Does Illiquidity Solve Its Own Problems? Evidence from Open-end Real Estate Funds*

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Abstract

This paper documents a new source of financial fragility and studies its interactions with common stabilization tools. Economists believe that open-end funds report stale values for their illiquid assets when those assets are not trading in the market. This staleness creates return predictability which in turn creates market-timing opportunities, investor-run incentives, and fund fragility risks. However, because the underlying assets are illiquid, managers limit the capital coming into and out of their funds in order to prevent pushing market prices. A secondary consequence of limiting capital flows is that managers create investor queues which deter market-timing and fund fragility risks. Paradoxically, illiquidity in the underlying assets creates *both* the opportunity for, and the friction against, exploiting buy-and-hold investors. Using cash to fulfill investor flows, however, reintroduces wealth transfer risks and increases the incentive for shareholders to run.

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1 Introduction

It is important to understand the mechanisms which stabilize and destabilize both intermediaries and markets. Economists have argued that open-end funds are exposed to the same bank-run-like risks analyzed in the banking literature (see Chen et al. (2010) and Goldstein et al. (2017)).[1] Funds may be forced to sell assets at a discount if too many investors redeem their shares and investors may redeem simply because they are unable to coordinate with other investors. While this is an important source of fragility, illiquid assets are also believed to have stale prices and predictable returns (see Getmansky et al. (2004), Geltner (1997), Quan and Quigley (1989), among others). Because stale prices affect incentives differently than random run concerns, it is important to understand how they interact with prominent stabilization tools. No theoretical or empirical paper has examined whether investors can exploit the return predictability created when open-end funds invest in illiquid assets. This paper attempts to fill this gap by theoretically and empirically analyzing the effects of stale pricing on NAV-timing in U.S. open-end private real estate (OPRE) funds.

In order to analyze these incentives, I model the interactions of investors and managers using two common stabilization tools: liquidity restrictions and liquidity buffers. In doing so, I obtain four predictions. First, investors will attempt to increase their holdings in funds after positive macroeconomic shocks. Second, investors will attempt to increase their holdings in those funds with the highest past performance. Third, managers will limit capital flows the most at those times and in those funds where NAV-timing strategies appear the most profitable. Lastly, when faced with either using liquid assets to meet investor flows (liquidity buffers) or suspending share issuances and redemptions (liquidity restrictions), funds which

[1] The International Organization of Securities Commissions (IOSCO), an international body of global securities regulators of which the U.S. Securities and Exchange Commission (SEC) and Commodity Futures Trading Commission (CFTC) are members, has written numerous reports in recent years detailing their concerns and recommendations for managing liquidity risk in open-end funds. Two recent articles include the "Recommendations for Liquidity Risk Management for Collective Investment Schemes" and "Open-ended Fund Liquidity and Risk Management - Good Practices and Issues for Consideration," both issued in February 2018. Additionally, the Financial Stability Board (FSB), an international body of financial system monitors of which the U.S. Board of Governors of the Federal Reserve System, the SEC and the U.S. Department of Treasury are members, has written multiple reports discussing liquidity risks in open-end funds as well. The most recent being, "Policy Recommendations to Address Structural Vulnerabilities from Asset Management Activities" issued in January of 2017. Lastly, many country regulators, including the SEC, have issued similar reports on the topic.

use liquidity buffers are more susceptible to runs and ultimate failure. I test the first three predictions using data from OPRE funds and I evaluate the fourth prediction by contrasting the OPRE fund performance with that which has been documented for German Open-end Real Estate (GORE) funds (see Gerlach and Maurer (2018) and Bannier et al. (2008), among others).

OPRE funds provide a near ideal setting to examine the exploitability of open-end fund return predictability. First, the Net Asset Values (NAVs) of OPRE funds are based almost entirely on valuation estimates. Therefore, the effects from valuation estimation should be more discernible than in other settings. Second, unlike hedge funds, OPRE funds report their unfulfilled subscription and redemption requests (queues). Estimating the returns investors could achieve by implementing an NAV-timing strategy requires estimating the returns they would achieve after going through the queue (queue-adjusted returns). Third, it is important to have a good proxy for the economic returns of the funds. Because commercial real estate has strong public and private markets, the returns from publicly traded real estate investment trusts (REITs) provide a good proxy for the economic returns of OPRE funds.[2] Fourth, funds cannot mechanically adjust their preexisting holdings to accommodate capital flows because asset ownership is discrete. This allows me to abstract away from the possibility that return predictability is driven by fund flow induced holdings adjustments (see Coval and Stafford (2007) and Lou (2012)).[3] Lastly, my data includes micro-level information on the assets these funds hold as well as a cross-section of investors within these funds. This gives me the ability to analyze return smoothing at the asset level as well as investor behavior at the individual investor level. The data come from three proprietary databases which together provide investor-level, fund-level, and asset-level information on OPRE funds.

I find that without trading constraints, NAV-timing strategies based on the return predictability are economically and statistically profitable. A long-short strategy based on investing in either an OPRE index or the 3-month T-bill achieved annualized private real

[2] Public and private real estate markets are distinguished by the market in which their securities trade. While both markets invest in real estate assets that trade privately, public real estate markets have securities that trade publicly on exchanges and private real estate markets have securities that are issued, redeemed, and traded privately.

[3] Further evidence of this is given by the existence of return predictability in the absence of flows and asset transactions.

estate factor and 5-factor alphas of 18.4% and 17.8% respectively from 2004 to 2015. Additionally, a long-short strategy using top and bottom quintile funds would have achieved annualized private real estate factor and 5-factor alphas of 5.9% and 3.5%. Each of these values is significantly larger than a simple buy-and-hold strategy, suggesting that achieving them would transfer significant wealth and create shareholder-run incentives.

I also find that investor behavior is consistent with these strategies. A one standard deviation increase in lagged public market returns and fund returns leads to 16% and 45% standard deviation increases in fund subscription requests respectively. Similarly, I find that funds limit capital in a manner which is consistent with these strategies. A one standard deviation increase in lagged public market returns and fund returns similarly leads to approximately 16% and 50% standard deviation increases in fund queues. The strategies that are the most profitable on paper also have the most oversubscriptions.

I find that the returns investors would achieve by implementing timing strategies are statistically and economically equivalent to those of buy-and-hold investors after accounting for non-discretionary liquidity restrictions (subscription frequency, lockup periods, and subscription notification periods) and discretionary liquidity restrictions (discretionary suspensions of share issuances and redemptions). While non-discretionary liquidity restrictions eliminate the superior performance of strategies that move from one fund to another, they have no effect on strategies which move in and out of the OPRE market. Additionally, they do not protect against wealth transfers to new investors in the highest performing funds. In contrast, discretionary liquidity restrictions, eliminate the superior performance of both types of strategies. In all, this evidence suggests that the liquidity in the underlying assets defends against exploiting the return predictability it creates. The novel finding in this is that investors behave as if they recognize the predictability, crowd each other out, and eliminate market-timing profits in a way that is similar to the winners curse found in the IPO literature.[4]

These results are in stark contrast to those found in analyzing GORE funds. Historically,

[4] Rock (1986) provides a model that predicts the size of IPO subscriptions will be positively correlated with the expected returns of the offering. According to Ritter (2003), the real winner's curse in IPOs is that strong demand in the most profitable offerings makes it difficult for any investor to obtain shares in those offerings thus dissipating the profits over many investors.

GORE funds have used large cash buffers (between 25% to 49% on average) as the primary mechanism to deter shareholder runs. This mechanism has proved to be insufficient as evidenced by the liquidity crises of 2005, 2008, and 2012. During the 2008 Global Financial Crisis (GFC), one third of the funds were required to suspend redemptions by regulators and 18 eventually announced liquidation. This evidence suggests that liquidity buffers do a poor job deterring shareholder runs when the return predictability is unrelated to shareholder coordination problems. In fact, liquidity buffers can increase shareholder run incentives when combined with redemption suspensions. By combining liquidity buffers with discretionary liquidity restriction, funds decrease the size of the liquidity restriction and make it easier for investors to reallocate capital and implement an NAV-timing strategy.

A large literature examines the depositor run risks associated with coordination problems in banks (Diamond and Dybvig (1983), among others). However, the liquidity mismatch in banks and open-ended funds is different. Banks have a liquidity mismatch between their assets and liabilities, while open-ended funds have a liquidity mismatch between their assets and equity. This difference is overlooked in many papers but is fundamental to understanding the effect stale pricing has on investor incentives. For instance, during the GFC, banks were encouraged to not mark-to-market their assets because comparable assets were selling at a significant discount to book values. Not marking-to-market created stale bank valuations, making them look more solvent on paper, which is believed to have deterred runs. However, not marking-to-market assets in open-end funds would likely have the exact opposite effect because share values would be overvalued relative to their true market value. It is also believed that historical cost accounting may be more optimal than marking-to-market for illiquid assets because doing so would decrease excessive price volatility (Plantin et al. (2008)). However, this logic would similarly distort open-end fund shareholder incentives for the same reasons.

Additionally, prior research has focused on the fragility risks of open-end funds investing in illiquid assets, but none has analyzed the stale valuations of illiquid assets as a potential source (Chen et al. (2010); Goldstein et al. (2017); Chernenko and Sunderam (2016); Morris et al. (2017); Zeng (2016)). Other papers have documented the relation between returns and liquidity restrictions as well as the potential negative effects of discretionary liquidity restrictions, but none have documented the benefits they provide (Aragon (2007); Teo (2011); Aiken et al. (2015)). Additionally, prior literature has shown that NAV-timing opportunities were created from nonsynchronous trading in mutual funds, but no paper has evaluated the ongoing source of NAV-timing risk due to the valuation bias in illiquid, difficult to value assets (Bhargava et al. (1998); Chalmers et al. (2001); Goetzmann et al. (2001)).

The rest of the paper is outlined as follows. In Section 2, I provide an overview of the OPRE market and discuss the return smoothing process. In Section 3, I describe the model which provides insight into the existence and protection against wealth transfer risks in open-end funds. In Section 4, I discuss the data and the variables of interest. Section 5 provides the results from my empirical analysis and I conclude in Section 6.

2 Real Estate Funds and Smoothed Returns

2.1 U.S. Open-end Private Real Estate Funds

Commercial Real Estate (CRE) covers all real estate product types other than single family homes and is fundamentally the way institutional investors invest in real estate.[5] By extrapolating previous estimates, I estimate the stock value of U.S. CRE to be around $30.0 trillion as of the fourth quarter 2015 (see Geltner (2015) and Florance et al. (2010)). While CRE has historically been a significant sector in the overall economy, its importance as an investment class has grown dramatically over the last 35 years. The average target allocation for institutional investors has grown from around 2% in the early 1980s to between 10% and 12% in 2018. Additionally, allocations are expected to continue increasing.[6]

There are a number of ways institutional investors invest in CRE: direct investment, separate accounts, joint ventures, club deals, comingled funds, and publicly traded REITs. The first five methods of investing in CRE are different ways of investing in the private real estate market while the last is the primary way to invest in the public real estate market,

[5]More specifically, Institutional Real Estate, Inc defines commercial real estate to be, "Buildings or land intended to generate a profit for investors, either from rental income or capital gain. Types of commercial real estate include office buildings, retail properties, industrial properties, apartments and hotels, as well as specialty niche property categories such as healthcare, student housing, senior housing, self-storage, data centers and farmland."

[6]Pension Real Estate Association (PREA) Investment Intentions Survey 2017.

which has a market capitalization of around $1 trillion. My analysis focuses on return predictability and shareholder runs in U.S. OPRE funds, which are a subset of commingled funds.

OPRE funds have a combination of characteristics similar to funds in more traditional asset classes. They are open to issuing and redeeming shares on a regular basis (quarterly) at reported Net Asset Values (NAVs), similar to open-end mutual funds and hedge funds. Fund NAVs are based on the appraised values of their underlying assets. Similar to hedge funds, they have both non-discretionary liquidity restrictions (redemption notification periods, lockup periods, and subscription intervals) as well as discretionary liquidity restrictions (gates). However, different than hedge funds, they also implement discretionary liquidity restrictions on capital entering the fund as well, similar to private equity funds. Because they have discretion on how much capital can enter or leave the fund in a given period, funds often have queues to either enter or leave the fund. Testing the effects of return smoothing on shareholder run incentives requires accurate queue measurements, as provided by OPRE funds. Lastly, they invest in real assets and actively manage the operations of the those assets similar to other private equity funds.

2.2 Return Smoothing

An extensive literature argues that valuation estimates are regularly stale for assets which trade infrequently (see Getmansky et al. (2004), Geltner (1997), and Quan and Quigley (1989), among others).[7] Econometric models suggest that reported returns follow autoregressive integrated moving average (ARIMA) processes of the true economic returns. Getmansky et al. (2004) suggest that reported returns (r_t^R) are simply a weighted average of lagged economic returns (r_t^E) where θ_j represents the weight given to the economic return at the j^{th} lag as shown in Equation 1.[8] Consistent with the intuition behind Equation 1, there are two primary information sets which could be used to predict future fund returns, and

[7]See Barkham and Geltner (1995), Blundell and Ward (1987), Bond and Hwang (2007), Brown (1991), Case and Shiller (1989), Childs et al. (2002), Fisher et al. (1994), Fisher and Geltner (2000), Geltner (1991), Geltner (1993a), Geltner (1993b), MacGregor and Nanthakumaran (1992), Quan and Quigley (1989), Quan and Quigley (1991), Ross and Zisler (1991) for theoretical and empirical analysis on return smoothing in real estate returns.

[8]While this model is for valuation estimates in general, similar models have been proposed specifically for the real estate market as well (see Geltner (1991) and Geltner (1993a)).

thus two ways in which investors could exploit buy-and-hold investors. First, investors could use prior macroeconomic return information to decide when to invest in an index of open-end funds (time-series strategy). Second, investors could use prior fund return information to decide which funds to invest in (cross-sectional strategy).

$$r_t^R = \theta_0 r_t^E + \theta_1 r_{t-1}^E + \cdots + \theta_k r_{t-k}^E \quad (1)$$

$$\theta_j \epsilon \left[0, 1\right], \; j = 0, \ldots, k \quad (2)$$

and

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \quad (3)$$

Stale pricing strategies are based on the assumption that economic returns are slowly incorporated into asset and fund returns. An important aspect of this assumption is that aggregate level returns are more predictable than asset returns. The fundamental reason reported returns are smoothed and predictable is that valuation experts are unable to determine how general, market-wide pricing movements affect individual assets. This is, however, less true at the aggregate level where idiosyncratic price movements become less relevant. Geltner (1997) provides further explanation on how aggregate level price movements are more predictable from macroeconomic shocks than are fund or asset values. Additionally, regardless of whether higher returns are due to luck, skill, or a greater risk exposure, those funds which have higher current period returns are more likely to have higher future returns simply due to the appraisal smoothing process.

3 Theoretical Model

3.1 Setup

I create a two-period model in order to formalize the ways stale pricing influences both investor and fund behavior. The model additionally provides intuition into how discretionary liquidity restrictions and liquidity buffers jointly influence incentives. In period 0, the open-end fund is created and assets are purchased at their true, economic values as shown in Equation 4. In period 1, the economic values of the assets purchased in period 0 are unobservable. After observing the reported returns from period 1, investors are able to submit subscription or redemption requests. The amount of capital either coming into or out of the fund in period 1 is the fund flow, FF_1, and is a percentage of the period 1 pre fund flow net asset value, $NAV_{1,a}$. The fund subsequently purchases or sells assets based upon the fund flows. The post fund flow net asset value, $NAV_{1,b}$, incorporates the values of the assets sold or purchased. In period 2, the fund is liquidated and all assets are sold for their true economic values, NAV_2^E, where E denotes the economic value, or return, of the underlying assets. There are two investors in the fund, a market-timing investor, MT, and a buy-and-hold investor, BH. As shown in Equation 5, the NAV of the fund is equal to the combined investments of the market-timing and a buy-and-hold investors in the fund during the period. Throughout the life of the fund, the market-timing investor has a percentage, ω_t, of his wealth, Π_t^{MT}, allocated to the fund while the rest of his wealth is invested in cash which provides a consistent risk-free return, R^f, of 1. The buy-and-hold investor maintains his entire wealth in the fund in each period until it is liquidated in period 2. The assumption that buy-and-hold investors exist is supported in the data. In addition to viewing investor-specific entries and exits from the funds, Table **??** in the Appendix provides additional evidence of their existence.

$$NAV_0^{Fund} = NAV_0^E \tag{4}$$

$$NAV_0^{Fund} = \omega_0 \Pi_0^{MT} + \Pi_0^{BH} \tag{5}$$

$$NAV_{1,a}^{Fund} = NAV_0^{Fund} R_1^{Fund} \tag{6}$$

$$NAV_{1,b}^{Fund} = NAV_0^{Fund} R_1^{Fund} (1 + FF_1) \tag{7}$$

$$NAV_2^{Fund} = NAV_0^{Fund} R_1^{Fund} R_2^{Fund} = NAV_0^{Fund} R_1^E R_2^E \tag{8}$$

The underlying assets are illiquid because they have they have the following characteristics. First, they are illiquid because they typically trade infrequently. In the model, period 1 is a period of illiquidity where no other participants are not trading except as requested by the fund. Therefore, the fund must complete fair value estimates of the assets in order to report an NAV upon which securities can be issued and redeemed.[9] The model assumes that $NAV_{1,a}$ is stale and that the level of staleness is represented by Θ as shown in Equation 9. Second, because the assets are illiquid, large capital flows into or out of the market will have a temporary price impact. This is represented in Equation 10 which reflects a transaction cost which is a function of the fund flows. This equation implies that $\frac{\delta P}{\delta Q} > 0$ and $\frac{\delta^2 P}{\delta Q^2} > 0$, where P represents the price to purchase and sell assets in the market. It is assumed that the assets do not provide dividends. It is also assumed that normal market participants are actively trading in period 2 which is what allows the assets to be sold at their true economic value. Lastly, the expected economic return for period 2 is 1. Because I am focusing on the effect of stale prices on investor and managerial behavior, investors act as if they are unaware of the price impact their investment or redemption requests will have on the returns to the fund.

$$R_1^{Fund} = \left(R_1^E\right)^{(1-\Theta)}, \; where \, 0 < \Theta < 1 \tag{9}$$

$$Transaction\, Cost_1 = \psi \left(FF_1\right)^2, \; where \, 0 < \psi < 1 \tag{10}$$

3.2 Investor Maximization

This analysis focuses on the way market-timing investors react to stale NAVs. The market-timing investor chooses his portfolio allocations in period 1. His allocation to the open-end fund in period 1 is denoted as, ω_1. As noted in Equation 11, the dollar fund flow equals the change in the market-timing investors percent allocation, $\omega_{1,b} - \omega_{1,a}$, of his period 1 wealth in the fund where $\omega_{1,a}$ represents the pre fund flow allocation and $\omega_{1,b}$ represents the post fund

[9]The Financial Accounting Standards Board (FASB) regulates the valuation of both liquid and illiquid assets through Accounting Standards Codification (ASC) 820 - "Fair Value Measurement." According to FASB ASC 820, the fair value of an asset is "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date."

flow allocation. An adjustment cost is incurred by the market-timing investor for adjusting his allocation in the fund, as represented by Equation 12.

$$NAV_{1,a}FF_1 = \Pi_1^{MT}\left(\omega_{1,b} - \omega_{1,a}\right) \tag{11}$$

$$Adjustment\ Cost_1 = \frac{\gamma}{2}\left(\omega_{1,b} - \omega_{1,a}\right)^2 \tag{12}$$

The period 2 return for the portfolio held by the market-timing investor is the weighted average return of the open-end fund return and the risk-free rate less any adjustment costs. This is represented by Equation 13. The reported return of the fund in period 1 equals the reported NAV in period 1 divided by the NAV in period 0. Additionally, the reported return to the fund in period 2 equals the NAV of the fund in period 2 divided by the reported NAV of the fund in period 1, as shown in Equation 15.

$$R_2^{MT} = \omega_{1,b}R_2^{Fund} + \left(1 - \omega_{1,b}\right)R^f - \frac{\gamma}{2}\left(\omega_{1,b} - \omega_{1,a}\right)^2 \tag{13}$$

$$R_1^{Fund} = \frac{NAV_1^{Fund}}{NAV_0^{Fund}} \tag{14}$$

$$R_2^{Fund} = \frac{NAV_2^{Fund}}{NAV_{1,b}^{Fund}} \tag{15}$$

The market-timing investor is interested in maximizing his period 2 return and his choice variable is his allocation in the fund, $\omega_{1,b}$. As derived in Section A.5 of the Appendix, the optimal allocation for the market-timing investor is given by Equation 17. The economic interpretation from this equation is that the optimal allocation is chosen such that the marginal cost of adjusting the fund allocation from $\omega_{1,a}$ to $\omega_{1,b}$ equals the marginal benefit from the increased expected return associated with adjusting the fund allocation. By combining the optimal allocation with Equation 11, I obtain the optimal fund flow as shown in Equation 18. The proof of this derivation is provided in Section A.1 of the Appendix.

$$\max_{\{\omega_{1,b}\}} \gamma_1 E_1\left(R_2^{MT}\right) - E_1\left(\frac{\gamma_2}{2}\left(\omega_{1,b} - \omega_{1,a}\right)^2\right) \tag{16}$$

$$\omega_{1,b} = \omega_{1,a} + E_1\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{17}$$

$$FF_1 = \frac{\Pi_1^{MT}}{NAV_{1,a}} E_1\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{18}$$

The overall wealth transfer from existing investors to incoming investors is represented by Equation 19 while the wealth transfer experienced by the buy-and-hold investor depends on his pre fund flow ownership in the fund, as shown in Equation 20. The wealth transfer from the buy-and-hold investor can be further derived into Equation 21 as shown in Section A.2. This assumes the market-timing investor is able to contribute or withdraw as much of his funds as he would like without liquidity restriction constraints. Two important results are represented in Equation 21. First, wealth transfers increase with the staleness in the reported returns. Second, wealth transfers increase with the size in the economic return experienced in period 1. These results lead to **Predictions 1** and **2** listed below.

$$E_1\left(WT\right) = E_1\left(NAV_0\left(R_1^E - R_1^{Fund}\right)FF_1\right) \tag{19}$$

$$E_1\left(WT^{BH}\right) = E_1\left(\frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0\left(R_1^E - R_1^{Fund}\right)FF_1\right) \tag{20}$$

$$E_1\left(WT^{BH}\right) = E_1\left(\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{NAV_1}\frac{\gamma_{10}}{\gamma_0}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{21}$$

Prediction 1. *Investors will attempt to increase their holdings in funds after positive macroeconomic shocks.*

Prediction 2. *Investors will attempt to increase their holdings in those funds with the highest past performance.*

3.3 Fund Maximization (liquidity restrictions)

This analysis focuses on the way in which the fund responds to management fee incentives. In this analysis, the manager has discretion over the amount of the fund flow request fulfilled.

This is represented by Equation 22 where DFF_1 represents the percent of the total requested fund flow, TFF_1, that the manager chooses to fulfill. The utility function of the manager has three components. One component reflects the contemporaneous fee from managing the assets, another reflects the effect of any price impact on future fees, and lastly one that reflects the effect of not fulfilling investor subscription or redemption requests on future fees. While this is a three-period model, the last two components reflect fees associated with either continuing the fund or starting a new fund. The fund is interested in maximizing it's lifetime earnings of fees. After observing the fund flow requests, the fund selects the optimal DFF_1 value which will maximize its utility function as shown in Equation 23. As derived in Section A.5 of the Appendix, the optimal percentage of the fund flow accepted is given by Equation 24. The economic interpretation of this equilibrium is that the optimal allocation is the one where the marginal cost to future fees from impacting prices now equals the marginal combined benefit from contemporaneous fees and future fees from fulfilling investor requests. It is important to note that the impact of the contemporaneous fees reverses when the fund flow requests are redemptive. During a period of positive fund flows, fulfilling a greater percentage of the requests has a marginal benefit while during a period of negative flows it has a marginal cost.

$$DFF_1 = \frac{FF_1}{TFF_1} \tag{22}$$

$$\max_{\{DFF_1\}} E_1 \left(\gamma_3 NAV_{1,b} - \frac{\gamma_4}{2} \psi \left(FF_1 \right)^2 - \gamma_5 \left(TFF_1 - FF_1 \right)^2 \right) \tag{23}$$

$$DFF_1 = \frac{\gamma_1 NAV_{1,a} + \gamma_3 TFF_1}{E_1 \left(\gamma_2 \psi + \gamma_3 \right) TFF_1} \tag{24}$$

After considering the incentives of the fund to potentially limit the amount of capital either coming into or out of the fund in period 1, the fund flow is jointly determined as shown in Equation 25. This value can be further substituted into Equation 20 to obtain the expected wealth transfer of the buy-and-hold investor, represented in Equation 26. Equation 26 shows us that as the illiquidity in the underlying assets increases, so does the staleness, Θ, *as well as* ,the price impact, ψ. Therefore, the illiquidity has somewhat of an offsetting effects in the wealth transfer function. It creates both the wealth transfer risk while deterring it at the same time. **Prediction 3** provides a hypothesis consistent with these results.

$$FF_1 = \frac{\Pi_1^{MT}}{NAV_1}\left(\frac{\gamma_{10}}{\gamma_0}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)\frac{\gamma_1 NAV_{1,a} TFF_1 + \gamma_3\left(TFF_1\right)^2}{E_1\left(\gamma_2\psi + \gamma_3\right)\left(TFF_1\right)^2} \tag{25}$$

$$E_1\left(WT^{BH}\right) = \left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{NAV_1}\left(\frac{\gamma_{10}}{\gamma_0}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)\cdot \frac{\gamma_1 NAV_{1,a} TFF_1 + \gamma_3\left(TFF_1\right)^2}{E_1\left(\gamma_2\psi + \gamma_3\right)\left(TFF_1\right)^2} \tag{26}$$

Prediction 3. *Managers will limit capital flows the most at those times and in those funds where NAV-timing strategies appear the most profitable.*

3.4 Fund Maximization (liquidity buffers)

This analysis focuses on the effect of using liquidity buffers on wealth transfer outcomes. The choice variables for the market-timing investor and fund remain the same. The only difference is that any and all fund flow requests are fulfilled using the liquidity buffer. As such, I remove the second component of fund's utility maximization equation, as shown in Equation 28. The new optimal DFF_1 is shown in Equation 29 and the proof is in Section A.8. The updated optimal approved fund flow is strictly larger than the one where no liquidity buffer is used. Similarly, the wealth transfer created when the fund uses a liquidity buffer is strictly larger than the wealth transfer when no liquidity buffer is used. I provide a proof and derivation of this in Section A.8.

The result that wealth transfers are larger when liquidity buffers are used provides unique insights. First, funds create wealth transfers that would not otherwise exist when they use liquidity buffers and NAVs are stale. These wealth transfers increase strategic complementarities and first-mover advantages which can destabilize fund and asset markets. In all, this evidence suggests that the tools most commonly used to stabilize markets may have be counterproductive and backfire in some situations. This evidence also supports **Prediction 4** listed below.

$$\max_{\{DFF_1\}} E_1\left(\gamma_3 NAV_{1,b} - \frac{\gamma_4}{2}\psi\left(FF_1\right)^2 - \gamma_5\left(TFF_1 - FF_1\right)^2\right) \tag{27}$$

$$\max_{\left\{DFF_1^{LB}\right\}} E_1\left(\gamma_1 NAV_{1,a}\left(1 + TFF_1 DFF_1^{LB}\right) - \frac{\gamma_3}{2}\left(TFF_1 - TFF_1 DFF_1^{LB}\right)^2\right) \tag{28}$$

$$DFF_1^{LB} = \frac{\gamma_1 NAV_{1,a} + \gamma_3 TFF_1}{\gamma_3 TFF_1} \tag{29}$$

$$DFF_1^{LB} \gg DFF_1 \tag{30}$$

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1^{LB} \tag{31}$$

$$E_1\left(WT^{BH,LB}\right) \gg E_1\left(WT^{BH}\right) \tag{32}$$

Prediction 4. *Funds which use liquidity buffers instead of liquidity restrictions are more susceptible to runs and ultimate failure.*

4 Data and Summary Statistics

The OPRE data come from NCREIF and Townsend.[10] [11] This paper is the first to combine the property-level information from the NCREIF NPI database with the fund-level information from the NCREIF NFI–OE database. Additionally, it is the first to add investor-level information data from Townsend. The NPI is NCREIF's flagship index which tracks the performance of institutional real estate markets at the property-level in the United States. It represents more than $470 billion in 7,225 investment properties as of the fourth quarter 2015. All of the fund-level data except for queue information comes the NCREIF NFI-OE.

[10] NCREIF is the leading collector of institutional real estate investment information and provides the primary industry benchmark for institutional investors and represents roughly $500 billion in assets under management as of the fourth quarter 2015.

[11] The Townsend Group is the largest real estate advisor to institutional investors in the world with roughly $270 billion in assets under management as of the fourth quarter 2015.

The queue data and investor-level data come from Townsend. The empirical analysis is carried out from 2004 through 2015 because the queue data is unavailable prior to 2004. The sample is survivorship bias free and consists of 1,361 fund-quarter observations over 48 quarters for 34 total funds. There is a minimum of 21 funds in each quarter. As of the fourth quarter 2015, the sample represents 34 funds with approximately 3,500 investment properties and $250 billion in Assets Under Management (AUM).

The primary response variables of interest are quarterly values of the Net Excess Return, Fund Flow, Net Queue, and Total Capital Flow. The explanatory variables of interest are quarterly values for the lagged Net Excess Returns, and Net Queues. Additionally, I use the following factor models to obtain portfolio α estimates. The NCREIF NFI–OE and FTSE NAREIT Indices are respectively used as proxies for the private and public CRE market factors. Quarterly 5-factor Model, Q-factor Model, and REIT Q-factor Model (see Fama and French (2015), Hou et al. (2015), and Bond and Xue (2017)) factors are obtained by taking the difference in the compounded monthly values from the respective portfolios. The factor model values were obtained from Kenneth French's website, Lu Zhang, and Chen Xue respectively. The 3-Month Treasury Bill rate comes from the Federal Research Economic Data (FRED) and proxies for the risk-free rate.

Subscription and redemption queue data is a combination of three sources provided by Townsend - data I hand collected from quarterly reports, data from the department working directly with OPRE funds, and the department overseeing the general data collection. Where available, I use the hand collected data which ranges from 2008 through 2015. When quarterly reports either did not report queue values or were unavailable, I supplement the hand collected data with data from the department working directly with OPRE funds and then from the department responsible for overall data collection. In order to address the existence of minor inconsistencies between the datasets, I complete robustness tests by rearranging the order of dataset priorities and redo the empirical analysis. The results are consistent.

I define each of the response and explanatory variables in Section 5 below. Additionally, I winsorize each of the variables except for the Net Excess Returns and the Indices returns at the 5th and 95th percentiles. I winsorize the Net Excess Returns variable at the 1st and

99th percentiles. Table 1 provides the summary statistics for each of these variables.

5 Empirical Results

5.1 Return Predictability

I first examine the predictability of OPRE fund returns. Real estate funds invest in illiquid assets which are difficult to value. Therefore, their returns should be predictable from both public market returns as well as from fund returns themselves (see Getmansky et al. (2004)).[12]

Figure 1 displays a public equities index, a public real estate index, and a private real estate market index - the S&P 500, the FTSE NAREIT, and the NFI-OE Indices respectively. The figure shows that the NFI-OE Index is much smoother and lags both public market indices by approximately four quarters. This supports the theory presented by Getmansky et al. (2004) and suggests that reported OPRE fund returns may be weighted averages of their lagged, true economic returns and that OPRE reported returns are predictable.

Table 2 empirically examines the relationships between OPRE fund returns and lagged public market index returns as well as lagged fund returns. Columns (1) and (2) demonstrate the relationship between fund returns and lagged market returns. Column (3) demonstrates the relation between current and lagged fund returns. This evidence additionally supports the claim that OPRE fund returns are predictable, which would allow investors to create market-timing strategies without restrictions. The rest of my analysis focuses on OPRE funds.

5.2 NAV-timing Returns

I next evaluate the profitability of implementing two different market-timing strategies based on reported returns. The first strategy is based on lagged public market returns and invests in either an index of the funds or the risk free rate. The second strategy is based on lagged fund returns and invests in a portfolio of the recent top performing funds. It is possible that while

[12] Giliberto (1990), Gyourko and Keim (1992), Myer and Webb (1993), Barkham and Geltner (1995), Myer and Webb (1993), and Quan and Titman (1999) provide evidence that private real estate market returns are correlated with lagged public market returns at the market-level and highly auto-correlated. Liu and Mei (1992), Mei and Liu (1994), Cooper et al. (2000), Nelling and Gyourko (1998), and Ling et al. (2000) provide evidence that public real estate market returns are predictable from past public real estate market returns.

fund returns are predictable, the profitability of trading on this would be either insignificant or captured by a traditional factor model. Wealth transfer risks are only significant to the extent these strategies are also significant. Equation 33 provides the base regression equation used in this analysis where r^p refers to the excess return of the portfolio, X refers to the risk factors in the corresponding factor model, and α refers to the average return of the portfolio unexplained by the factor model.

$$r^p = \alpha + \beta X + \varepsilon \tag{33}$$

Table 3 reports the return performance achieved by implementing the first strategy with no trading constraints. Panel A reports the alpha values of the portfolio returns in excess of the risk-free rate while Panel B reflects the portfolio returns in excess of the NFI-OE return. The Long portfolio invests in the NFI-OE Index in every quarter except for those preceded by a four quarter cumulative FTSE NAREIT Index return is less than 0. The Long portfolio invests in the 3-month T-bill in every quarter it is not invested in the NFI-OE Index. The Short portfolio invests in the 3-month T-bill in every quarter except for those quarters preceded by a four quarter cumulative FTSE NAREIT Index return is less than 0. The Short portfolio invests in the NFI-OE Index in every quarter it is not invested in the 3-month T-bill. The Long-Short portfolio is created by taking the difference in the returns between the Long and Short portfolios. It is important to note that it is not possible to short OPRE funds. The purpose of analyzing the Long-Short portfolio is to isolate the effect of the return predictability on return performance and to compare the performance between two strategies that are mutually exclusive on the dimension of predictability.

Row (1) reports the results obtained by regressing the Long portfolio excess returns on different factor models. Rows (2) and (3) report the results obtained by regressing the the Short and Long-Short Portfolio excess returns on the risk factors respectively. Column (1) provides the mean excess return for each of the three portfolios over the entire sample. Column (2) contains the primary regressions of interest and presents the alphas obtained by regressing the excess portfolio returns on the NFI-OE Index. Columns (3), (4), (5), (6), and (7) present the NAREIT, REIT Q-factor, and 5-factor alphas for the three portfolios respectively. Based on the results in Table 3, the Strategy-Complement portfolio produced private real estate market factor and 5-factor model alphas of 19.1% and 16.5% respectively.

Table 4 reports the return performance achieved by implementing the second market-timing strategy with no trading constraints. Figure 2 provides a graphical representation of the raw return results. Panel A reports the alpha values of the portfolio returns in excess of the risk-free rate while Panel B reflects the portfolio returns in excess of the NFI-OE return. Each quarter, funds are assigned to one of five portfolios based on prior four quarter cumulative return and quintile breakpoints. Portfolio returns are the value-weighted returns of all funds within a given portfolio in the quarter after allocations are made. Portfolio assignments are made quarterly. The $5-1$ portfolio is created by taking the difference in the returns between Portfolio 5 and Portfolio 1. The purpose of analyzing the $5-1$ Portfolio return is to, similarly, isolate the effect of the return predictability on a cross-section of portfolio returns.

Column (1) provides the mean excess return for each of the three portfolios over the entire sample. Column (2) contains the primary regressions of interest and presents the alphas obtained by regressing the excess portfolio returns on the NFI-OE Index. Columns (3), (4), (5), (6), and (7) present the NAREIT, REIT Q-factor, and 5-factor alphas for the three portfolios respectively. Annualized NFI-OE Index alpha coefficients and statistical significance increase monotonically from -3.9% to 1.8% for Portfolios 1 to 5. Additionally, the alphas from Portfolio $5-1$ are economically and statistically significant at 5.9% and 3.2% for the NFI-OE and 5-factor alphas respectively.

The results from Tables 3 and 4 suggest that without mechanisms to do deter them, market-timing strategies would be profitable and transfer significant wealth from buy-and-hold investors. They also provide evidence that both time-series and cross-sectional predictability are important in explaining the predictability that smoothing has on achievable returns.

5.3 Investor and Fund Behavior

I next examine the behavior of OPRE investors to see if it is consistent with the NAV-timing strategies discussed and **Predictions 1** and **2**. This analysis looks at the relation between prior fund returns and the total capital trying to either enter or leave the fund in a given quarter. The total capital trying to enter or leave a fund (Total Capital Flow) is calculated as the actual amount entering the fund (Fund Flow) plus the amount requested but unable to enter the fund (Net Queue). Fund Flow, Net Queue, and Total Flow are calculated as shown in Equations 34, 35, and 36.

$$Fund\ Flow_{i,t} = \left[NAV_{i,t} - NAV_{i,t-1} \cdot (1 + r_{i,t})\right] / NAV_{i,t-1} \tag{34}$$

$$Net\ Queue_{i,t} = \left[Subscription\ Queue_{i,t} - Redemption\ Queue_{i,t}\right] / NAV_{i,t-1} \tag{35}$$

$$Total\ Flow_{i,t} = Fund\ Flow_{i,t} + Net\ Queue_{i,t} \tag{36}$$

Table 5, provides the results of regressing investor flows on lagged public market returns as well as prior fund returns. Columns (1) and (2) provide the results of regressing Total Flows on lagged NAREIT FTSE returns while columns (3) through (6) show the results of regressing Total Flows on lagged fund returns. Consistent with the basis for both the time-series and cross-sectional strategies, the explanatory variable returns are cumulative returns over four quarters - from one to five lags. The standard errors are robust, Newey-West standard errors with four lags and are clustered by fund and time. As shown, both prior market returns as well as prior fund returns are significant in explaining investor flow variation. A one standard deviation increase in lagged four quarter NAREIT and fund returns leads to approximate 0.17 and 0.45 standard deviation increases in the Total Flow respectively. These results provide evidence that without fund intervention, wealth transfers from buy-and-holders would exist.

I next analyze the behavior of funds in fulfilling subscription and redemption requests and

Prediction 3. The way funds fulfill subscription and redemption requests determines the extent to which wealth is transferred. It is possible that funds issue and redeem shares in a way that is unrelated to NAV-timing strategies.

Figure 3 plots the average net queue size as a percentage of NAV for funds within different performance quintiles based on the cumulative return for the prior four quarters. Table 6 presents the empirical results of the relation between Net Queues and prior public market and fund returns. Columns (1) and (2) provide the results regressing Net Queues on lagged NAREIT FTSE returns while columns (3) through (6) show the results of regressing Net Queues on lagged fund returns. Explanatory variable returns are similarly cumulative returns over prior four quarters in this analysis. As shown, Net Queues are related to both prior public market returns as well as fund returns. A one standard deviation increase in lagged four quarter NAREIT and fund returns leads to approximate 0.16 and 0.51 standard deviation increases in the Total Flow respectively. This evidence suggests that investor queues significantly decrease the ability market-timing investors to exploit the predictability in OPRE fund returns.

5.4 Realizable Market-timing Returns

My next analysis looks at the returns investors could achieve by investing in a NAV-timing strategy. In doing so, I analyze the effect of both non-discretionary liquidity restrictions as well as discretionary liquidity restrictions on timing performance. Non-discretionary liquidity restrictions refer to those liquidity restrictions which are set out in the articles of incorporation at the inception of the fund and include lockup periods, notification periods, and subscription intervals. Discretionary liquidity restrictions refer to those liquidity restrictions over which the manager has full discretion on implementing and includes gates and queues.

5.4.1 Non-discretionary Liquidity Restrictions

The results from my analysis on the effect of non-discretionary liquidity restrictions in deterring market-timing are reported in Tables 7 and 8. Table 7 shows that the results to timing when to enter and leave the NFI-OE index are not affected by non-discretionary liquidity restrictions. This is evidence that the subscription notification and lockup periods are non-binding. Another interpretation of this is that the predictability of the market as a whole is longer than the liquidity restrictions imposed. Table 8, however, shows that the results from timing which funds to enter and leave is entirely removed by non-discretionary liquidity restrictions. This is evidence that the subscription notification and lockup periods are binding with this strategy and that the liquidity restrictions are longer than the relative predictability of funds.

5.4.2 Discretionary Liquidity Restrictions

I obtain queue-adjusted return estimates in order to evaluate the returns investors could actually achieve by implementing timing strategies after waiting in the queue. If return predictability lasts longer than the time in the queue, then NAV-timing strategies create viable wealth transfer opportunities. In contrast, wealth transfer opportunities are are removed if queues durations last longer than return predictability.

The results from my analysis on the queue-adjusted returns are reported in Tables 9 and 10. As shown in Table 9, the queue-adjusted returns from timing when to enter and leave the OPRE market are approximately half of those from the unconstrained analysis. In contrast, the returns from switching between funds was completely eliminated after considering the queues, as shown in Table 10. This evidence suggests that a secondary benefit of fund enacting queues in order to limit pushing market prices is that they deter wealth transfers from buy-and-hold investors to market-timing investors.

I calculate queue-adjusted returns in the following ways. For the first strategy of investing in the NFI-OE index and the risk-free return, I obtain quarterly capital flow and queue estimates for the index based on the weighted-average fund flows and queues from the individual funds. I then obtain estimates for the total capital interested in either entering or leaving the index by adding these together each quarter. Absorption estimates are obtained by dividing the capital flow estimates by the total capital interested estimates. NFI-OE allocations in the Long portfolio are calculated as the lagged NFI-OE allocations plus the 3-month T-bill allocations times the absorption rates. Returns to Long and Short portfolios are then determined as the returns of the NFI-OE Index and the 3-month T-bill times their respective allocations in the funds.

For the second strategy of investing in quintiles, I obtain absorption estimates for each quintile based on the method discussed in the first strategy. However, fund allocations in each portfolio are obtained slightly differently for this strategy. Each fund is allocated to a specific quintile portfolio based on prior returns and the allocations of that fund into different quintiles adjusts over time based on whether the fund remains in the quintile performance or is reallocated. Allocation adjustments are made based on the absorption values calculated such that a fund can be allocated across different funds in a given quarter, but the overall fund allocations add up to one. Quintile portfolio returns are obtained by calculating the allocations of each fund in the given portfolio during the quarter times the weighted return of that fund.

It is important to note that queue-adjusted return estimates are dependent upon the desired entry and exit from the funds. For example, the queue-adjusted return of a buy-and-hold investor would simply be the reported returns of the funds. Queue adjustments only become relevant to the extent that investment strategies suggest either entering or leaving the fund and queues exist at that time.

5.5 Liquidity Buffers

As shown in the Table 1, cash holdings make up a small portion of the assets held by these funds. The average cash holdings is less than 5%. This suggests that OPRE funds do not actively use cash buffers to accommodate investor flows, which is in stark contrast to GORE funds. Additionally, OPRE funds minimize the negative impact that cash buffers have on expected returns by keeping cash reserves low.

GORE funds have existed since 1959 and are regulated by the German Investment Companies Act of 1969. At the time of the GFC in 2008, the market size of these funds was roughly $140 B. As mentioned, historically the primary mechanism GORE funds used to deter shareholder runs was to use large cash buffers. While all of the OPRE funds remained active and solvent both during and after the GFC, a third of the GORE funds were required to suspend redemptions by regulators and 18 were liquidated. This evidence suggests that liquidity buffers do a poor job deterring shareholder runs when the return predictability is not due to shareholder coordination problems. In fact, liquidity buffers can increase shareholder run incentives when combined with redemption suspensions. By combining liquidity buffers with discretionary liquidity restriction, funds decrease the size of the liquidity restriction and make it easier for investors to reallocate capital and implement an NAV-timing strategy.

6 Conclusion

This paper has three main insights. First, open-end funds create predictable returns and market-timing risks when they invest in illiquid, difficult to value assets. Next, managers protect against these risks by limiting capital flows into and out of the funds in order to prevent fire sales and fire purchases. Greater illiquidity in the underling assets means greater return predictability, but it also means taking longer to transact in the underlying marketplace without pushing prices. Lastly, funds reintroduce wealth transfer and shareholder-run risks when funds use liquid assets to meet redemptions, instead of suspending them. Using liquid assets makes it easier for investors to enter and leave the fund and implement timing strategies.

The findings in this paper are important to both practitioners and policy makers. For practitioners, my findings suggest that funds should be cautious about using liquidity buffers especially if they have the ability to suspend issuing and redeeming shares. This is especially the case after significantly negative economic shocks. A better approach would be to suspend issuing and redeeming shares so as to to keep a roughly constant mix of liquid and illiquid assets. This allows the manager to transact in the underlying market without pushing prices and slows down the process for both entering and leaving the fund, deterring the ability of investors to exploit the return predictability.

Next, this evidence suggests that investors would benefit from increased transparency and standardization in the reporting of unfulfilled commitments and redemptions. It also suggests that investors should evaluate queue-adjusted returns when making investment decisions. No adjustment is necessary for buy-and-hold investors. However, if an investor anticipates leaving the fund when liquidity is low, this should be taken into consideration. Additional research on the interacting effects that liquidity buffers have on coordination failures and other forms of predictability seems warranted.

For regulators, preventing funds from suspending the redemption and issuance of shares may not be optimal. Requiring mutual funds to fulfill redemptions over a short window could have the unintended consequence of imposing financial fragility onto the fund. Consistent with this, if regulators counter these consequences by requiring mutual funds to limit their exposure to illiquid assets, it could push the liquidity transformation services they provide into more opaque intermediaries, such as hedge funds. This could decrease the overall transparency of the service and end up doing more harm than good. A more optimal solution may be to deregulate the liquidity requirements currently binding mutual funds.

Table 1

Summary Statistics

This table presents summary statistics for U.S. open-end private real estate (OPRE) funds from January 2004 through December 2015. For the OPRE funds, Excess Net Returns are the quarterly net of fee returns reported by the funds less the 3-month T-bill interest rate. Fund Flow is the capital flow into the fund during a given quarter as a percent of the lagged total net assets. It is calculated as: $FF_{i,t} = \left[TNA_{i,t} - (TNA_{i,t-1} \cdot R_{i,t})\right] / TNA_{i,t-1}$. Net Queue is the difference between the unfulfilled capital commitments (investment queue) and the unfulfilled redemption requests (redemption queue) divided by the lagged total net assets. Total Capital Flow is defined as the sum of the Fund Flow and the Net Queue.

stats	Excess Net Return (Quarterly)	Fund Flow (% TNA)	Net Queue (% TNA)	Total Capital Flow (% TNA)	Cash Balance (% TNA)
mean	1.58	2.88	8.67	11.44	4.89
sd	4.47	6.76	19.44	22.91	3.71
min	-15.62	-9.59	-16.10	-17.83	0.84
p5	-9.88	-3.86	-16.10	-17.83	0.84
p10	-3.79	-2.26	-9.98	-11.91	1.25
p25	1.55	-0.51	0.00	-0.80	2.06
p50	2.73	0.50	1.75	5.17	3.64
p75	3.70	3.95	12.70	16.38	6.80
p90	4.84	12.92	34.10	43.98	10.95
p95	5.82	21.32	69.19	78.33	14.24
max	7.47	23.34	69.19	78.33	14.24

Table 2
Return Predictability

This table presents the results of my analysis on return predictability of U.S. Open-end Private Real Estate fund returns on lagged returns from 1980 through 2015. Columns (1) and (2) report the estimates from regressing fund returns on lagged public market returns while Columns (3) through (6) report the results of regressing fund returns on lagged fund returns with and without fund and time fixed effects. All returns are in excess of the 3-month T-bill interest rate. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_{i,t} = \beta_0 + \beta_1 r_{M,t-1} + \cdots + \beta_8 r_{M,t-8} + \varepsilon_{i,t}$$

$$r_{i,t} = \beta_0 + \beta_1 r_{i,t-1} + \cdots + \beta_4 r_{i,t-4} + \varepsilon_{i,t}$$

	Market	NAREIT Index	Fund Returns			
r_{t-1}	0.076**	0.085**	0.554***	0.540***	0.162***	0.137***
	(2.11)	(2.38)	(5.78)	(5.30)	(5.10)	(4.63)
r_{t-2}	0.087***	0.087***	0.215***	0.210***	0.131***	0.110***
	(3.10)	(3.93)	(4.32)	(4.02)	(3.77)	(3.06)
r_{t-3}	0.101***	0.107***	-0.038	-0.041	0.061	0.041
	(3.43)	(4.46)	(-0.77)	(-0.83)	(1.62)	(1.05)
r_{t-4}	0.103***	0.120***	-0.009	-0.020	0.195***	0.173***
	(3.72)	(5.37)	(-0.14)	(-0.30)	(3.65)	(3.21)
r_{t-5}	0.079***	0.086***				
	(3.06)	(3.95)				
r_{t-6}	0.054**	0.065***				
	(2.40)	(3.38)				
r_{t-7}	0.030	0.048**				
	(1.27)	(2.48)				
r_{t-8}	0.029	0.045***				
	(1.25)	(3.19)				
Fund f.e.	No	No	No	Yes	No	Yes
Time f.e.	No	No	No	No	Yes	Yes
N	3,222	3,222	3,222	3,222	3,222	3,222
R^2	0.23	0.36	0.47	0.48	0.71	0.72

Table 3
Time-Series NAV-timing Returns

This table presents the first of my results on the analysis of trading profitability of return predictability (without liquidity restrictions). Long returns are the those obtained by either investing in a value-weighted portfolio of the funds or the T-bill, depending on the recent returns observed in the public real estate market. Short returns are those obtained by taking the opposite investment position as the Long portfolio. Long-Short returns are those obtained by subtracting the Panel A reports the results of the portfolio returns less the 3-month T-bill while Panel B reports the results less the value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_t = \alpha + \beta\,(risk\ factors_t) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	2.569***	2.161***	2.715***	2.616***	48
	(12.30)	(13.21)	(12.60)	(11.96)	
Short	-1.045**	-2.161***	-0.961**	-1.086*	48
	(-2.24)	(-13.21)	(-2.07)	(-1.95)	
Long-Short	3.613***	4.323***	3.676***	3.703***	48
	(9.37)	(13.21)	(8.89)	(8.34)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	1.045**	2.161***	0.961**	1.086*	48
	(2.24)	(13.21)	(2.07)	(1.95)	
Short	-2.569***	-2.161***	-2.715***	-2.616***	48
	(-12.30)	(-13.21)	(-12.60)	(-11.96)	
Long-Short	3.613***	4.323***	3.676***	3.703***	48
	(9.37)	(13.21)	(8.89)	(8.34)	

Table 4

Cross-Sectional NAV-timing Results

This table presents the second of my results on the analysis of trading profitability from return predictability (without liquidity restrictions). Quintile portfolio returns are calculated as the value-weighted excess return of the funds within a given portfolio in the quarter after portfolios are created. Funds are allocated to quintile portfolios based on their four quarter relative prior performance. Panel A reports the results of the portfolio returns less the T-bill while Panel B reports the results less a value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_t = \alpha + \beta\,(risk\ factors_t) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	0.915	-0.996***	1.261*	1.045	48
	(1.18)	(-6.07)	(1.74)	(1.07)	
2	1.436**	-0.126	1.636***	1.474*	48
	(2.28)	(-1.05)	(2.63)	(1.92)	
3	1.700***	0.220*	1.996***	1.663**	48
	(2.84)	(1.74)	(3.61)	(2.35)	
4	1.780***	0.413***	1.941***	1.744***	48
	(3.22)	(4.62)	(3.54)	(2.75)	
5	1.936***	0.441***	2.143***	1.917***	48
	(3.17)	(2.64)	(3.38)	(2.91)	
5 - 1	1.020***	1.437***	0.882***	0.872**	48
	(3.75)	(4.66)	(3.35)	(2.21)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Quintile	Excess Return	NFI-OE Alpha	REIT-Factor Alpha	5-Factor Alpha	N
1	-0.608***	-0.996***	-0.493***	-0.485*	48
	(-3.06)	(-6.07)	(-2.62)	(-1.72)	
2	-0.088	-0.126	-0.117	-0.056	48
	(-1.11)	(-1.05)	(-1.35)	(-0.58)	
3	0.177**	0.220*	0.242***	0.133	48
	(2.06)	(1.74)	(2.96)	(1.39)	
4	0.257***	0.413***	0.187**	0.214*	48
	(2.69)	(4.62)	(2.20)	(1.83)	
5	0.412***	0.441***	0.389***	0.387***	48
	(3.32)	(2.64)	(2.81)	(2.61)	
5 - 1	1.020***	1.437***	0.882***	0.872**	48
	(3.75)	(4.66)	(3.35)	(2.21)	

Table 5

Investor Responses to Prior Returns

This table reports the results from my analysis on the behavior of investors. Total Capital Flow is defined as the sum of the Fund Flow and the Net Queue, all divided by the lagged NAV, $TCF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\, Queue_{i,t} - Redemption\, Queue_{i,t}] / TNA_{i,t-1}$. Excess Returns are calculated as the quarterly reported net of fee return less the 3-month T-bill rate. Columns (1) and (2) report the results of regressing the Total Capital Flow on the lagged cumulative four quarter NAREIT FTS Index return with no fixed effects and with fund fixed effects. Columns (3) and (4) report the results of regressing the Total Capital Flow on the lagged fund Excess Returns with time fixed effects and both fund and time fixed effects. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$Total\ Flow_{i,t} = \beta_0 + \beta_1 r_{NAREIT,t-1 \Rightarrow t-5} + \varepsilon_t$$

$$Total\ Flow_{i,t} = \beta_0 + \beta_1 r_{i,t-1 \Rightarrow t-5} + \varepsilon_t$$

$r_{NAREIT,t-1 \Rightarrow t-5}$	0.201***	0.210***				
	(3.24)	(3.11)				
$r_{i,t-1 \Rightarrow t-5}$			0.382***	0.334***	0.879***	0.404**
			(6.25)	(4.60)	(3.49)	(2.12)
Fund f.e.	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	Yes	Yes
Fixed Effects	None	Time	None	Time	Fund	Time & Fund
N	1,117	1,117	1,117	1,117	1,117	1,117
R^2	0.04	0.41	0.07	0.41	0.16	0.53

Table 6

Fund Responses to Capital Flows

This table reports the results from my analysis on the behavior of funds. Net Queue is defined as the difference in the subscription and redemption queues, all divided by the lagged Total Net Assets (TNA), $Net\ Queue_{i,t} = [Subscription\ Queue_{i,t} - Redemption\ Queue_{i,t}]/TNA_{i,t-1}$. Excess Returns are calculated as the quarterly reported net of fee return less the 3-month T-bill rate. Columns (1) and (2) report the results of regressing the Net Queue on the lagged cumulative four quarter NAREIT FTS Index return with no fixed effects and with fund fixed effects. Columns (3) and (4) report the results of regressing the Net Queues on the lagged fund Excess Returns with time fixed effects and both fund and time fixed effects. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and quarter. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$Net\ Queue_{i,t} = \beta_0 + \beta_1 r_{NAREIT,t-1 \Rightarrow t-5} + \varepsilon_t$$

$$Net\ Queue_{i,t} = \beta_0 + \beta_1 r_{i,t-1 \Rightarrow t-5} + \varepsilon_t$$

$r_{NAREIT,t-1 \Rightarrow t-5}$	0.157***	0.162***				
	(2.97)	(2.92)				
$r_{i,t-1 \Rightarrow t-5}$			0.320***	0.273***	0.815***	0.404**
			(5.92)	(4.42)	(3.67)	(2.47)
Fund f.e.	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	Yes	Yes
N	1,117	1,117	1,117	1,117	1,117	1,117
R^2	0.04	0.41	0.07	0.42	0.16	0.53

Table 7
Time-Series NAV-timing Returns (NDLRs)

This table presents the first of my results on the analysis of trading profitability from return predictability with non-discretionary liquidity restrictions (NDLRs). Long returns are the those obtained by either investing in a value-weighted portfolio of the funds or the T-bill, depending on the recent returns observed in the public real estate market. Short returns are those obtained by taking the opposite investment position as the Long portfolio. Long-Short returns are those obtained by subtracting the Panel A reports the results of the portfolio returns less the 3-month T-bill while Panel B reports the results less the value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_t = \alpha + \beta \left(risk\ factors_t \right) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	2.575***	2.168***	2.723***	2.625***	48
	(12.41)	(13.42)	(12.77)	(12.06)	
Short	-1.051**	-2.168***	-0.969**	-1.095**	48
	(-2.26)	(-13.42)	(-2.09)	(-1.98)	
Long-Short	3.626***	4.336***	3.692***	3.721***	48
	(9.46)	(13.42)	(9.01)	(8.49)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	1.051**	2.168***	0.969**	1.095**	48
	(2.26)	(13.42)	(2.09)	(1.98)	
Short	-2.575***	-2.168***	-2.723***	-2.625***	48
	(-12.41)	(-13.42)	(-12.77)	(-12.06)	
Long-Short	3.626***	4.336***	3.692***	3.721***	48
	(9.46)	(13.42)	(9.01)	(8.49)	

Table 8

Cross-Sectional NAV-timing Results (NDLRs)

This table presents the second of my results on the analysis of trading profitability from return predictability with non-discretionary liquidity restrictions (NDLRs). Quintile portfolio returns are calculated as the value-weighted excess return of the funds within a given portfolio in the quarter after portfolios are created. Funds are allocated to quintile portfolios based on their four quarter relative prior performance. Panel A reports the results of the portfolio returns less the T-bill while Panel B reports the results less a value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_t = \alpha + \beta\,(risk\ factors_t) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	1.344**	0.022	1.645***	1.602**	48
	(2.48)	(0.14)	(3.30)	(2.50)	
2	1.389**	-0.132	1.542**	1.396*	48
	(2.21)	(-0.72)	(2.47)	(1.86)	
3	1.484**	-0.077	1.703***	1.441**	48
	(2.36)	(-0.88)	(2.81)	(2.02)	
4	1.794***	0.460***	2.035***	1.758***	48
	(3.33)	(5.48)	(3.81)	(2.83)	
5	1.738***	0.144	2.020***	1.758**	48
	(2.69)	(1.11)	(3.11)	(2.44)	
5 - 1	0.394*	0.122	0.375*	0.157	48
	(1.87)	(0.58)	(1.65)	(0.81)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	-0.180	0.022	-0.108	0.072	48
	(-1.24)	(0.14)	(-0.73)	(0.55)	
2	-0.135	-0.132	-0.212	-0.134	48
	(-0.85)	(-0.72)	(-1.29)	(-0.68)	
3	-0.040	-0.077	-0.050	-0.089	48
	(-0.59)	(-0.88)	(-0.70)	(-1.33)	
4	0.270**	0.460***	0.281**	0.228*	48
	(2.51)	(5.48)	(2.48)	(1.75)	
5	0.214**	0.144	0.267**	0.228**	48
	(2.12)	(1.11)	(2.50)	(2.18)	
5 - 1	0.394*	0.122	0.375*	0.157	48
	(1.87)	(0.58)	(1.65)	(0.81)	

Table 9

Time-Series NAV-timing Strategy Results (NDLRs and DLRs)

This table presents the first of my results on the analysis of trading profitability from return predictability with non-discretionary and discretionary liquidity restrictions (NDLRs and DLRs). Long returns are the those obtained by either investing in a value-weighted portfolio of the funds or the T-bill, depending on the recent returns observed in the public real estate market. Short returns are those obtained by taking the opposite investment position as the Long portfolio. Long-Short returns are those obtained by subtracting the Panel A reports the results of the portfolio returns less the 3-month T-bill while Panel B reports the results less the value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively.

$$r_t = \alpha + \beta\,(risk\ factors_t) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	1.704***	1.106***	1.789***	1.793***	48
	(6.59)	(11.47)	(6.41)	(6.44)	
Short	-0.180	-1.106***	-0.036	-0.263	48
	(-0.47)	(-11.47)	(-0.10)	(-0.56)	
Long-Short	1.884***	2.212***	1.825***	2.056***	48
	(8.04)	(11.47)	(6.70)	(7.63)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	0.180	1.106***	0.036	0.263	48
	(0.47)	(11.47)	(0.10)	(0.56)	
Short	-1.704***	-1.106***	-1.789***	-1.793***	48
	(-6.59)	(-11.47)	(-6.41)	(-6.44)	
Long-Short	1.884***	2.212***	1.825***	2.056***	48
	(8.04)	(11.47)	(6.70)	(7.63)	

Table 10

Cross-Sectional NAV-timing Strategy Results (NDLRs and DLRs)

This table presents the second of my results on the analysis of trading profitability from return predictability with non-discretionary and discretionary liquidity restrictions (NDLRs and DLRs). Quintile portfolio returns are calculated as the value-weighted excess return of the funds within a given portfolio in the quarter after portfolios are created. Funds are allocated to quintile portfolios based on their four quarter relative prior performance. Panel A reports the results of the portfolio returns less the T-bill while Panel B reports the results less a value-weighted index of the fund returns. Standard errors are heteroskedasticity adjusted and robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively

$$r_t = \alpha + \beta\,(risk\ factors_t) + \varepsilon_t$$

Panel A: Value-weighted portfolio returns in excess of the 3-month T-bill

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	1.478**	0.045	1.730***	1.584**	48
	(2.53)	(0.41)	(3.14)	(2.28)	
2	1.485**	0.047	1.673***	1.514**	48
	(2.57)	(0.83)	(2.97)	(2.26)	
3	1.518**	-0.060	1.762***	1.464*	48
	(2.39)	(-0.74)	(2.94)	(1.92)	
4	1.566**	0.021	1.783***	1.525**	48
	(2.52)	(0.29)	(2.85)	(2.14)	
5	1.421**	-0.286***	1.671**	1.462*	48
	(2.06)	(-2.61)	(2.40)	(1.82)	
5 - 1	-0.058	-0.331*	-0.059	-0.122	48
	(-0.30)	(-1.78)	(-0.27)	(-0.68)	

Panel B: Value-weighted portfolio returns in excess of the NFI-OE Index Return

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	-0.045	0.045	-0.024	0.054	48
	(-0.40)	(0.41)	(-0.19)	(0.59)	
2	-0.038	0.047	-0.081	-0.016	48
	(-0.55)	(0.83)	(-1.06)	(-0.22)	
3	-0.006	-0.060	0.008	-0.066	48
	(-0.10)	(-0.74)	(0.17)	(-1.05)	
4	0.042	0.021	0.029	-0.005	48
	(0.73)	(0.29)	(0.50)	(-0.11)	
5	-0.103	-0.286***	-0.082	-0.068	48
	(-0.91)	(-2.61)	(-0.64)	(-0.60)	
5 - 1	-0.058	-0.331*	-0.059	-0.122	48
	(-0.30)	(-1.78)	(-0.27)	(-0.68)	

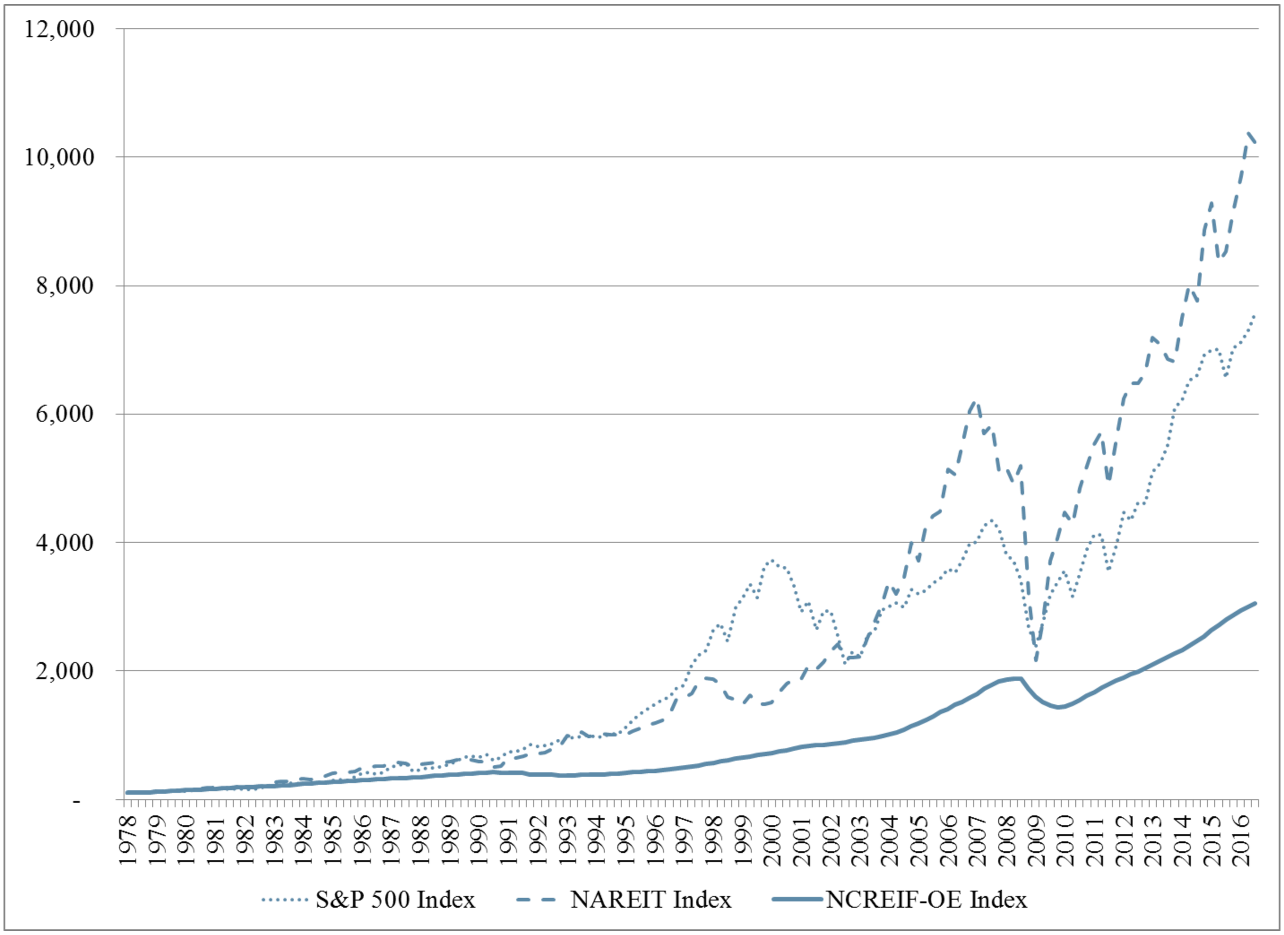

Figure 1
S&P 500, NAREIT, and NFI-OE Indices over Time

This figure shows the S&P 500 Index, FTSE National Association of Real Estate Investment Trusts (NAREIT) Index, and the National Council of Real Estate Investment Fiduciaries (NCREIF) Open-end (NFI-OE) Index over time from the first quarter of 1978 through the fourth quarter of 2015.

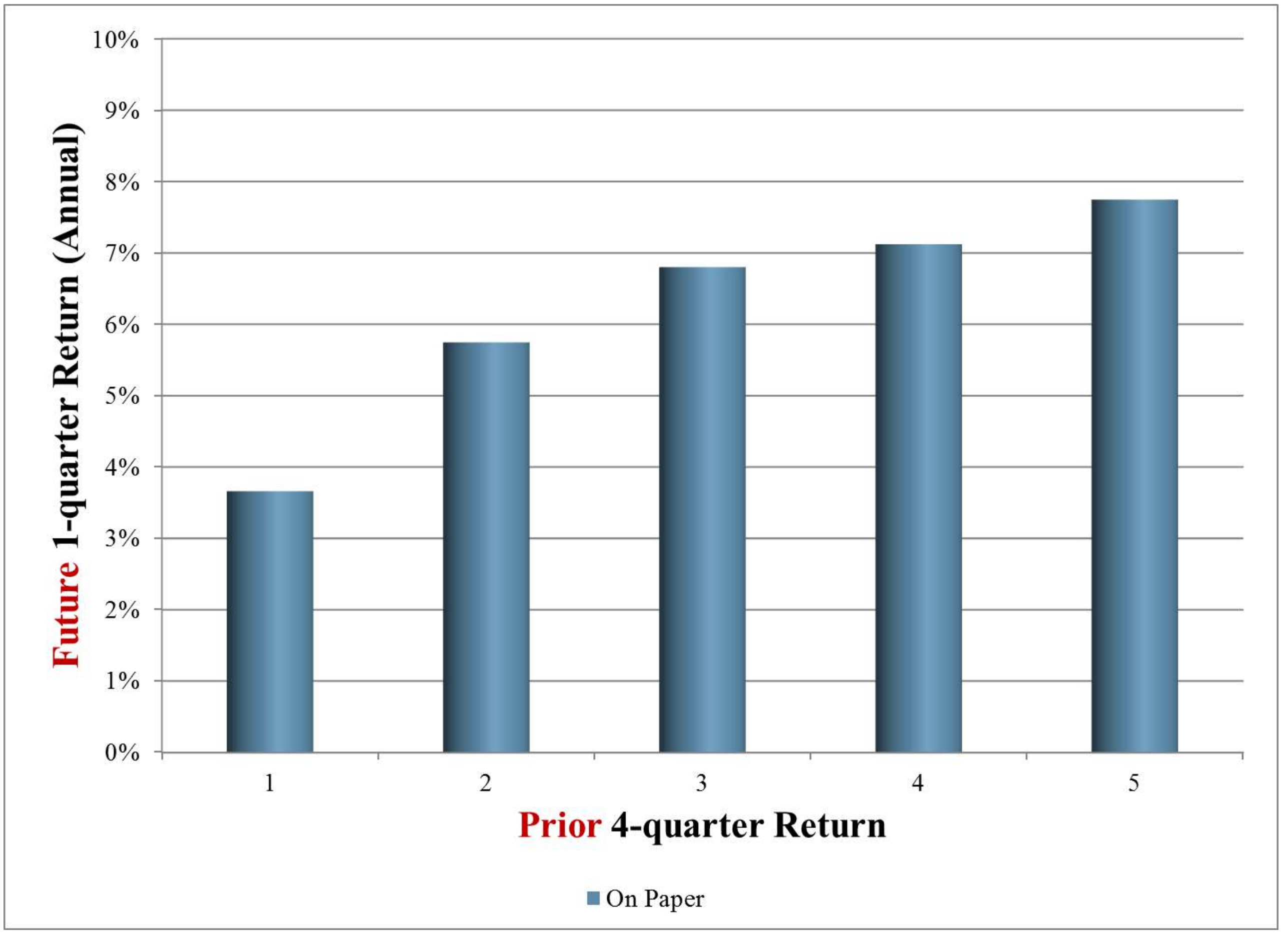

Figure 2
Future Returns by Prior Return Quintiles

This figure shows the equal-weighted average net queue for funds within one of five performance quintiles. Net queue is calculated as the dollar value of the Investment Queue less Redemption Queue divided by the lagged Assets Under Management (AUM). Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period.

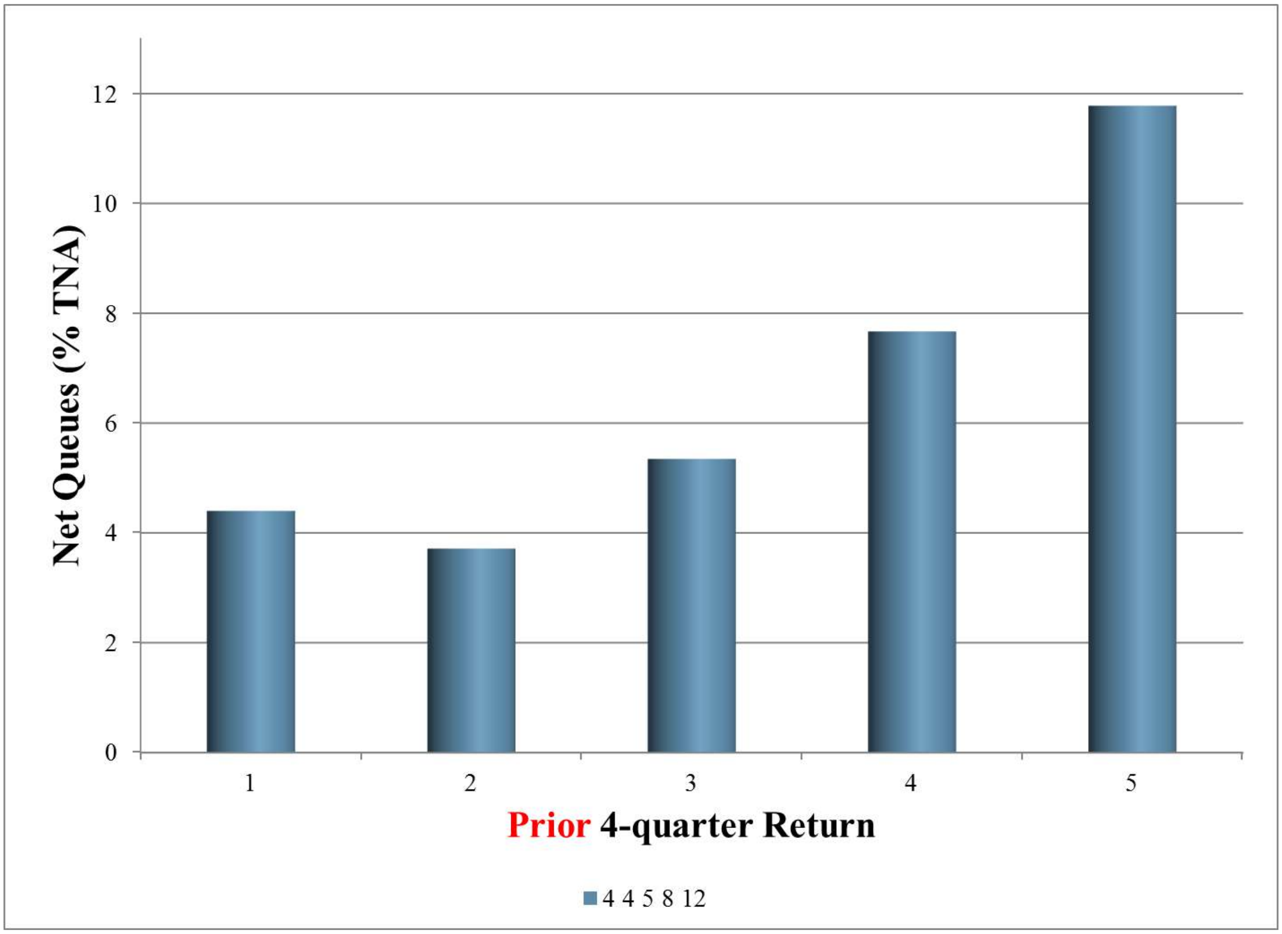

Figure 3
Queue Size (%AUM) by Prior Return Quintiles

This figure shows the equal-weighted average net queue for funds within one of five performance quintiles. Net queue is calculated as the dollar value of the Investment Queue less Redemption Queue divided by the lagged Assets Under Management (AUM). Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period.

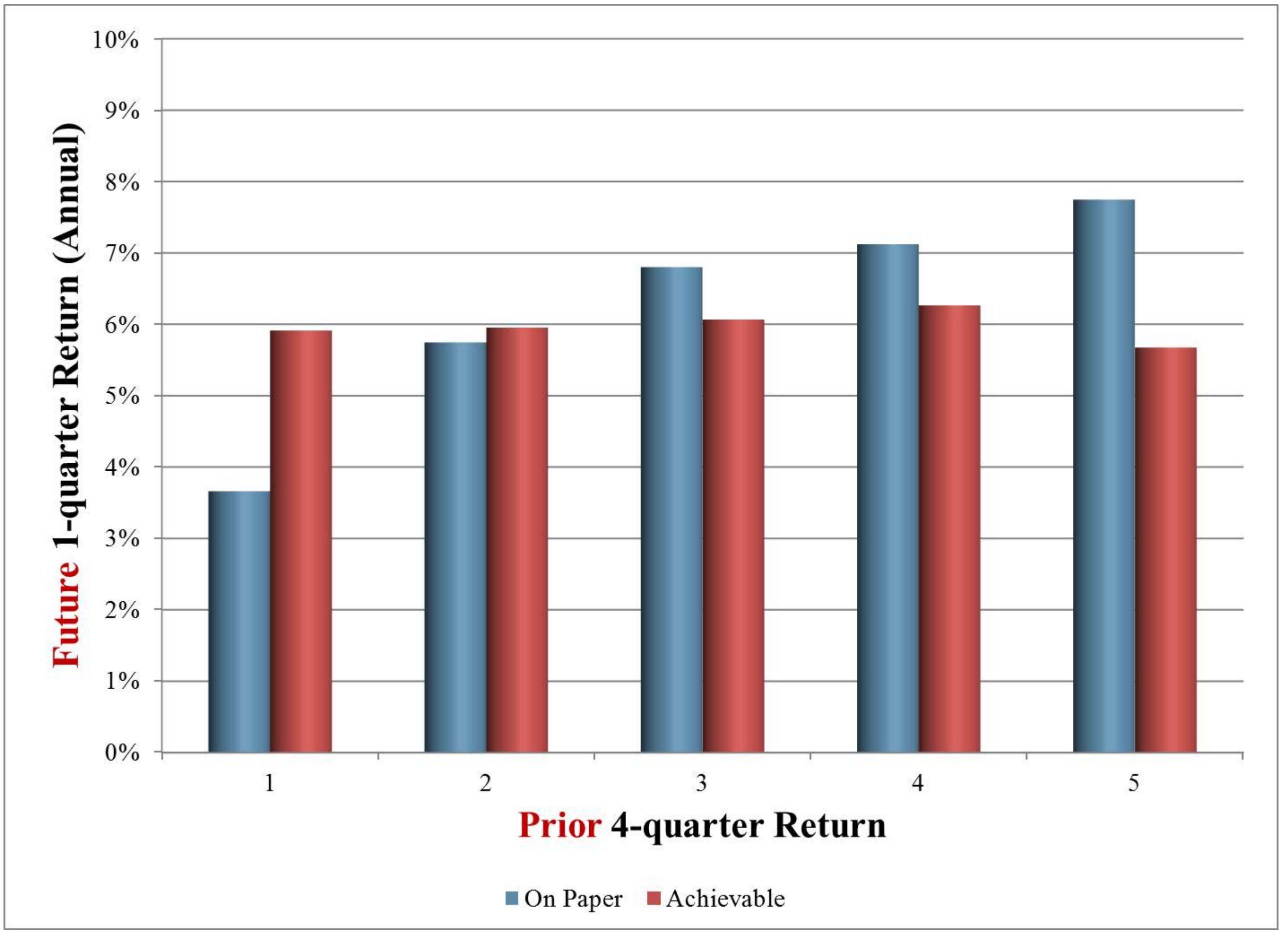

Figure 4
Raw and Q-adjusted Returns by Prior Return Quintiles

This figure shows the mean fund flow queue size for funds within one of five performance quintiles. The fund flow queue is calculated as the investment queue less the redemption queue divided by the Assets Under Management (AUM) divided by the mean fund flow for the given fund. Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period. The contraction period is from defined as the period from the second quarter 2008 through the second quarter 2010. The expansion period is defined as the first quarter 2004 through the fourth quarter 2015 except for the contraction period.

Appendix A Model Proof

This section details the proof of the model described in Section 3.

A.1 Fund Flow Proof

By substituting the market-timing investor's post fund flow fund allocation into equation 11 we obtain the optimal fund flow as follows.

$$NAV_{1,a}FF_1 = \Pi_1^{MT}\left(\omega_{1,b} - \omega_{1,a}\right) \tag{A.1}$$

$$NAV_{1,a}FF_1 = \Pi_1^{MT}\left(\omega_{1,a} + \frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right) - \omega_{1,a}\right) \tag{A.2}$$

$$FF_1 = \frac{\Pi_1^{MT}}{NAV_{1,a}}\left(\omega_{1,a} + \frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right) - \omega_{1,a}\right) \tag{A.3}$$

$$FF_1 = \frac{\Pi_1^{MT}}{NAV_{1,a}}\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{A.4}$$

A.2 Internal Wealth Transfer Proof

By substituting the market-timing investors optimal fund flow into equation 19, we are able to obtain the expected wealth transfer based on the staleness of the reported fund NAV as follows.

$$E_1\left(WT\right) = NAV_0\left(R_1^E - R_1^{Fund}\right)FF_1 \tag{A.5}$$

$$E_1\left(WT\right) = NAV_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.6}$$

The wealth transfer that the buy-and-hold investor will experience depends on their overall ownership percentage in the fund. It can be calculated as follows.

$$E_1\left(WT^{BH}\right) = \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0}NAV_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.7}$$

$$E_1\left(WT^{BH}\right) = \left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.8}$$

$$E_1\left(WT^{BH}\right) = \left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{NAV_1}\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right) \tag{A.9}$$

$$E_1\left(WT^{MT}\right) = \left(\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 - NAV_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.10}$$

$$E_1\left(WT^{MT}\right) = \left(\omega_0^{MT}\Pi_0^{MT} - NAV_0\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.11}$$

$$E_1\left(WT^{MT}\right) = \left[\left(\omega_0^{MT}\Pi_0^{MT} - NAV_0\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\right]FF_1 \tag{A.12}$$

$$E_1\left(WT^{MT}\right) = \left[\left(\omega_0^{MT}\Pi_0^{MT} - NAV_0\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\right]\left(\omega_1\Pi_1^{MT} - \Pi_0^{MT}\omega_0\left(R_1^E\right)^{(1-\Theta)}\right) \tag{A.13}$$

A.3 Expected Fund Return Proof

The return return achieved by the fund is obtained as follows. Starting with equation 15 I substitute equivalent values using the variables description in Section 3 above.

$$R_2^{Fund} = \frac{NAV_0^{Fund}R_1^E R_2^E + NAV_0^{Fund}R_1^{Fund}FF_1R_2^E - NAV_0^{Fund}R_1^{Fund}\psi\left(FF_1\right)^2}{NAV_0^{Fund}R_1^{Fund}\left(1+FF_1\right)} \tag{A.14}$$

$$R_2^{Fund} = \frac{R_1^E R_2^E + R_1^{Fund}FF_1R_2^E - R_1^{Fund}\psi\left(FF_1\right)^2}{R_1^{Fund}\left(1+FF_1\right)} \tag{A.15}$$

$$R_2^{Fund} = \frac{R_1^E R_2^E + \left(R_1^E\right)^{(1-\Theta)}FF_1R_2^E - \left(R_1^E\right)^{(1-\Theta)}\psi\left(FF_1\right)^2}{\left(R_1^E\right)^{(1-\Theta)}\left(1+FF_1\right)} \tag{A.16}$$

$$R_2^{Fund} = \frac{\left(R_1^E\right)^{\Theta}\left(R_1^E R_2^E + \left(R_1^E\right)^{(1-\Theta)} FF_1 R_2^E - \left(R_1^E\right)^{(1-\Theta)} \psi \left(FF_1\right)^2\right)}{\left(R_1^E\right)\left(1 + FF_1\right)} \tag{A.17}$$

$$R_2^{Fund} = \frac{\left(\left(R_1^E\right)^{\Theta} R_1^E R_2^E + R_1^E FF_1 R_2^E - R_1^E \psi \left(FF_1\right)^2\right)}{\left(R_1^E\right)\left(1 + FF_1\right)} \tag{A.18}$$

$$R_2^{Fund} = \frac{\left(\left(R_1^E\right)^{\Theta} + FF_1 - \psi \left(FF_1\right)^2\right)}{\left(1 + FF_1\right)} \tag{A.19}$$

$$R_2^{Fund} = \frac{\left(R_1^E\right)^{\Theta} + FF_1 - \psi \left(FF_1\right)^2}{\left(1 + FF_1\right)} \tag{A.20}$$

A.4 Wealth Destruction Proof

$$E_1\left(WD\right) = NAV_{1,b}\left[E_1\left(R_2^{Fund,b}\right) - E_1\left(R_2^{Fund,c}\right)\right] \tag{A.21}$$

$$E_1\left(WD\right) = NAV_{1,a}\left(1 + FF_1\right)\left[E_1\left(R_2^{Fund,b}\right) - E_1\left(R_2^{Fund,c}\right)\right] \tag{A.22}$$

$$E_1\left(WD\right) = NAV_0 R_1^{Fund}\left(1 + FF_1\right)\left[E_1\left(R_2^{Fund,b}\right) - E_1\left(R_2^{Fund,c}\right)\right] \tag{A.23}$$

$$E_1\left(WD\right) = NAV_0 R_1^{Fund}\left(1 + FF_1\right) E_1\left[\frac{\left(R_1^E\right)^{\Theta} + FF_1}{\left(1 + FF_1\right)} - \frac{\left(R_1^E\right)^{\Theta} + FF_1 - \psi \left(FF_1\right)^2}{\left(1 + FF_1\right)}\right] \tag{A.24}$$

$$E_1\left(WD\right) = NAV_0 R_1^{Fund}\left(1 + FF_1\right) E_1\left[\frac{\left(R_1^E\right)^{\Theta} + FF_1 - \left(R_1^E\right)^{\Theta} - FF_1 + \psi \left(FF_1\right)^2}{\left(1 + FF_1\right)}\right] \tag{A.25}$$

$$E_1\left(WD\right) = NAV_0 R_1^{Fund}\left(1 + FF_1\right)\frac{\psi \left(FF_1\right)^2}{\left(1 + FF_1\right)} \tag{A.26}$$

$$E_1\left(WD\right) = NAV_0 R_1^{Fund} \psi \left(FF_1\right)^2 \tag{A.27}$$

$$E_1\left(WD\right) = NAV_0\left(R_1^E\right)^{(1-\Theta)}\psi\left(FF_1\right)^2 \tag{A.28}$$

$$E_1\left(WD\right) = \frac{NAV_{1,b}}{NAV_{1,b}}NAV_0\left(R_1^E\right)^{(1-\Theta)}\psi\left(FF_1\right)^2 \tag{A.29}$$

$$E_1\left(WD\right) = \frac{\left(NAV_0-\omega_0^{MT}\Pi_0^{MT}\right)NAV_0R_1^{Fund}+\left(\omega_0^{MT}\Pi_0^{MT}\right)NAV_0R_1^{Fund}+NAV_0R_1^{Fund}FF_1}{NAV_0R_1^{Fund}(1+FF_1)}\cdot NAV_0R_1^{Fund}\psi\left(FF_1\right)^2 \tag{A.30}$$

$$E_1\left(WD^{BH}\right) = \frac{\left(NAV_0-\omega_0^{MT}\Pi_0^{MT}\right)NAV_0R_1^{Fund}}{NAV_0R_1^{Fund}\left(1+FF_1\right)}NAV_0R_1^{Fund}\psi\left(FF_1\right)^2 \tag{A.31}$$

$$E_1\left(WD^{MT}\right) = \frac{\left(\omega_0^{MT}\Pi_0^{MT}\right)NAV_0R_1^{Fund}+NAV_0R_1^{Fund}FF_1}{NAV_0R_1^{Fund}\left(1+FF_1\right)}NAV_0R_1^{Fund}\psi\left(FF_1\right)^2 \tag{A.32}$$

A.5 Investor's Response to Stale Pricing Incentives

$$\max_{\left\{\omega_{1,b}\right\}}\gamma_1E_1\left(R_2^{MT}\right) - \frac{\gamma_2}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2 \tag{A.33}$$

$$= \max_{\left\{\omega_{1,b}\right\}}\gamma_1E_1\left(\left(1-\omega_{1,b}\right)R_2^{rf}+\omega_{1,b}R_2^{Fund}\right) - \frac{\gamma_2}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2 \tag{A.34}$$

$$= \max_{\left\{\omega_{1,b}\right\}}\gamma_1E_1\left(R_2^{rf}-\omega_{1,b}R_2^{rf}+\omega_{1,b}R_2^{Fund}\right) - \frac{\gamma_2}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2 \tag{A.35}$$

$$= \max_{\left\{\omega_{1,b}\right\}}\gamma_1E_1\left(R_2^{rf}-\omega_{1,b}R_2^{rf}+\omega_{1,b}\frac{R_1^ER_2^E}{R_1^{Fund}}\right) - \frac{\gamma_2}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2 \tag{A.36}$$

First Order Condition:

$$0 = \gamma_1\left(\frac{R_1^EE_1\left(R_2^E\right)}{R_1^{Fund}} - R_2^{rf}\right) - \gamma_2\left(\omega_{1,b}-\omega_{1,a}\right) \tag{A.37}$$

$$0 = \gamma_1\left(\frac{R_1^EE_1\left(R_2^E\right)}{R_1^{Fund}} - 1\right) - \gamma_2\left(\omega_{1,b}-\omega_{1,a}\right) \tag{A.38}$$

$$\gamma_2\left(\omega_{1,b}-\omega_{1,a}\right)=\gamma_1\left(\frac{R_1^E E_1\left(R_2^E\right)}{R_1^{Fund}}-1\right) \tag{A.39}$$

$$\omega_{1,b}-\omega_{1,a}=\frac{\gamma_1}{\gamma_2}\left(\frac{R_1^E E_1\left(R_2^E\right)}{R_1^{Fund}}-1\right) \tag{A.40}$$

$$\omega_{1,b}=\omega_{1,a}+\frac{\gamma_1}{\gamma_2}\left(\frac{R_1^E E_1\left(R_2^E\right)}{R_1^{Fund}}-1\right) \tag{A.41}$$

$$\omega_{1,b}=\omega_{1,a}+\frac{\gamma_1}{\gamma_2}\left(\frac{R_1^E}{\left(R_1^E\right)^{(1-\Theta)}}-1\right) \tag{A.42}$$

$$\omega_{1,b}=\omega_{1,a}+\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta}-1\right) \tag{A.43}$$

A.6 Fund's Response to Price Impact Incentives

$$\max_{\{DFF_1\}}\gamma_3 NAV_{1,b}-\frac{\gamma_4}{2}\psi\left(FF_1\right)^2-\gamma_5\left(TFF_1-FF_1\right)^2 \tag{A.44}$$

$$=\max_{\{DFF_1\}}\gamma_3\left(NAV_{1,a}\left(1+FF_1\right)\right)-\frac{\gamma_4}{2}\psi\left(FF_1\right)^2-\gamma_5\left(TFF_1-FF_1\right)^2 \tag{A.45}$$

$$=\max_{\{DFF_1\}}\gamma_3\left(NAV_{1,a}\left(1+DFF_1TFF_1\right)\right)-\frac{\gamma_4}{2}\psi\left(DFF_1TFF_1\right)^2-\frac{\gamma_5}{2}\left(TFF_1-DFF_1TFF_1\right)^2 \tag{A.46}$$

First Order Condition:

$$0=\gamma_3 NAV_{1,a}TFF_1-\gamma_4\psi DFF_1\left(TFF_1\right)^2+\gamma_5\left(TFF_1-DFF_1TFF_1\right)TFF_1 \tag{A.47}$$

$$0=\gamma_3 NAV_{1,a}TFF_1-\gamma_4\psi DFF_1\left(TFF_1\right)^2+\gamma_5\left(TFF_1\right)^2-\gamma_5 DFF_1\left(TFF_1\right)^2 \tag{A.48}$$

$$\gamma_4\psi DFF_1\left(TFF_1\right)^2+\gamma_5 DFF_1\left(TFF_1\right)^2=\gamma_3 NAV_{1,a}TFF_1+\gamma_5\left(TFF_1\right)^2 \tag{A.49}$$

$$DFF_1\left(\left(\gamma_4\psi+\gamma_5\right)\left(TFF_1\right)^2\right)=\gamma_3 NAV_{1,a}TFF_1+\gamma_5\left(TFF_1\right)^2 \tag{A.50}$$

$$DFF_1=\frac{\gamma_3 NAV_{1,a}+\gamma_5 TFF_1}{\left(\gamma_4\psi+\gamma_5\right)TFF_1} \tag{A.51}$$

A.7 Joint Solutions: Investor and Fund Responses

$$TFF_1=\frac{\Pi_1^{MT}}{NAV_1}\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta}-1\right)\right) \tag{A.52}$$

$$DFF_1=\frac{\gamma_3 NAV_{1,a}TFF_1+\gamma_5\left(TFF_1\right)^2}{\left(\gamma_4\psi+\gamma_5\right)\left(TFF_1\right)^2} \tag{A.53}$$

$$FF_1=TFF_1 DFF_1 \tag{A.54}$$

$$FF_1=\frac{\Pi_1^{MT}}{NAV_1}\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta}-1\right)\right)\frac{\gamma_3 NAV_{1,a}TFF_1+\gamma_5\left(TFF_1\right)^2}{\left(\gamma_4\psi+\gamma_5\right)\left(TFF_1\right)^2} \tag{A.55}$$

$$\begin{aligned}E_1\left(WT^{BH}\right)= \quad & \left(NAV_0-\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)\tfrac{\Pi_1^{MT}}{NAV_1}\left(\tfrac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta}-1\right)\right)\cdot \\ & \tfrac{\gamma_3 NAV_{1,a}TFF_1+\gamma_5\left(TFF_1\right)^2}{\left(\gamma_4\psi+\gamma_5\right)\left(TFF_1\right)^2}\end{aligned} \tag{A.56}$$

A.8 Liquidity Management and Liquidity Buffers

- **Fund Optimization DFF selection:**

$$\max_{\{DFF_1\}}\gamma_3 NAV_{1,b}-\frac{\gamma_4}{2}\psi\left(FF_1-\Delta NAV_{1,a}^{Liquid}\right)^2-\frac{\gamma_5}{2}\left(TFF_1-FF_1\right)^2 \tag{A.57}$$

$$\max_{\left\{DFF_1^{LB}\right\}}\gamma_3 NAV_{1,a}\left(1+TFF_1 DFF_1^{LB}\right)-\frac{\gamma_5}{2}\left(TFF_1-TFF_1 DFF_1^{LB}\right)^2 \tag{A.58}$$

First Order Condition:

$$0=\gamma_3 NAV_{1,a}TFF_1+\gamma_5 TFF_1 TFF_1-\gamma_5 TFF_1 DFF_1^{LB}TFF_1 \tag{A.59}$$

$$DFF_1^{LB}\gamma_5\left(TFF_1\right)^2 = \gamma_3 NAV_{1,a} TFF_1 + \gamma_5 TFF_1 TFF_1 \tag{A.60}$$

$$DFF_1^{LB} = \frac{\gamma_3 NAV_{1,a} + \gamma_5 TFF_1}{\gamma_5 TFF_1} \tag{A.61}$$

$$DFF_1^{LB} = \frac{\gamma_3 NAV_{1,a} + \gamma_5 TFF_1}{\gamma_5 TFF_1} \gg \frac{\gamma_3 NAV_{1,a} + \gamma_5 TFF_1}{\left(\gamma_4\psi + \gamma_5\right) TFF_1} = DFF_1 \tag{A.62}$$

$$DFF_1^{LB} \gg DFF_1 \tag{A.63}$$

- **Wealth Transfer**

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) FF_1^{LB} \tag{A.64}$$

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1^{LB} \tag{A.65}$$

$$\begin{aligned} E_1\left(WT^{BH,LB}\right) = & \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1^{LB} \gg \\ & \frac{\left(NAV_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{NAV_0} NAV_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1 = E_1\left(WT^{BH}\right) \end{aligned} \tag{A.66}$$

$$E_1\left(WT^{BH,LB}\right) \gg E_1\left(WT^{BH}\right) \tag{A.67}$$

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