Liquidity Transformation Risks and Stabilization Tools: Evidence from Open-end Private Equity Real Estate Funds*

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Abstract

Open-end funds provide a liquidity transformation service by issuing and redeeming shares that are more liquid than their assets. However, because these assets are illiquid, managers need time to transfer capital to the underlying market. Liquidity buffers and liquidity restrictions enable this. Additionally, because of this illiquidity, their returns are predictable and susceptible to NAV-timing strategies which transfer wealth. I show NAV-timing strategies appear profitable on paper and investors appear to follow these strategies. I also show liquidity restrictions protect against these NAV-timing risks while liquidity buffers do not. In fact, liquidity buffers amplify them when added to liquidity restrictions.

JEL Classification: G11, G12, G13, G14, G17, G23, R33
Keywords: Fair Valuation, Financial Fragility, NAV-timing, Real Estate

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1. Introduction

The number and size of open-end funds investing in illiquid assets has grown dramatically in recent years.[1] As such, it is important to understand the mechanisms which can destabilize and restabilize these intermediaries. Economists have argued that open-end funds are exposed to bank-run-like risks when they invest in illiquid assets (see Chen et al. (2010) and Goldstein et al. (2017)).[2] Funds may be forced to sell illiquid assets at a discount if too many investors redeem shares quickly and investors might redeem shares quickly simply due to coordination issues. While this is an important fragility risk, funds that invest in illiquid assets are also believed to have stale prices (see Getmansky et al. (2004), Geltner (1993a), Geltner (1997), and Couts et al. (2020) among others). As such, their reported returns are believed to be weighted averages of the lagged economic returns, which mechanically creates spurious serial autocorrelation and return predictability. Because stale pricing potentially affects fragility risks differently than sources discussed in the banking literature, it is important to understand how they interact with prominent stabilization tools. This is the first paper to evaluate the stale pricing fragility risks created when open-end funds invest in illiquid assets.[3] Additionally, no other paper has evaluated the effectiveness of liquidity restriction

[1]For example, in October of 2021, Sequoia announced the creation of The Sequoia Capital Fund which is an open-end evergreen fund that provides liquidity to investors while investing in both liquid public securities and illiquid venture capital sub-funds. In 2016, Blackstone founded the open-end BREIT fund. As of June 2022, the BREIT fund had over $125B in total assets under management. Additionally, interval funds provide quarterly liquidity to their investors while investing in illiquid investments such as infrequently traded credit, private equity, real estate, or insurance related derivatives. Interval funds have nearly doubled their total net assets from 2018 to 2022 ($26 to $50 billion).

[2]The International Organization of Securities Commissions (IOSCO), an international body of global securities regulators, has written numerous reports in recent years detailing their concerns and recommendations for managing illiquidity risk in open-end funds. Additionally, the Financial Stability Board (FSB), an international body of financial system monitors, has written multiple reports discussing liquidity risks in open-end funds as well. Additionally, many country regulators, including the SEC, have issued similar reports on the topic. None of these reports addresses the concerns discussed in this paper.

[3]As further evidence this risk not well known, I set up a call with the Financial Accounting Standards Board (FASB) in April of 2018 to share the results of this paper. They were adamant fair valuations were not systematically stale for illiquid assets. FASB 820 is the accounting standard governing the fair valuation measurement of assets.

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and liquidity buffers in mitigating these risks.[4] [5] This paper attempts to fill this gap by theoretically and empirically analyzing the effects of stale pricing, liquidity restrictions, and liquidity buffers on Net Asset Value-timing (NAV-timing) profits in U.S. Open-end Private Equity Real Estate (OPERE) funds.

In order to evaluate the incentives of investors and managers, I qualitatively model their interactions in a setting with open-end funds, illiquid assets, and stale prices. In doing so, investors choose their fund allocations and managers choose the level of their discretionary liquidity restrictions.[6] I obtain four predictions from the model. First, investors will attempt to decrease their holdings in these funds after negative macroeconomic shocks, and increase them after positive macroeconomic shocks. These incentives increase with the magnitudes of the shocks. Second, investors will attempt to decrease their holdings the most in those funds which performed the worst, and increase them the most in those funds which performed the best. Third, managers will increasingly limit fund flows as subscription and redemption requests increase, enabling them to place and redeem capital prudently. Combining these three predictions implies managers discretionarily limit fund flows the most when NAV-timing strategies would be the most profitable and transfer the most wealth. In this way, illiquidity in the underlying assets creates both the opportunity for, and the friction against, exploiting buy-and-hold investors. However, the model also predicts managers will increase investor run and wealth transfer risks if they add liquidity buffers to discretionary liquidity restrictions. While mathematically sound, this prediction contrasts the finding that liquidity buffers stabilize open-end intermediaries from other types of fragility risks.[7] I evaluate these

[4]Liquidity buffers refer to the use liquid assets to absorb the capital flow shocks from investors coming into and out of intermediaries. Liquidity buffers are used by managers to prevent them from having to acquire or sell illiquid assets too quickly when they have large fund flows. Liquidity buffers can be made up of cash or other forms of liquid assets, such as publicly traded securities.

[5]Liquidity restrictions refer to the limitations placed on the amount of capital that can either enter or leave an intermediary over a given period of time. Liquidity restrictions are similarly used by managers to prevent them from having to acquire or sell illiquid assets too quickly when they have large fund flow requests. Liquidity restrictions can be classified into discretionary and non-discretionary liquidity restrictions which will be discussed later in the paper.

[6]The relationship between the reported and economic returns is based on the econometric models provided by Getmansky et al. (2004) and Geltner (1997).

[7]Liquidity buffers have been shown to protect both banks (see Diamond and Dybvig (1983)) and open-end equity funds (see Agarwal et al. (2018)) against forced fire-sales. They give open-end funds the ability to meet capital flow requests without having to redeem capital too quickly from the underlying market, which also helps mitigate bank-run-like risks. Partly because of this, some new open-end funds investing in illiquid assets have large allocations to liquid publicly traded financial assets exposed to the same underlying

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predictions using U.S. OPERE fund data from 2004 through 2015.

OPERE funds provide a near ideal setting to evaluate the predictions relating stale prices and fund fragility.[8] Stale valuations are believed to be the primary source of autocorrelation for illiquid funds and assets (see Getmansky et al. (2004)). Consistent with this, commercial real estate assets are some of the most illiquid assets and are almost always valued through an appraisal, or valuation estimation, process. Therefore, the fragility risks coming from stale valuation estimates should be easier to isolate and observe. Additionally, OPERE funds report their uncalled capital commitments and unfulfilled redemption requests (queues).[9] Estimating the returns investors could achieve by implementing NAV-timing strategies requires estimating the returns they would realize after going through these queues (queue-adjusted returns). It is also important to have a good proxy for the true economic returns of the funds being evaluated. Because commercial real estate has both strong public and private markets, returns from the publicly traded real estate investment trust (REIT) market provide a good proxy for the economic returns of the OPERE fund market.[10] Lastly, these funds cannot mechanically adjust their holdings to accommodate fund flows because they hold individually unique, wholly owned, real assets. As such, I am able to abstract away from the possibility that the return predictability is mechanically driven by fund flow induced holding adjustments (see Coval and Stafford (2007) and Lou (2012)).[11] The data come from two proprietary databases which provide fund-level information from

markets as their private assets. For example, Figure 6 provides the portfolio of investments for the Griffin Institutional Access Real Estate Fund from June 2018. As shown, 20% of their investments were in publicly traded real estate securities while 78% were invested in open-end private equity real estate funds. Similarly, the newly created open-end Sequoia Capital Fund invests in both publicly traded technology securities as well as private venture capital investments.

[8]OPERE funds have existed since the late 1970's. In doing so, they have survived multiple market cycles and economic downturns including the global financial crisis. Additionally, their popularity has increased significantly over the last four decades of their existence. This is all further evidence of the importance to evaluate the mechanisms which stabilize them from fragility risks.

[9]Similar to OPERE funds, hedge funds use discretionary liquidity restrictions to gate capital outflows in order to not be forced to sell illiquid assets at a discount. However, unlike OPERE funds, hedge funds do not report the size of their unfulfilled redemption requests.

[10]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.

[11]Additionally, funds exhibit nearly identical levels of return predictability even when they do not buy or sell assets. This is further evidence that the return predictability is not driven by fund flow induced holding adjustments.

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2004 to 2015.[12]

I find that without trading constraints, NAV-timing strategies are statistically and economically significant. A long-short strategy based on investing in either the index of OPERE funds or the 3-month T-bill would have achieved annualized private real estate factor and 5-factor alphas of 18.2% and 15.5%, respectively, from 2004 to 2015. Additionally, a long-short strategy based on investing in either the top or 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 those of a simple buy-and-hold strategy. These findings suggest significant shareholder-run incentives and wealth transfer risks exist. This evidence further suggests the greatest fragility risks came from those strategies associated with timing when to enter and leave the overall market. In large part, this is due to the relatively larger time-series return variation compared to the relative smaller cross-sectional return variation. An important source of return variation in the sample came from the Global Financial Crisis (GFC) which had a larger impact on time-series variation than cross-sectional variation. This illustrates an important point regarding the NAV-timing and wealth transfer risks created from stale pricing. These risks appear to be the greatest when the overall economy experiences significantly negative macroeconomic shocks, or left tail events. This is important because it is also when investors and regulators are most concerned about fragility risks.[13]

I also find that investor behavior is consistent with these strategies. A one standard deviation increase in lagged public market index returns, private market index returns, and fund-level returns leads to 18%, 21%, and 43% standard deviation increases in fund subscription requests, respectively. This evidence suggests stale pricing is an important fragility risk and that significant wealth could be transferred without an appropriate protective mechanism. Similarly, I find that funds choose to limit capital flows in a manner consistent with these strategies. A one standard deviation increase in public market index returns, private market index returns, and fund-level returns leads to 18%, 19%, and 47% standard deviation increases in fund queues. This evidence suggests the strategies which are most profitable on paper also become the most overallocated and diluted. Lastly, this evidence suggests man-

[12] The sample starts in 2004 because it is the first year queue data is widely reported for these funds.

[13] Stale valuation risks become irrelevant as value changes converge to zero. As such, fund fragility risks increase as the amplitude in market cycles increase.

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agers limit the vast majority of the fund flow requests in order to redeem and place capital prudently.

After accounting for investor queues, I find that the returns to NAV-timing strategies are statistically and economically equivalent to those of buy-and-hold strategies. I also find that lockup and notification periods are ineffective at protecting against these strategies. Specifically, I find lockup periods have no effect on strategies moving into and out of the overall market while they dampen the returns associated with investing in the top quintile funds by roughly half. Additionally, a one quarter notification period has no effect on either strategy as both baseline strategies include this notification period. In all, this evidence suggests managers protect against the wealth transfer and NAV-timing risks created by stale prices when they discretionarily choose to limit fund flows in order to prevent selling assets at a discount or buying them at a premium. One of the novel findings of this paper is that, in equilibrium, investors behave as if they recognize returns are predictable, crowd each other out, and eliminate the trading opportunities in a way that is similar to the "winner's curse" discussed in the IPO literature.[14] [15] Another novel finding is that it is the illiquidity in the underlying assets which creates both the risk and the mitigant.

Lastly, I find that capital outflows correlate positively with lagged cash balances when investors want to leave the fund. 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 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. While it is intuitive for cash holdings to be related to capital flows, especially when funds have discretionary liquidity restrictions, this evidence suggests funds increase wealth transfers and shareholder run risks by holding more cash (or other liquid assets). This is consistent with

[14] 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 offerings, thus dissipating the profits over many investors.

[15] It is important to note that I cannot distinguish between investors using an NAV-timing strategy or simply chasing returns. However, their motivation is irrelevant as either strategy would transfer wealth and increase the fragility risk to the fund.

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the finding that OPERE funds hold little cash. The median cash holding for OPERE funds over the sample period was 3.6%. Due to endogeneity concerns, I interpret this evidence with caution. However, it is consistent with the economic intuition developed by the model and is a mathematical outcome of the econometric models generally accepted and used in the literature (see Getmansky et al. (2004), Geltner (1997), and Couts et al. (2020)). Additionally, it is also consistent with many private placement memorandums governing OPERE funds.[16] In all, this evidence supports the conclusion that liquidity buffers can increase fund fragility risks when added to discretionary liquidity restrictions.

This paper contributes to the return manipulation risk literature associated with intermediaries investing in difficult to value assets.[17] Aragon et al. (2021) provide evidence that managers engage in more return mismanagement in countries with weaker investor protection. They also provide evidence that fund flows are more sensitive to poor fund performance in those countries. Consistent with these findings is the evidence that hedge funds smooth returns more during economic downturns (see Bollen and Pool (2008), Bollen and Pool (2009), and Bollen and Pool (2012)). My paper contributes to this literature by demonstrating another mechanism through which return manipulation can lead to fund fragility risks. It also provides evidence that these risks are significant even in economies with strong investor protection. Additionally, the evidence that managers smooth returns the most after negative macroeconomic shocks suggests that stale pricing and NAV-timing risks are the largest when economists are the most concerned about fragility risks.

A large literature examines the depositor run risks associated with coordination problems in banks (Diamond and Dybvig (1983), among others). However, the liquidity mismatch in

[16] OPERE funds have redemption clauses in their private placement memorandums giving them discretion on when to fulfill redemption requests. These clauses typically have language consistent with the following, "Redemption requests will be accommodated to the extent excess cash is available. Fund managers will have full discretion to determine the extent to which cash is available for redemptions or ongoing expenses."

[17] Choi et al. (2022) explores the effect of fragility and wealth transfer risks caused by the stale pricing of illiquid assets in bond mutual funds. My analysis adds to their findings in that it also evaluates the stabilizing mechanisms used by open-end funds to protect against fragility risks. Specifically, I provide evidence detailing which stabilization mechanisms are effective and which are not. Moreover, I show that investors are not concerned with fire-sale risks in my setting (see Section D of the Appendix), which contrasts with some of their findings. Similarly, I find that investors cannot profit from strategies that explore stale prices in my setting, whereas they find large wealth transfers in their setting. Exploring the differences between the real estate and bond markets that lead to these drastically different results is an important challenge for future research, but out of the scope of this paper.

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banks and open-ended funds is different. Banks have a liquidity mismatch between their assets and debt, 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 significant discounts 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 not directly related to the value of the underlying assets; thus, the only negative externality redemptions create 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. The redemption values for their shares thus become stale when their asset values are stale. Therefore, investors create a negative externality to other investors in the fund simply by removing their capital in a declining market. Thus, not marking-to-market assets would likely have the opposite effect in open-end funds than it would have with banks.[18] Economists have argued historical cost accounting is better for illiquid assets than marking-to-market because it decreases excessive price volatility (Plantin et al. (2008)). However, doing so would similarly distort shareholder incentives and create negative externalities for the same reason in open-end funds.

Additionally, prior research has focused on the fragility risks created by open-end funds investing in illiquid assets and offering liquid claims to those assets. However, none of these have analyzed stale valuations of illiquid assets as a potential fragility source (see Chen et al. (2010); Goldstein et al. (2017)). Consistent with the banking literature, much of this literature focuses on liquidity buffers as the primary mechanism to deter this risk (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 the risks associated with return predictability. In fact, it provides evidence liquidity buffers amplify fragility risks when added to discretionary liquidity restrictions. Other papers have

[18]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."

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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 these restrictions provide (see Aragon (2007); Teo (2011); Aiken et al. (2015)). Additionally, prior literature showed that NAV-timing opportunities were created from nonsynchronous trading in mutual funds (see Bhargava et al. (1998); Chalmers et al. (2001); Goetzmann et al. (2001)). This research prompted regulators to modify the fair valuation techniques of the time to avoid nonsynchronous trading issues. Although the source of predictability discussed in this paper is different, this paper provides evidence NAV-timing risks remain important considerations even after the regulations created to address them.

It is important to consider other sources of serial correlation besides stale pricing and how they could influence the NAV-timing predictions. For instance, commercial real estate returns are believed to have a degree of non-spurious serial correlation. This could be due to either limits to arbitrage, transaction costs, or potentially sentiment (see Clayton et al. (2009), Ling et al. (2014), and Sagi (2021)). However, each of these sources of serial correlation is enabled only because of market frictions and the underlying assets are illiquid. Because of these frictions, asset values are believed to continue their momentum past where they would be if the assets were liquid. This momentum creates predictability in both the prices and returns, which is consistent with the econometric models of stale pricing outlined in Getmansky et al. (2004) and Geltner (1997). As such, the fragility predictions coming from the econometric models of stale pricing and the conclusions of this paper remain regardless of whether the source of predictability is truly due to stale pricing or illiquid asset market frictions. Additionally, Getmansky et al. (2004) consider other sources of serial correlation and conclude that stale pricing, either intentionally or unintentionally, is the primary source for serial correlation in hedge funds. This paper focuses on stale pricing because it is generally accepted as the primary source of serially correlated returns, and because the econometric models used to explain them present clear, testable predictions.

It is also important to consider how limiting fund flows 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 not receive much from

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this benefit if managers limit fund flows at the time when investors want to use it the most. Extending the logic of Diamond and Dybvig (1983), however, suggests that investors are strictly better off investing in open-end funds which intermittently limit issuances and redemptions, than they are investing directly in the assets themselves. According to Diamond and Dybvig (1983), the primary benefit of investing in an open-end intermediary that invests in illiquid assets is the risk sharing that occurs among the investors. Investors achieve higher expected returns by pooling their capital together and investing in illiquid assets collectively when they are independently exposed to the risk of a liquidity shock. Consistent with this intuition, open-end funds that limit fund flows at times, provide liquidity to those investors whose fund flow requests are not positively correlated with those of other investors. These funds are therefore open and liquid to the extent that fund flow requests are idiosyncratic. However, these funds limit fund flows when their these requests become systematically correlated in order to purchase and sell assets prudently. In these cases, funds become illiquid and closed to the extent their underlying assets are illiquid. In doing so, these funds provide strictly more liquidity to investors when fund flow requests are idiosyncratic and strictly no worse liquidity when they are systematic.[19] [20]

The rest of the paper is outlined as follows. Section 2 provides an overview of the OPERE market and discusses the return smoothing process. Section 3 describes the model which provides insight into the wealth transfer risks created by stale pricing and how to protect against them. 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.

[19] This does not, however, take into consideration the governance costs and benefits associated with investing directly.

[20] There are three ways managers deter fragility risks when they limit redemptions and subscriptions. First, managers are able to transact in the underlying market prudently. They are not forced to purchase or sell assets quickly. Second, it takes longer for investors to move capital into, and out of, the fund. This decreases the predictability of returns investors achieve when they implement NAV-timing strategies. Third, any remaining wealth transfers are diluted over investor bases that correlate positively with wealth transfer opportunities. This crowding out effect creates strategic substitutes for NAV-timing strategies and decreases the marginal benefit of implementing them.

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2. Real estate funds and smoothed returns

2.1. U.S. open-end private equity real estate funds

Commercial Real Estate (CRE) encompasses all real estate property types except owner-occupied single family homes. I estimate the overall value to the U.S. CRE market to be around \$35.0 trillion as of the fourth quarter 2021.[21] The importance of CRE as an asset class has increased dramatically in the last four decades. The target allocations for real estate have increased significantly for institutional investors over this time period, going from around 2% to 10%. Additionally, they are currently under-allocated relative to their targets and their targets are expected to increase.[22]

Institutional investors can invest in both public and private CRE markets. They can also take both equity and debt positions in CRE. The primary way for investors to invest in public CRE is through publicly traded REITs. Investor can also invest in private CRE through direct investments, joint ventures, separate accounts, club deals, and comingled funds. My analysis focuses on the return predictability and shareholder run risks created by stale pricing in U.S. OPERE funds, which are a subset of commingled funds.

OPERE 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 value of their individually appraised assets less their liabilities. Similar to hedge funds, they have both non-discretionary liquidity restrictions (redemption notification periods, lockup periods, and subscription intervals) and discretionary liquidity restrictions (discretion to limit share redemptions).[23] However, OPERE funds also have discretionary liquidity restrictions on capital entering the fund in a way that is 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 uncalled capital commitments or unfulfilled redemption

[21] This estimate is based on extrapolating the estimate of \$30 trillion provided by Geltner (2015) using the NCREIF Property Price Index. This includes traded and non-traded CRE assets. Florance et al. (2010) approximate the stock value of traded CRE assets to be around \$11 trillion as of the fourth quarter of 2009.

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

[23] As mentioned in Section A, the majority of OPERE funds do not have lockup periods and the few that do have them typically have a 12 month lockup from the first investment.

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requests which are commonly referred to as queues. Testing the effects of return smoothing on shareholder run incentives requires accurate queue measurements, which OPERE funds report quarterly. Lastly, they invest in real assets and actively manage asset operations, similar to traditional private equity funds. I provide additional technical details on both open-end and closed-end private equity real estate funds in Section A of the Appendix.

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).[24] 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.[25] Consistent with the intuition behind Equations 1 and 4, there are two primary 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

[24] 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.

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

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

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

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 from luck, skill, or simply greater risk exposure.

3. Theoretical model

3.1. Setup

I create a two-period qualitative 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

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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.

$$\begin{aligned} TNA_0^{Fund} &= TNA_0^E \\ &= \omega_0 \Pi_0^{MT} + \Pi_0^{BH} \end{aligned} \tag{5}$$

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

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

$$TNA_2^{Fund} = TNA_2^E \tag{8}$$

There are two investors in the fund - a buy-and-hold investor, BH, and a market-timing investor, MT. As shown in Equation 5, 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.

The model assumes the underlying assets have two characteristics associated with being illiquid. First, they have stale reported values. Second, large capital flows either into or out of the asset market have a temporary price impact. The level of staleness is represented by Θ, as shown in Equation 9, and influences the $TNA_{1,a}$ value at which investors enter and leave the fund. The assumption that capital flows have a price impact is reflected in Equation 10 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 the assets do not produce dividends. It is also assumed the assets will be sold for their true economic value in period 2. Lastly, the expected economic return for period 2 is 1. Because I am focusing on the effect of stale prices on investor and

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managerial behavior, investors act as if they are unaware of the impact their subscription or redemption requests will have on the future returns of the fund.

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

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

3.2. Investor maximization

This analysis focuses on the way market-timing investors respond 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 11, 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 12.

$$TNA_{1,a}TFF_1 = \Pi_1^{MT} \left(\omega_{1,b} - \omega_{1,a}\right) \tag{11}$$

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

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

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

$$R_1^{Fund} = \frac{TNA_1^{Fund}}{TNA_0^{Fund}} \tag{14}$$

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$$R_2^{Fund} = \frac{TNA_2^{Fund}}{TNA_{1,b}^{Fund}} \tag{15}$$

The market-timing investor is interested in maximizing his period 2 return, and his choice variable is his allocation in the fund, $\omega_{1,b}$. As derived in Section E.2 of the Appendix, the optimal allocation for the market-timing investor is given by Equation 17. The economic interpretation of this equation is that the optimal allocation is chosen such that the marginal cost of adjusting the fund allocation from $\omega_{1,a}$ to $\omega_{1,b}$ equals the marginal benefit from the increased expected return associated with adjusting the fund allocation. By combining the optimal allocation with Equation 11, I obtain the optimal fund flow request, TFF_1, as shown in Equation 18. The proof of this derivation is provided in Section E.3 of the Appendix.

$$\max_{\{\omega_{1,b}\}} E_1 \left(\left(\omega_{1,b} R_2^{Fund} + (1 - \omega_{1,b}) R^f \right) - \frac{\phi}{2} (\omega_{1,b} - \omega_{1,a})^2 \right) \tag{16}$$

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

$$TFF_1 = \frac{\Pi_1^{MT}}{TNA_{1,a}} \frac{1}{\phi} \left(\left(R_1^E \right)^{\Theta} - 1 \right) \tag{18}$$

The overall wealth transfer from existing investors to incoming investors is reflected in Equation 19. The wealth transfer experienced by the buy-and-hold investor depends on his period 0 percentage ownership of the fund, as shown in Equation 20. This wealth transfer amount assumes the market-timing investor is able to contribute or withdraw as much as he would like without restrictions. Three important outcomes of the model are demonstrated in Equation 20. First, wealth transfers increase with staleness in reported returns. Second, wealth transfers increase with the size of the economic return experienced in period 1. Third, wealth transfers increase with the magnitude of the fund flows allowed. The first two outcomes lead to **Predictions 1** and **2** listed below. The third outcome influences **Predictions 3** and **4** discussed below.

$$WT = TNA_0 \left(R_1^E - R_1^{Fund} \right) FF_1 \tag{19}$$

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$$
\begin{aligned}
WT^{BH} &= \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - R_1^{Fund}\right)FF_1 \\
&= \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{TNA_1}\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)
\end{aligned} \tag{20}
$$

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 (discretionary 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 the manager has full discretion over how much of the fund flow request to fulfill, as reflected in Equation 21. DFF_1 is the percentage of the total fund flow request, TFF_1, the manager chooses to fulfill. The maximization function of the manager has three components. The first component reflects the period 1 fee, which is a function of the amount of assets managed by the fund in that period. The second component reflects the impact the fund flow has on future returns. The loading on this component reflects the managers concern with the flow-performance relationship and their ultimate desire to form other funds in the future. The third component reflects the effect of not fulfilling investor subscription or redemption requests. It assumes investors are less willing to invest with managers tomorrow if their fund flow requests are not fulfilled in a timely manner today. Fund managers are interested in maximizing their 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 22. As derived in Section E.2 of the Appendix, optimal percentage fund flow accepted by the fund is given in Equation 23. 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

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positive fund flow, while it has a marginal cost during periods with a negative fund flow.[26]

$$DFF_1 = \frac{FF_1}{TFF_1} \tag{21}$$

$$\max_{\{DFF_1\}} E_1 \left(\gamma_1 \left(1 + FF_1\right) - \frac{\gamma_2}{2} \psi \left(FF_1\right)^2 - \gamma_3 \left(TFF_1 - FF_1\right)^2 \right) \tag{22}$$

$$DFF_1 = \frac{\gamma_1 + \gamma_3 TFF_1}{\left(\gamma_2 \psi + \gamma_3\right) TFF_1} \tag{23}$$

The optimal fund flow in period 1 is jointly determined by the fund and the investors and is reflected in Equation 24. The wealth transfer from the buy-and-hold investor to the market-timing investor is obtained by substituting Equation 24 into Equation 20 as shown in Equation 25. Equation 25 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 mitigant. **Prediction 3** provides a hypothesis consistent with this outcome.

$$FF_1 = \frac{\gamma_1 + \gamma_3 \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{1}{\phi} \left(\left(R_1^E\right)^{\Theta} - 1 \right) \right)}{\left(\gamma_2 \psi + \gamma_3\right)} \tag{24}$$

$$WT^{BH} = \left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right) \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)} \right) \cdot \frac{\gamma_1 + \gamma_3 \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{1}{\phi} \left(\left(R_1^E\right)^{\Theta} - 1 \right) \right)}{\left(\gamma_2 \psi + \gamma_3\right)} \tag{25}$$

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

[26]The optimal discretionary fund flow, DFF_1, must be between 0 and 1. Alternatively, funds would be able to force investors to invest or divest at their discretion. As an example, if $\gamma_2 \psi$ was sufficiently small and γ_1 was sufficiently positive and large, DFF_1 could mathematically be larger than 1. However, this does not occur in markets with illiquid assets. This is evidenced by the fact of both open-end and closed-end private equity funds regularly taking multiple years to call all of their capital commitments.

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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 the fund uses a cash, liquidity buffer to mitigate the transaction cost associated with interacting with the underlying market, $\psi\left(FF_1\right)^2$. As such, I remove the second component of fund's utility maximization equation, as shown in Equation 26. The new optimal DFF_1^{LB} is shown in Equation 27 and the proof is in Section E.6 of the Appendix. The new optimal fund flow is strictly larger than the one without a liquidity buffer. As such, the wealth transfer is strictly larger when the fund uses a liquidity buffer. I provide a proof and derivation of this in Section E.6. Liquidity buffers are effective at deterring the fragility risks associated with having to place or redeem capital too quickly in the underlying market, $\psi\left(FF_1\right)^2$. However, they are ineffective at protecting against the fragility risks associated with stale pricing.

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 in the model.

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 these funds. In all, this evidence suggests the tools most commonly used to stabilize funds can be counterproductive and backfire in some situations. This evidence also supports **Prediction 4,** listed below.

$$\max_{\left\{DFF_1^{LB}\right\}} E_1\left(\gamma_1\left(1+FF_1^{LB}\right)-\frac{\gamma_3}{2}\left(TFF_1-FF_1^{LB}\right)^2\right) \tag{26}$$

$$DFF_1^{LB}=\frac{\gamma_1+\gamma_3 TFF_1}{\gamma_3 TFF_1} \tag{27}$$

$$DFF_1^{LB} \gg DFF_1 \tag{28}$$

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$$\left|FF_1^{LB}\right| \gg |FF_1| \tag{29}$$

$$WT^{BH,LB} = \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)FF_1^{LB} \tag{30}$$

$$WT^{BH,LB} = \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\gamma_1 + \gamma_3\frac{\Pi_1^{MT}}{TNA_{1,a}}\left(\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)}{(\gamma_3)} \tag{31}$$

$$WT^{BH,LB} \gg WT^{BH} \tag{32}$$

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

4. Data and summary statistics

The fund-level data, except for queue information, comes the NCREIF NFI-OE.[27] The queue data come from Townsend.[28] 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 Fund 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

[27]NCREIF is the leading collector of institutional real estate investment data. It produces the primary benchmark institutional investors use in evaluating the performance of their private real estate investments. It represents roughly $500 billion in assets under management as of the fourth quarter 2015.

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

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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 OPERE 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 OPERE funds and then from the department responsible for overall data collection. In order to address the existence of minor inconsistencies between the datasets, I complete robustness tests by rearranging the order of dataset priorities and redo the empirical analysis. The results are consistent.

I define each of the response and explanatory variables in Section 5 below. Additionally, I winsorize each of the variables except for the 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 OPERE 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)).[29]

[29] 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

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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 OPERE fund returns may be autoregressive moving averages of their lagged, economic returns, and that OPERE reported returns are predictable.

Table 2 empirically examines the relationships between OPERE 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 OPERE fund returns are predictable, which would allow investors to create NAV-timing strategies in the absence of restrictions.

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 OPERE market and invests either in an index of the OPERE funds or the risk-free rate (time-series strategy). The second strategy is based on lagged fund returns and invests in a portfolio of the recent top performing funds (cross-sectional strategy). It is possible that while fund returns are predictable, the profitability of trading on it would be either insignificant, or captured by traditional factor models. Investors risk having their wealth transferred to other investors to the extent either of these strategies is profitable. Equation 33 provides the base regression equation used in this analysis where r^p refers to the excess return of the portfolio, X refers to the risk factors in the corresponding factor model, and α refers to the average return of the portfolio unexplained by the factor model.

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.

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

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 OPERE 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.

The economic theory discussed in Section 3 suggests the first NAV-timing strategy could also be based off of public market return information. In unreported results, I find that a strategy of entering and leaving the OPERE market based on lagged NAREIT Index returns provides consistent results with the one based on lagged OPERE market returns.[30]

Table 4 reports the return performance achieved by implementing the second market-

[30] In this case, the strategy would be based on the cumulative four quarter return of the publicly traded NAREIT Index instead of the one quarter return of the NFI-OE Index.

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timing strategy in the absence of trading frictions. Figure 3 provides a graphical representation of the raw return results. Each quarter, funds are assigned to one of five portfolios based on the 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 increasing 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. These results 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 OPERE 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 Fund Flow) is calculated as the actual amount entering the fund (Fund Flow) plus the amount requested to enter the fund (Net Queue). Fund Flow, Net Queue, and Total Fund Flow are calculated as shown in Equations 34, 35, and 36.

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

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

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

Table 5 provides the empirical results from my analysis on the relation between Total Fund Flows and public market returns, private market returns, and fund returns. Columns (1) and (2) provide the results of regressing Total Fund Flows on lagged public market returns as proxied by the NAREIT Index returns. Columns (3) and (4) show the results of regressing Total Fund Flows on the lagged private market returns, as proxied by the NFI-OE Index returns. Lastly, columns (5) through (8) show the results of regressing Total Fund Flows on lagged fund returns. The explanatory variables are consistent with both the time-series and cross-sectional NAV-timing strategies. 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 public market, private market, and fund returns leads to 0.18, 0.21, and 0.21 standard deviation increases in the Total Fund Flow, respectively.[31] These results provide strong evidence that investors behave as if they recognize these returns are predictable and act accordingly. Additionally, it provides strong evidence that significant wealth transfers would exist without a mechanism to properly protect against it.

I next analyze the behavior of funds in fulfilling their subscription and redemption requests in accordance with **Prediction 3**. The way funds fulfill subscription and redemption requests determines the extent to which wealth is actually transferred. If managers fulfill these requests quickly, they will enable investors to take advantage of the return predictability. They could do this by either transferring these flows quickly into the underlying market, which would likely push prices, or they could use a liquidity buffer. However, if managers fulfill these requests at the rate it takes to place and redeem capital from the underlying market

[31] In Appendix D I evaluate the responsiveness of investor flows to both positive and negative returns. The evidence suggests a strong sensitivity to incrementally better or worse returns regardless of whether they are positive or negative.

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prudently, they will have to fulfill these requests slowly, which would deter the ability of investors to take advantage of the predictability.

Table 6 provides the empirical results from my analysis on the relation between Net Queues and public market returns, private market returns, and fund returns. Columns (1) and (2) provide the results of regressing Net Queues on lagged public market returns, as proxied by the NAREIT Index returns. Columns (3) and (4) show the results of regressing Net Queues on prior private market returns, as proxied by the NFI-OE Index returns. Lastly, 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 public market, private market, and fund returns leads to 0.17, 0.19, and 0.25 standard deviation increases in Net Queues respectively. This evidence suggests managers limit the vast majority of capital trying to enter and leave their fund through the queuing mechanism. It also suggests managers do not transfer the capital flows into the underlying market quickly or use liquidity buffers. Lastly, this evidence suggests investors are unlikely to be able to exploit the return predictability found in OPERE funds.

Figure 2 provides a visual representation of the relation between private market returns, Total Fund Flows, and Net Queues. Total Fund Flows and Net Queues are obtained by taking the equally-weighted average of those values for the various funds. As shown, the relationship between each of these three variables is significant. This evidence is consistent with the results provided in Tables 5 and 6 and further reinforces the conclusion the queuing mechanism mitigates the NAV-timing risk created by stale pricing.

5.4. Realizable NAV-timing returns

My next analysis looks at the effectiveness of different fragility deterrents and the returns investors could achieve by implementing either the time-series or cross-sectional 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 private placement memorandum and articles of incorporation at the inception of the fund. Typical

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non-discretionary liquidity restriction include lockup periods, notification periods, and subscription intervals. Discretionary liquidity restrictions refer to discretion managers have on when to call committed capital and fulfill redemption requests.

5.4.1. Lockup-adjusted returns

The results from my analysis on the effectiveness of using lockup periods to deter the NAV-timing fragility risks are reported in Tables 7 and 8.[32] As shown in Table 7, the results associated with timing when to enter and leave the overall OPERE market are unaffected by lock-up periods. This is an important finding as it suggests lockup periods are ineffective at protecting against the stale pricing fragility risks associated with market timing. The intuition behind this finding and its interpretation is straightforward. This NAV-timing strategy recommends investing in the overall market except after significant market downturns. Since significant market downturns happen infrequently, lockup periods become nonbinding when they happen, and investors would be able to remove all of their capital on a moments notice.[33]

As shown in Table 8, the results associated with investing in the top funds is significantly dampened by lockup periods, but not eliminated. Lockup periods diminish approximately 50% of cross-sectional NAV-timing profits. The reason cross-sectional profits are dampened while time-series profits are unaffected is also intuitive. This happens because the cross-sectional strategy requires moving capital into and out of funds much more frequently. This has the effect of making lockup periods more binding. However, cross-sectional profits are not entirely eliminated because relative fund performance is very persistent, due in large part to stale prices. In all, this evidence suggests lockup periods do a poor job protecting against the NAV-timing risks associated with stale pricing.

In Section B of the Appendix, I also evaluate the effect of implementation delays on both time-series and cross-sectional NAV-timing strategies. As shown, delays to both strategies

[32] I also evaluate the effect of delaying NAV-timing strategies on their profits in Section B of the Appendix. As shown in Tables A.1 and A.2, NAV-timing results decay significantly as delays increase. NAV-timing profits are mostly eliminated as the implementation delay reaches four quarters. Most funds require a one quarter notification period which would have no impact on the results discussed in the main body of the paper.

[33] A lockup period of one year is used in this analysis. As discussed in Section A of the Appendix, while the vast majority of OPERE funds do not use any lockup period, the few that use them typically lock capital up for one year after the first investment. However, the results to this analysis would not change even if lockup periods were excessively extended (such as for five years).

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are effective at reducing their profitability. Profits are completely eliminated once the delay reaches four quarters in the time-series strategy and once it reaches a three quarter delay in the cross-sectional strategy. Managers could delay NAV-timing strategies by having longer subscription and redemption notification periods. The majority of open-end funds have a one quarter notification period which would have no effect on the strategies discussed in this paper.

5.4.2. Queue-adjusted returns

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 NAV-timing strategies and going through 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 lockup 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 OPERE 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 investors cannot short these funds. As shown in Table 10, the queue-adjusted returns for quintiles 1 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.

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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 OPERE 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 and 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.

Figures 3 through 5 provide a visual representation of the relation between return predictability, queues, and queue-adjusted returns. As shown, the predictability in the returns is eliminated after going through the queuing process. This evidence further reinforces the finding that discretionary liquidity restrictions do a good job mitigating the NAV-timing wealth transfer risks created by stale pricing.

5.5. Liquidity buffers

My last analysis evaluates **Prediction 4** of the model. Specifically, it evaluates the effect of liquidity buffers on NAV-timing wealth transfer risks. To evaluate this prediction, I first analyze the extent to which OPERE funds use cash buffers. I also analyze the effect lagged cash has on negative fund flows, both during the GFC as well as during the entire sample. Managers allow more wealth to be transferred to outgoing investors when they fulfill more redemption requests and their NAVs are overvalued.

As shown in Table 1, cash holdings make up a small portion of the overall assets held by

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OPERE funds. The median cash holding over the sample period was 3.6%. Most OPERE funds have clauses stating redemption requests are fulfilled to the extent excess cash is available, at the discretion of the manager. This suggests, in equilibrium, OPERE funds do not actively use cash to buffer capital flows.

Table 11 reports the results from my analysis on the relation between cash holdings and negative fund flows. 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. I evaluate this relation both over the entire sample period as well as only 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 **Prediction 4** of the theoretical model and suggests liquidity buffers increase the ability of investors to take advantage of NAV-timing strategies when combined with discretionary liquidity restrictions.

6. Conclusion

This paper has four main insights. First, open-end funds create NAV-timing fragility risks when they invest in illiquid assets. Illiquid assets are associated with having stale prices and predictable returns. Next, managers protect against these risks when they use discretionary liquidity restrictions, but do not when they use liquidity buffers. Discretionary liquidity restrictions and liquidity buffers are primarily used to prevent managers from having to buy or sell illiquid assets too quickly. Additionally, discretionary liquidity restriction also provide a secondary protection against the fragility risks created by stale pricing. Greater illiquidity in the underlying assets leads to greater return predictability, but it also leads to longer transaction timeframes in the underlying market. This in turn influences managers to slow the capital coming into and out of their fund through greater discretionary liquidity restrictions. Interestingly, it is the illiquidity in the underlying market which creates both

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the risk and the risk mitigant. Lastly, I find that funds amplify NAV-timing and wealth transfer risks when they add liquidity buffers to discretionary liquidity restrictions.

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 keep a constant mix of liquid and illiquid assets by suspending their issuance and redemption activities. This allows the manager to transact in the underlying market without buying at a premium and selling at a discount. It also slows the process of capital entering and leaving the fund which deters the ability of investors to exploit the stale valuatoins and 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 combined effects coming from liquidity buffers also seems warranted.

For regulators, preventing funds from suspending their issuance and redemption activities 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 or require greater transparency for hedge funds.

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Table 1

Summary Statistics

This table presents summary statistics for U.S. Open-end Private Equity Real Estate (OPERE) funds from January 2004 through December 2015. For the OPERE 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 Fund 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 Fund 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

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Table 2
Return Predictability

This table presents the results from my analysis on the return predictability of U.S. Open-end Private Equity Real Estate (OPERE) 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 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***
	(2.11)	(2.38)	(5.78)	(5.30)	(5.10)	(4.63)
r_{t-2}	0.087***	0.087***	0.215***	0.210***	0.131***	0.110***
	(3.10)	(3.93)	(4.32)	(4.02)	(3.77)	(3.06)
r_{t-3}	0.101***	0.107***	-0.038	-0.041	0.061	0.041
	(3.43)	(4.46)	(-0.77)	(-0.83)	(1.62)	(1.05)
r_{t-4}	0.103***	0.120***	-0.009	-0.020	0.195***	0.173***
	(3.72)	(5.37)	(-0.14)	(-0.30)	(3.65)	(3.21)
r_{t-5}	0.079***	0.086***				
	(3.06)	(3.95)				
r_{t-6}	0.054**	0.065***				
	(2.40)	(3.38)				
r_{t-7}	0.030	0.048**				
	(1.27)	(2.48)				
r_{t-8}	0.029	0.045***				
	(1.25)	(3.19)				
Fund f.e.	No	No	No	Yes	No	Yes
Time f.e.	No	No	No	No	Yes	Yes
N	3,222	3,222	3,222	3,222	3,222	3,222
R^2	0.23	0.36	0.47	0.48	0.71	0.72

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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 OPERE return predictability (without liquidity restrictions). Long returns are those obtained by either investing in the OPERE market (as proxied by the NFI-OE) or the 3-month T-bill based on prior OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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
	(11.60)	(11.69)	(12.14)	(10.74)	
Short	-1.020**	-2.130***	-0.967*	-1.066*	48
	(-2.17)	(-11.69)	(-1.99)	(-1.82)	
Long-Short	3.564***	4.260***	3.688***	3.662***	48
	(8.92)	(11.69)	(8.50)	(7.88)	

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
	(2.47)		(2.82)	(1.99)	

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Table 4

Cross-Sectional NAV-timing Results

This table presents the second set of results from my analysis on the trading profitability from OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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
	(1.17)	(-5.95)	(1.67)	(1.00)	
2	1.436**	-0.126	1.636**	1.474*	48
	(2.25)	(-1.03)	(2.51)	(1.80)	
3	1.700***	0.220*	1.996***	1.663**	48
	(2.81)	(1.70)	(3.45)	(2.20)	
4	1.780***	0.413***	1.941***	1.744**	48
	(3.19)	(4.52)	(3.39)	(2.57)	
5	1.936***	0.441**	2.143***	1.917***	48
	(3.13)	(2.58)	(3.23)	(2.73)	
5 - 1	1.020***	1.437***	0.882***	0.872**	48
	(3.71)	(4.56)	(3.21)	(2.06)	

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Table 5

Investor Responses to Prior Returns

This table reports the results from my analysis on the behavior of investors. Total Fund Flow is defined as the sum of the Fund Flow and the Net Queue, all divided by the lagged TNA, $TFF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\,Queue_{i,t} - Redemption\,Queue_{i,t}] / TNA_{i,t-1}$. 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 Fund 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 Fund 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 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.

$$Total\ Fund\ Flow_{i,t} = \beta_0 + \beta_1 r_{Public\,Market} + \varepsilon_{i,t}$$

$$Total\ Fund\ Flow_{i,t} = \beta_0 + \beta_1 r_{Private\,Market} + \varepsilon_{i,t}$$

$$Total\ Fund\ Flow_{i,t} = \beta_0 + \beta_1 r_{Funds} + \varepsilon_{i,t}$$

$r_{Public\,Market}$	0.216***	0.231***						
	(3.50)	(3.73)						
$r_{Private\,Market}$			2.242***	2.252***				
			(4.82)	(4.85)				
r_{Funds}					0.392***	0.342***	0.870***	0.431**
					(5.53)	(4.82)	(3.41)	(2.54)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	No	No	Yes	Yes
N	1,174	1,174	1,174	1,174	1,131	1,130	1,131	1,130
R^2	0.04	0.41	0.07	0.43	0.07	0.41	0.17	0.53

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

$$Net\,Queue_{i,t} = \beta_0 + \beta_1 r_{Public\,Market} + \varepsilon_{i,t}$$

$$Net\,Queue_{i,t} = \beta_0 + \beta_1 r_{Private\,Market} + \varepsilon_{i,t}$$

$$Net\,Queue_{i,t} = \beta_0 + \beta_1 r_{Funds} + \varepsilon_{i,t}$$

$r_{Public\,Market}$	0.172***	0.181***						
	(3.45)	(3.65)						
$r_{Private\,Market}$			1.797***	1.776***				
			(4.65)	(4.66)				
r_{Funds}					0.327***	0.278***	0.808***	0.424**
					(5.14)	(4.47)	(3.42)	(2.69)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	No	No	Yes	Yes
N	1,174	1,174	1,174	1,174	1,131	1,130	1,131	1,130
R^2	0.04	0.40	0.07	0.42	0.07	0.42	0.16	0.52

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Table 7

Time-Series NAV-timing Results (lockup-adjusted)

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 those obtained by either investing in the OPERE market (as proxied by the NFI-OE), or the 3-month T-bill based on prior OPERE market performance. In contrast to the results provided in Table 3, allocations in this analysis 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. 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 robust, adjusted for heteroskedasticity, and clustered by 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	2.544***	2.130***	2.721***	2.596***	48
	(11.60)	(11.69)	(12.14)	(10.74)	
Short	-1.020**	-2.130***	-0.967*	-1.066*	48
	(-2.17)	(-11.69)	(-1.99)	(-1.82)	
Long-Short	3.564***	4.260***	3.688***	3.662***	48
	(8.92)	(11.69)	(8.50)	(7.88)	

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Table 8

Cross-Sectional NAV-timing Results (lockup-adjusted)

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. Standard errors are robust, adjusted for heteroskedasticity, and clustered by 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	1.263**	-0.219	1.551***	1.534**	48
	(2.05)	(-0.94)	(2.70)	(2.14)	
2	1.632**	-0.007	1.870***	1.624*	48
	(2.43)	(-0.05)	(2.70)	(1.98)	
3	1.456***	0.154**	1.654***	1.443**	48
	(2.75)	(2.43)	(3.17)	(2.18)	
4	1.697***	0.257***	1.958***	1.644**	48
	(2.89)	(3.25)	(3.37)	(2.28)	
5	1.872***	0.450*	2.038***	2.005**	48
	(3.12)	(1.68)	(3.10)	(2.66)	
5 - 1	0.609**	0.669	0.487**	0.472*	48
	(2.56)	(1.67)	(2.19)	(1.93)	

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Table 9

Time-Series NAV-timing Results (queue-adjusted)

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 those obtained by either investing in the OPERE market (as proxied by the NFI-OE) or the 3-month T-bill based on prior OPERE 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 OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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
	(3.45)	(10.58)	(3.81)	(2.79)	
Short	-0.577	-1.422***	-0.437	-0.592	48
	(-1.63)	(-13.73)	(-1.23)	(-1.28)	
Long-Short	2.196***	1.887***	2.242***	2.227***	48
	(12.73)	(13.86)	(10.93)	(12.54)	

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Table 10

Cross-Sectional NAV-timing Results (queue-adjusted)

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 robust, adjusted for heteroskedasticity, and clustered by 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
	(1.81)	(-3.25)	(2.20)	(1.36)	
2	1.393**	-0.088	1.606**	1.416*	48
	(2.30)	(-0.81)	(2.61)	(1.83)	
3	1.552**	-0.000	1.804***	1.558*	48
	(2.46)	(-0.00)	(2.87)	(1.94)	
4	1.523**	-0.010	1.769***	1.488*	48
	(2.44)	(-0.12)	(2.73)	(1.92)	
5	1.341*	-0.454***	1.603**	1.217	48
	(1.82)	(-2.81)	(2.06)	(1.30)	
5 - 1	0.159	-0.046	0.200	0.059	48
	(0.78)	(-0.25)	(0.85)	(0.31)	

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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: $Fund\ Flow_{i,t} = [TNA_{i,t} - (TNA_{i,t-1} \cdot R_{i,t})] / TNA_{i,t-1}$. 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 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**
	(-4.62)	(-4.74)	(-4.59)	(-5.74)	(-1.15)	(-2.06)	(-1.19)	(-2.52)
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

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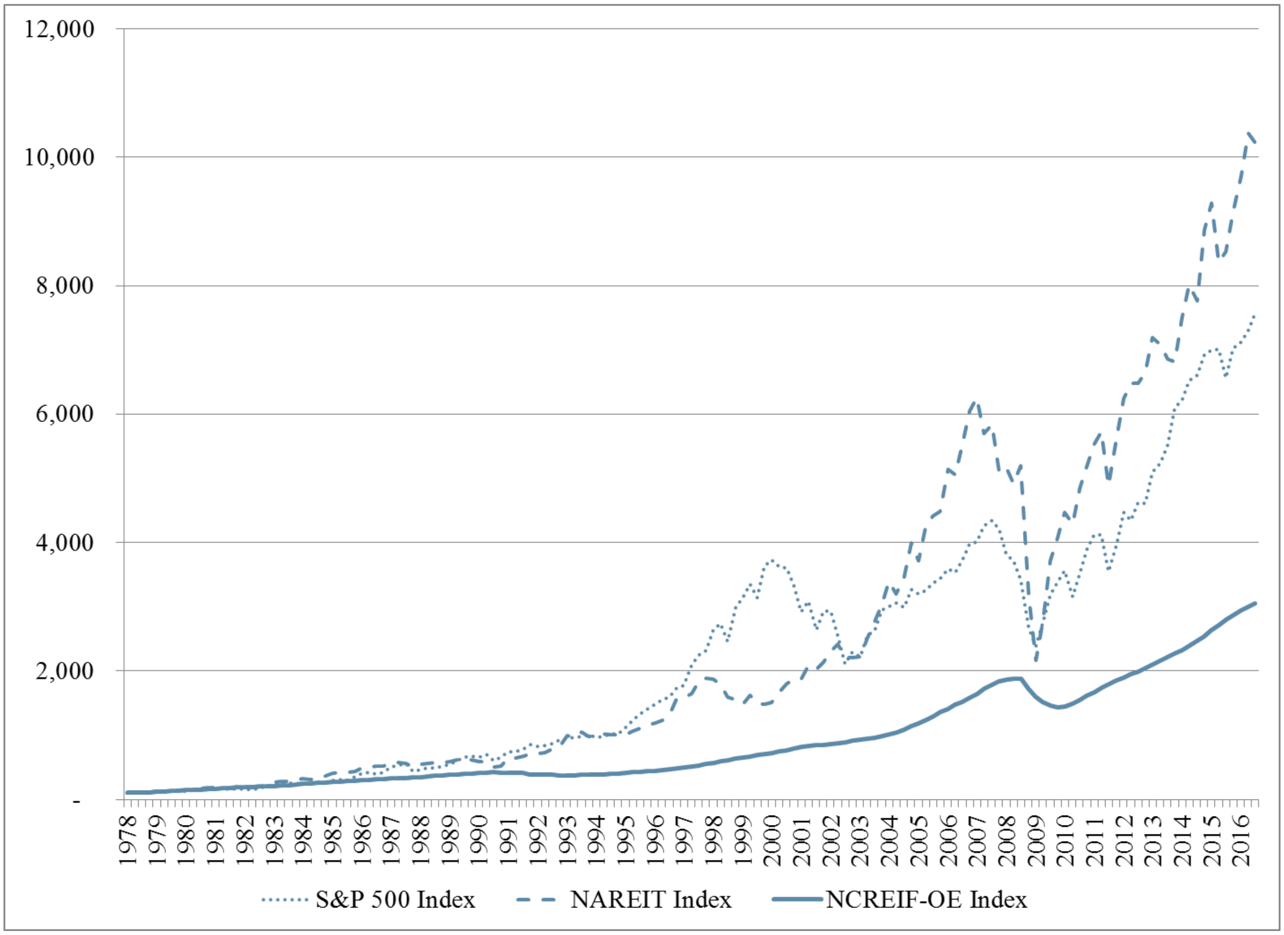

Figure 1
S&P 500, NAREIT, and NFI-OE Indices over Time

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.

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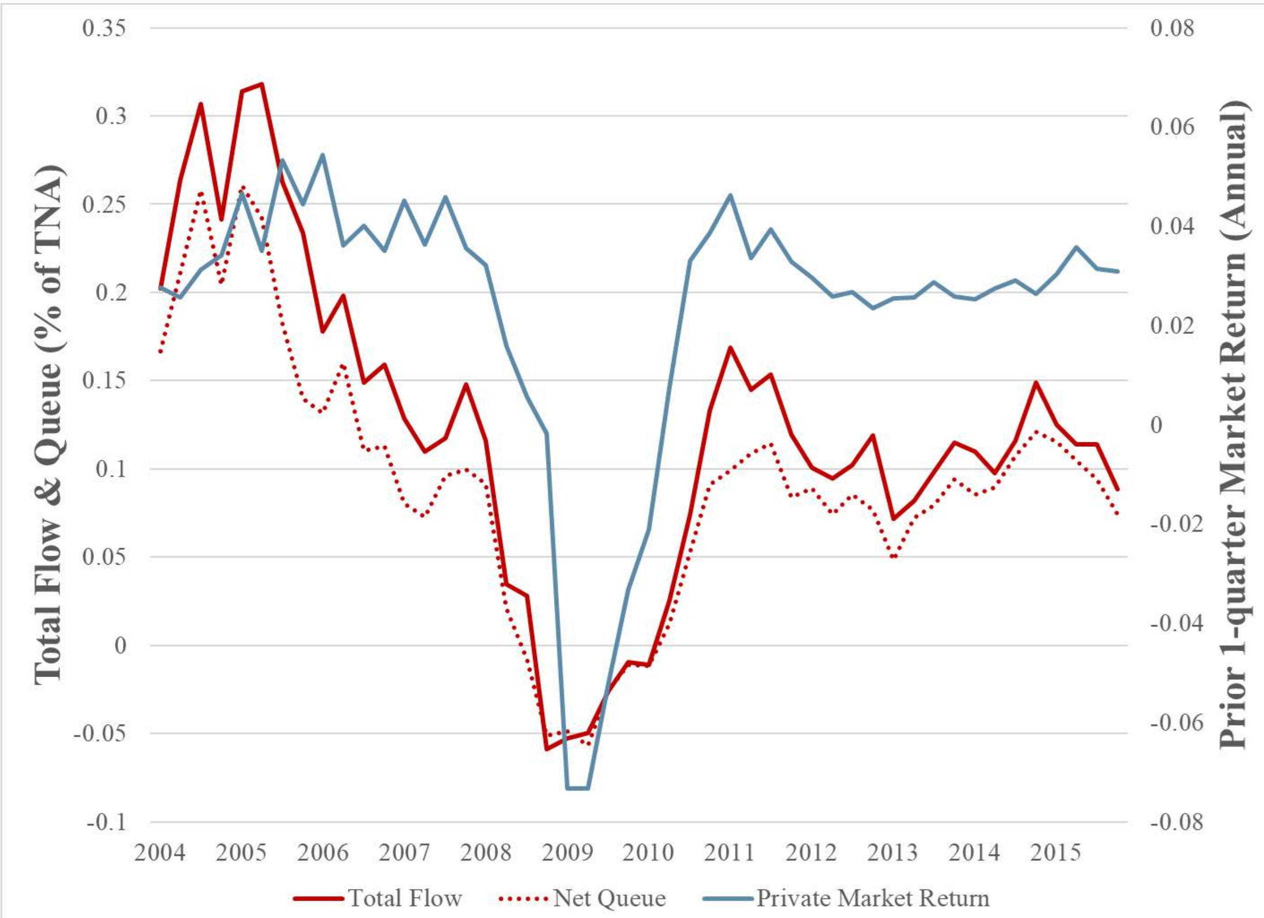

Figure 2
Market Returns, Fund Flows, and Queues

This figure shows the relation between Total Fund Flows, Net Queues, and lagged Private Market Returns. The Total Fund Flow is calculated as the Fund Flow plus the New Queue. The Net Queue is calculated as the dollar value of the Investment Queue less Redemption Queue divided by the lagged Total Net Assets (TNA). Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period.

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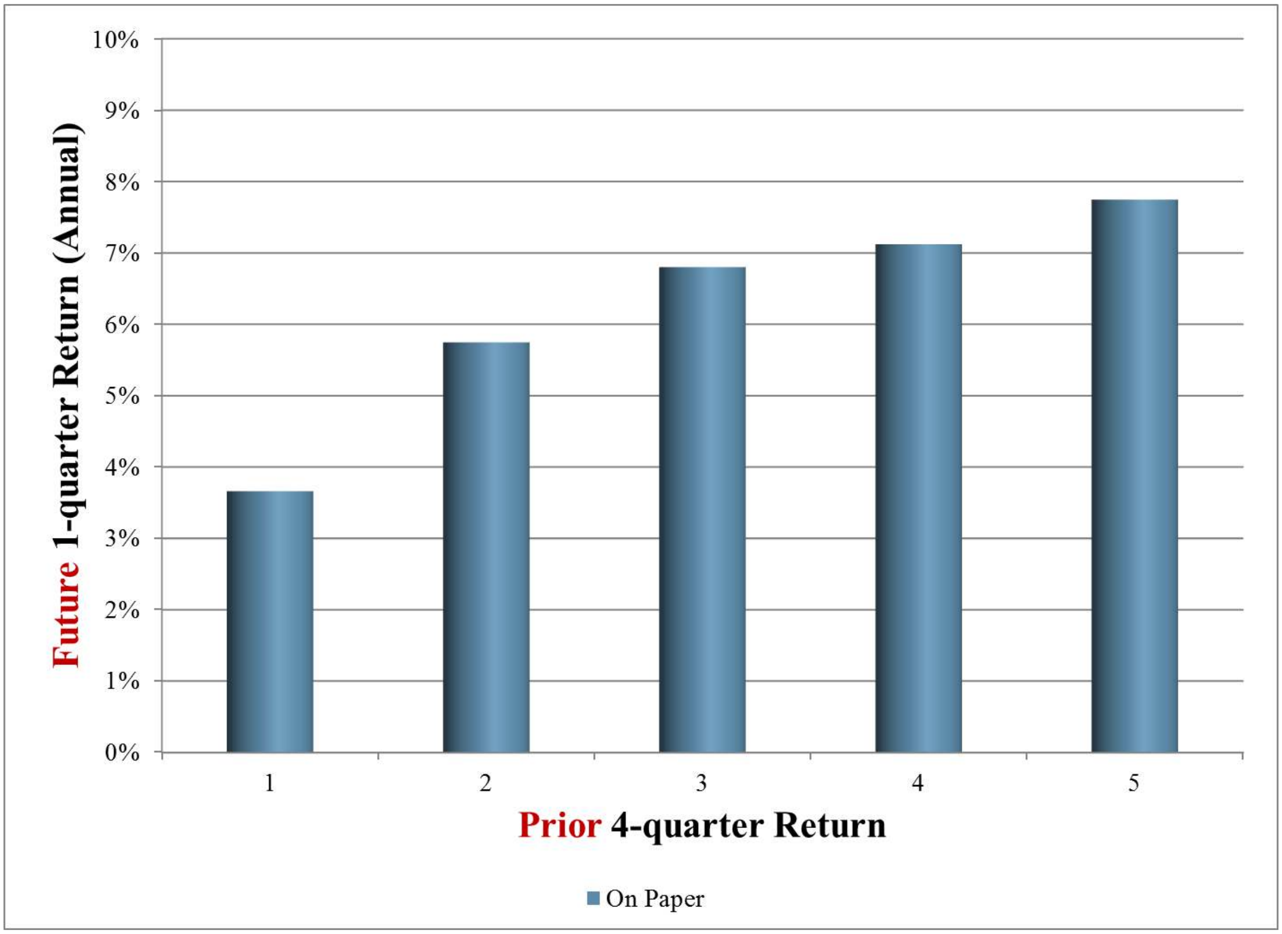

Figure 3
Future Returns by Prior Return Quintiles

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 Total Net Assets (TNA). Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period.

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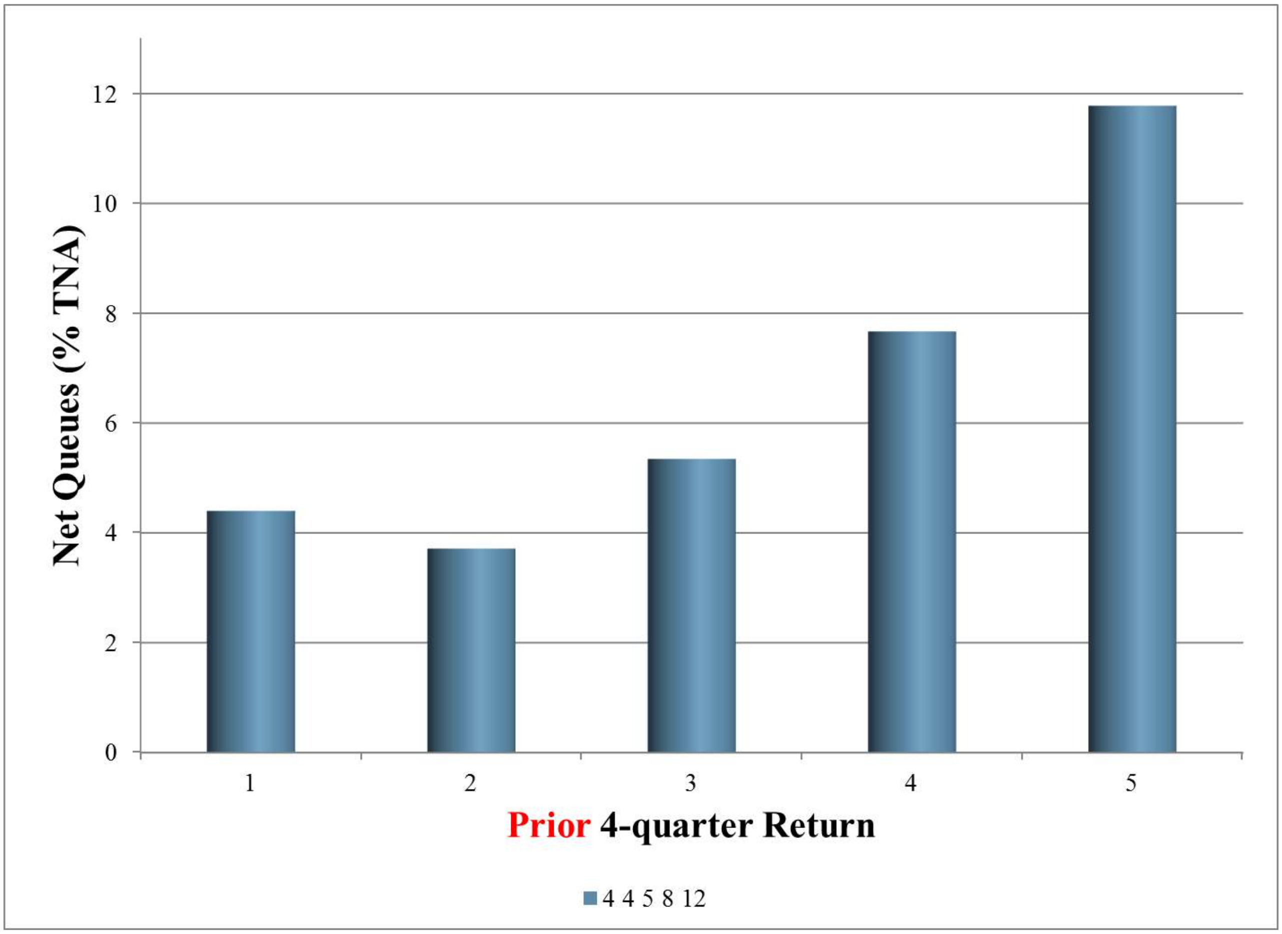

Figure 4
Queue Size (%AUM) by Prior Return Quintiles

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 Total Net Assets (TNA). Funds are categorized into performance quintiles based on their cumulative net return for the previous four quarter period.

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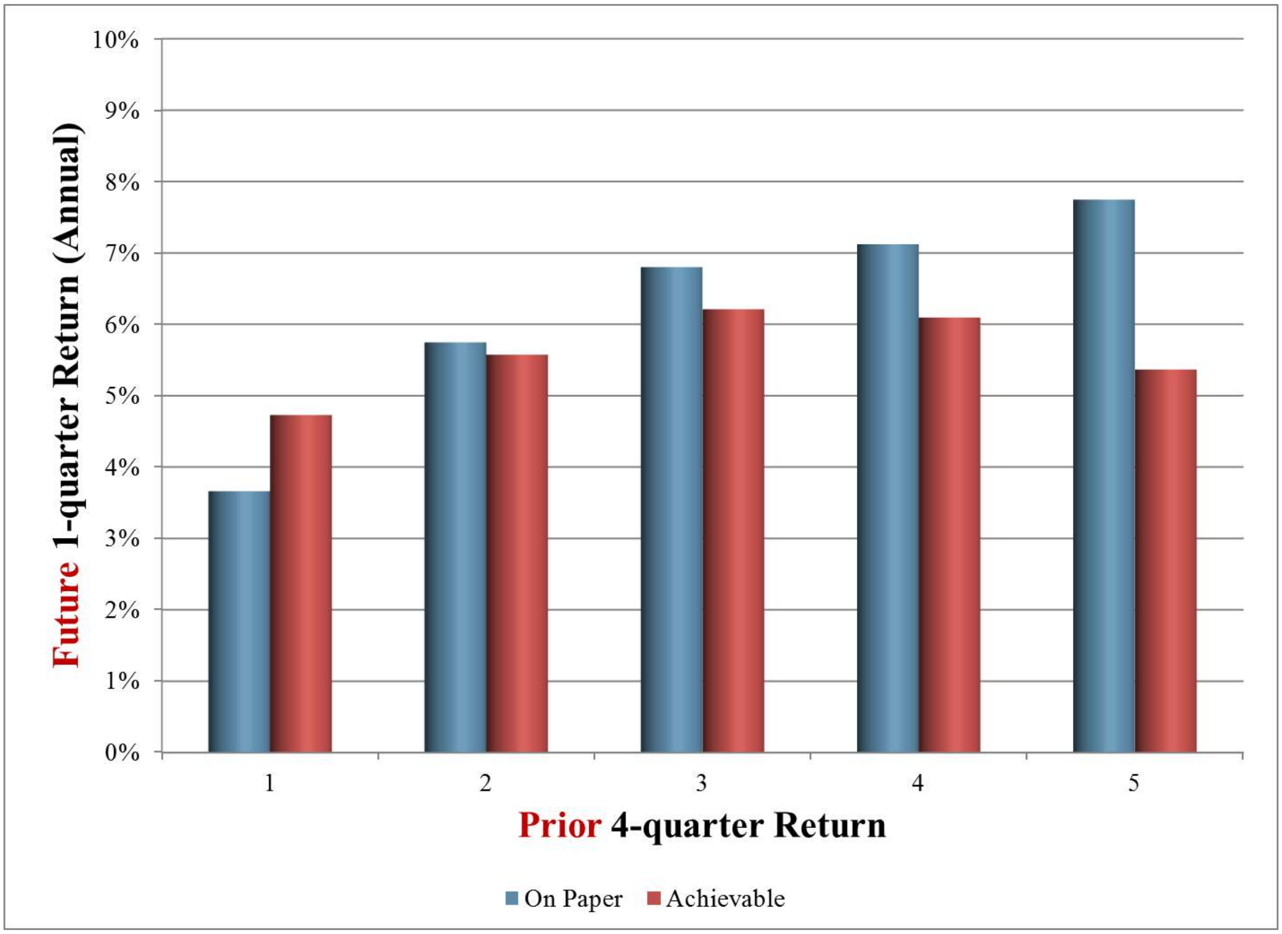

Figure 5
Raw and Q-adjusted Returns by Prior Return Quintiles

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 Total Net Assets (TNA) 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.

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GRIFFIN INSTITUTIONAL ACCESS REAL ESTATE FUND
PORTFOLIO OF INVESTMENTS
June 30, 2018 (Unaudited)

Description	Shares	Value (Note 2)
REAL ESTATE INVESTMENT TRUSTS (98.03%)		
Private Investment Funds (77.66%) *(a)		
AEW Core Property Trust	54, 208	$ 54,653,312
American Core Realty Fund, LP	445	55,266,237
Barings Core Property Fund, LP	139,016	18,021,808
BlackRock US Core Property Fund	N/A	48,099,966
Brookfield Senior Mezzanine Real Estate Finance Fund	42,867	43,868,234
CBRE U.S. Core Partners, LP	69,536,378	96,989,899
Clarion Lion Industrial Trust	54,291	96,979,932
Clarion Lion Properties Fund, LP	151,580	222,953,708
GRE U.S. Property Fund L.P.	N/A	68,005,614
Hancock U.S. Real Estate Fund L.P.	70,700	86,487,271
Heitman America Real Estate Trust, L.P.	34,986	42,893,400
Heitman Core Real Estate Debt Income Trust, L.P.	75,586	77,576,247
MEPT Edgemoor LP	33,699	69,470,057
MetLife Commercial Mortgage Income Fund, LP	9,816	10,036,426
Morgan Stanley Prime Property Fund	13,432	248,357,103
Oaktree Real Estate Income Fund, L.P.	N/A	86,279,627
PGIM Real Estate US Debt Fund L.P.	47,428	50,004,260
PRISA LP	119,181	189,547,043
RREEF America REIT II, Inc.	248,080	30,230,957
Sentinel Real Estate Fund, LP	650	56,521,739
Stockbridge Smart Markets Fund	47,709	72,739,523
TCM CRE Credit Fund LP	27,861	27,905,510
UBS Trumbull Property Fund	3,804	42,297,964
USAA US Government Building Fund LLC	N/A	61,653,060
		1,856,838,897
Publicly Traded Securities (20.37%) (a)		
Alexandria Real Estate Equities, Inc.	107,410	13,551,920
American Homes 4 Rent, Class A	546,140	12,113,385
Americold Realty Trust	169,070	3,722,921
AvalonBay Communities, Inc.	141,650	24,348,219
Boston Properties, Inc.	156,790	19,664,602
Brandywine Realty Trust	239,780	4,047,486
Camden Property Trust	169,250	15,423,753
Chesapeake Lodging Trust	153,330	4,851,361
Corporate Office Properties Trust	55,570	1,610,974
Cousins Properties, Inc.	484,280	4,692,673
CubeSmart	414,180	13,344,880
CyrusOne, Inc.	201,680	11,770,045

Figure 6
Griffin Institutional Access Real Estate Fund Holdings

This figure shows a partial list of the holdings Griffin Institutional Access Real Estate Fund had on June 30, 2018. As shown, 78% of investments were in the same type of open-end private equity real estate funds evaluated in this paper. 20% of investments were in publicly traded real estate securities. Griffin Institutional Access Real Estate Fund is an interval fund founded in 2014 and offers quarterly liquidity to investors. Holdings data was provided by EDGAR.

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Appendix A Private Equity Real Estate Market Overview

This section discusses the Private Equity Real Estate (PERE) market in greater detail. It supplements the discussion provided in Subsection 2.1. As mentioned above, institutional investors can invest in PERE through direct investments, separate accounts, joint ventures, club deals, and comingled funds. Two important subsets of comingled funds are open-end private equity (OPERE) funds and closed-end private equity funds (CPERE).

OPERE funds have a combination of characteristics similar to open-end funds in more traditional asset classes as well as those of closed-end private equity funds. OPERE funds are open-end in that they are open to issuing and redeeming shares on a regular basis, similar to open-end mutual funds and hedge funds. They offer to issue and redeem shares on a quarterly basis at stated net asset values. However, similar to other open-end funds that invest in illiquid assets, they have limitations on the extent to which they are open. Consistent with these other funds they use liquidity restrictions (both discretionary and non-discretionary) to prevent having to buy or sell assets too quickly. Non-discretionary liquidity restrictions include provisions such as notification periods, lockup periods, and intermittent issuance and redemption intervals. Discretionary liquidity restrictions include discretionary limits to issuances and redemptions similar to gates for hedge funds and capital call provisions for private equity funds. In contrast, CPERE funds are not open to issuing or redeeming shares.

As mentioned in Subsection 2.1, OPERE total net assets are determined quarterly as the cumulative value of the individual fair market estimates of their underlying assets less the sum of their liabilities. The vast majority of their underlying assets are commercial real estate properties. Each property is unique and trades infrequently requiring valuation, or appraisal, estimates be used to determine reported fair market values. The appraisal process is well documented as having a smoothing effect on price movements which spuriously creates serially correlated returns and causes a downward bias in return variances and covariances, similar to both nonsynchronous trading and hedge fund illiquidity exposure.[34] Valuation

[34]See Barkham and Geltner (1995), Blundell and Ward (1987), Case and Shiller (1989), Childs et al.

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estimates are based on the transaction information of other similar assets. However, because these assets are unique and similar assets trade infrequently, market pricing information is believed to be incorporated slowing into reported values.

The vast majority of OPERE funds do not have lockup periods. For those funds that do have lockup periods, it is typically only required when the fund is just starting out. A typical lockup period requirement for newer funds might require investors to keep their capital in the fund until two years after fund inception or until the fund achieves $1 billion in assets under management, whichever comes first. There are very few mature OPERE funds that have lockup periods. The typical lockup period for these funds is one year. However, as discussed in Subsection 5.4.1, even multi-year lockup periods are ineffective at deterring the risks associated with timing when to enter and leave the overall market. Also, as discussed, the risks associated with timing when to enter and leave the overall market were the ones found to be substantially more important than the cross-sectional risks.

CPERE funds have a similar structure to other traditional private equity funds such as buyout and venture capital funds. They raise capital commitments from investors and then close the fund at its inception. They then call capital from their investors and deploy it into the market over the subsequent three to seven years. Funds then return capital to their investors either when they sell assets or when they liquidate the fund, somewhere between eight to 12 years after inception.

OPERE funds are similar to CPERE funds in that they invest in real assets and actively manage those assets. However, the majority of OPERE funds invest in lower risk assets and use relatively lower leverage while CPERE funds typically invest in riskier assets and have higher leverage. OPERE funds primarily invest in core and core+ investments while CPERE funds primarily invest in value-add and opportunistic investments. Consistent with these risk profiles, the majority of OPERE funds have a set fee structure which is a percentage of their total net assets, while incentive fees are a larger portion of CPERE fund fee structures. A few of the OPERE funds that invest in value-add strategies have a portion of their fee structures based on smaller performance incentives. In the sample, about a third of OPERE

(2002), Brown (1991), 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.

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managers also manage CPERE funds, buyout funds, and venture capital funds. Another third are primarily banking or insurance institutions, and the last third encompasses real estate managers who focus solely on PERE funds.

Because of their different risk and return profiles and fund characteristics, OPERE and CPERE funds often attract investors with differing investment goals. Many OPERE investors are more interested in simply obtaining a diverse exposure to the overall commercial real estate market and passively managing it. In contrast, many CPERE investors are more interested in actively managing their exposure to commercial real estate to obtain the highest expected return. Because of this, OPERE investors are at greater risk of being taken advantage of than investors in their closed-end counterparts.

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Appendix B Implementation Delays

This section provides the results from my analysis evaluating the decaying effect on the NAV-timing profitability. This Section supplements the evidence discussed in Section 5.4 of the main body of the paper. Table A.1 provides the results of delaying the time-series NAV-timing strategy. The long-short results are consistent with those provided in row 5 of Table 3. Table A.2 provides the results of delaying the cross-sectional NAV-timing strategy. The 5 - 1 results are consistent with those provided in row 11 of Table 4.

As shown, NAV-timing profits diminish significantly as delays increase. In all, this evidence further supports the conclusion that liquidity restrictions help deter the fragility risks associated with stale pricing.

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Table A.1
Time-series Implementation Delays

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 robust, adjusted for heteroskedasticity, and clustered by period. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Portfolio	Excess Return	NFI-OE Alpha	REIT Q-Factor Alpha	5-Factor Alpha	N
Long-Short (0q delay)	3.564***	4.260***	3.688***	3.662***	48
Long-Short (1q delay)	2.895***	3.081***	2.769***	2.708***	48
Long-Short (2q delay)	2.036***	1.397	1.800***	1.442***	48
Long-Short (3q delay)	1.426**	0.442	1.162	1.147**	48
Long-Short (4q delay)	0.922	-0.311	0.998	0.796	48
Long-Short (5q delay)	0.560	-0.711**	0.572	0.863	48
Long-Short (6q delay)	0.423	-0.823**	0.365	0.708	48
Long-Short (7q delay)	0.487	-0.789**	0.658	1.011	48

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Table A.2
Cross-sectional Implementation Delays

This table presents the results from my analysis on the robustness of trading profitability that comes from OPERE return predictability (without liquidity restrictions). In particular, this table presents the results to a trading strategy of investing in either the OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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
5 - 1 (0q delay)	1.020***	1.437***	0.882***	0.872**	48
5 - 1 (1q delay)	0.884***	1.114***	0.778***	0.644*	48
5 - 1 (2q delay)	0.658***	0.662**	0.552***	0.428**	48
5 - 1 (3q delay)	0.149	-0.230	-0.056	-0.169	48
5 - 1 (4q delay)	-0.075	-0.502*	-0.017	-0.184	48
5 - 1 (5q delay)	-0.641	-1.510***	-0.654	-0.529	48
5 - 1 (6q delay)	-0.542	-1.290***	-0.272	-0.379	48
5 - 1 (7q delay)	-0.446	-0.975***	-0.328	-0.334	48

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Appendix C NAV-timing Profitability Potency

This section provides the results from my analysis on the strength of the NAV-timing results discussed in Subsection 5.2. In this analysis, I add year fixed effects to the results to the evidence provided in Tables 3 and 4. As shown in Tables A.3 and A.4, the results to the NAV-timing strategies are slightly larger in both economic and statistical terms. However, the results to the buy-and-hold strategy have slightly decreased. In all, this evidence further supports the conclusion that the stale pricing risks associated with open-end funds investing in illiquid assets should be a significant consideration for policy makers, investors, and managers.

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Table A.3
Time-Series NAV-timing Results

This table presents the first set of results from my analysis on the trading profitability that comes from OPERE return predictability (without liquidity restrictions). Long returns are those obtained by either investing in the OPERE market (as proxied by the NFI-OE) or the 3-month T-bill based on prior OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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***	2.344***	2.615***	2.458***	48
	(19.95)	(9.27)	(20.87)	(14.68)	
Short	-1.020***	-2.344***	-1.151***	-1.463***	48
	(-3.30)	(-9.27)	(-4.24)	(-4.86)	
Long-Short	3.564***	4.688***	3.766***	3.922***	48
	(10.46)	(9.27)	(12.49)	(12.74)	

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	1.464***	0.995**	48
	(4.64)		(4.94)	(2.64)	

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Table A.4

Cross-Sectional NAV-timing Results

This table presents the second set of results from my analysis on the trading profitability from OPERE 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 robust, adjusted for heteroskedasticity, and clustered by 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**	-0.891***	0.902**	0.373	48
	(2.27)	(-6.77)	(2.70)	(0.70)	
2	1.436***	-0.081	1.341***	0.913**	48
	(4.26)	(-0.47)	(4.56)	(2.26)	
3	1.700***	0.059	1.716***	1.186**	48
	(4.70)	(0.52)	(5.52)	(2.72)	
4	1.780***	0.534***	1.669***	1.254***	48
	(6.39)	(4.78)	(6.49)	(4.13)	
5	1.936***	0.377*	1.873***	1.400***	48
	(5.41)	(1.72)	(4.98)	(3.65)	
5 - 1	1.020***	1.268***	0.971***	1.028***	48
	(4.96)	(3.96)	(5.24)	(3.02)	

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Appendix D Investor Responses to Positive & Negative Returns

In this paper, the purpose of evaluating how investors respond to returns is to determine if their actions are consistent with the NAV-timing strategies. If so, this would suggest significant wealth transfer risks exist when open-end funds invest in illiquid assets. However, it might also be important to understand whether their behavior is influenced more by positive return information or negative return information. This section provides the results from my analysis on how investors respond to both positive and negative return information and its importance on fund fragility.

Economists evaluate how investor flows respond differently to positive and negative return information to gauge the level of their concern for bank-run-like risks in open-end funds (see Chen et al. (2010)). Investors might be concerned negative returns would lead to a disproportionate number of redemption requests. If so, the fund might be forced to sell their illiquid assets too quickly at fire sale prices. Doing so would significantly impact the future returns to those investors that kept their capital in the fund. Economists typically interpret larger parameter estimates on negative returns as evidence suggesting investors are concerned with potential fire-sale risks.

In order to evaluate this question, I regress both Total Fund Flows and Net Queues on public market returns, private market returns, and fund returns. In doing so, I use the returns from the NAV-timing strategies discussed in Section 5.2 with one exception. Because the NAV-timing strategy which uses relative fund returns never has a period of negative return, I use the one-period lagged fund return in this analysis. The results from may analysis are provided in Tables A.5 through A.7 below.

As shown, in Table A.5, the parameter estimates on both the indicator variable for positive public market returns and the interaction between the public market returns and this indicator are insignificant. I find the same pattern when evaluating the fund returns as shown in Table A.7. In contrast, I find the parameter estimate on the interaction between the indicator for positive returns and the market returns to be both statistically and economically significant. This finding suggests investor flows are significantly more sensitive to the

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return variation in positive returns than they are in the return variation of negative returns. This finding provides evidence suggesting investors in these funds are less concerned about funds being forced to sell assets at fire sale prices. This is further evidence that discretionary liquidity restrictions do a good job protecting against the fragility risks created when liquid funds invest in illiquid assets.

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Table A.5

Investor & Fund Responses to Public Market Returns

This table reports the results from my analysis on the behavior of investors and funds with respect to the public market excess return as proxied by the NAREIT FTS Index return. Total Fund Flow is defined as the sum of the Fund Flow and the Net Queue, all divided by the lagged TNA, $TFF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\,Queue_{i,t} - Redemption\,Queue_{i,t}]/TNA_{i,t-1}$. 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 Total Fund Flow on the lagged excess returns with no fixed effects and with fund fixed effects, respectively. Columns (3) and (4) report the results of regressing the Total Fund Flow on the lagged excess return, an indicator variable indicating if the excess return is positive, and an interaction variable between the excess return and the indicator variable. Columns (5) through (8) provide the results from similar regressions, except for evaluating the Net Queue instead of the Total Fund Flow. Excess Returns with no fixed effects, fund fixed effects, time fixed effects, and both fund and time fixed effects. Standard errors are 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.

$$Total\ Fund\ Flow_{i,t} = \beta_0 + \beta_1 r_{Public,t-1} + \varepsilon_{i,t}$$

$$Net\ Queue_{i,t} = \beta_0 + \beta_1 r_{Public,t-1} + \varepsilon_{i,t}$$

	Total Fund Flow				Net Queue			
$r_{Pubilic}$	0.216***	0.231***	0.225**	0.225*	0.172***	0.181***	0.173	0.173
	(3.50)	(3.73)	(2.34)	(1.74)	(3.45)	(3.65)	(1.52)	(1.30)
$r_{Public} \cdot r_{Public} > 0 \in \{0,1\}$			-0.160	-0.067			-0.145	-0.069
			(-1.16)	(-0.38)			(-1.03)	(-0.42)
$r_{Public} > 0 \in \{0,1\}$			0.067	0.036			0.066	0.038
			(1.17)	(0.60)			(1.34)	(0.75)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	No	No	No	No
N	1,174	1,174	1,174	1,174	1,174	1,174	1,174	1,174
R^2	0.04	0.41	0.05	0.41	0.04	0.40	0.05	0.41

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Table A.6

Investor & Fund Responses to Private Market Returns

This table reports the results from my analysis on the behavior of investors and funds with respect to the private market excess return as proxied by the NFI-OE Index return. Total Fund Flow is defined as the sum of the Fund Flow and the Net Queue, all divided by the lagged TNA, $TFF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\,Queue_{i,t} - Redemption\,Queue_{i,t}]/TNA_{i,t-1}$. 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 Total Fund Flow on the lagged excess returns with no fixed effects and with fund fixed effects, respectively. Columns (3) and (4) report the results of regressing the Total Fund Flow on the lagged excess return, an indicator variable indicating if the excess return is positive, and an interaction variable between the excess return and the indicator variable. Columns (5) through (8) provide the results from similar regressions except for evaluating the Net Queue instead of the Total Fund Flow. Excess Returns with no fixed effects, fund fixed effects, time fixed effects, and both fund and time fixed effects. Standard errors are 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.

$$Total\,Fund\,Flow_{i,t} = \beta_0 + \beta_1 r_{Private,t-1} + \varepsilon_{i,t}$$

$$Net\,Queue_{i,t} = \beta_0 + \beta_1 r_{Private,t-1} + \varepsilon_{i,t}$$

	Total Fund Flow				Net Queue			
$r_{Private} > 0 \in \{0,1\}$	2.242***	2.252***	0.168	0.168	1.797***	1.776***	0.250	0.250
	(4.82)	(4.85)	(0.50)	(0.88)	(4.65)	(4.66)	(0.91)	(1.40)
$r_{Private} \cdot r_{Private} > 0 \in \{0,1\}$			3.949***	5.134***			2.753***	3.699***
			(4.78)	(5.27)			(3.86)	(4.61)
$r_{Private}$			0.031	-0.017			0.032	-0.010
			(1.24)	(-0.56)			(1.27)	(-0.39)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	No	No	No	No
N	1,174	1,174	1,174	1,174	1,174	1,174	1,174	1,174
R^2	0.07	0.43	0.09	0.45	0.07	0.44	0.07	0.44

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Table A.7

Investor & Fund Responses to Fund Returns

This table reports the results from my analysis on the behavior of investors and funds with respect to excess fund returns. Total Fund Flow is defined as the sum of the Fund Flow and the Net Queue, all divided by the lagged TNA, $TFF_{i,t} = [TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t}) + Investment\, Queue_{i,t} - Redemption\, Queue_{i,t}] / TNA_{i,t-1}$. 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 Total Fund Flow on the lagged excess returns with no fixed effects and with fund fixed effects, respectively. Columns (3) and (4) report the results of regressing the Total Fund Flow on the lagged excess return, an indicator variable indicating if the excess return is positive, and an interaction variable between the excess return and the indicator variable. Columns (5) through (8) provide the results from similar regressions except for evaluating the Net Queue instead of the Total Fund Flow. Excess Returns with no fixed effects, fund fixed effects, time fixed effects, and both fund and time fixed effects. Standard errors are 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.

$$Total\, Fund\, Flow_{i,t} = \beta_0 + \beta_1 r_{i,t-1} + \varepsilon_{i,t}$$

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

	Total Fund Flow				Net Queue			
r_{Fund}	1.294***	1.112***	0.874**	0.725***	1.051***	0.876***	0.794**	0.641***
	(6.28)	(5.11)	(2.47)	(3.04)	(6.11)	(4.74)	(2.60)	(2.91)
$r_{Fund} \cdot r_{Fund} > 0 \in \{0,1\}$			0.392	0.049			0.150	-0.212
			(0.48)	(0.07)			(0.22)	(-0.35)
$r_{Fund} > 0 \in \{0,1\}$			0.046	0.057			0.032	0.045
			(0.79)	(1.32)			(0.61)	(1.19)
Fund f.e.	No	Yes	No	Yes	No	Yes	No	Yes
Time f.e.	No	No	No	No	No	No	No	No
N	1,171	1,171	1,171	1,171	1,171	1,171	1,171	1,171
R^2	0.07	0.40	0.07	0.41	0.06	0.40	0.06	0.41

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Appendix E Model Proof

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

E.1 Wealth Transfer Proof

The overall wealth transfer, WT, from existing investors to incoming investors is represented by Equation A.2. As shown, the size of the wealth transfer is a function of two components: the staleness of the valuations, Θ, and the fund flow, FF_1. Wealth transfers are greater when either of these is greater. As shown in Equation A.2, this equation can be rewritten in terms of only the economic return and the fund flow by substituting the economic return for the fund return based on Equation A.1. Equations A.1 and A.2 correspond to Equations 9 and 19 in the main body of the paper.

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

$$\begin{aligned} WT &= TNA_0 \left(R_1^E - R_1^{Fund}\right) FF_1 \\ &= TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) FF_1 \end{aligned} \tag{A.2}$$

The wealth transfer of the buy-and-hold investor, WT^{BH}, can be determined by multiplying the overall wealth transfer by their percent ownership in the fund. This can be determined by calculating their percent ownership using Equation A.3 and adding it into Equation A.2 and combining like terms. Equations A.3 and A.4 correspond to Equations 5 and 20 in the main body of the paper.

$$TNA_0^{Fund} = \omega_0 \Pi_0^{MT} + \Pi_0^{BH} \tag{A.3}$$

$$\begin{aligned} WT^{BH} &= \frac{\left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right)}{TNA_0} TNA_0 \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) FF_1 \\ &= \left(TNA_0 - \omega_0^{MT} \Pi_0^{MT}\right) \left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) FF_1 \end{aligned} \tag{A.4}$$

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E.2 Investor's Response to Stale Pricing Incentives

In this model, the market-timing investor maximizes the period 2 expected return to his overall investment portfolio, R_2^{MT}, by selecting his optimal period 1 fund allocation, $\omega_{1,b}$. This maximization function is subject to a an adjustment cost, $\frac{\phi}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2$, as reflected in Equation A.5. The expectation notation is dropped in the second line of the derivation to reduce clutter. The optimal fund allocation be obtained by taking the first order condition and solving for the post fund flow allocation. The expected period 2 fund return as a function of the economic returns is then substituted into this equation to obtain the optimal allocation as reflected by Equation A.9.[35] As noted in the main body of the paper, $E_1\left(R_2^E\right) = 1$. Equation A.9 corresponds to Equation 17 in the main body of the paper.

$$\begin{aligned}\max_{\{\omega_{1,b}\}} E_1\left(R_2^{MT}\right) &= \max_{\{\omega_{1,b}\}} E_1\left(\left(1-\omega_{1,b}\right)R_2^{rf} + \omega_{1,b}R_2^{Fund} - \frac{\phi}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2\right) \\ &= \max_{\{\omega_{1,b}\}} R_2^{rf} - \omega_{1,b}R_2^{rf} + \omega_{1,b}R_2^{Fund} - \frac{\phi}{2}\left(\omega_{1,b}-\omega_{1,a}\right)^2\end{aligned} \tag{A.5}$$

First Order Condition:

$$0 = R_2^{Fund} - R_2^{rf} - \phi\left(\omega_{1,b}-\omega_{1,a}\right) \tag{A.6}$$

$$\phi\left(\omega_{1,b}-\omega_{1,a}\right) = R_2^{Fund} - 1 \tag{A.7}$$

$$\omega_{1,b}-\omega_{1,a} = \frac{1}{\phi}\left(R_2^{Fund} - 1\right) \tag{A.8}$$

[35] As noted in the main body of the paper, investors act as if they are unaware of the impact their subscription or redemption requests will have on the future returns of the fund. Their subscription or redemption requests will impact the fund return in two ways. First, it will lower the future returns of the fund through the transaction costs the fund will incur due to the illiquidity of the assets. Second, it will lower the returns of the fund by increasing or decreasing the dollar basis of the fund. Neither of these change the conclusions of the model.

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$$
\begin{aligned}
\omega_{1,b} &= \omega_{1,a} + \frac{1}{\phi}\left(\frac{R_1^E R_2^E}{R_1^{Fund}} - 1\right) \\
&= \omega_{1,a} + \frac{1}{\phi}\left(\frac{R_1^E R_2^E}{\left(R_1^E\right)^{(1-\Theta)}} - 1\right) \\
&= \omega_{1,a} + \frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)
\end{aligned}
\tag{A.9}
$$

E.3 Fund Flow Requested Proof

Based on the market-timing investor's optimal fund allocation, the requested fund flow, TFF_1, can be derived as follows. The market-timing investor's post fund flow fund allocation is substituted into the equation which equates the dollar change in the market-timing investors allocation to the fund with the dollar change in the total net assets of the fund as shown in Equation A.10. Both sides are then divided by the pre-fund flow Total Net Assets leaving the optimal Fund Flow percentage as shown in Equation A.11 below. Equations A.10 and A.11 correspond to Equations 11 and 18 in the main body of the paper.

$$
\begin{aligned}
TNA_{1,a}TFF_1 &= \Pi_1^{MT}\left(\omega_{1,b} - \omega_{1,a}\right) \\
&= \Pi_1^{MT}\left(\omega_{1,a} + \frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right) - \omega_{1,a}\right) \\
&= \Pi_1^{MT}\left(\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)
\end{aligned}
\tag{A.10}
$$

$$
TFF_1 = \frac{\Pi_1^{MT}}{TNA_{1,a}}\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right) \tag{A.11}
$$

Based on this fund flow, the overall wealth transfer and the wealth transfer experienced by the buy-and-hold investor would be as follows. Equation A.13 corresponds with Equation 20 in the main body of the paper.

$$
E_1\left(WT\right) = E_1\left(TNA_0\left(R_1^E - R_1^{Fund}\right)\frac{\Pi_1^{MT}}{TNA_{1,a}}\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{A.12}
$$

$$
E_1\left(WT^{BH}\right) = E_1\left(\left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right)\frac{\Pi_1^{MT}}{TNA_{1,a}}\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right) \tag{A.13}
$$

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E.4 Fund's Response to Price Impact Incentives

In this model, funds maximize their lifetime earning of fees, π, by selecting their optimal period 1 discretionary fund flow, DFF_1. This discretionary fund flow is a percentage of the fund flow requested by investors as reflected by Equation A.14. This maximization function is subject to a a transaction cost, $\frac{\gamma_2}{2}\psi\left(FF_1\right)^2$, and an investor sentiment cost, $\frac{\gamma_3}{2}\left(TFF_1 - FF_1\right)^2$, representing an investors desire to have their fund flow requests fulfilled in a timely manner. These constraints are reflected in the fund's maximization function shown in Equation A.5. The expectation notation is dropped in the second line of the derivation to reduce clutter.

This equation can be expanded by substituting the product of the discretionary fund flow and the total fund flow requested for the actual fund flow based on Equation A.14. The optimal discretionary fund flow can then be obtained by taking the first order condition and solving for this fund flow ratio. As noted in the main body of the paper, DFF_1 must be between 0 and 1. Otherwise, the fund could force investors to invest beyond their desired allocations. Equations A.14, A.15, and A.19 correspond to Equations 21, 22, and 23 in the main body of the paper.

$$DFF_1 = \frac{FF_1}{TFF_1} \tag{A.14}$$

$$\begin{aligned}\max_{\{DFF_1\}} E_1\left(\pi\right) &= \max_{\{DFF_1\}} E_1\left(\gamma_1 FF_1 - \frac{\gamma_2}{2}\psi\left(FF_1\right)^2 - \frac{\gamma_3}{2}\left(TFF_1 - FF_1\right)^2\right) \\ &= \max_{\{DFF_1\}} \gamma_1 DFF_1 TFF_1 - \frac{\gamma_2}{2}\psi\left(DFF_1 TFF_1\right)^2 - \frac{\gamma_3}{2}\left(TFF_1 - DFF_1 TFF_1\right)^2\end{aligned} \tag{A.15}$$

First Order Condition:

$$\begin{aligned}0 &= \gamma_1 TFF_1 - \gamma_2\psi DFF_1 TFF_1 TFF_1 + \gamma_3\left(TFF_1 - DFF_1 TFF_1\right) TFF_1 \\ &= \gamma_1 TFF_1 - \gamma_2\psi DFF_1\left(TFF_1\right)^2 + \gamma_3\left(TFF_1\right)^2 - \gamma_3 DFF_1\left(TFF_1\right)^2\end{aligned} \tag{A.16}$$

$$\gamma_2\psi DFF_1\left(TFF_1\right)^2 + \gamma_3 DFF_1\left(TFF_1\right)^2 = \gamma_1 TFF_1 + \gamma_3\left(TFF_1\right)^2 \tag{A.17}$$

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$$DFF_1 \left(\gamma_2\psi + \gamma_3\right) \left(TFF_1\right)^2 = \gamma_1 TFF_1 + \gamma_3 \left(TFF_1\right)^2 \tag{A.18}$$

$$DFF_1 = \frac{\gamma_1 + \gamma_3 TFF_1}{\left(\gamma_2\psi + \gamma_3\right) TFF_1} \tag{A.19}$$

E.5 Joint Solutions: Investor and Fund Responses

Based on Equation A.14, the chosen fund flow can be derived by multiplying the fund's optimal discretionary fund flow, given by Equation A.19, with the investor's optimal fund allocation, given by Equation A.11. Equation A.20 corresponds to Equation 24 in the main body of the paper.

$$FF_1 = \frac{\gamma_1 + \gamma_3 \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)}{\left(\gamma_2\psi + \gamma_3\right)} \tag{A.20}$$

The wealth transfer can then be rewritten in terms of the investor and fund optimizations by substituting the variables for the fund flow based on Equation A.20. The wealth transfer with liquidity restrictions is strictly less than the one without discretionary liquidity restrictions. This is based on the assumptions that both stale pricing, Θ, and transaction costs, ψ, increase as illiquidity increases. Equation A.21 corresponds to Equation 25 in the main body of the paper.

$$WT^{BH} = \left(TNA_0 - \omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E - \left(R_1^E\right)^{(1-\Theta)}\right) \frac{\gamma_1 + \gamma_3 \frac{\Pi_1^{MT}}{TNA_{1,a}} \left(\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta} - 1\right)\right)}{\left(\gamma_2\psi + \gamma_3\right)} \tag{A.21}$$

E.6 Fund's Response Using Liquidity Buffers

The fund's optimal discretionary fund flow assuming it uses a liquidity buffer can be derived as follows. The component related to the transaction cost, ψ , is removed from the optimization function given the fund uses a liquidity buffer to not incur these costs. The wealth transfer with liquidity buffers added to liquidity restrictions is strictly greater than the one with only liquidity restrictions. Equation A.29 corresponds to Equation 31 in the main body of the paper.

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- **Fund Optimization DFF selection:**

$$\begin{aligned}\max_{\{DFF_1\}} E_1(\pi) &= \max_{\{DFF_1^{LB}\}} E_1\left(\gamma_1\left(1+FF_1^{LB}\right)-\frac{\gamma_3}{2}\left(TFF_1-FF_1^{LB}\right)^2\right)\\ &= \max_{\{DFF_1^{LB}\}} \gamma_1\left(1+TFF_1DFF_1^{LB}\right)-\frac{\gamma_3}{2}\left(TFF_1-TFF_1DFF_1^{LB}\right)^2\end{aligned} \tag{A.22}$$

First Order Condition:

$$\begin{aligned}0 &= \gamma_1TFF_1+\gamma_3\left(TFF_1-DFF_1^{LB}TFF_1\right)TFF_1\\ &= \gamma_1TFF_1+\gamma_3\left(TFF_1\right)^2-\gamma_3DFF_1^{LB}\left(TFF_1\right)^2\end{aligned} \tag{A.23}$$

$$DFF_1^{LB}\gamma_3\left(TFF_1\right)^2=\gamma_1TFF_1+\gamma_3\left(TFF_1\right)^2 \tag{A.24}$$

$$DFF_1^{LB}=\frac{\gamma_1+\gamma_3TFF_1}{\gamma_3TFF_1} \tag{A.25}$$

$$DFF_1^{LB}=\frac{\gamma_1+\gamma_3TFF_1}{\gamma_3TFF_1}\gg\frac{\gamma_1+\gamma_3TFF_1}{\left(\gamma_2\psi+\gamma_3\right)TFF_1}=DFF_1 \tag{A.26}$$

$$DFF_1^{LB}\gg DFF_1 \tag{A.27}$$

$$\left|FF_1^{LB}\right|\gg\left|FF_1\right| \tag{A.28}$$

- **Wealth Transfer**

$$WT^{BH,LB}=\left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)\cdot\frac{\gamma_1+\gamma_3\frac{\Pi_1^{MT}}{TNA_{1,a}}\left(\frac{1}{\phi}\left(\left(R_1^E\right)^{\Theta}-1\right)\right)}{\left(\gamma_3\right)} \tag{A.29}$$

$$\begin{aligned}WT^{BH,LB}=\left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)FF_1^{LB}\gg\\ \left(TNA_0-\omega_0^{MT}\Pi_0^{MT}\right)\left(R_1^E-\left(R_1^E\right)^{(1-\Theta)}\right)FF_1=WT^{BH}\end{aligned} \tag{A.30}$$

$$WT^{BH,LB}\gg WT^{BH} \tag{A.31}$$

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