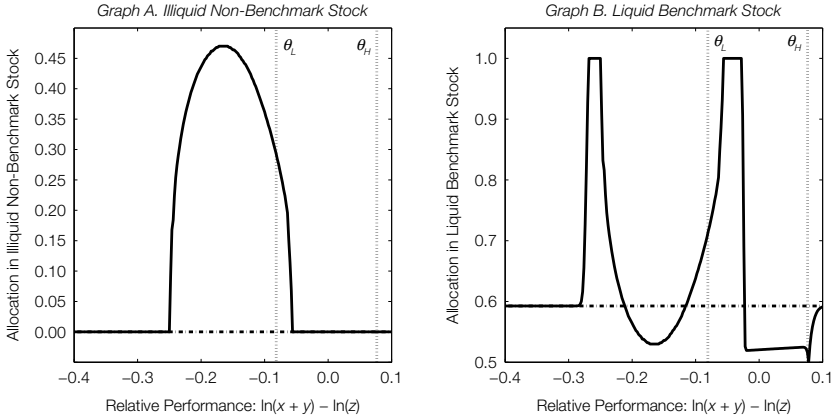
[46] The effective relative risk aversion (ERRA) is calculated as $\mathrm{ERRA}(t, w, z) = -wV_{ww}(t, w, z)/V_w(t, w, z)$, where V is the manager's value function, z is the value of the benchmark portfolio, and w is the value of the fund's assets under management. We consider only the case in which $\lambda = \infty$, to isolate the effects of relative-performance concerns. In the case where $\lambda = \infty$, the value function depends only on t, w, and z.

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FIGURE A1

Liquid and Illiquid Stock Allocations for Balanced Benchmark

Figure A1 illustrates the fund manager's optimal weight on the illiquid nonbenchmark stock S_I (Graph A) and on the liquid benchmark stock S_L (Graph B) as a function of relative performance at mid-year (i.e., $t=0.5$) and conditional on the arrival of a liquidity event at that time. The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The two vertical dashed lines indicate the performance thresholds that define the flow–performance function. For $\ln(x+y)-\ln(z)<\theta_L=-0.08$, the flow function is flat at the level of $f_L=-0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y)-\ln(z)\geq\theta_L=-0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When it reaches $\ln(x+y)-\ln(z)\geq\theta_H=0.08$, the flow–performance relation returns to flat at the level of $f_H=0.5$ (i.e., inflow of 50% of AUM by year-end). The remaining parameter values used to generate these plots are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=3$, intensity of the Poisson process $\lambda=12$ (i.e., liquidity events occur once a month, on average), and the weight of the benchmark on the liquid stock $\beta=0.5$ (i.e., balanced benchmark).



incentives created by the flow–performance relation.[47] Even though the fund manager has a constant coefficient of relative risk aversion $\gamma=2$, the presence of money flows endogenously induces additional risk appetite as a function of relative performance. The manager's willingness to accept gambles is higher for the values of relative performance where the impact of the gamble on the value of assets under management is also larger. This coincides with the risk-shifting range identified in Graph A of Figure 1 in the underperformance region (i.e., $\ln(x+y)-\ln(z)<0$).

In other words, the presence of money flows creates additional high-marginal-utility states. In contrast to the standard Merton model, our fund manager's marginal value of the assets under management is high when the fund is underperforming the benchmark. In this region, the fund manager is expected to experience future redemption requests, which leads to high marginal utility. This in turn induces additional curvature in the value function and overinvestment in the illiquid nonbenchmark stock compared with the Merton solution.

c. Dynamics of the Optimal Policy

Figure A3 shows the time dynamics of the optimal allocation on the illiquid nonbenchmark stock. It plots snapshots of the optimal policy at the end of the first, second, and third quarters (i.e., $t\in\{0.25,0.50,0.75\}$) within the 1-year investment horizon. It shows that the risk-shifting incentive strengthens over time. Moreover, the risk-shifting range

[47] To generate Figure A2, we (exogenously) impose short-selling and borrowing constraints. In the presence of illiquidity, these constraints are endogenous for S_I.

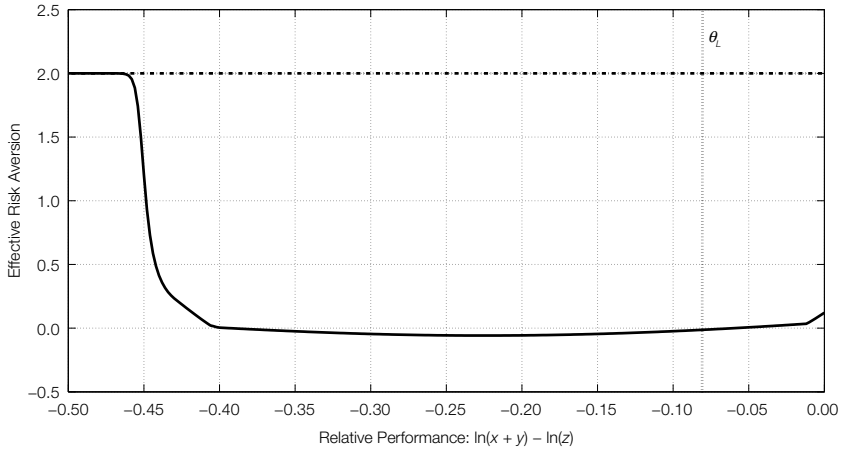
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FIGURE A2

Effective Risk Aversion and Relative Performance Concerns

Figure A2 plots the fund manager's effective risk aversion as a function of relative performance at mid-year (i.e., $t=0.5$). It shows the underperformance region: $\ln(x+y)-\ln(z)<0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The effective risk aversion measures the fund manager's willingness to pay to avoid gambles on the nonbenchmark stock S_I. In this figure, the nonbenchmark stock S_I is perfectly liquid (i.e., $\lambda=\infty$) to isolate the effect of relative performance on the endogenous risk aversion of the fund manager. The vertical dashed line indicates θ_L, the lower threshold of the flow-performance function. For $\ln(x+y)-\ln(z)<\theta_L=-0.08$, the flow function is flat at the level of $f_L=-0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y)-\ln(z)\geq\theta_L=-0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. The remaining parameter values used to generate this plot are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, and the weight of the benchmark on the liquid stock $\beta=1$ (i.e., all-equity liquid benchmark).



shrinks as we approach the flow date. These results are similar to those reported by Basak et al. (2007).

6. Decomposition of the Delegation Costs

In our model, when the investor and the manager have different appetites for risk, the investor's utility cost of delegation includes the effect of such disparity in risk appetites as well as the effect of the risk-shifting incentives of the fund manager, which are induced by the positive and convex flow–performance relation. In that case, we need to decompose the delegation costs to understand the relative contributions of those two effects. In what follows, we describe how we carry out such decomposition.

Let $\Pi(\gamma_0,\kappa)$ be the optimal investment policy of an agent with CRRA coefficient γ_0 and where $\kappa=1$ identifies the case in which the agent has implicit incentives, whereas $\kappa=0$ identifies the case in which implicit incentives are absent. Therefore, $\Pi(\gamma,1)$ represents the fund manager's optimal policy, whereas $\Pi(\gamma_I,0)$ represents the investor's optimal policy. Also, let $\mathrm{CE}(\gamma_0,\kappa)$ be the certainty equivalent rate of return generated by the investor's utility function when the investment policy $\Pi(\gamma_0,\kappa)$ is adopted.

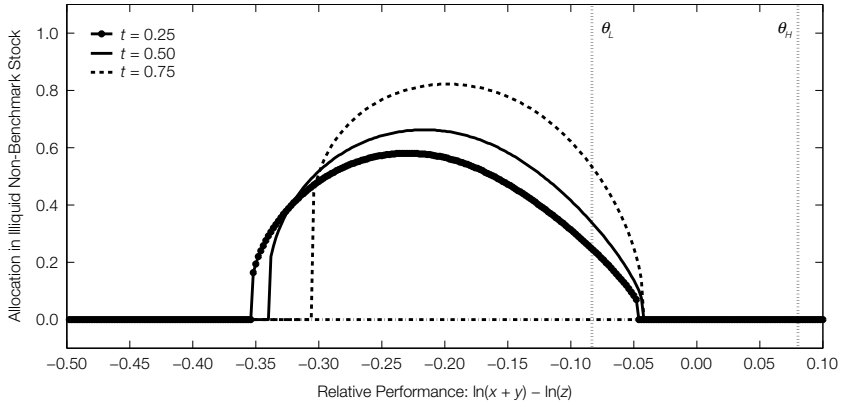
The total utility cost of portfolio delegation, which accrues to the investor, is given by

$$L_{\text{total}} = \mathrm{CE}(\gamma,1)/\mathrm{CE}(\gamma_I,0)-1, \tag{A-21}$$

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FIGURE A3
Time Variation in the Optimal Investment Policy

Figure A3 illustrates the fund manager's optimal weight on the illiquid nonbenchmark stock S_I as a function of relative performance for different points in time within the investment horizon $t \in \{0, T\}$. It plots snapshots of the optimal policy at the end of the first, second, and third quarters (i.e., $t \in \{0.25, 0.50, 0.75\}$) within the 1-year horizon (i.e., $T = 1$). The underperformance region is $\ln(x+y) - \ln(z) < 0$, and the overperformance region is $\ln(x+y) - \ln(z) > 0$, where z is the value of the benchmark, and $x+y$ is the value of the fund's portfolio. The two vertical dashed lines indicate the performance thresholds that define the flow–performance function. For $\ln(x+y) - \ln(z) < \theta_L = -0.08$, the flow function is flat at the level of $f_L = -0.2$ (i.e., the fund experiences an outflow of 20% of assets under management (AUM) at year-end). When the relative performance reaches $\ln(x+y) - \ln(z) \geq \theta_L = -0.08$, the flow function displays a local convexity followed by an upward-sloping linear segment. When it reaches $\ln(x+y) - \ln(z) \geq \theta_H = 0.08$, the flow–performance relation returns to flat at the level of $f_H = 0.5$ (i.e., inflow of 50% of AUM by year-end). The remaining parameter values used to generate this plot are as follows: risk-free rate $r = 0.04$, expected return of the liquid stock $\alpha_L = 0.08$, volatility of the liquid stock $\sigma_L = 0.15$, expected return of the illiquid stock $\alpha_I = r = 0.04$, volatility of the illiquid stock $\sigma_I = 0.50$, correlation between the returns of the two stocks $\rho = 0$, coefficient of relative risk aversion $\gamma = 2$, intensity of the Poisson process $\lambda = 12$ (i.e., liquidity events occur once a month, on average), and the weight of the benchmark on the liquid stock $\beta = 1$ (i.e., all-equity liquid benchmark).



whereas the utility cost that is due exclusively to implicit incentives is computed as follows:

$$L_{\text{imp}} = \text{CE}(\gamma, 1)/\text{CE}(\gamma, 0) - 1, \tag{A-22}$$

where the CRRA coefficient of the investor is set equal to that of the manager.

Therefore, the utility cost that is due to explicit incentives is the difference between the two costs defined previously:

$$L_{\text{exp}} = L_{\text{total}} - L_{\text{imp}}. \tag{A-23}$$

7. Deterministic Liquidity and Implications for Delegation Costs

In our baseline model, we assume that trading opportunities on the illiquid stock S_I arrive in intervals of uncertain duration. Here, we consider an alternative definition of illiquidity in which the stock S_I can only be traded at deterministic time points $\{t_j : 1 \leq j \leq G\}$. Following Ang et al. (2014), we assume that these time points are equally spaced. Therefore, different values of G represent different rebalancing frequencies. For example, $G = 4$ represents the case in which the portfolio can be rebalanced on a quarterly basis, and $G = 12$ represents the case in which portfolio rebalancing occurs on a monthly basis.

We solve this model using the same baseline parameter values as before. The HJB equation for the value function V_1 is now given by

$$\frac{\partial V_1}{\partial t} + \sup_{\pi \in [0,1]} \mathcal{L}^{\pi} V_1 = 0, \text{ for } t \in (t_j, t_{j+1}), \tag{A-24}$$

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where $\mathcal{L}^{\pi}$ is defined as in Section 1 of the Appendix, and the boundary condition is the same as in equation (A-3):

$$V_1(T,x,y,z) = U\left[\left(1+f\left(\ln\frac{x+y}{z}\right)\right)(x+y)\right]. \tag{A-25}$$

The connect condition at each rebalancing time t_j is defined as follows:

$$V_1(t_j,x,y,z) = \sup_{I\in[-y,x]} V_1(t_j+,x-I,y+I,z). \tag{A-26}$$

In a model with deterministic liquidity, the optimal asset allocation is characterized entirely by I_{t_j}, or $(Y_{t_j+})/(X_{t_j+}+Y_{t_j+})$, which represents the optimal portfolio allocations chosen at the rebalancing time t_j.

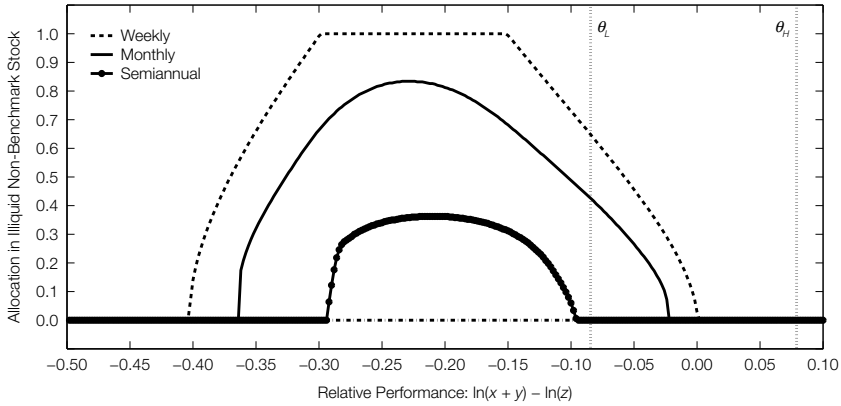
Figure A4 plots these optimal portfolio allocations as a function of relative performance. These allocations are computed at time $t=0.5$ for the cases in which the stock S_I is allowed to trade either quarterly, monthly, or weekly. Similar to what we observe in Figure 4, when we reduce the trading frequency of the nonbenchmark stock, the fund manager also reduces the size of the gambles in the underperformance region (i.e., $\ln(x+y)-\ln(z)<0$).

Table A1 reports the utility costs of portfolio delegation generated by this model. The main implication of our baseline model still holds under this alternative definition of liquidity: The lack of stock liquidity can weaken the incentive of fund managers to take extra risks in response to beating their performance benchmarks, which in turn reduces the costs of portfolio delegation that accrue to fund investors. For example, Panel A shows that, when $\gamma_I=2$ and the rebalancing of the nonbenchmark stock occurs on a weekly basis, the portfolio-delegation cost to the investor is 2.41% of his or her initial wealth. This cost decreases to 0.89% when the rebalancing of the nonbenchmark stock occurs instead on a

FIGURE A4

Risk-Shifting Incentives and (Deterministic) Stock Illiquidity

Figure A4 illustrates the fund manager's optimal weight on the illiquid stock S_I as a function of relative performance for equally spaced intervals between liquidity events. Specifically, this figure plots snapshots of the fund manager's optimal policy at mid-year (i.e., $t=0.50$, for $T=1$) when liquidity events occur on a quarterly, monthly, and weekly basis, respectively. The underperformance region is $\ln(x+y)-\ln(z)<0$, and the overperformance region is $\ln(x+y)-\ln(z)>0$. The two vertical dashed lines indicate the relative performance thresholds (θ_L and θ_H) that define the flow–performance function. The remaining parameter values used to generate this plot are as follows: risk-free rate $r=0.04$, expected return of the liquid stock $\alpha_L=0.08$, volatility of the liquid stock $\sigma_L=0.15$, expected return of the illiquid stock $\alpha_I=r=0.04$, volatility of the illiquid stock $\sigma_I=0.50$, correlation between the returns of the two stocks $\rho=0$, coefficient of relative risk aversion $\gamma=2$, and the weight of the benchmark on the liquid stock $\beta=1$ (i.e., all-equity liquid benchmark).



semiannual basis. Panel B reports similar patterns for the case in which the investor is more risk averse ($\gamma_I = 4$). Like in Section III, the delegation costs are uniformly higher when the investor is more risk averse.

TABLE A1

Utility Costs of Portfolio Delegation and (Deterministic) Stock Illiquidity

Table A1 reports the utility costs of portfolio delegation when liquidity events for stock S_I arrive in equally spaced (deterministic) time intervals (e.g., weekly, biweekly, monthly, quarterly, and semiannually). These costs are due to differences in risk appetite between investors and managers (explicit incentives), as well as the risk-shifting incentives of fund managers that are created by the positive and convex flow–performance relation (implicit incentives). Panel A only accounts for the effect of implicit incentives (i.e., $\gamma = \gamma_I$), whereas Panel B considers the costs of both implicit and explicit incentives (i.e., $\gamma \neq \gamma_I$). The utility costs are measured at the level of the investor's centralized problem. The certainty equivalent rate of return $\text{CE}(\Pi)$ makes the investor indifferent between following policy Π and earning a risk-free rate on the same initial wealth over the same period of time. The policy Π_1 is the optimal policy of the investor if investing directly, whereas policy Π_2 is the optimal policy of the fund manager. The total cost of portfolio delegation is given by $I(\Pi_1, \Pi_2) = |\text{CE}(\Pi_2)/\text{CE}(\Pi_1) - 1|$. The larger the values of $I(\Pi_1, \Pi_2)$, the costlier it is for the investor to delegate instead of investing directly. In Panel B, the total cost of portfolio delegation $I(\Pi_1, \Pi_2)$ is decomposed into two parts: one that is exclusively due to explicit incentives, and the other that is due to implicit incentives. The flow–performance function (equation 10) is calibrated according to the empirical estimations of Chevalier and Ellison (1997): $f_L = -0.20$, $f_H = 0.50$, $\theta_L = -0.08$, and $\theta_H = 0.08$. The remaining parameter values used to compute these costs of delegation are as follows: investment horizon $T = 1$, risk-free rate $r = 0.04$, expected return of the liquid stock $\alpha_L = 0.08$, volatility of the liquid stock $\sigma_L = 0.15$, expected return of the illiquid stock $\alpha_I = 0.04$, volatility of the illiquid stock $\sigma_I = 0.50$, correlation between the returns of the two stocks $\rho = 0$, and the weight of the benchmark on the liquid stock $\beta = 1$ (i.e., all-equity liquid benchmark).

	Frequency of Portfolio Rebalancing				
	Weekly	Biweekly	Monthly	Quarterly	Semiannually
Panel A. $\gamma = \gamma_I = 2$					
$\text{CE}(\Pi_2)$	1.042	1.043	1.045	1.052	1.055
$\text{CE}(\Pi_1)$	1.060	1.060	1.060	1.060	1.060
$I(\Pi_1, \Pi_2)$ (%)	1.68	1.58	1.33	0.68	0.38
Panel B. $\gamma = 2$, $\gamma_I = 4$					
$\text{CE}(\Pi_2)$	1.011	1.013	1.018	1.031	1.036
$\text{CE}(\Pi_1)$	1.050	1.050	1.050	1.050	1.050
$I(\Pi_1, \Pi_2)$ (%)	3.68	3.53	3.03	1.78	1.31
Implicit $I(\Pi_1, \Pi_2)$ (%)	2.82	2.66	2.16	0.91	0.43
Explicit $I(\Pi_1, \Pi_2)$ (%)	0.86	0.87	0.87	0.87	0.88

8. Data Sample and Variable Construction

We obtain fund returns, investment objectives, fees, TNA, and other fund characteristics from the CRSP Survivor-Bias-Free Mutual Fund Database. We use the Wharton Research Data Services MFLINKS file to merge this database with Thomson Financial Mutual Fund Holdings, which contains information on stock positions of funds and identifies fund families (see Wermers (2000)). We restrict our analysis to diversified domestic actively managed equity mutual funds.[48] We compute fund-level variables by aggregating across all the share classes. For instance, a fund's expense and turnover ratios are the TNA-weighted averages of the ratios of its different share classes. The age of the fund is equal to the age of its oldest share class, and the TNA of the fund is the sum of the TNAs of all its share classes.

Reported fund objectives do not always accurately characterize a fund. Following Kacperczyk, Sialm, and Zheng (2008) and Glode (2011), we exclude funds that hold on average less than 80% or more than 105% of their net assets in equity. We also exclude funds with TNA of less than \$15 million because Elton, Gruber, and Blake (2001) show

[48] More specifically, and following existing literature, we include in our sample funds with AGG, GMC, GRI, GRO, ING, and SCG Strategic Insight codes; EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE Lipper codes; and G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG Wiesenberger codes. We exclude international, balanced, sector, bond, money market, and index funds.

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that the returns of such small funds tend to be biased upwardly in the CRSP database. Additionally, we remove observations associated with funds that have less than 18 months since inception at a given point in time, to minimize the effects of incubation bias (see Evans (2010)).

Following Reed and Wu (2005) and Basak et al. (2007), we use daily fund returns to study how mutual fund managers respond to beating their benchmarks. However, whereas they use the S&P 500 as a yardstick for the average fund manager, we instead use the full list of official benchmarks that mutual funds disclose in their prospectuses. We study how fund managers change their tracking errors from the first to the second half of the year in response to performance relative to their declared benchmarks.[49] We use daily fund returns from CRSP and daily benchmark returns from FactSet to compute the tracking-error ratio (TER) defined in Section V.A. A TER greater than 1 indicates that the fund manager increases the tracking error from the first to the second half of the year.

To capture the risk-shifting incentives of fund managers, we need a measure of the excess return of each fund relative to the index at mid-year. We compound daily returns for the first 6 months of a given year for both the fund and its benchmark index. We then take the difference between these compounded returns and denote this variable as EXRET(1,6). We require at least 100 daily observations to compute EXRET(1,6) and a minimum of 200 daily observations to compute EXRET(1,12).

To examine how a fund's performance relative to the benchmark at mid-year creates incentives to increase the tracking-error volatility in the second half of the year, we study the relationship between EXRET(1,6) and TER. We identify control variables that may jointly affect EXRET(1,6) and TER. Specifically, we control for a number of fund characteristics, including the value of total assets under management (TNA), the expense ratio (EXP), the turnover ratio (TURN), the number of years since inception (AGE), and the number of funds affiliated with the same family (NFUNDS). We use the natural logarithm of AGE and NFUNDS, which we denote as ln(AGE) and ln(FAM), respectively, due to significant skewness in those variables.

We also use an indicator LOAD that is equal to 1 if the fund has a share class with either front-end or back-end loads, and 0 otherwise. We control for whether a fund has one or multiple share classes using and indicator MULTI that equals 1 for multiple-share-class funds, and 0 otherwise. These characteristics are all evaluated at the beginning of the calendar year. We also include in our list of controls the money flow that each fund experiences over the first 6 months of the year (FLOW(1,6)). It is given by the growth rate of assets under management, after adjusting for the appreciation of the funds' assets, measured at mid-year. Therefore, it is computed as follows: $\text{FLOW}(1,6) = [\text{TNA}(6) - (1+\text{RET}(1,6)) \times \text{TNA}(-1)]/\text{TNA}(-1)$, where TNA(6) is the value of assets under management at month 6 of year T, TNA(−1) is the value of the assets at the end of year $T-1$, and RET(1,6) is the return of the fund in the first 6 months of year T (compounded daily). We also control for the mid-year deviation of a fund's stock holdings from its declared benchmark (i.e., the active-share measure of Cremers and Petajisto (2009)). We winsorize all continuous variables at the 1% and the 99% levels, and we add style dummies to all of our regression specifications.

[49] A list of the official benchmark indices of mutual funds, as stated in their prospectuses, is available on Antti Petajisto's Web site (http://www.petajisto.net/data.html). This data set includes 5 indices from S&P, 12 indices from Russell, and 2 indices from Dow Jones/Wilshire. All the variables in this data set are described by Petajisto (2013).

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