Stale Prices, Fragility, and Detrimental Cash: Evidence from Private 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 funds report stale Net Asset Values (NAVs) when they invest in illiquid assets. This staleness creates return predictability, NAV-timing risks, and fund fragility risks for open-end funds. However, because their assets are illiquid, managers limit fund flows to deter buying assets at a premium or selling them at a discount. Limiting flows has the secondary effect of protecting against the risks stale NAVs create. Interestingly, illiquidity in the underlying assets creates the opportunity for, and the friction against, exploiting buy-and-hold investors.

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1. Introduction

It is important to understand the mechanisms that 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 their shares 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 and forced fire sale concerns, it is important to understand how they interact with prominent stabilization tools. No prior paper has examined the NAV-timing risks created when open-end funds invest in illiquid assets nor the effects that common stabilization tools have on these risks. This paper attempts to fill this gap by theoretically and empirically analyzing the effects of stale pricing and stabilization tools on NAV-timing profits and wealth transfers in U.S. Open-end Private Real Estate (OPRE) funds.

In order to evaluate the behavior of investors and managers in a setting with stale prices, I model their interactions with both 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, as well as decrease them after negative shocks. Second, investors will attempt to increase their holdings the most in funds with the highest recent past performance. Third, managers will limit capital flows the most at those times, and

[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 "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.

in those funds, where NAV-timing strategies appear to be most profitable. Lastly, when faced with either using cash to meet investor flows (liquidity buffers) or suspending share issuances and redemptions (liquidity restrictions), funds which use liquidity buffers allow greater wealth transfers and are more susceptible to runs and ultimate failure. I evaluate these predictions using U.S. OPRE fund data.

OPRE funds provide a great setting to examine the exploitability of open-end fund return predictability. Their Total Net Asset (TNA) and Net Asset Values (NAVs) are based almost entirely off of valuation estimates of their assets. This is because they hold infrequently traded, illiquid assets. Therefore, the NAV-timing risks that come from valuation estimates should be more pronounced in this setting. Additionally, unlike hedge funds, OPRE funds report their unfulfilled subscription and redemption requests (queues). Estimating the returns investors could achieve by implementing NAV-timing strategies requires estimating the returns they would achieve after going through the queues (queue-adjusted returns). It is also important to have a valid proxy for the true economic returns of the funds being evaluated. Because commercial real estate has both strong public and private markets, the returns from the publicly traded real estate investment trust (REIT) market proxy well for the economic returns of OPRE fund market.[2] Lastly, funds cannot mechanically increase or decrease their holdings in assets to accommodate capital flows. Because they hold real assets instead of financial assets, I can abstract away from the possibility that the return predictability is mechanically driven by holding adjustments (see Coval and Stafford (2007) and Lou (2012)).[3] 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 stale pricing principles are statistically significant and economically profitable. A long-short strategy based on investing in either an OPRE index or the 3-month T-bill achieved annualized private real estate factor and 5-factor alphas of 18.2% and 15.5%, respectively, from 2004 to 2015.

[2]Public and private real estate markets are distinguished by the market in which their securities trade. Both markets invest in real estate assets that trade privately, but public real estate markets have securities that trade publicly on exchanges, while 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.

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%, respectively. Each of these is significantly larger than that which would be accomplished through a simple buy-and-hold strategy, suggesting that achieving them would transfer substantial wealth and create shareholder-run incentives. This evidence further suggests the greatest wealth transfer and fund fragility risks come from strategies associated with timing when to enter and leave the overall market as compared to those associated with switching between funds. This characteristic is largely due to commercial real estate prices increasing and decreasing so dramatically around the GFC. Stale reported prices are irrelevant if economic prices do not change.

I also find investor behavior to be consistent with these strategies. A one standard deviation increase in lagged public market index, private market index, and fund returns leads to 16%, 26%, and 45% standard deviation increases in fund subscription requests, respectively. Similarly, I find that funds limit capital flows in a manner consistent with these strategies. A one standard deviation increase in public market index, private market index, and fund returns leads to 16%, 25%, and 50% standard deviation increases in fund queues. The strategies most profitable on paper have the most oversubscriptions.

I find the returns investors could achieve by implementing NAV-timing strategies are statistically and economically equivalent to those of buy-and-hold investors, after accounting for investor queues. I also find that lock-up and notification periods eliminate the NAV-timing profits which come from switching between funds. However, they have no effect on the performance of strategies which move into and out of the overall OPRE market. Additionally, they do not protect against the wealth transfers to new buy-and-hold investors entering the market for the first time. In all, this evidence suggests that funds protect against the wealth transfer and fragility risks created by stale pricing when they suspend issuing and redeeming shares. A novel finding of this paper is that investors behave as if they recognize returns are predictable, crowd each other out, and eliminate trading opportunities similar to the "winner's curse" discussed in the IPO literature.[4]

[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 strong demand in the most profitable offerings makes it difficult for any investor to obtain shares in those

I also find that funds have larger capital outflows when they hold more cash. Specifically, for funds that had either a negative fund flow or a redemption queue, larger capital outflows occurred both at those times and in those funds with larger lagged cash holdings. A one standard deviation increase in lagged cash corresponded with a 25.8% standard deviation increase in outflows over the entire sample period. Additionally, for funds that had a redemption queue during the GFC, a one standard deviation increase in cash corresponded with a 19.8% standard deviation increase in outflows. OPRE funds hold little cash on average, the median cash holding for OPRE funds over the sample period was 3.64%. Together this evidence suggests that, in equilibrium, OPRE funds do not use large liquidity buffers and liquidity buffers do a poor job of deterring the shareholder run risks associated with stale pricing. I interpret this evidence with caution because of endogeneity concerns. However, it is consistent with the general practice of OPRE fund documents stating, "redemptions will be made to the extent excess cash is available."

A large amount of 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 debt (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 appear more solvent on paper, which is believed to have deterred runs. This is primarily because the redemption value for bank deposits is unrelated to the value of the underlying assets; thus, the only negative externality created by their redemptions is when they force banks to sell assets at a discount. In contrast, open-end fund redemption amounts are directly related to the value of the underlying assets and because of this, when asset values are stale, so are the redemption values of the shares. Therefore, investors create a negative externality to the other investors when they remove capital from a fund that has stale asset values in a declining market. Thus, not marking-to-market as-

offerings, thus dissipating the profits over many investors.

sets would likely have the opposite effect in open-end funds than it would have in the bank setting.[5] Economists have argued historical cost accounting is more optimal for illiquid assets than marking-to-market because it decreases excessive price volatility (Plantin et al. (2008)). However, doing so would similarly distort open-end fund shareholder incentives for the reasons mentioned above.

Additionally, prior research has focused on the fragility risks of open-end funds investing in illiquid assets, but failed to analyze the stale valuations of illiquid assets as a potential source (Chen et al. (2010); Goldstein et al. (2017)). Consistent with this, much of the literature focuses on liquidity buffers as the primary mechanism used to deter fragility in open-end funds (see Chernenko and Sunderam (2016); Morris et al. (2017); Zeng (2017); Agarwal et al. (2018)). In contrast, this paper provides evidence that liquidity buffers do not deter fragility risks when the return predictability is unrelated to forced fire sales. In fact, this paper provides evidence that liquidity buffers can amplify fragility risks in these situations. Other papers have documented the relation between returns and liquidity restrictions as well as the potential negative effects of discretionary liquidity restrictions, but little evidence has been provided documenting 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 prior 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)). Compounding this concern is evidence that hedge funds smooth returns even more during market downturns (see Bollen and Pool (2008)).

It is possible that funds investing in illiquid assets can have predictable returns for reasons other than stale pricing. This paper focuses on stale pricing because it is generally accepted as the primary reason funds investing in illiquid assets have serially correlated returns. However, the finding that liquidity buffers can increase fragility risks is maintained regardless of the reason for the autocorrelation. As cited previously, Coval and Stafford (2007) and Lou (2012)

[5] 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.”

provide evidence that momentum may partly be due to the temporary price impact fund trades have on their existing holdings. Further evidence shows that some illiquid asset classes (such as residential and commercial real estate), have some degree of serial autocorrelation in the economic returns of their underlying markets due to either financial constraints or limits to arbitrage (see Ling et al. (2014)). Lastly, returns could be predictable due to varying degrees of managerial skill (see Goldstein et al. (2017)). In each of these cases, allowing investors to leave a fund quickly creates first-mover advantages, negative externalities, and wealth transfer risks.

There are three ways managers deter fragility risks when they limit share issuances and redemptions. First, managers are able to transact in the underlying market prudently when they limit issuances and redemptions. They are not forced to purchase or sell assets too quickly or at undesirable prices. Second, it takes longer for investors to move capital into, and out of, the fund. This decreases the predictability of returns investors achieve by implementing NAV-timing strategies based on stale pricing principles. Third, managers dilute any remaining wealth transfers when they allocate the limited issuances and redemptions on a prorata basis. This is because issuance and redemption requests positively correlate with the size of the wealth transfer opportunities. This crowding out effect creates strategic substitutes for NAV-timing strategies and decreases the marginal benefit of implementing them.

It is important to consider how suspending share issuances and redemptions affects the liquidity transformation service funds provide. Open-end funds provide a valuable service when they offer shares that are more liquid than the assets they hold. However, investors may benefit more by investing directly in the illiquid assets if they are not able to enter or leave intermediaries at their will. Extending the logic of Diamond and Dybvig (1983), however, suggests that investors are strictly better off investing in open-end funds which limit issuances and redemptions, than they are investing directly in the assets themselves. According to Diamond and Dybvig (1983), the advantage investors receive by pooling their capital is that they share the risk of idiosyncratic liquidity shocks. Consistent with this intuition, open-end funds that limit issuances and redemptions provide liquidity to those investors whose issuances and redemptions are uncorrelated with those of other investors.

However, when their requests are correlated with those of other investors, funds limit capital flows to the extent needed to purchase and sell assets prudently. In doing so, these funds provide strictly more liquidity to their investors when their liquidity shocks are idiosyncratic and strictly no worse liquidity when they are systematic.

The rest of the paper is outlined as follows. Section 2 provides an overview of the OPRE market and discuss the return smoothing process. Section 3 describes the model which provides insight into the existence of, and protection against, wealth transfer risks in open-end funds. Section 4 discusses the data and the variables of interest. Section 5 reviews 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 the primary way institutional investors invest in real estate.[6] 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. Furthermore, allocations are expected to continue increasing.[7]

There are a number of ways institutional investors can invest in CRE - direct investments, separate accounts, joint ventures, club deals, comingled funds, and publicly traded REITs. The first five methods of investing in CRE are different avenues of investing in the private real estate market. The last method is the primary way to invest in the public real estate market, which has a market capitalization of around $1 trillion. My analysis focuses on return

[6]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."

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

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 stated NAVs, similar to open-end mutual funds and hedge funds. Fund NAVs are based on the cumulative appraised values of the individual assets they hold. Similar to hedge funds, they have both non-discretionary liquidity restrictions (redemption notification periods, lockup periods, and subscription intervals) and discretionary liquidity restrictions (discretionary redemption limits). However, OPRE funds also implement discretionary liquidity restrictions on capital entering the fund in a way similar to traditional private equity funds. With 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, which OPRE funds report quarterly. Lastly, they invest in real assets and actively manage asset operations, similar to traditional private equity funds.

2.2. Return smoothing

An extensive amount of literature argues valuation estimates are stale for assets which trade infrequently (see Getmansky et al. (2004), Geltner (1997), and Quan and Quigley (1989), among others).[8] Econometric models suggest that reported returns follow autoregressive integrated moving average (ARIMA) processes of true economic returns. Getmansky et al. (2004) suggest reported returns (r_t^R) are simply weighted averages of lagged economic returns (r_{t-j}^E) where θ_j represents the weight given to the economic return at the j^{th} lag as shown in Equation 1. Similarly, Geltner (1997) argues reported returns are weighted averages of current economic returns (r_t^E) and one period lagged reported returns (r_{t-1}^R) as shown in Equation 4.[9] Consistent with the intuition behind Equations 1 and 4, there are two primary

[8]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.

[9]Geltner (1991) and Geltner (1993a) review similar models to evaluate appraisal smoothing in real estate.

information sets which could be used to predict future fund returns and thus, two ways in which investors could exploit buy-and-hold investors. First, investors could use prior macroeconomic return information to determine 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).

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

$$\theta_j \epsilon \left[0, 1\right], \ j = 0, \ldots, k \tag{2}$$

and

$$1 = \theta_0 + \theta_1 + \cdots + \theta_k \tag{3}$$

$$r_t^R = \left(1 - \Phi\right) r_t^E + \Phi r_{t-1}^R \tag{4}$$

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

3. Theoretical model

3.1. Setup

I create a two-period model to evaluate how stale pricing influences investor and fund behavior. The model provides intuition into how discretionary liquidity restrictions and liquidity buffers jointly influence NAV-timing wealth transfers and incentives. The open-end fund is created in period 0 and assets are purchased at their true economic values as represented by Equation 5, where E denotes the economic value of the underlying assets. 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 total net asset value, $TNA_{1,a}$. The fund subsequently sells or purchases assets to meet the fund flow. The post fund flow total net asset value, $TNA_{1,b}$, 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, TNA_2^E.

$$TNA_0^{Fund} = TNA_0^E \tag{5}$$

$$TNA_{1,a}^{Fund} = TNA_0^{Fund} R_1^{Fund} \tag{6}$$

$$TNA_{1,b}^{Fund} = TNA_0^{Fund} R_1^{Fund} (1 + FF_1) \tag{7}$$

$$TNA_2^{Fund} = TNA_0^{Fund} R_1^{Fund} R_2^{Fund} = TNA_0^{Fund} R_1^E R_2^E = TNA_2^E \tag{8}$$

There are two investors in the fund, a buy-and-hold investor, BH, and a market-timing investor, MT. As shown in Equation 9, the TNA value of the fund is equal to the combined investments of the market-timing and 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 overall wealth, Π_t^{MT}, allocated to the fund while the rest of his wealth is invested in cash that 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.

$$TNA_0^{Fund} = \omega_0 \Pi_0^{MT} + \Pi_0^{BH} \tag{9}$$

The model assumes that the underlying assets have two characteristics associated with being illiquid - they trade infrequently and large capital flows either into or out of the asset market have a temporary price impact. Normal market participants are only trading in periods 0 and 2, they are not trading in period 1. The only market participants trading in period 1 are the fund and those needed to offset the trades of the fund. Because of the lack of trading in period 1, the fund has to estimate the fair value of their assets in order to report its TNA and NAV. The model assumes that $TNA_{1,a}$ is stale and that the level of staleness is represented by Θ as shown in Equation 10. The assumption that capital flows have a price impact is reflected in Equation 11 where the transaction cost is a function of the period 1 fund flow. 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 underlying market. It is assumed that the assets do not produce dividends. It is also assumed that the assets will be sold for their true economic value in period 2 because of the existence of normal market participants in that period. 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 future returns of the fund.

$$R_1^{Fund} = \left(R_1^E\right)^{(1-\Theta)}, \; where \, 0 < \Theta < 1 \tag{10}$$

$$Transaction\, Cost_1 = \psi \left(FF_1\right)^2, \; where \, 0 < \psi < 1 \tag{11}$$

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 percent allocation to the open-end fund in period 1 is denoted by, ω_1. As reflected in Equation 12, the dollar amount of the fund flow equals the dollar change in the market-timing investor's allocation to the fund. $\omega_{1,a}$ represents the pre-fund flow allocation and $\omega_{1,b}$ represents the post fund flow allocation. An adjustment cost is incurred by the market-timing investor for adjusting his allocations, as represented by Equation 13.

$$TNA_{1,a}FF_1 = \Pi_1^{MT}\left(\omega_{1,b} - \omega_{1,a}\right) \tag{12}$$

$$Adjustment\,Cost_1 = \frac{\gamma}{2}\left(\omega_{1,b} - \omega_{1,a}\right)^2 \tag{13}$$

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 14. The reported return of the fund in period 1 equals the reported TNA in period 1 divided by the TNA in period 0. Additionally, the reported return to the fund in period 2 equals the TNA of the fund in period 2 divided by the reported TNA of the fund in period 1, as shown in Equation 16.

$$R_2^{MT} = \omega_{1,b}R_2^{Fund} + \left(1 - \omega_{1,b}\right)R^f - \frac{\gamma}{2}\left(\omega_{1,b} - \omega_{1,a}\right)^2 \tag{14}$$

$$R_1^{Fund} = \frac{TNA_1^{Fund}}{TNA_0^{Fund}} \tag{15}$$

$$R_2^{Fund} = \frac{TNA_2^{Fund}}{TNA_{1,b}^{Fund}} \tag{16}$$

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 B.5 of the Appendix, the optimal allocation for the market-timing investor is given by Equation 18. 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 12, I obtain the optimal fund flow as shown in Equation 19. The proof of this derivation is provided in Section B.1 of the Appendix.

$$\max_{\{\omega_{1,b}\}} \gamma_1 E_1\left(R_2^{MT}\right) - E_1\left(\frac{\gamma_2}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2\right) \tag{17}$$

$$\omega_{1,b} = \omega_{1,a} + E_1\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{18}$$

$$FF_1 = \frac{\Pi_1^{MT}}{TNA_{1,a}} E_1\left(\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{19}$$

The overall wealth transfer from existing investors to incoming investors is reflected in Equation 20. The wealth transfer experienced by the buy-and-hold investor depends on his period 0 percentage ownership of the fund, as shown in Equation 21. The wealth transfer from the buy-and-hold investor can be further derived into Equation 22 as shown in Section B.2 of the Appendix. This assumes the market-timing investor is able to contribute or withdraw as much as he would like without restrictions. Two important outcomes of the model are demonstrated in Equation 22. First, wealth transfers increase with staleness in reported returns. Second, wealth transfers increase with the size of the economic return experienced in period 1. These results lead to **Predictions 1** and **2** listed below.

$$E_1\left(WT\right) = E_1\left(TNA_0\left(R_1^E - R_1^{Fund}\right)FF_1\right) \tag{20}$$

$$E_1\left(WT^{BH}\right) = E_1\left(\frac{\left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{TNA_0} TNA_0\left(R_1^E - R_1^{Fund}\right)FF_1\right) \tag{21}$$

$$E_1\left(WT^{BH}\right) = E_1\left(\left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{TNA_1}\frac{\gamma_{10}}{\gamma_0}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{22}$$

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

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

3.3. Fund maximization (liquidity restrictions)

This analysis focuses on the way in which the fund responds to fund flow requests and how this influences wealth transfers. The model assumes that the manager has full discretion over how much of the fund flow request to fulfill, as reflected in Equation 23. DFF_1 is the percentage of the total fund flow requested, TFF_1, that the manager chooses to fulfill. The utility function of the manager has three components. The first component reflects the period 1 fee that is a function of the size of assets the fund manages, $TNA_{1,b}$. The second component reflects the impact that the fund flow has on future returns. This impact ultimately affects future fees through the flow-performance relationship. The third component reflects the effect of not fulfilling investor subscription or redemption requests on future fees. It assumes that investors are less willing to invest with fund managers tomorrow if their fund flow requests are not fulfilled today. The fund is interested in maximizing its lifetime earnings of fees.

After observing fund flow requests, the fund selects the optimal DFF_1 that will maximize its utility function. This maximization function is represented by Equation 24. As derived in Section B.5 of the Appendix, optimal percentage fund flow accepted by the fund is given in Equation 25. Accordingly, the fund's optimal fund flow occurs when the marginal cost of decreasing future fees, due to overpaying for assets, equals the marginal benefit from increasing contemporaneous and future fees, by fulfilling investor requests. It is important to note the impact on the contemporaneous fee reverses when the fund flow request is negative. Fulfilling a greater percentage of the requests has a marginal benefit during periods with a positive fund flow, while it has a marginal cost during periods with a negative fund flow.

$$DFF_1 = \frac{FF_1}{TFF_1} \tag{23}$$

$$\max_{\{DFF_1\}} E_1\left(\gamma_3 TNA_{1,b} - \frac{\gamma_4}{2}\psi\left(FF_1\right)^2 - \gamma_5\left(TFF_1 - FF_1\right)^2\right) \tag{24}$$

$$DFF_1 = \frac{\gamma_1 TNA_{1,a} + \gamma_3 TFF_1}{E_1\left(\gamma_2\psi + \gamma_3\right) TFF_1} \tag{25}$$

The optimal fund flow in period 1 is jointly determined by the fund and the investors and is reflected in Equation 26. The expected wealth transfer from the buy-and-hold investor to the market-timing investor is obtained by substituting Equation 26 into Equation 21 as shown in Equation 27. Equation 27 depicts the importance of one of the novel characteristics of illiquidity - as illiquidity increases so does staleness, Θ, *and* price impact, ψ. Therefore, in this setup, the illiquidity has offsetting effects in the wealth transfer function. It creates both a wealth transfer risk and a wealth transfer deterrent. **Prediction 3** provides a hypothesis consistent with this outcome.

$$FF_1 = \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{\gamma_{10}}{\gamma_0} \left(\left(R_1^E\right)^{\Theta} - 1 \right) \right) \frac{\gamma_1 TNA_{1,a} TFF_1 + \gamma_3 \left(TFF_1\right)^2}{E_1 \left(\gamma_2 \psi + \gamma_3\right) \left(TFF_1\right)^2} \tag{26}$$

$$E_1\left(WT^{BH}\right) = \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{\gamma_{10}}{\gamma_0} \left(\left(R_1^E\right)^{\Theta} - 1 \right) \right) \cdot \frac{\gamma_1 TNA_{1,a} TFF_1 + \gamma_3 \left(TFF_1\right)^2}{E_1 \left(\gamma_2 \psi + \gamma_3\right) \left(TFF_1\right)^2} \tag{27}$$

Prediction 3. *Managers will limit capital flows the most at those times and in those funds where NAV-timing strategies appear 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 any and all fund flow requests are fulfilled using a cash, liquidity buffer. As such, I remove the second component of fund's utility maximization equation, as shown in Equation 29. The new optimal DFF_1 is shown in Equation 30 and the proof is in Section B.8 of the Appendix. The new optimal fund flow is strictly larger than the one without a liquidity buffer. Similarly, the wealth transfer is strictly larger when the fund uses a liquidity buffer. I provide a proof and derivation of this in Section B.8. The purpose of this model is to evaluate the effect of using a liquidity buffer in combination with a discretionary liquidity restriction on the wealth transfer. The model does not attempt to find the optimal combination of liquidity buffers and liquidity restrictions. Accordingly, the liquidity buffer amount is not a choice variable.

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 have stale NAVs. These wealth transfers increase strategic complementarities and first-mover advantages, which can destabilize funds and asset markets. In all, this evidence suggests the tools most commonly used to stabilize markets can be counterproductive and backfire in some situations. This evidence also supports **Prediction 4,** listed below.

$$\max_{\{DFF_1\}} E_1 \left(\gamma_3 TNA_{1,b} - \frac{\gamma_4}{2} \psi \left(FF_1 \right)^2 - \gamma_5 \left(TFF_1 - FF_1 \right)^2 \right) \tag{28}$$

$$\max_{\left\{DFF_1^{LB}\right\}} E_1 \left(\gamma_1 TNA_{1,a} \left(1 + TFF_1 DFF_1^{LB} \right) - \frac{\gamma_3}{2} \left(TFF_1 - TFF_1 DFF_1^{LB} \right)^2 \right) \tag{29}$$

$$DFF_1^{LB} = \frac{\gamma_1 TNA_{1,a} + \gamma_3 TFF_1}{\gamma_3 TFF_1} \tag{30}$$

$$DFF_1^{LB} \gg DFF_1 \tag{31}$$

$$E_1 \left(WT^{BH,LB} \right) = \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT} \right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E \right)^{(1-\Theta)} \right) TFF_1 DFF_1^{LB} \tag{32}$$

$$E_1 \left(WT^{BH,LB} \right) \gg E_1 \left(WT^{BH} \right) \tag{33}$$

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 fund-level data except for queue information comes the NCREIF NFI-OE.[10] The queue data come from Townsend.[11] 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 response variables of interest are the quarterly values of the Net Excess Return, Fund Flow, Net Queue, and Total Capital Flow. The explanatory variables of interest are the quarterly values for the lagged Net Excess Returns, Net Queues, and Cash. 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, and REIT Q-factor Model (see Fama and French (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 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 general data collection. Where available, I use the hand-collected data which ranges from 2008 through 2015. Where quarterly reports either do not report queue values or they are 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

[10]NCREIF is the leading collector of institutional real estate investment information, 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.

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 returns at the 5th and 95th percentiles. I winsorize the return variables at the 1st and 99th percentiles. Table 1 provides the summary statistics for the 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 believed to have stale prices. Therefore, their returns should be predictable from both prior public market returns as well as prior fund returns (see Getmansky et al. (2004) and Geltner (1997)).[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 the NFI-OE Index is much smoother and lags both public market indices by approximately four quarters. This supports the econometric theories presented by Getmansky et al. (2004) and Geltner (1997) and suggests that reported OPRE fund returns may be autoregressive moving averages of their lagged, 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) illustrate the relationship between fund returns and lagged market returns. Columns (3) through (6) illustrate 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 NAV-timing strategies in the absence of restrictions.

[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 are 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.

5.2. NAV-timing returns

I next evaluate the profitability of implementing two different NAV-timing strategies based on reported returns. The first strategy is based on the lagged returns of the overall OPRE market and invests either in an index of the OPRE 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 fund returns are predictable, the profitability of trading on this would be either insignificant, or captured by a traditional factor model. Investors risk having their wealth transferred to other investors to the extent that these strategies are profitable. Equation 34 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.

$$r^p = \alpha + \beta X + \varepsilon \tag{34}$$

Table 3 reports the return performance achieved by implementing the first strategy in the absence of trading frictions. The Long portfolio invests in the NFI-OE Index in every quarter following a positive return in the NFI-OE Index. 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 following a positive return in the NFI-OE Index. 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 return predictability on return performance and to compare the performance between two strategies that are mutually exclusive on the dimension of predictability. For comparison purposes, Panel B reflects the performance of a buy-and-hold investment in the NFI-OE over the entire sample period.

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 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) and (4) present the REIT Q-factor and 5-factor alphas for the three portfolios respectively.

An NAV-timing strategy of when to invest in the OPRE market or the risk-free rate could also be based on lagged public market returns. Table A.2 in the Appendix provides the results to the strategy based on the cumulative return of the prior four quarter publicly traded NAREIT Index. As shown, the results are consistent with those from the strategy based on prior NFI-OE returns. I chose the NFI-OE Index returns to be the primary basis for my analysis because they correlate with future NFI-OE returns better than any other index. As shown in Table A.1, lagged NFI-OE returns are better able to predict future NFI-OE returns than lagged NAREIT returns.

Table 4 reports the return performance achieved by implementing the second market-timing strategy in the absence of trading frictions. Figure 2 provides a graphical representation of the raw return results. 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 returns between Portfolio 5 and Portfolio 1. The purpose of analyzing the $5 - 1$ Portfolio return is, similarly, to 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) and (4) present the REIT Q-factor and 5-factor alphas for the six 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 preventative mechanisms to deter them, market-timing strategies would be profitable and transfer significant wealth from buy-and-hold investors. They also provide evidence that stale prices and return smoothing create both time-series and cross-sectional return predictability.

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 as well as **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 35, 36, and 37.

$$Fund\ Flow_{i,t} = \left[TNA_{i,t} - TNA_{i,t-1} \cdot (1 + r_{i,t})\right] / TNA_{i,t-1} \tag{35}$$

$$Net\ Queue_{i,t} = \left[Subscription\ Queue_{i,t} - Redemption\ Queue_{i,t}\right] / TNA_{i,t-1} \tag{36}$$

$$Total\ Flow_{i,t} = Fund\ Flow_{i,t} + Net\ Queue_{i,t} \tag{37}$$

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 public market NAREIT Index returns. Columns (3) and (4) show the results of regressing Total Flows on prior private market NFI-OE Index returns while columns (5) through (8) show the results of regressing Total Flows on lagged fund returns. The explanatory variables are consistent with the basis of both NAV-timing strategies. The robust, Newey-West standard errors with four lags are clustered by fund and time. As shown, prior public market returns, private market returns and fund returns are significant in explaining investor flow variation. A one standard deviation increase in lagged four quarter NAREIT, NFI-OE, and fund returns leads to approximate 0.17, 0.19, 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 of regressing Net Queues on lagged public market NAREIT Index returns. Columns (3) and (4) show the results of regressing Net Queues on prior private market NFI-OE Index returns while columns (5) through (8) show the results of regressing Net Queues on lagged fund returns. As shown, Net Queues are related to prior public market returns, private market returns, and fund returns. A one standard deviation increase in lagged four quarter NAREIT and fund returns leads to approximate 0.16, 0.18, and 0.51 standard deviation increases in the Net Queues respectively. This evidence suggests investor queues significantly decrease the ability of market-timing investors to exploit the OPRE return predictability.

5.4. Realizable NAV-timing returns

My next analysis looks at the returns investors could achieve by implementing a NAV-timing strategy. In doing so, I analyze the effects of both non-discretionary liquidity restrictions as well as discretionary liquidity restrictions on NAV-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 over which the manager has discretion to implement and include 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 NAV-timing fragility risks are reported in Tables 7 and 8. Table 7 shows the superior performance associated with timing when to enter and leave the OPRE market is not affected by non-discretionary liquidity restrictions. This is evidence the subscription notification and lockup periods are non-binding for this trading strategy. Table 8, however, shows the non-discretionary liquidity restrictions eliminate the superior performance associated with switching between funds. This is evidence the subscription notification and lockup periods are binding with this strategy. In all, this evidence suggests that nondiscretionary liquidity restrictions do a good job of eliminating the fragility risks associated with investors switching between funds, but do a poor job of deterring the fragility risks associated with timing when to enter and leave the overall OPRE market.

5.4.2. Discretionary liquidity restrictions

The results from my analysis on the effect of discretionary liquidity restrictions on deterring NAV-timing fragility risks are reported in Tables 9 and 10. I obtain queue-adjusted return estimates in order to evaluate the returns investors could achieve by implementing the timing strategies after waiting in the queue. In order to isolate the effect of the queue on the returns, I only consider those liquidity restrictions essential to the queue - the queue size and the notification period. I do not consider the lock-up period. 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 removed if queue durations last longer than return predictability.

As shown in Table 9, the queue-adjusted returns from the strategy associated with timing when to enter and leave the OPRE market are roughly 60% of those from the unconstrained analysis. Additionally, the returns to the Long Portfolio returns are no longer statistically or economically different from the returns to a buy-and-hold strategy. This finding is relevant considering that investors cannot short these funds. As shown in Table 10, the queue-adjusted returns for quintiles 2 through 5 are no longer statistically different from each other. Similarly, the 5 - 1 portfolio is no longer statistically or economically different from zero.

Lastly, and most importantly, none of the quintile queue-adjusted returns are statistically or economically larger than those from a buy-and-hold strategy. It is interesting to note that even the returns to the lowest performing strategy (quintile 1) are improved after considering the queues. In all, this evidence is consistent with the econometric theory associated with stale pricing and suggests that return performance becomes more random and unpredictable after considering the queues.

Queue-adjusted returns are estimated in the following way. I obtain both incoming and outgoing quarterly absorption rates for each fund. I define the absorption rate as the percentage of the capital that investors want to invest or redeem, and are able to do so. Absorption rates are calculated as either the fund flow divided by the combined fund flow and queue, or simply the change in the queue. If the fund flow is in the direction suggested by the strategy, then the absorption rate is estimated as a fraction of fund flow and queue. If the fund flow is not in the direction suggested by the strategy, then the absorption rate is calculated as the change in the queue. Absorption rates are assigned a value of 100% when queues are not observed.

Allocations and investments into each fund are then calculated quarterly for each of the OPRE market and quintile strategies in the following way. When strategies suggest increasing fund allocations, the absorption rate is multiplied by the sum of one minus the lagged allocation are then added to the lagged allocation. When strategies suggest decreasing fund allocations, the absorption rate is multiplied by the lagged allocation and then subtracted from the lagged allocation. Queue-adjusted returns are then calculated as weighted average allocation times the return.

5.5. Liquidity buffers

My last analysis evaluates the fourth prediction: funds that use liquidity buffers instead of liquidity restrictions to deter NAV-timing are more susceptible to runs and failure. To evaluate this prediction, I analyze the extent to which OPRE funds use cash buffers. I also analyze the effect that lagged cash has on negative fund flows, both during the GFC as well as during the entire sample. Funds allow more wealth to be transferred to outgoing investors when they allow more capital to leave the fund when their NAVs are overvalued.

As shown in Table 1, cash holdings make up a small portion of the overall assets held by OPRE funds. The median cash holding over the sample period was slightly above 3.5%. Anecdotally, most quarterly reports reviewed have a clause stating that redemption requests will be fulfilled to the extent that excess cash is available at the discretion of the manager. This suggests that, in equilibrium, OPRE funds do not actively use cash to buffer their capital flows.

The results from my analysis of cash holdings on negative fund flows is reported in Table 11. In order to isolate the effect of cash holdings on the ability to redeem, I only consider those observations where either fund flows or queues are negative for the entire sample and only when there were negative queues during the 2008 and 2009 GFC. As shown, more capital was able to leave both in those funds and at those times when there was a greater cash balance in the previous quarter. Specifically, a one standard deviation increase in lagged cash corresponds with a 25.8% standard deviation increase in outflows over the entire sample period. Similarly, a one standard deviation increase in cash corresponded to an approximate 19.8% standard deviation increase in outflows during the GFC. In all, this evidence is consistent with the theoretical model and suggests that liquidity buffers can increase the incentive to run when return predictability is unrelated to forced fire sales.

6. Conclusion

This paper has three main insights. First, open-end funds create market-timing and fragility risks when they invest in infrequently traded, difficult-to-value assets. Next, managers protect against these risks by limiting capital flows into and out of their funds in order to prevent fire sales and fire purchases. Greater illiquidity in the underlying assets means greater return predictability, but it also means longer transaction timeframes are needed in the underlying market to not push prices. Lastly, funds reintroduce wealth transfer and shareholder-run risks when they 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 take advantage of stale prices.

The findings in this paper are important to both practitioners and policy makers. For practitioners, my findings suggest funds should be cautious about using liquidity buffers, especially if they have the ability to suspend issuing and redeeming shares. This is particularly the case after significantly negative economic shocks. A better approach may be to suspend issuing and redeeming shares to generally keep a 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 of capital entering and leaving the fund, deterring the ability of investors to exploit the return predictability.

Next, this evidence suggests investors would benefit from increased transparency and standardization in the reporting of unfulfilled commitments and redemptions. It also suggests 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 conflicting effects of liquidity buffers on coordination failures, forced fire sales, and other forms of predictability appears 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 exposure to illiquid assets, it could push the liquidity transformation services they provide into more opaque intermediaries, such as hedge funds. This would likely decrease the overall transparency of the service and could ultimately cause 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 than the 3-month T-bill interest rate. Fund Flow is capital flow into the fund during a given quarter as a percent of the lagged total net assets. It is calculated as: $Fund\,Flow_{i,t} = \left[TNA_{i,t} - (TNA_{i,t-1} \cdot R_{i,t})\right]/TNA_{i,t-1}$. 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. Cash balance is the lagged percent amount of cash held by the fund in a given quarter and is calculated as $Cash_{i,t-1} = Dollar\,Cash_{i,t-1}/TNA_{i,t-1}$.

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 from my analysis on the 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. The symbols *, **, 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***
	(2.09)	(2.43)	(5.64)	(5.09)	(5.99)	(5.56)
r_{t-2}	0.087***	0.087***	0.215***	0.210***	0.131***	0.110***
	(2.67)	(4.69)	(5.78)	(5.51)	(4.13)	(3.43)
r_{t-3}	0.101***	0.107***	-0.038	-0.041	0.061	0.041
	(2.99)	(4.02)	(-0.73)	(-0.81)	(1.62)	(1.05)
r_{t-4}	0.103***	0.120***	-0.009	-0.020	0.195***	0.173***
	(3.18)	(5.60)	(-0.10)	(-0.23)	(3.34)	(2.95)
r_{t-5}	0.079***	0.086***				
	(2.68)	(3.79)				
r_{t-6}	0.054**	0.065***				
	(2.37)	(3.33)				
r_{t-7}	0.030	0.048**				
	(1.22)	(2.49)				
r_{t-8}	0.029	0.045***				
	(1.15)	(3.18)				
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 Results

This table presents the first set of results from my analysis on the trading profitability that comes from OPRE return predictability (without liquidity restrictions). Long returns are the those obtained by either investing in the OPRE market (as proxied by the NFI-OE) or the 3-month T-bill based on prior OPRE market performance. Short returns are those obtained by taking the opposite investment position as the Long portfolio. Long-Short returns are those obtained by subtracting Short portfolio returns from the Long portfolio returns. Panel A reports the results of Long and Short portfolio returns less the 3-month T-bill while Panel B reports the results of a buy-and-hold investment in the NFI-OE less the 3-month T-bill. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, 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	2.544***	2.130***	2.721***	2.596***	48
	(11.42)	(11.86)	(12.48)	(11.43)	
Short	-1.020**	-2.130***	-0.967**	-1.066*	48
	(-2.16)	(-11.86)	(-2.06)	(-1.94)	
Long-Short	3.564***	4.260***	3.688***	3.662***	48
	(8.93)	(11.86)	(8.82)	(8.43)	

Panel B: NFI-OE returns in excess of the 3-month T-bill

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Buy-and-hold	1.524**	N/A	1.754***	1.530**	48
	(2.07)		(2.67)	(2.08)	

Table 4

Cross-Sectional NAV-timing Results

This table presents the second set of results from my analysis on the trading profitability from OPRE 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 prior four quarter relative performance. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	0.915	-0.996***	1.261	1.045	48
	(0.97)	(-5.84)	(1.58)	(1.05)	
2	1.436*	-0.126	1.636**	1.474*	48
	(1.94)	(-1.05)	(2.41)	(1.90)	
3	1.700**	0.220*	1.996***	1.663**	48
	(2.44)	(1.68)	(3.29)	(2.32)	
4	1.780***	0.413***	1.941***	1.744***	48
	(2.68)	(4.31)	(3.21)	(2.70)	
5	1.936***	0.441***	2.143***	1.917***	48
	(2.68)	(2.89)	(3.10)	(2.88)	
5 - 1	1.020***	1.437***	0.882***	0.872**	48
	(3.28)	(4.88)	(3.14)	(2.18)	

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 TNA, $TCF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\,Queue_{i,t} - Redemption\,Queue_{i,t}]/TNA_{i,t-1}$. Excess Returns are calculated quarterly as the 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) through (6) report the results of regressing the Total Capital Flow on the lagged fund Excess Returns with no fixed effects, fund fixed effects, 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 period. The symbols *, **, 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)						
$r_{NFI-OE,t-1}$			2.043***	2.069***				
			(5.10)	(4.28)				
$r_{i,t-1\Rightarrow t-5}$					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	No	Yes
Time f.e.	No	No	No	No	No	No	Yes	Yes
N	1,117	1,117	1,117	1,117	1,117	1,117	1,117	1,117
R^2	0.04	0.41	0.07	0.43	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 quarterly as the 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) through (6) report the results of regressing the Net Queues on the lagged fund Excess Returns with no fixed effects, fund fixed effects, 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 period. The symbols *, **, 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)						
$r_{NFI-OE,t-1}$			1.648***	1.645***				
			(5.09)	(4.32)				
$r_{i,t-1\Rightarrow t-5}$					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	No	Yes
Time f.e.	No	No	No	No	No	No	Yes	Yes
N	1,117	1,117	1,117	1,117	1,117	1,117	1,117	1,117
R^2	0.04	0.41	0.06	0.44	0.07	0.42	0.16	0.53

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

This table presents the first set of results from my analysis on the effect of non-discretionary liquidity restrictions (NDLRs) on NAV-timing profitability. Long returns are the those obtained by either investing in the OPRE market (as proxied by the NFI-OE), or the 3-month T-bill based on prior OPRE market performance. In contrast to Table 3, allocations cannot switch from the NFI-OE to the 3-month T-bill until four quarters after switching from the 3-month T-bill to the NFI-OE. A one quarter notification delay is used from the quarter returns are realized to the date target allocations are determined. Short returns are those obtained by taking the opposite NFI-OE and 3-month T-bill allocation as the Long portfolio. Long-Short returns are those obtained by subtracting the Short portfolio returns from the Long portfolio returns. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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)	

Table 8

Cross-Sectional NAV-timing Results (NDLRs)

This table presents the second set of results from my analysis on the effect of non-discretionary liquidity restrictions (NDLRs) on NAV-timing profitability. Quintile portfolio returns are calculated as the value-weighted excess return of the funds within a given quintile portfolio in the quarter after portfolios are created. Funds are allocated to target quintile portfolios based on their four quarter relative prior performance. However, actual allocations are updated conditional on a given quintile holding the fund for at least four quarters. A one quarter notification delay is used from the quarter returns are realized to the date target allocations are determined. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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)	

Table 9
Time-Series NAV-timing Results (DLRs)

This table presents the first set of results from my analysis on the effect of discretionary liquidity restrictions (DLRs) on NAV-timing profitability. Long returns are the those obtained by either investing in the OPRE market (as proxied by the NFI-OE) or the 3-month T-bill based on prior OPRE market performance. Short returns are those obtained by taking the opposite investment strategy as the Long portfolio. In contrast to Table **3**, NFI-OE allocations for both Long and Short portfolios only adjust to the extent capital is able to either enter or leave the OPRE funds after considering DLRs. A one quarter notification delay is used from the quarter returns are realized to the date target allocations are determined. Long-Short returns are those obtained by subtracting the Short portfolio returns from the Long portfolio returns. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	1.620***	0.465***	1.805***	1.636***	48
	(3.47)	(10.52)	(3.98)	(2.99)	
Short	-0.577	-1.422***	-0.437	-0.592	48
	(-1.64)	(-13.45)	(-1.29)	(-1.37)	
Long-Short	2.196***	1.887***	2.242***	2.227***	48
	(12.50)	(13.56)	(11.47)	(13.43)	

Table 10

Cross-Sectional NAV-timing Results (DLRs)

This table presents the second set of results from my analysis on the effect of discretionary liquidity restrictions (DLRs) on NAV-timing profitability. Quintile portfolio returns are calculated as the value-weighted excess return of the funds within a given quintile portfolio in the quarter after portfolios are created. Funds are allocated to target quintile portfolios based on their four quarter relative prior performance. However, actual allocations are updated only to the extent that capital attempting to enter or leave a fund is able to do so (fund flow / fund flow + net queue). A one quarter notification delay is used, from the quarter returns are realized, to the date target allocations are determined. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Quintile	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
1	1.182*	-0.408***	1.403**	1.157	48
	(0.66)	(0.12)	(0.61)	(0.80)	
2	1.393**	-0.088	1.606***	1.416*	48
	(0.61)	(0.11)	(0.59)	(0.73)	
3	1.552**	-0.000	1.804***	1.558**	48
	(0.64)	(0.06)	(0.61)	(0.76)	
4	1.523**	-0.010	1.769***	1.488**	48
	(0.63)	(0.08)	(0.63)	(0.73)	
5	1.341*	-0.454***	1.603**	1.217	48
	(0.74)	(0.16)	(0.76)	(0.88)	
5 - 1	0.159	-0.046	0.200	0.059	48
	(0.21)	(0.19)	(0.23)	(0.18)	

Table 11

Negative Flows and Cash

This table presents the results from my analysis on the effect of cash holdings on negative fund flows. 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: $Fund\ Flow_{i,t} = \left[TNA_{i,t} - (TNA_{i,t-1} \cdot R_{i,t})\right] / TNA_{i,t-1}$. Cash is the percentage of assets held by the fund as cash in the prior quarter and is calculated as $Cash_{i,t-1} = Dollar\ Cash_{i,t-1}/TNA_{i,t-1}$. Columns (1) through (4) evaluate the relation between Fund Flows and Cash for all funds having either a negative flow or a redemption queue from 2004 through 2015. Columns (5) through (8) evaluate the relation between Fund Flows and Cash for all funds having a redemption queue during the Global Financial Crisis of 2008 and 2009. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

$$Fund\ Flows_{i,t} = \beta_0 + \beta_1 Cash_{i,t-1} + \varepsilon_{i,t}$$

	Entire Sample (funds with negative flows or redemption queues)				Global Financial Crisis (2008/2009) (funds with redemption queues)			
$Cash_{i,t-1}$	-0.388***	-0.424***	-0.369***	-0.469***	-0.133	-0.328*	-0.136	-0.361**
	(-4.54)	(-4.68)	(-4.43)	(-5.68)	(-1.21)	(-2.17)	(-1.21)	(-2.70)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	Yes	Yes	No	No	Yes	Yes
N	1,628	1,628	1,628	1,628	131	131	131	131
R^2	0.10	0.21	0.22	0.30	0.04	0.31	0.07	0.35

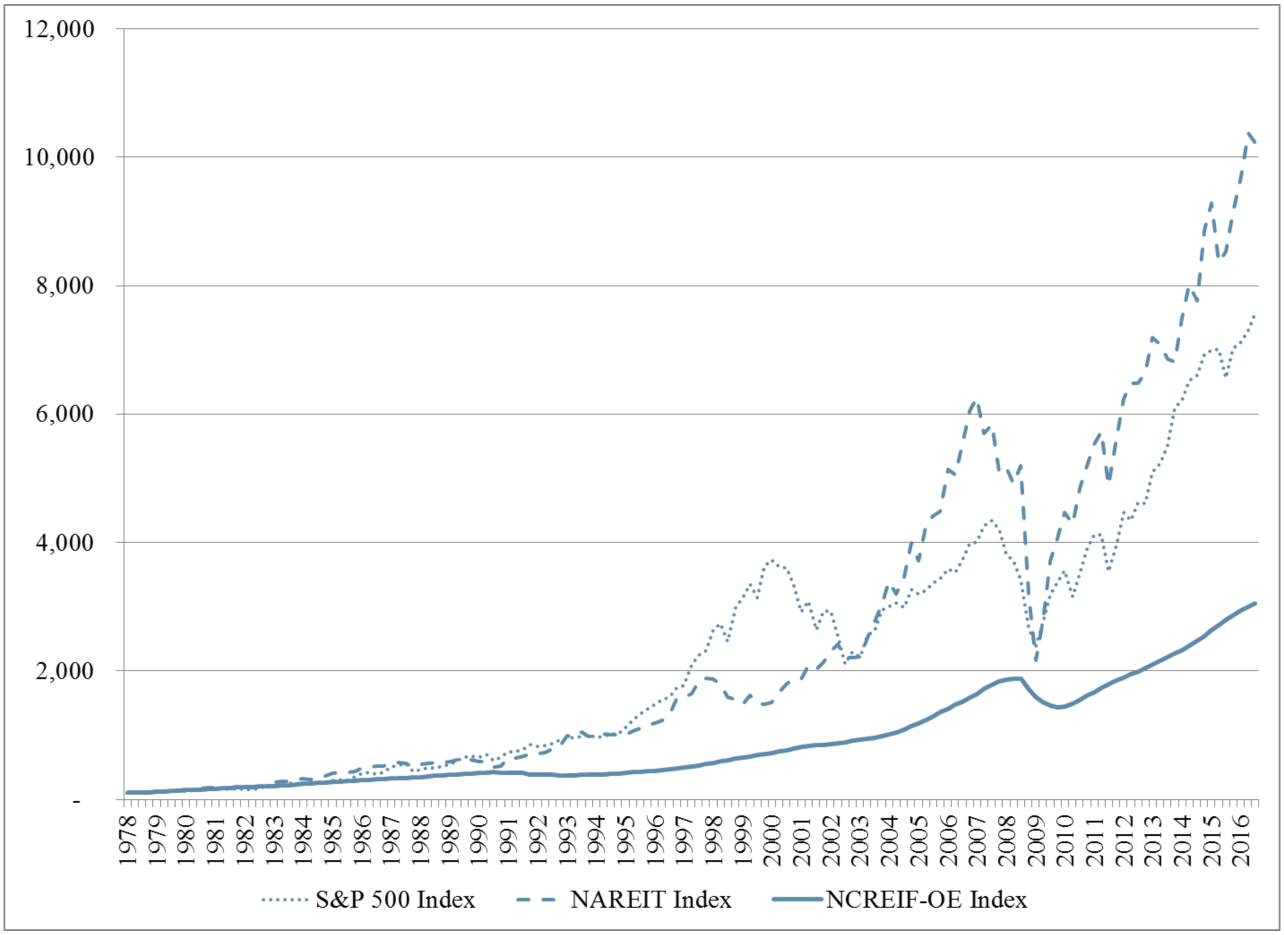

Figure 1
S&P 500, NAREIT, and NFI-OE Indices over Time

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.

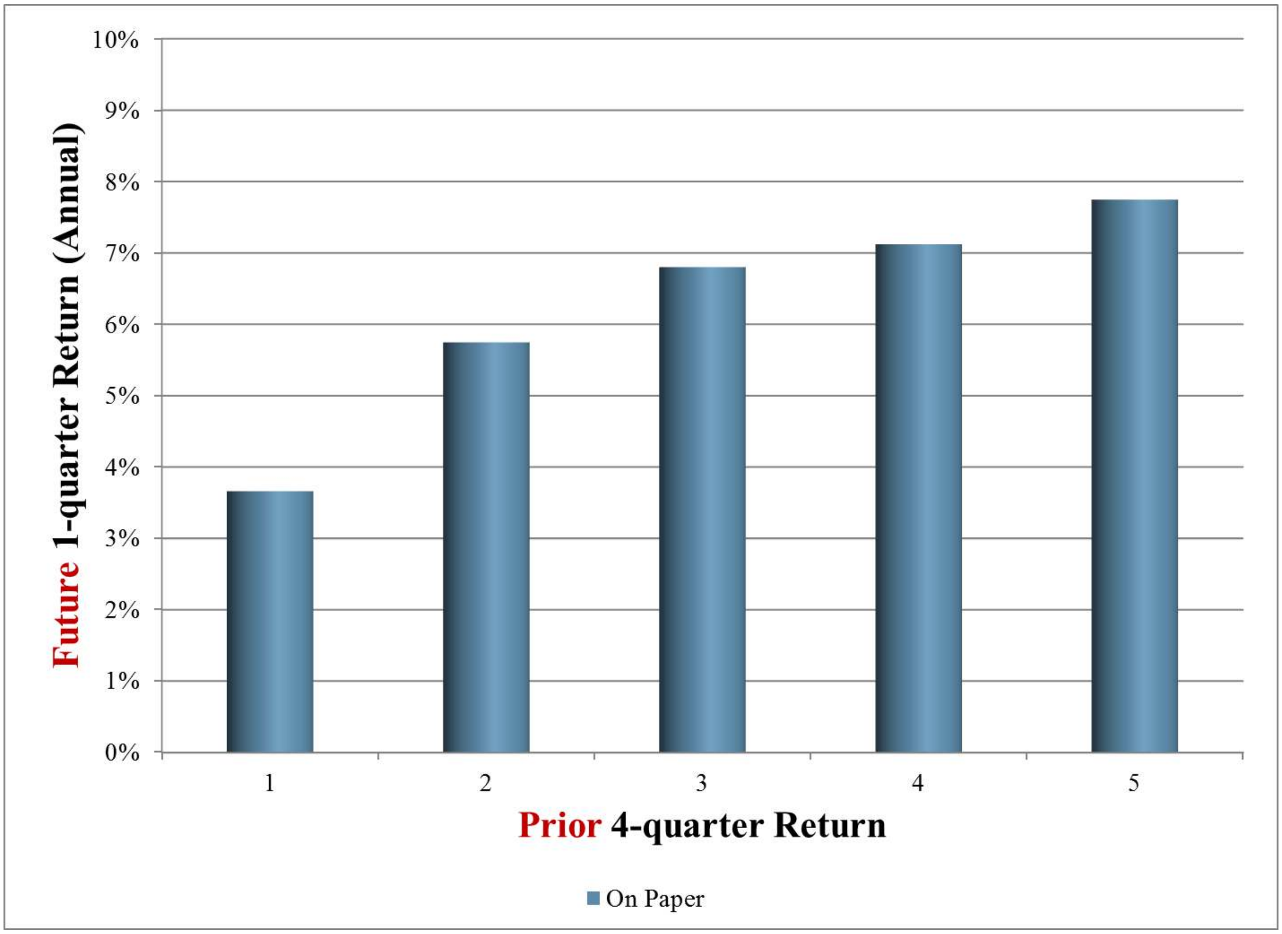

Figure 2
Future Returns by Prior Return Quintiles

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.

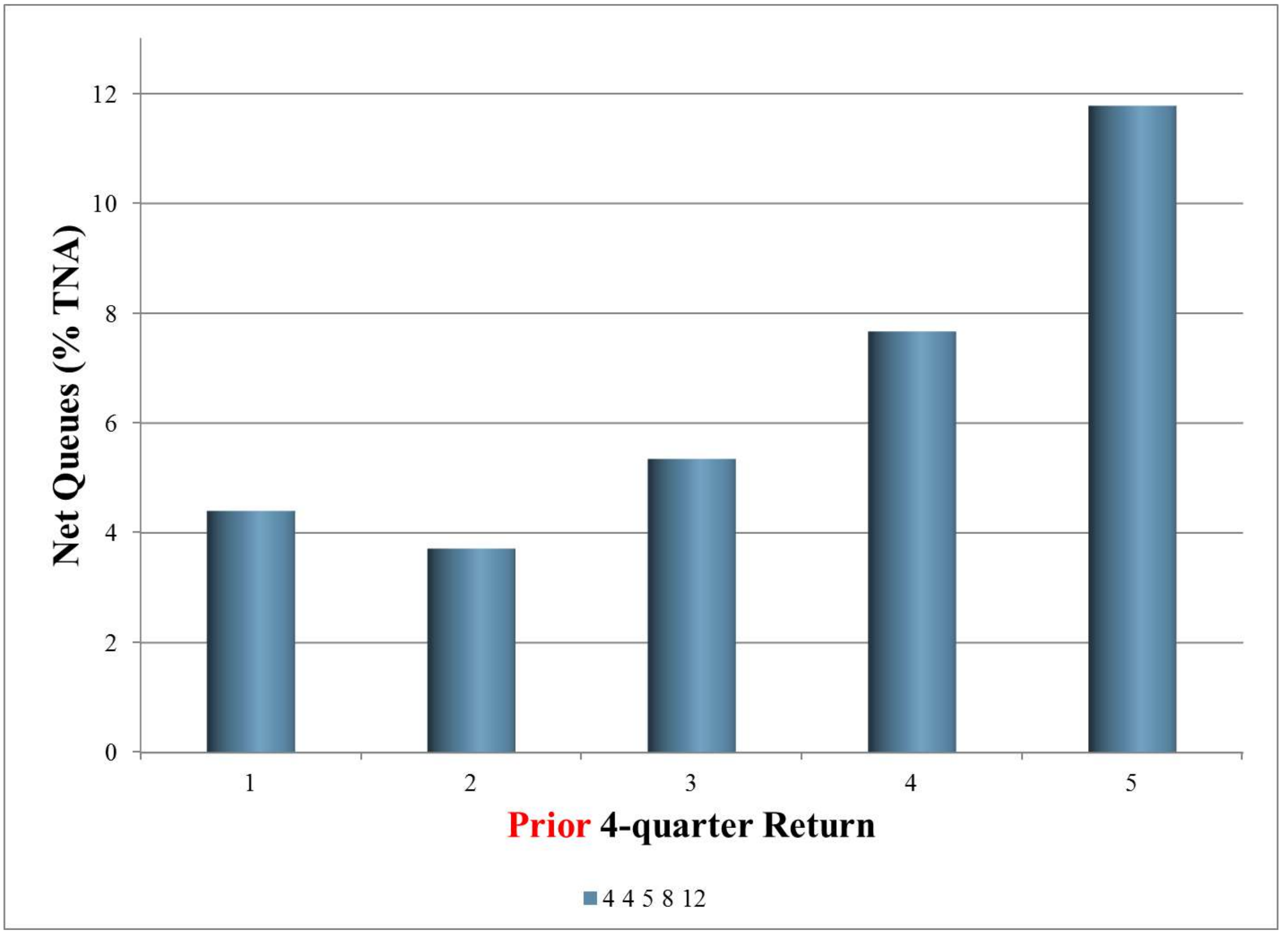

Figure 3
Queue Size (%AUM) by Prior Return Quintiles

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.

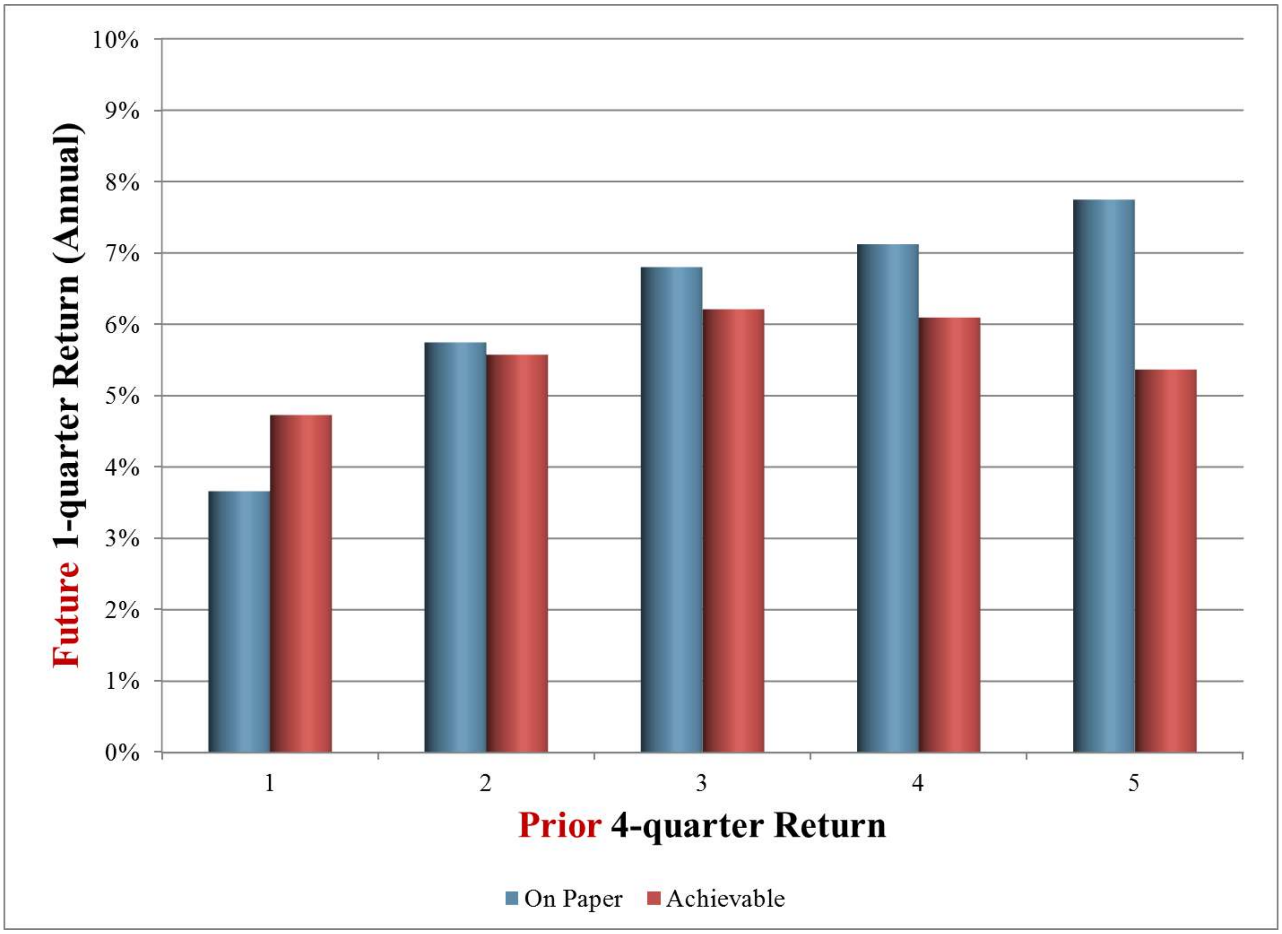

Figure 4
Raw and Q-adjusted Returns by Prior Return Quintiles

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 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 Time-Series Strategies Based on Prior Public Market Returns

This section provides the results from my analysis comparing the use of public market to private market information sets in creating NAV-timing strategies. Table A.1 compares the return predictability of prior OPRE fund returns and FTSE NAREIT returns. Table A.2 presents the results from my analysis on the NAV-timing profitability (without liquidity restrictions) using prior public return data as the basis of the timing strategy.

Table A.1

OPRE Return Predictability

This table presents the results from my analysis on which explanatory variable best explains future NFI-OE Index return variation. The first explanatory variable is the lagged NFI-OE Index return. The second explanatory variable is the lagged cumulative return for the prior four quarters of NAREIT Index returns. The third explanatory variable is the lagged cumulative return for the prior six quarters of NAREIT Index returns. The fourth explanatory variable is the lagged cumulative return for the prior eight quarters of NAREIT Index returns. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 r_{NAREIT,t-1\Rightarrow t-5} + \beta_3 r_{NAREIT,t-1\Rightarrow t-7} + \beta_4 r_{NAREIT,t-1\Rightarrow t-9} + \varepsilon_t$$

r_{t-1}	0.850**				0.607*
	(41.03)				(12.40)
$r_{NAREIT,t-1\Rightarrow t-5}$		0.071*			0.024
		(10.52)			(5.02)
$r_{NAREIT,t-1\Rightarrow t-7}$			0.062**		0.009*
			(16.69)		(9.76)
$r_{NAREIT,t-1\Rightarrow t-9}$				0.045**	0.001
				(59.71)	(0.37)
Fund f.e.	No	No	No	No	No
Time f.e.	No	No	No	No	No
N	48	48	48	48	48
R^2	0.72	0.46	0.54	0.42	0.76

Table A.2
Time-Series NAV-timing Results (public returns)

This table presents the results from my analysis on the robustness of trading profitability that comes from OPRE return predictability (without liquidity restrictions). In particular, this table presents the results to a trading strategy of investing in either the OPRE market or the risk-free rate based on the observation of prior publicly traded REIT returns. The Long portfolio invests in the NFI-OE Index when the prior four quarter cumulative return for the NAREIT Index is positive and the 3-month T-bill otherwise. The Short portfolio invests in the 3-month T-bill when the prior four quarter cumulative return for the NAREIT Index is positive and the NFI-OE Index otherwise. Standard errors are Newey-West robust, adjusted for heteroskedasticity, and double clustered by fund and period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long	2.569***	2.161***	2.715***	2.616***	48
	(10.41)	(12.81)	(11.23)	(11.44)	
Short	-1.045*	-2.161***	-0.961*	-1.086*	48
	(-1.94)	(-12.81)	(-1.91)	(-1.93)	
Long-Short	3.613***	4.323***	3.676***	3.703***	48
	(8.58)	(12.81)	(8.32)	(8.07)	

Appendix B Model Proof

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

B.1 Fund Flow Proof

By substituting the market-timing investor's post fund flow fund allocation into equation 12, I obtain the optimal fund flow as follows.

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

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

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

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

B.2 Internal Wealth Transfer Proof

By substituting the market-timing investor's optimal fund flow into equation 20, I obtain the expected wealth transfer based on the staleness of the reported fund NAV as follows.

$$E_1\left(WT\right) = TNA_0\left(R_1^E - R_1^{Fund}\right)FF_1 \tag{A.5}$$

$$E_1\left(WT\right) = TNA_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.6}$$

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.

$$E_1\left(WT^{BH}\right) = \frac{\left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)}{TNA_0}TNA_0\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.7}$$

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

$$E_1\left(WT^{BH}\right)=\left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{TNA_1}\frac{\gamma_1}{\gamma_2}\left(\left(R_1^E\right)^{\Theta}-1\right) \tag{A.9}$$

$$E_1\left(WT^{MT}\right)=\left(\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)FF_1-TNA_0\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.10}$$

$$E_1\left(WT^{MT}\right)=\left(\omega_0^{MT}\Pi_0^{MT}-TNA_0\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)FF_1 \tag{A.11}$$

$$E_1\left(WT^{MT}\right)=\left[\left(\omega_0^{MT}\Pi_0^{MT}-TNA_0\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)\right]FF_1 \tag{A.12}$$

$$E_1\left(WT^{MT}\right)=\left[\left(\omega_0^{MT}\Pi_0^{MT}-TNA_0\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)\right]\left(\omega_1\Pi_1^{MT}-\Pi_0^{MT}\omega_0\left(R_1^E\right)^{(1-\Theta)}\right) \tag{A.13}$$

B.3 Expected Fund Return Proof

The return achieved by the fund is obtained as follows. Starting with equation 16, I substitute equivalent values using the variables described in Section 3 above.

$$R_2^{Fund}=\frac{TNA_0^{Fund}R_1^ER_2^E+TNA_0^{Fund}R_1^{Fund}FF_1R_2^E-TNA_0^{Fund}R_1^{Fund}\psi\left(FF_1\right)^2}{TNA_0^{Fund}R_1^{Fund}\left(1+FF_1\right)} \tag{A.14}$$

$$R_2^{Fund}=\frac{R_1^ER_2^E+R_1^{Fund}FF_1R_2^E-R_1^{Fund}\psi\left(FF_1\right)^2}{R_1^{Fund}\left(1+FF_1\right)} \tag{A.15}$$

$$R_2^{Fund}=\frac{R_1^ER_2^E+\left(R_1^E\right)^{(1-\Theta)}FF_1R_2^E-\left(R_1^E\right)^{(1-\Theta)}\psi\left(FF_1\right)^2}{\left(R_1^E\right)^{(1-\Theta)}\left(1+FF_1\right)} \tag{A.16}$$

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

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

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

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

B.4 Wealth Destruction Proof

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

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

$$E_1\left(WD\right) = TNA_0 R_1^{Fund}\left(1+FF_1\right)\left[E_1\left(R_2^{Fund,b}\right) - E_1\left(R_2^{Fund,c}\right)\right] \tag{A.23}$$

$$E_1\left(WD\right) = TNA_0 R_1^{Fund}\left(1+FF_1\right) E_1\left[\frac{\left(R_1^E\right)^{\Theta} + FF_1}{\left(1+FF_1\right)} - \frac{\left(R_1^E\right)^{\Theta} + FF_1 - \psi\left(FF_1\right)^2}{\left(1+FF_1\right)}\right] \tag{A.24}$$

$$E_1\left(WD\right) = TNA_0 R_1^{Fund}\left(1+FF_1\right) E_1\left[\frac{\left(R_1^E\right)^{\Theta} + FF_1 - \left(R_1^E\right)^{\Theta} - FF_1 + \psi\left(FF_1\right)^2}{\left(1+FF_1\right)}\right] \tag{A.25}$$

$$E_1\left(WD\right) = TNA_0 R_1^{Fund}\left(1+FF_1\right)\frac{\psi\left(FF_1\right)^2}{\left(1+FF_1\right)} \tag{A.26}$$

$$E_1\left(WD\right) = TNA_0 R_1^{Fund} \psi\left(FF_1\right)^2 \tag{A.27}$$

$$E_1\left(WD\right)=TNA_0\left(R_1^E\right)^{(1-\Theta)}\psi\left(FF_1\right)^2 \tag{A.28}$$

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

$$\begin{aligned}E_1\left(WD\right)= & \frac{\left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)TNA_0R_1^{Fund}+\left(\omega_0^{MT}\Pi_0^{MT}\right)TNA_0R_1^{Fund}+TNA_0R_1^{Fund}FF_1}{TNA_0R_1^{Fund}(1+FF_1)}\cdot\\ & TNA_0R_1^{Fund}\psi\left(FF_1\right)^2\end{aligned} \tag{A.30}$$

$$E_1\left(WD^{BH}\right)=\frac{\left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)TNA_0R_1^{Fund}}{TNA_0R_1^{Fund}\left(1+FF_1\right)}TNA_0R_1^{Fund}\psi\left(FF_1\right)^2 \tag{A.31}$$

$$E_1\left(WD^{MT}\right)=\frac{\left(\omega_0^{MT}\Pi_0^{MT}\right)TNA_0R_1^{Fund}+TNA_0R_1^{Fund}FF_1}{TNA_0R_1^{Fund}\left(1+FF_1\right)}TNA_0R_1^{Fund}\psi\left(FF_1\right)^2 \tag{A.32}$$

B.5 Investor's Response to Stale Pricing Incentives

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

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

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

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

<u>First Order Condition:</u>

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

$$0 = \gamma_1 \left(\frac{R_1^E E_1 \left(R_2^E \right)}{R_1^{Fund}} - 1 \right) - \gamma_2 \left(\omega_{1,b} - \omega_{1,a} \right) \tag{A.38}$$

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

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

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

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

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

B.6 Fund's Response to Price Impact Incentives

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

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

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

First Order Condition:

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

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

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

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

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

B.7 Joint Solutions: Investor and Fund Responses

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

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

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

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

$$E_1\left(WT^{BH}\right) = \left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right) \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{\gamma_1}{\gamma_2} \left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \cdot \frac{\gamma_3 TNA_{1,a} TFF_1 + \gamma_5 \left(TFF_1\right)^2}{\left(\gamma_4 \psi + \gamma_5\right) \left(TFF_1\right)^2} \tag{A.56}$$

B.8 Liquidity Management and Liquidity Buffers

- **Fund Optimization DFF selection:**

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

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

First Order Condition:

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

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

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

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

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

- **Wealth Transfer**

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) FF_1^{LB} \tag{A.64}$$

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1^{LB} \tag{A.65}$$

$$E_1\left(WT^{BH,LB}\right) = \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1^{LB} \gg \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) TFF_1 DFF_1 = E_1\left(WT^{BH}\right) \tag{A.66}$$

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

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