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THREE ESSAYS ON INVESTMENTS

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THREE ESSAYS ON INVESTMENTS

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
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By
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ABSTRACT OF DISSERTATION

THREE ESSAYS ON INVESTMENTS

This dissertation consists of three essays on investments. The first essay examines the incidence, determinants, and consequences of hedge fund share restriction changes. This paper finds that nearly one in five hedge funds change their share restrictions (e.g., lockup) over the period of 2007-2012. Share restriction changes are not random. Fund's asset illiquidity, liquidity risk, and performance are related to share restriction changes. A hazard model indicates that funds who actively manage liquidity concerns live longer by adjusting share restrictions. The paper examines whether changes in share restrictions create an endogeneity bias in the share illiquidity premium (Aragon, 2007) and find that 18% of the premium can be explained by the dynamic nature of contract changes.

The second essay examines why mutual funds appear to underperform hedge funds. Utilizing a unique panel of mutual fund contracts changes, this paper explores several possible channels, including: alternative investment practices (e.g., short sales and leverage), performance-based compensation, and the ability to restrict the funding risk of fund flows. This paper documents that over our sample period, mutual funds were more likely to shift their contracting environment closer to that of hedge funds. However, this shift provided no benefit to mutual funds and the paper finds no causal link between these contract changes and improvements in performance. Rather, this paper casts doubt on the binding nature of investment restrictions in the mutual fund industry.

The third essay examines whether the 52-week high effect (George and Hwang, 2004) can be explained by risk factors. The paper finds that it is more consistent with investor underreaction caused by anchoring bias: the presumably more sophisticated institutional investors suffer less from this bias and buy (sell) stocks close to (far from) their 52-week highs. Further, the effect is mainly driven by investor underreaction to industry instead of firm-specific information. The 52-week high strategy works best among stocks whose values are more affected by industry factors. The 52-week high strategy based on industry measurement is more profitable than the one based on idiosyncratic measurement.

KEYWORDS: Hedge funds, share restrictions, mutual funds, investment restrictions, 52-week high effects

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THREE ESSAYS ON INVESTMENTS

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To my parents and wife

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Chapter One: The Dynamics of Hedge Fund Share Restrictions

1. Introduction

Hedge funds have become increasingly popular with investors. According to the HFR Global Hedge Fund Industry Report, investors allocated over $40 billion of new capital into the hedge fund industry in the second quarter of 2013, and the total capital invested in the global hedge fund industry increased to $2.41 trillion. Hedge funds hold a variety of asset classes and typically apply sophisticated financial instruments, often with illiquid assets (Sadka, 2010). Hedge fund liquidity risk, especially the liquidity spiral during the recent financial crisis discussed in Brunnermeier and Pedersen (2009), has received considerable attention. A significant body of literature has examined the effect of hedge fund liquidity risk on fund performance (e.g., Getmansky et al., 2004; Aragon, 2007; Brunnermeier and Pedersen, 2009; Sadka, 2010; Boyson et al., 2010; Cao et al., 2011; Ben-David et al., 2012).

Hedge funds typically use share restrictions, such as lockups and limited redemption frequency, to manage liquidity risk. Share restrictions are supposed to enable funds to invest in illiquid assets and prevent funds from selling assets at fire sale prices in response to sudden investor withdrawal requests. However, the literature finds mixed evidence concerning the relation of share restrictions, asset illiquidity, and liquidity risk. Aragon (2007) finds that hedge fund share restriction is negatively related to the liquidity of fund assets and positively related to fund performance. Aragon (2007) attributes this outperformance to share restrictions that enable funds to invest in illiquid assets and earn an illiquidity premium. However, Sadka (2010) suggests that hedge fund share restrictions are not necessarily related to funds' liquidity risk. Sadka (2010) finds that the difference in returns between high and low liquidity risk loading funds is independent of the liquidity a fund provides to its investors as measured by lockup and redemption notice periods.

The inconsistency in the conclusions linking asset liquidity, liquidity risk, and share restrictions may be attributed to a limitation of the hedge fund databases used in the literature. All major hedge fund databases only provide an updated snapshot of the funds' characteristics. While historical returns and assets under management data are available, funds' share restrictions are overwritten by the updated data. Therefore, share restriction data used in the literature are measured only at the end of the sample period. Typically, the literature implicitly assumes that hedge funds do not change share restrictions over time. This measurement error may cause an endogeneity bias, as share restrictions may change over time based on the funds' performance and flows.

In this paper, we use monthly snapshots of hedge fund characteristics obtained from BarclayHedge, a large commercial data provider, from January 2007-May 2012.[1] As a result, we utilize a large panel dataset of share restrictions to provide an empirical study of hedge fund share restriction changes and their impact on investors.

We begin by documenting the incidence of share restriction changes. We find that 18.40% of the funds changed their share restriction structure during our 65-month sample period. This contrasts with the prevailing assumption that share restrictions are largely fixed. Funds are more likely to change share restrictions during the financial crisis of 2007Q3 to 2009Q2. Further, share restriction changes are symmetric with similar incidences of share restriction increase and decrease. More importantly, the magnitude of

[1] Utilizing the monthly snapshots of the BarclayHedge data from December 2006-May 2012, we can examine the hedge fund share restriction changes from January 2007-May 2012.

share restriction changes is economically significant. The median level of change in the share restrictions is near the median level of share restrictions before a change.

Next, we examine the determinants of share restriction changes. We find that hedge fund asset liquidity and liquidity risk are related to share restriction changes. Hedge funds with high asset liquidity and low liquidity risk are more likely to decrease share restrictions. One standard deviation increase in asset liquidity will increase the relative risk ratio of a share restriction decrease by 1.23. This finding is consistent with Aragon (2007) who notes that fund share restrictions are negatively related to the liquidity of fund assets. We also find mean reversion associated with share restriction changes. Funds with high (low) share restrictions are more likely to decrease (increase) share restrictions. Share restrictions are also related to fund performance and flows. Funds within a family with good performance and high flows are more likely to increase share restrictions suggesting that share restrictions also serve as a bargaining tool between fund managers and investors.

Fund's asset illiquidity, liquidity risk, and performance are related to share restriction changes. It will cause endogeneity bias if we assume share restrictions are fixed. We examine the potential endogeneity bias in the share illiquidity premium. Aragon (2007) finds that funds with high share illiquidity have better performance. We find that 18% of the share illiquidity premium can be explained by the dynamic nature of contract changes.

We also examine the costs and benefits of share restriction changes for hedge funds and their investors. We find that funds underperform their comparable peers following share restriction decreases. Average monthly style-adjusted returns decrease by

0.30% as compared to matched peers following share restriction decreases. However, investors' flows reward funds that decrease share restrictions. Average monthly style-adjusted net flows increase by 0.62% as compared to matched peers following share restriction decreases. Further, we note that funds who actively manage liquidity concerns live longer by adjusting share restrictions. Failure rates decrease by nearly 50% for funds that adjust share restrictions relative to those funds who never adjust their share restrictions. Additionally, we examine the coincidence of hedge fund share restriction, fee, strategy, and manager changes. We find that fee, strategy, and manager changes are highly correlated with share restriction changes. Funds that increase share restrictions are more likely to increase their fees simultaneously.

The remainder of the paper is organized as follows. Section 2 discusses the background literature and develops hypotheses. Section 3 reviews the data and summary statistics. Section 4 provides the methodologies and the empirical results. Section 5 discusses extensions to our main analyses. Section 6 provides our conclusions.

2. Literature and hypotheses

2.1 Liquidity risk

Liquidity is a primary attribute of many investment plans and financial instruments (Amihud and Mendelson, 1986). The effect of liquidity on asset pricing has been addressed in various ways in the literature. Most of the studies find that illiquid assets have high returns. Amihud and Mendelson (1986) examine the effect of securities' bid-ask spreads on their returns and find that market-observed average returns are an increasing function of the spreads. They argue that this positive association reflects the compensation required by investors for their trading costs. Further, Brennan and

Subrahmanyam (1996) decompose estimated trading costs into variable and fixed components and find that there is a significant return premium associated with both the fixed and variable transaction costs.

Pastor and Stambaugh (2003) examine whether the market-wide liquidity is a state variable important in asset pricing. They determine that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. They find that from 1966-1999, the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually, adjusted for exposures to the market return as well as size, value, and momentum factors. They also note that the liquidity risk factor accounts for half of the profits in a momentum strategy. Sadka (2010) decomposes firm-level liquidity into variable and fixed price effects and finds unexpected systematic variations in the variable component. The fixed component of liquidity is found to be priced within the context of momentum and post-earnings announcement drift portfolio returns.

There are also studies investigating the correlation between the volatility of liquidity and stock returns. Chordia et al. (2001) examine how aggregate market liquidity varies over time and find that stocks with greater volatility of liquidity have lower returns. Pereira and Zhang (2010) offer a rational explanation for this negative relation and argue that a fully rational, utility maximizing, risk-averse investor can take advantage of this time-varying liquidity by adapting his trades to the state of liquidity. Hameed et al. (2010) confirm that market liquidity drops after large negative market returns as the aggregate collateral of financial intermediaries falls and many asset holders are forced to liquidate. They also note significant returns to supplying liquidity following periods of large drops in market valuations.

2.2 Hedge fund liquidity risk

The impact of liquidity risk on hedge fund performance has been well established. Brunnermeier and Pedersen (2009) find that a shock to funding liquidity leads to deleveraging, thus reducing hedge fund asset liquidity. Boyson et al. (2010) suggest that hedge funds experience contagion in worst returns. They also find that this contagion is linked to asset and funding liquidity shocks.

Cao et al. (2011) investigate hedge fund managers' ability to time market liquidity and examine whether fund managers possess liquidity-timing ability by adjusting their portfolios' market exposure as aggregate market-liquidity conditions change. They find that hedge fund managers increase (decrease) their market exposure when equity market liquidity is high (low), and this effect is both economically and statistically significant. Ben-David et al. (2012) examine hedge fund stock trading during the financial crisis of 2007-2009 and find that hedge funds reduce their equity holdings during the crisis. They argue that this is driven by capital withdrawals on the part of investors and the pressure of lenders.

Aragon and Strahan (2012) use the bankruptcy of Lehman Brothers as an exogenous shock to demonstrate that hedge funds act as liquidity providers. They find that stocks traded by the Lehman-connected hedge funds experienced greater declines in market liquidity following the bankruptcy. They conclude that shocks to traders' funding liquidity reduce the market liquidity of the assets that they trade.

2.3 Hedge fund share restrictions

Johnson (2004) suggests that mutual fund investors receive no or low cost liquidity, but their trades in fund shares may force the fund to make costly transactions in its portfolio. Therefore, he argues that short-term investors can impose significant liquidity costs on long-term investors within the same fund. Hedge funds often hold more illiquid assets than mutual funds, so the liquidity cost is expected to be higher for hedge funds. However, unlike mutual funds, hedge funds usually impose share restrictions on investor subscriptions and redemptions. Share restrictions have been introduced as a way to protect long-term investors.

Share restrictions often involve a minimum investment requirement, a lockup period, a redemption frequency provision, and a redemption notice period. It is not easy to get into a hedge fund. Hedge funds require a minimum investment. The mean minimum investment is $0.89 million in our sample. Hedge funds also often require a lockup period, which is the minimum time an investor is required to keep his money invested in a hedge fund before he is eligible to redeem his shares. Even after the lockup period, investors cannot exit a fund whenever they wish. Hedge funds usually offer limited chances for redemption each year. The redemption frequency provision specifies how frequently investors can redeem their shares. It could be quarterly, semi-annually, or even longer. The redemption notice period is the advance notice that investors are required to give before actual redemption.

The literature finds mixed evidence regarding the relationship between hedge fund share restrictions and asset liquidity. Aragon (2007) examines the correlation between hedge fund returns and restrictions imposed by funds that limit the liquidity of fund investors. He finds that funds with lockup restrictions have approximately 4%-7% excess returns per year when compared to those participating in non-lockup funds. He confirms that share restrictions are negatively related to the liquidity of fund assets. He argues that the illiquidity premium is the reason why hedge funds with lockup restrictions can deliver excess returns.

Agarwal et al. (2009) argue that lockup, notice, and redemption periods have two contrary effects, the discretion effect and implicit incentive effect, on fund performance. The discretion effect predicts the funds with longer lockup, notice, and redemption periods have more flexibility to invest in arbitrage opportunities that take time to become profitable. In contrast, the implicit incentive effect predicts that funds with shorter lockup, notice, and redemption periods have more incentive to perform well since investors can withdraw their capital quickly following poor performance. Agarwal et al. (2009) find a positive net effect of lockup and restriction periods on performance.

Sadka (2010) determines that hedge funds that significantly load on liquidity risk subsequently outperform low loading funds by about 6% annually. However, he finds that the returns are independent of the liquidity a fund provides to its investors as measured by lockup and redemption notice periods. He argues that share restrictions may not be correlated with a fund’s liquidity risk exposure. Teo (2011) suggests that hedge fund share restrictions should permit funds to liquidate in an orderly fashion and avoid fire sales if assets and liabilities are perfectly matched. However, he finds that hedge funds often take on greater liquidity risk exposure than they should and do not always choose to use share restrictions to manage systematic liquidity risk exposure.

Other studies find that hedge fund share restrictions hurt investors. Ang and Bollen (2010) estimate that a two-year lockup with a three-month notice period costs investors 1.5% of their initial investment. Ozik and Sadka (2012) determine that hedge fund share restrictions can induce information asymmetry between managers and their clients about future fund flows. They argue that it provides managers with an incentive to trade in advance of their clients since fund flows, in turn, can predict future fund returns.

Share restrictions can also affect hedge fund flows. Ding et al. (2009) find that hedge funds exhibit a convex flow-performance relation in the absence of share restrictions (similar to mutual funds), but exhibit a concave relationship in the presence of restrictions. They find that fund flows predict future hedge fund performance, but this "smart money" effect is eliminated among funds with high share restrictions.

With the exception of contractual share restrictions, hedge funds may use discretionary liquidity restrictions in extreme circumstances. Aiken et al. (2014) find that more than 30% of hedge fund managers used their discretion to restrict investor liquidity through the use of "gates" or "side pockets" during the recent financial crisis.

2.4 The dynamics of hedge fund contracts

One potential reason for the mixed evidence concerning the relation of share restrictions, asset liquidity, and liquidity risk is bias as hedge fund contract characteristics are measured only at the end of the sample period. All major hedge fund databases provide a time series of returns and assets under management, but only offer an updated snapshot of the funds' other characteristics. Existing funds' characteristics are overwritten by the updated data. In the recent literature, there have been several studies using multiple snapshots of funds' characteristics to examine the dynamics of hedge fund fee structures, return revisions, and closure to new investors.

Deuskar et al. (2012) use multiple snapshots of fund fees from the Lipper TASS database and find considerable cross-sectional and time series variation in hedge fund fees. They also determine that hedge funds with good performance are more likely to increase management fees and funds that increase management fees experience a larger drop in subsequent capital inflow. Agarwal and Ray (2012) use daily fee change data from the Lipper TASS database and find that hedge funds respond to past performance symmetrically by increasing and decreasing the incentive fee subsequent to good and bad performance. They also note that the changes in management fees tend to be driven by capital flows with the increases used to mitigate decreasing returns to scale and decreases used to pass on the economies of scale to the investors. Schwarz (2007) uses nine hedge fund data sets from 1998-2006 and find that hedge funds' fee levels are related to fund characteristics that change agency and overhead costs, but are unrelated to net of fee alpha performance.

Patton et al. (2011) use multiple snapshots of several major hedge fund databases captured at different points in time and analyze the reliability of voluntarily disclosed hedge fund performance in these databases. They conclude that historical returns are routinely revised. They also find that funds that revise their performance histories significantly and predictably underperform those that have never revised. Aragon and Nanda (2011) examine the timing of hedge fund managers' voluntary disclosures of fund performance by using 547 daily updates of the Lipper TASS database. They confirm that strategic delay plays an important role in the disclosure of hedge fund returns.

Liang and Schwarz (2011) examine when hedge funds close and reopen to new investors. They investigate whether large incentive fees motivate managers to prevent overinvestment by closing funds to new investors and find that hedge funds do not close funds before the occurrence of significant diseconomies of scale. They also note that hedge funds reopen to new investors when they are still too large to generate outperformance.

2.5 Hypotheses development

Motivated by the prior literature outlined above, we develop three hypotheses related to the determinants and consequences of share restriction changes in the hedge fund industry.

Our first hypothesis concerns the relation of share restrictions, asset liquidity, and liquidity risk. The mixed evidence in the literature concerning the relation of share restrictions, asset illiquidity, and liquidity risk may be caused by the bias as hedge fund contract characteristics are measured only at the end of the sample period. Share restrictions are supposed to enable funds to better manage liquidity risk and invest in more illiquid assets. If funds do match share restrictions with asset liquidity and liquidity risk, we would expect that funds with high asset liquidity and low liquidity risk are more likely to decrease share restrictions. If the matching hypothesis holds, we have one subsequent prediction for consequences of share restriction changes. If funds actively manage liquidity concerns by adjusting share restrictions, we would expect that funds with share restriction changes prevent fire sale and live longer.

Our second hypothesis concerns the relation of share restrictions and fund performance. If share restrictions serve as a bargaining tool between fund managers and investors, the bargaining hypothesis would predict managers increasing share restrictions after good performance. A fund manager has more bargaining power following better performance. If a fund manager can increase share restriction without losing new fund flows, total management fee that the hedge fund manager can collect will increase. Lan, Wang, and Yang (2013) and Lim, Sensoy, and Weisbach (2013) find that management fee is a major component of hedge fund managerial compensation. Thus, we would expect that fund managers adjust share restrictions to maximize their compensation.

Our third hypothesis concerns the relation of share restrictions and industry competition. Agarwal and Ray (2012) find mean reversion in hedge fund fee changes and suggest that the hedge fund industry competition influence the fee changes. If share restrictions serve as a bargaining tool, we would expect that funds adjust share restrictions towards the industry conventional level in response to competition.

3. Data and summary statistics

3.1 Data

Our data set consists of hedge funds covered by the BarclayHedge database. We use monthly snapshots of the BarclayHedge database from January 2007-May 2012. Each snapshot of the BarclayHedge database contains an updated snapshot of the funds' administrative characteristics, which include fee structures, share restriction policies, and other contractual information. This allows us to construct a panel dataset of monthly hedge fund share restrictions.

3.2 Measuring share Restriction changes

We use lockup periods, redemption notice periods, minimum initial investment amounts, and redemption frequencies to measure funds' share restrictions. We use four variables, including $Lockup_{i,t}$, $Notice_{i,t}$, $Min\ Invest_{i,t}$, and $Redemption_{i,t}$, to measure changes in lockup periods, notice periods, minimum initial investment amounts, and redemption frequencies for fund *i* and month *t*, respectively.[2] $Lockup_{i,t}$ is equal to one if the lockup period of fund *i* increases at month *t*. $Lockup_{i,t}$ is equal to -1 if the lockup period of fund *i* decreases at month *t*. $Lockup_{i,t}$ is equal to zero otherwise. We construct the other three share restriction change variables in the same manner.

$$Lockup_{i,t} = \begin{cases} 1, \text{ if the lockup period of fund } i \text{ increases at month } t \\ -1, \text{ if the lockup period of fund } i \text{ decreases at month } t \\ 0, \text{ otherwise} \end{cases} \tag{1}$$

We also combine these four separate measurements and construct another dummy variable, $\Delta Restriction_{i,t}$, to measure the overall share restriction changes.[3]

$$\Delta Restricton_{i,t} = \begin{cases} 1, \text{ if } Max(Lockup_{i,t},\ Notice_{i,t},\ Min\ Invest_{i,t},\ Redemption_{i,t}) = 1 \\ -1, \text{ if } Min(Lockup_{i,t},\ Notice_{i,t},\ Min\ Invest_{i,t},\ Redemption_{i,t}) = -1 \\ 0, \text{ otherwise} \end{cases} \tag{2}$$

3.3 Measuring fund asset liquidity and liquidity risk

To measure hedge fund asset liquidity, ideally, we would look at hedge fund assets directly. However, hedge fund detailed holding data are not available, except the quarterly large long positions in the US equity for large hedge fund companies from 13F filings. Following Aragon (2007), we use the Getmansky et al. (2004) method to measure

[2] We use the number of days between two redemption dates to measure redemption frequency.
[3] We find 122 cases that a hedge fund increases one share restriction provision and decreases another one in the same month. We exclude those observations since we cannot measure whether overall share restriction level increases or decreases.

asset liquidity based on reported fund return data. The Getmansky et al. (2004) model assumes that hedge fund reported returns are a linear combination of current and lagged economic returns.

$$R_t^0 = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2} \tag{3}$$

$$\theta_j \in [0,1],\ j = 0,1,2, \text{ and } \theta_0 + \theta_1 + \theta_2 = 1 \tag{4}$$

where R_t^0 is the fund's reported return and R_t is the fund's economic return in period *t.* θ_0 measures the fraction of a fund's reported return that is caused by contemporaneously economic returns. If a hedge fund holds more liquid assets, the economic return should be incorporated into reported return more quickly and θ_0 should be larger. We assume that demeaned economic returns are mean-zero, normal random variables, and use demeaned reported returns to estimate θs by a rolling 12-month MA(2) model.

We use the Pastor and Stambaugh (2003) traded liquidity factor loading to measure the fund's sensitivity to market liquidity risk. Pastor and Stambaugh (2003) argue that stock returns should partially reverse in the future if the stock has high trading volume and is not perfectly liquid. They construct a traded liquidity factor based on the difference in returns between stocks most and least sensitive to aggregate liquidity innovations. We estimate a rolling 12-month regression of hedge fund excess returns on the Carhart (1997) four factors and the Pastor and Stambaugh (2003) traded liquidity factor.[4]

$$Ret_{i,t} - Rf_{i,t} = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UNM_t + \beta_5 LIQ_t + \varepsilon_{i,t} \tag{5}$$

where LIQ is the Pastor and Stambaugh (2003) traded liquidity factor. Hedge funds with high market liquidity risk exposure should have larger liquidity factor loading β_5.

[4] We also use alternative rolling windows of 24 and 36 month to estimate asset liquidity θ_0 and liquidity risk β_5 and find the results are qualitatively similar.

3.4 Other variables

We measure hedge fund performance using the style-adjusted return. Each hedge fund in the database is classified into one of the following investment-style groups: 1) Convertible Arbitrage, 2) Dedicated Short Bias, 3) Emerging Markets, 4) Equity Market Neutral, 5) Event Driven, 6) Fixed Income Arbitrage, 7) Fund of Funds, 8) Global Macro, 9) Long/Short Equity, 10) Managed Futures, 11) Multi Strategy, and 12) Options Strategy. We compute benchmark returns for each style by taking the asset-weighted average of the monthly returns. Then, for each fund, we calculate the style-adjusted return as the excess return relative to the benchmark return.

We also account for the impact of fund flows on share restriction changes. The monthly fund flow is calculated as follows:

$$Flow_{i,t} = \frac{AUM_{i,t} - (1 + Ret_{i,t}) * AUM_{i,t-1}}{AUM_{i,t-1}} \tag{6}$$

where $AUM_{i,t}$ and $Ret_{i,t}$ represent the asset under management and monthly return for fund i at the end of month t, respectively. We also measure style-adjusted flow as the excess flow relative to the style asset-weighted average of flow.

3.5 Summary statistics

Funds are dropped from the sample if they do not report returns net of fees, do not report returns in U.S. dollars, or cannot be classified into one of the 12 investment-style groups. Following Fung and Hsieh (2000), to avoid back-fill bias in our analyses, we exclude the first 12 months of fund data. Our final sample includes 6,038 funds and 175,177 fund-month observations from January 2007-May 2012.

We start by reporting the summary statistics on the number of share restriction changes in Table 1.1. Panel A reports that of the 6,038 hedge funds, 909 hedge funds changed share restrictions (either in the lockup period, redemption frequency, the redemption notice period, or minimum investment) once, 153 hedge funds changed twice, and 49 hedge funds changed three times or more. In total, 18.40% of the hedge funds changed share restrictions from January 2007-May 2012. This is in contrast to the prevailing assumption in the literature that hedge fund share restriction changes are infrequent.

Panel B tabulates the number of share restriction changes over time. Hedge funds are more likely to change share restrictions during the financial crisis (2007Q3-2009Q2).[5] Hedge funds have, on average, 8.32 share restriction increases and 8.44 share restriction decreases each month in the non-crisis period. During the crisis, however, hedge funds typically have 13.63 share restriction increases and 15.46 share restriction decreases each month. Hedge funds have more incentives to change share restrictions during a financial crisis. Ben-David et al. (2012) find that redemptions and margin calls forced hedge funds to sell equity holdings, especially liquid stock holdings, during this crisis. A drop in asset liquidity may force hedge funds to change share restrictions. Alternatively, Ben-David et al. (2012) also determine that hedge fund investors are more sensitive to poor performance than mutual fund investors as hedge fund investors may fear future restrictions on redemptions in the case of prolonged poor performance. Therefore, in response to an initial loss, hedge funds may choose to decrease share restrictions and provide share liquidity to retain existing investors.

[5] There are most share restriction changes in 2008Q3. The results regarding to the determinants of share restriction changes are qualitatively similar if we drop 2008Q3.

Share restriction changes are symmetric with similar incidences of increase and decrease. There are 668 share restriction increases and 717 share restriction decreases. Studies concerning share restriction effects typically focus on lockup periods and redemption notice periods. Panel B indicates that hedge funds use more minimum investment changes and redemption frequency changes than lockup period changes to manage overall share restriction levels.

Panel C tabulates the number of share restriction changes by investment style. We note that fund of funds and long/short equity funds dominate the share restriction change events. This is consistent with the sample distribution across styles. Fund of funds account for 32.86% of the final sample and long/short equity funds account for 31.60% of the final sample.

Table 1.2 reports the level of share restrictions prior to changes and the magnitude of the changes. Share restriction changes are economically large. The median decrease (increase) in the lockup period is 365 days (365 days) corresponding to an initial median lockup period of 365 days (0 days). The median decrease (increase) in the redemption period is 275 days (60 days) corresponding to an initial median redemption period of 365 days (30 days). The median decrease (increase) in the notice period is 23 days (29 days) corresponding to an initial median redemption period of 60 days (30 days). The median decrease (increase) in the initial minimum investment accounts is $0.5 million ($0.5 million) corresponding to an initial minimum investment account of $1.0 million ($0.25 million). We also note that share restrictions prior to a decrease are much higher than those prior to an increase. For example, the median of the redemption period is 365 days (30 days) prior to a redemption decrease (increase).

Table 1.3 presents summary statistics for various fund characteristics. The mean initial minimum investment is $0.89 million. The mean lockup period, redemption notice period, and redemption period are 141.91 days, 47.41 days, and 89.23 days, respectively. Share restrictions also exhibit considerable dispersion. The standard deviation of the minimum investment is $1.77 million. The standard deviation of the lockup period, redemption notice period, and the redemption period are 216.00 days, 32.87 days, and 111.64 days, respectively. The mean of the management fee and the performance fee are 1.43% and 14.97%, respectively. The mean of the hedge fund asset liquidity measure (*Asset_Liq*) is 0.77 implying that 77% of a fund's actual return is contemporaneously reflected in its reported return. It is close to 79% for funds with a lockup period and 83% for funds without a lockup period as documented in Aragon (2007).

Next, we compare the cross-sectional summary statistics between funds that change share restrictions and funds that never change share restrictions. If a fund changes share restrictions at least once, the fund's entire time series of observations are included in the ever-change fund group. For each fund, we measure the mean of each fund characteristic over the sample period. From Panel A of Table 1.4, we determine that funds with share restriction changes have lower asset liquidity, higher liquidity risk, higher share restrictions, lower fees, higher returns, higher flows, greater size, and are older than funds without share restriction changes. For example, funds with (without) share restriction changes have 115.94 days (79.24 days) of redemption periods, $1.07 million ($0.89 million) of initial minimum investments, and 14.10% (15.40%) of performance fees. We also find that funds with share restriction changes live longer. Hedge funds are assumed to have failed if they stop reporting to the BarclayHedge database. Panel A shows that 77% of the funds with share restriction changes and 69% of the funds without share restriction change survive at the end of sample period.

We also compare the dollar value of hedge fund managerial compensation. We assume fund managers charge management fee and performance fee at the end of each month. We use the following equation to calculate monthly management fee:

$$Management\ fee_t = AUM_{t-1} * Management\ fee\ percentage_t / 12 \qquad (7)$$

To calculate the monthly performance fee, for funds without a high-water mark provision, we assume that the performance fee is charged if the monthly return is positive. For funds with a high-water mark provision, we assume that the high-water mark is same for all investors and the hurdle rate is zero. We compare monthly AUM to the highest historical AUM. If the current AUM is higher than the highest historical AUM, the performance fee is charged.

$$Performance\ fee_t = AUM_{t-1} * Return_t * Performance\ fee\ percentage_t / 12 \qquad (8)$$

The total managerial compensation is the sum of management fee and performance fee. We convert monthly managerial compensation to annual compensation by multiplying the monthly compensation by 12. We also calculate the total managerial compensation during our sample period by adding monthly compensation together. Consistent with Lan, Wang, and Yang (2013) and Lim, Sensoy, and Weisbach (2013), we find that management fee is a major component of hedge fund total fee. While there is no significant difference in annual performance fee, funds with share restriction changes charge nearly two times of the total compensation charged by funds without share restriction changes.

In Panel B of Table 1.4, we examine various fund characteristics prior to share restriction changes. We match each fund-month observation with share restriction changes with all of the funds within the same style, return, and flow quartile. We then comp ute a benchmark by taking the average of the fund characteristics for each group. Panel B of Table 1.4 indicates that prior to a share restriction increase (decrease), funds have low (high) share restriction levels. Funds that increase share restrictions also have higher returns and flows than comparable funds prior to the restriction changes. This suggests that funds are more likely to negotiate a new share restriction contract when they perform well.

4. Methodologies and empirical results

4.1 Determinants of share restriction changes

Table 1.4 demonstrates that share restriction changes are not random. Funds with share restriction changes are significantly different than other funds. In this section, we further examine the determinants of share restriction changes. If share restrictions are related to asset liquidity and liquidity risk, then funds with high asset liquidity and low liquidity risk are more likely to decrease share restrictions. Hedge funds can choose to increase or decrease share restrictions over time.[6] Therefore, we use the following multinomial logit model to examine the determinants of share restriction changes:

$$ln\frac{P(\Delta Restriction_{i,t}=j)}{P(\Delta Restriction_{i,t}=0)}=\alpha+\beta*Liquidity_{i,t}+\gamma*Fund\ \ characteristics_{i,t},\ j=1\ or\ \ -1 \qquad (9)$$

where *Liquidity* is the asset liquidity measured by the Getmansky et al. (2004) model or the liquidity risk measured by the Pastor and Stambaugh (2003) liquidity factor loading model. Fund characteristics include the trailing quarterly style-adjusted cumulative return

[6] We also add the 122 cases that a fund increases one share restriction and decreases another one in the same month as a separate group and find the results regarding to the determinants of share restriction increase or decrease are qualitatively similar.

and flow, the funds trailing 12-month style-adjusted return volatility, offshore dummy, age, size, redemption notice period, initial minimum investment, lockup period, and redemption period. Since our sample is from January 2007-May 2012, we use two time indicator variables, *Crisis* and *After_crisis*, for the crisis period and the after crisis period. We set the crisis indicator, *Crisis*, equal to one from 2007Q3-2009Q2. We set the after crisis indicator, *After_crisis*, equal to one beginning in 2009Q3. The strategic behavior of hedge fund families has been well examined in the literature (e.g., Agarwal et al., 2003; Kolololova, 2011; Aragon, Nanda, 2011; Ramadorai, Streatfield, 2011; Deuskar et al., 2012; Agarwal et al., 2014; Aiken et al., 2014). A hedge fund share restriction change decision may also be affected by the performance of affiliated funds within the same family. For each hedge fund family, we construct a value-weighted average of trailing quarterly style-adjusted cumulative return and flow. We include hedge fund style dummies to control for the cross-sectional variation in the incidence of share restriction changes across different styles. We also include calendar year dummies of fund origination to control for the effect that funds launch at different times might have different restrictions that are conventional at time of origination.

The regression results are presented in Table 1.5. In Model 1 of Panel A of Table 1.5, we examine the determinants of overall share restriction changes. We find that asset liquidity (*Asset_Liq*) is positively related with the probability of share restriction decreases. One standard deviation increase in asset liquidity will increase the relative risk ratio of a share restriction decrease by (exp (0.22*0.9403) =) 1.23. This result suggests that funds with high asset liquidity are more likely to decrease share restrictions. It is consistent with Aragon (2007) who notes that hedge fund share restrictions are negatively related to the liquidity of fund assets. We also find that funds with high family returns and flows are more likely to increase share restrictions. Similar to Agarwal and Ray (2012), who confirm that changes in hedge fund fees tend to be mean reverting, we find a mean reversion in share restriction changes. Funds with higher (lower) share restrictions are more likely to decrease (increase) the share restriction level suggesting that industry completion can bring fund share restrictions in line with other funds.

Ben-David et al. (2012) find that hedge funds were liquidity demanders during the financial crisis as market liquidity dried up and hedge funds received substantial withdrawal requests. However, we determine that funds are more likely to decrease share restrictions during the crisis. One possibility is that hedge funds choose to enact “gates” and “side pockets” to prevent existing investor withdrawal and decrease share restrictions to advertise to potential investors. Aiken et al. (2014) find that more than 30% of hedge fund managers used gates or side pockets during the recent financial crisis. Another possibility is that funds try to retain existing inventors by providing share liquidity. For example, if a fund decreases its notice period from three months to one month, investors can wait two more months to submit redemption requests and are treated no differently than those who submit redemption requests before the notice period decrease.

Model 1 also indicates that offshore funds are more likely to decrease share restrictions and less likely to increase share restrictions. These results are consistent with Aragon et al. (2013), who find that onshore funds are associated with greater share restrictions than offshore funds.

Models 2-5 provide the determinants of the changes in minimum investment, the lockup period, the notice period, and the redemption period, respectively. The results are qualitatively similar to Model 1. For example, funds with high asset liquidity are more likely to decrease the redemption period and minimum investment.[7]

In Panel B of Table 1.5, we examine the relationship between share restrictions and liquidity risk. High liquidity factor loading responds to high liquidity risk. Panel B confirms that liquidity risk is related to share restriction changes. Fund's liquidity risk is positively related with the probability of share restriction increase and negatively related with the probability of share restriction decrease.

To assure that our results are not driven by the specific model, here we explore the robustness of our results in Table 1.5. The unconditional probability of share restriction change is (1385/175177=) 0.79%. To correct for potential rare event bias, we use the method proposed by King and Zeng (2001) for the logistic regression of rare events.[8] After correcting the potential rare event bias, the results are qualitatively unchanged. We also examine how changes in asset liquidity and liquidity risk affect share restriction changes. We find that funds with asset liquidity increase and liquidity risk decrease are more likely to decrease share restrictions. Following Deuskar et al. (2012), we also consider the termination of advisory contract (fund failure) as the extreme case of share restriction change and use fund failure as an alternative to share restriction changes. After controlling the fund failure as an alternative outcome, the results are qualitatively similar to Table 1.5. Therefore, our inferences are robust to changes in model specifications. For brevity, the results are not reported.

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[7] We also examine the effect of asset liquidity on the share restriction level. We find that asset liquidity is negatively related to the level of the notice period, the redemption period, the lockup period, and the minimum investment. For simplicity, we do not report the results here.

[8] King and Zeng (2001) find that rare events are difficult to explain and predict. They argue that popular statistical procedures are inefficient and can underestimate the probability of rare event.

Overall, our results suggest that share restriction changes are not random. Share restriction changes are related to fund's asset liquidity, liquidity risk, trailing fund family performance and flows, and share restriction levels. Hedge funds with high asset liquidity and low liquidity risk are more likely to decrease share restrictions suggesting that funds match share restrictions with asset liquidity and liquidity risk. This finding is consistent with Aragon (2007) who determines that fund share restrictions are negatively related to the liquidity of fund assets. Funds within a family with good performance and high flows are more likely to increase share restrictions. Funds with high (low) restriction levels are more likely to decrease (increase) share restrictions. The results suggest that share restrictions also serve as a bargaining tool between fund managers and investors.

4.2 The effect of share restriction changes on returns and flows

Having studied the determinants of share restriction changes, we now examine how share restriction changes affect fund investors and how these investors respond to the share restriction changes. In this section, we study the effects of share restriction changes on fund returns and flows. Specifically, we examine the average style-adjusted return and flow six months before and after share restriction changes.

To control for factors that simultaneously affect a fund's decision to change share restrictions and its future performance and flows, we conduct a difference-in-difference analysis using the propensity score matching approach (PSM). First, we use the logit model to create a propensity score that indicates the probability of share restriction increases or decreases, respectively. The dependent variable is a share restriction increase (decrease) indicator. The independent variables include all of the independent variables used in Equation (9). We match each share restriction change fund at its event date with three funds without share restriction changes that have the closest propensity score.[9] We report the mean of monthly style-adjusted returns and flows across both groups.

In Panel A of Table 1.6, we find strong evidence that share restriction decrease funds underperform the control funds. Following the share restriction decrease, event funds have an average of 0.40% decrease in monthly style-adjusted returns. The control funds have an average of 0.10% decrease in monthly style-adjusted returns. The resulting difference of 0.30% is significant at the 5% level. This result is consistent with Aragon (2007) who finds that hedge fund share restrictions are positively related with fund performance. Further, we divide the event funds into large or small share restriction decrease funds in relation to whether the magnitude of the share restriction decrease is greater than the sample mean of the corresponding share restriction provision level. We find a decrease in performance following a share restriction decrease is generally driven by funds with large share restriction decreases. Although fund performance deteriorates following share restriction decreases, fund investors reward fund managers for providing share liquidity. Event funds have an average 0.62% increase in monthly style-adjusted flow when compared to the control group. Funds with large share restriction decreases have even higher increases in fund flows.

Panel B reports the change in fund performance and flows following share restriction increases. Share restriction increases have no significant effect on fund performance and flows. Agarwal and Ray (2012) find that funds have poorer future performance following fee increases. They argue that it indicates the opportunistic behavior of the fund managers in expropriating surplus from their investors. Our results

[9] We exclude share restriction change events with simultaneous fee changes.

also suggest that hedge fund managers opportunistically negotiate with investors for higher share restrictions following good performance and fail to deliver higher returns following share restriction increases.

Overall, we find that funds have lower returns following share restriction decrease. Investors reward fund managers for providing share liquidity by increasing flows.

4.3 Share restriction changes and hedge fund survival

Thus far, we have shown that share restriction changes are related to fund asset liquidity, liquidity risk, trailing fund family performance, and flows. We also confirm that fund share restriction changes have a significant effect on fund future performance and flows. If funds strategically adjust share the restriction level, a natural question is whether funds with active liquidity risk management through adjustment of the share restriction level live longer. Panel A of Table 1.4 indicates that 77% of the funds with share restriction changes survive at the end of sample period when compared to 69% for other funds. The resulting difference of 8% is significant at the 1% level.

To further test the effect of share restriction change on hedge fund failure, we use a semi-parametric Cox proportional hazard model. Following Aragon and Straham (2012), our estimation uses fund year observations from 2007-2011. The time variable is equal to the number of months since fund inception. Failure is defined as funds that exit from the database. We model the hazard rate of time to failure as a function of the share restriction change indicator, performance, flows, size, share restriction level, and style and year dummies. Table 1.7 reports the hazard ratios. The results suggest that funds with restriction changes over the sample period are less likely to fail, even after controlling the share restriction level. For example, Model 1 of Panel A of Table 1.7 indicates that the failure rate of funds with any share restriction changes is 49% lower relative to that of other funds without share restriction changes. Consistent with Aragon and Strahan (2012), we also confirm that larger funds, funds with high return and flows, are more likely to survive. Models 3-6 demonstrate that both the increase and decrease of share restrictions have a significant effect on fund survival. Our results suggest that funds who actively manage liquidity concerns live longer by adjusting share restrictions.

While funds optimally changing share restrictions can increase their chances for survival, another possibility is that funds that have lived longer have old restrictions in place which are not compatible with current market situation and have to change them. To disentangle these two effects, we repeat the analysis for old and new funds separately. If the above funding is mainly driven by the possibility that old funds have old restrictions not compatible with current market situation and have to change them, we should expect that the positive relation between share restriction changes and possibility of fund survival does not exist among young funds. We split funds into old and new funds based on the median age observed at the beginning of the sample period. If a fund with age above the median age at the beginning of sample period, then the fund is an old fund. All other funds are new funds. Panel B of Table 1.7 shows that both old and new funds that change share restrictions do live longer, which means funds can increase their chances for survival by optimally changing restrictions.

5. Extension

5.1 Coincidence of share restriction, fee, strategy, and manager changes

Having studied the determinants and consequences of share restriction changes, we now examine how share restriction changes coincide with fund fee, strategy, and manager changes.Panel A of Table 1.8 reports the number of fee, strategy, and manager changes within each share restriction change category. Fund strategies are classified into 12 investment-style groups listed above. Strategy change indicates that a fund changes one of the 12 strategies to another. Manager change indicates that both manager company name and managerial principal change.

We find that fee, strategy, and manager changes are highly correlated with share restriction changes. For example, within 668 observations containing share restriction increases, 16.32% of the observations incur fee changes simultaneously. However, only 0.19% of the observations without share restriction changes have fee changes. Within 717 observations containing share restriction decreases, 0.70% of the observations incur manager changes simultaneously. However, only 0.06% of the observations without share restriction changes have manager changes.

Further, we examine whether hedge fund fees and share restrictions are complementary or supplementary. Previous literature suggests that hedge funds with high performance are more likely to increase fees (Deuskar et al., 2012; Agarwal and Ray, 2012). We find that funds with high family performance and flows are more likely to increase share restrictions. One possibility is that greater bargaining power following good performance enables funds to increase fees and share restrictions simultaneously. Another possibility is that fund investors are willing to pay extra fees for more favorable share liquidity terms as fees and share restrictions can be supplementary.

Panel B reports the multinomial logit model of fee changes conditional on share restriction changes. Model 1 of Panel B provides the determinants of any fee changes. Funds with share restriction increases are more likely to increase fees as compared to those funds with share restriction decreases. The results suggest that hedge fund fees and share restrictions are complementary. Model 2 and 3 present the determinants of management fee and performance fee changes. Consistent with Agarwal and Ray (2012), we find that funds increase management fees after high capital flows and increase incentive fees after high performance.

Overall, we find that hedge fund strategy and manager changes are less frequent than share restriction and fee changes. Hedge fund fee, strategy, and manager changes are highly correlated with share restriction changes. Funds with share restriction increases are more likely to increase fees than funds with share restriction decreases.

5.2 Share restriction and managerial compensation

If fund performance deteriorates and investor flow increases following share restriction decreases, how does the corresponding managerial compensation change? Decrease in returns leads to decrease in dollar performance fee, but increase in flows results to increase dollar management fee. We examine what motivates fund manages to change share restrictions and how does their compensation change responding to share restriction changes. Hedge fund managerial compensation contains unique features, such as performance-based fee and high-water mark provision. Following Aiken et al. (2014), we use the model developed in Goetzmann, Ingersoll, and Ross (2003) (henceforth GIR) to quantify the hedge fund managerial compensation.

GIR contain a closed-form solution for the valuation of hedge fund managerial compensation (N) as the present value of expected future management fees and performance fees. GIR argue the fund managerial compensation is determined by eleven different parameters.[10] GIR show that the value of managerial compensation is critically dependent on the liquidation threshold parameter (b), which represents the fraction of the high-water mark that fund value can fall to before investors liquidate the fund.

Using the GIR model, Table 1.9 shows how the value of the fund managerial compensation (given as a percentage of AUM) changes as the fund's NAV to high-water mark ratio (S/H), total withdrawal rate (ω), excess return (α) and liquidation threshold (b) vary.

To illustrate the benefits of share restriction changes for managers, we argue that share restriction changes can be viewed analogously to a reduction in the liquidation threshold (b) based on the results in Table 1.7 that funds are more likely to survive if they change share restrictions. Table 1.9 shows that managerial compensation increases when the liquidation threshold decreases.

Based on the results in Table 1.6 that funds choose to decrease share restrictions have lower return and higher flow, we argue that share restriction decrease can also be viewed analogously to a reduction in excess return generated by the manager (α) and total withdraw rate (ω). Table 1.9 shows that changes in managerial compensation is more sensitive to liquidation threshold parameter (b) and withdraw rate (ω) than to excess return (α). Suppose a fund has b = 0.5, ω = 0.10, and α = 0, total managerial compensation (V) equals to 16.94% when the fund has lost 10% of its value relative to its

[10] See Goetzmann et al. (2003) and Aiken et al. (2014) for details.

high-water mark. If the fund decreases share restriction, the liquidation threshold (b), withdraw rate (ω), and excess return (α) will decrease. Suppose the fund has b = 0.2, ω = 0.05, and α = -0.01 after share restriction decrease.[11] The managerial compensation (V) will increase to 30.42%. Though decrease in returns leads to decrease in dollar performance fee, increase in flows and the probability of survival can lead to increase in dollar management fee. Since management fee is the major component of total hedge fund fee (Lan, Wang, and Yang, 2013; Lim, Sensoy, and Weisbach, 2013), total fund managerial compensation increases following share restriction decreases.

5.3 The endogeneity bias in share restrictions

We find share restriction changes are not random. In this section, we examine how the endogeneity issue affects the share illiquidity premium documented in the literature.

Using share restrictions measured at the end of sample period, Aragon (2007) finds that excess returns of funds with lockup periods are 4-7% per year higher than those of non-lockup funds. Within funds with lockup periods at the end of the sample period, we compare the excess return between funds with and without lockup period increases or any share restriction increases. Each fund is sorted into one of two equal-weighted portfolios according to whether or not the funds add lockup periods or increase any share restrictions. Panel A of Table 1.10 reports the CAPM, Carhart (1997), and Fung and Hsieh (2004) alphas of the portfolios. Conditional on funds with lockup periods at the end of the sample period, the results reveal a positive excess return differential between funds that add lockup periods during the sample period and funds that have initial lockup

[11] We also use several alternative number combinations and find the results are qualitatively similar.

periods at the beginning of the sample period. For example, the Fung and Hsieh (2004) alpha of funds that add lockup periods is 0.29% per month higher than funds that have initial lockup periods.

Panel B reports the results of a cross-sectional regression of estimated individual fund Fung and Hsieh (2004) alpha ($\hat{\alpha}_i$) on fund characteristics:

$$\begin{aligned}\hat{\alpha}_i &= \gamma_0 + \gamma_1 * Lockup\ Dummy + \gamma_2 * Add\ \ Lockup + \gamma_3 * Log(Minimum + 1) \\ &+ \gamma_4 * Log(Redemption + 1) + \gamma_5 * Log(Notice + 1) + \gamma_6 * Log(AUM) + \varepsilon_i \end{aligned} \quad (10)$$

where *Lockup Dummy* is an indication variable equal to one if funds have lockup periods at the end of sample period. *Add Lockup* is an indicator equal to one if funds add lockup periods during the sample period. *Log(AUM)* is the natural log of the fund's average AUM.[12] Model 1 of Panel B demonstrates that the estimated monthly fund Fung and Hsieh (2004) alpha is 0.25%. Model 6 shows that funds produce negative risk-adjusted return after controlling for share liquidity and assets. Consistent with Aragon (2007), we find that lockup period is positively related with excess returns. Funds with lockup periods have a monthly Fung and Hsieh (2004) alpha 7.88 basis points higher than funds without lockup periods. Model 7 shows that, conditional on having lockup periods at the end of sample period, funds that add lockup periods have much higher excess return than funds that have initial lockup periods. After controlling the dynamic nature of lockup period changes, the lockup illiquidity premium decreases to 6.74 basis points. The results suggest that part of the share illiquidity premium documented in the literature can be explained by the dynamic nature of contract changes.

[12] We also use the AUM measured at the beginning and end of the sample period. The results are qualitatively similar.

6. Conclusion

In this paper, we examine the dynamics of hedge fund share restrictions. Using monthly snapshots of the BarclayHedge database from January 2007-May 2012, we find that 18.40% of the funds changed their share restriction structure, which is contrary to the conventionally held belief that hedge fund share restrictions are largely fixed.

We confirm that share restriction changes are not random. Hedge funds with high asset liquidity and low liquidity risk are more likely to decrease share restrictions suggesting that funds match share restrictions to asset liquidity and liquidity risk. This finding is consistent with Aragon (2007) who notes that fund share restrictions are negatively related to the liquidity of fund assets. Funds with high family returns and flows are more likely to increase share restrictions suggesting that share restrictions also serve as a bargaining tool between fund managers and investors.

We examine the effect of share restriction changes on fund performance and flows. While funds have lower returns following share restriction decreases, investors reward fund managers for providing share liquidity by increasing flows. More importantly, funds that strategically adjust share restriction levels live longer, even after controlling for the share restriction level. The results suggest that hedge funds actively manage liquidity concerns through the adjustment of the share restriction level.

Further, we examine the coincidence of hedge fund share restriction, fee, strategy, and manager changes. We find that hedge fund fee, strategy, and manager changes are highly correlated with share restriction changes. Funds that increase share restrictions are more likely to increase their fees simultaneously than funds that decrease share restrictions. We also examine the endogeneity bias in the share illiquidity premium

(Aragon, 2007) created by share restriction changes. We find that 18% of the premium can be explained by the dynamic nature of contract changes.

Table 1.1: The number of share restriction changes

This table reports the number of share restriction changes from January 2007-May 2012. Panel A reports the number of funds with a different number of share restriction changes. Panel B provides the number of share restriction changes over time. Since our sample period is from January 2007-May 2012, 2012Q2 in Panel B includes April and May only. Panel C presents the number of share restriction changes by investment style.

Panel A: The number of funds with a different number of share restriction changes

	# Funds	Percentage	Cumulative Percentage
One change	909	15.05%	15.05%
Two changes	153	2.53%	17.59%
Three changes	32	0.53%	18.12%
Four changes	13	0.22%	18.33%
Five changes	2	0.03%	18.37%
Six changes	2	0.03%	18.40%
No changes	4,927	81.60%	100.00%

Panel B: The number of share restriction changes over time

Year	Any		Lockup Period		Notice Period		Min Invest		Redemption	
	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.
2007Q1	64	43	12	9	32	8	25	15	8	13
2007Q2	42	21	3	8	17	5	23	4	2	6
2007Q3	58	43	9	3	24	8	24	28	8	7
2007Q4	62	39	7	13	32	9	34	18	4	12
2008Q1	68	24	3	6	33	7	33	13	6	4
2008Q2	39	33	11	5	8	7	20	16	4	9
2008Q3	25	135	4	1	7	5	16	4	9	127
2008Q4	22	11	4	5	10	2	7	5	5	0
2009Q1	35	64	5	12	16	23	16	38	6	13
2009Q2	18	22	1	11	5	6	13	9	1	4
2009Q3	21	12	1	5	11	4	9	6	2	1
2009Q4	32	35	3	16	17	10	7	7	10	21
2010Q1	28	30	6	11	7	9	14	14	5	12
2010Q2	21	32	7	10	9	8	6	9	2	13
2010Q3	24	21	2	5	8	8	12	12	5	6
2010Q4	13	22	0	7	9	10	4	6	1	5
2011Q1	24	30	2	5	17	11	7	9	4	15
2011Q2	16	16	3	3	5	4	6	7	4	6
2011Q3	10	13	5	4	4	7	2	3	2	1
2011Q4	17	32	2	5	5	3	9	24	6	3
2012Q1	20	27	7	5	8	4	7	15	4	10
2012Q2	9	12	0	6	4	3	5	3	1	2
Crisis (total)	327	371	44	56	135	67	163	131	43	176
Non-crisis (total)	341	346	53	99	153	94	136	134	56	114
Crisis (per month)	13.63	15.46	1.83	2.33	5.63	2.79	6.79	5.46	1.79	7.33
Non-crisis (per month)	8.32	8.44	1.29	2.41	3.73	2.29	3.32	3.27	1.37	2.78
Total	668	717	97	155	288	161	299	265	99	290

Panel C: The number of share restriction changes by investment style

Style	Any		Lockup Period		Notice Period		Min Invest		Redemption	
	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.	Inc.	Dec.
Fund of Funds	270	295	17	44	163	55	101	134	34	102
Long/Short Equity	161	184	34	46	56	47	74	68	26	79
Event Driven	59	59	13	23	14	7	38	12	5	31
Multi-Strategy	43	41	10	16	7	14	24	11	8	18
Emerging Markets	39	33	1	4	20	13	16	6	11	15
Fixed Income Arbitrage	28	38	6	12	10	9	7	8	7	17
Equity Market Neutral	19	30	1	5	4	7	14	8	1	15
Global Macro	26	18	9	1	10	5	13	14	5	5
Convertible Arbitrage	12	8	5	2	1	1	5	2	2	4
Options Strategy	5	6	0	1	1	2	4	2	0	1
Managed Futures	6	2	1	0	2	1	3	0	0	1
Dedicated Short Bias	0	3	0	1	0	0	0	0	0	2

Table 1.2: Magnitude of share restriction changes

This table reports the magnitude of the lockup period, the redemption period, the notice period, and minimum investment prior to a change and the magnitude of share restriction changes from January 2007-May 2012. For each variable, the number of observations, means, 10th, 50th, and 90th percentiles, and standard deviations are presented.

			N	Mean	Median	10%	90%	Std. Dev.
Lockup (days)	Decrease	Prior	155	441.43	365.00	180.00	730.00	267.10
		Change		-363.68	-365.00	-545.00	-90.00	207.24
	Increase	Prior	97	94.75	0.00	0.00	365.00	164.40
		Change		354.42	365.00	90.00	640.00	272.31
Redemption (days)	Decrease	Prior	290	404.37	365.00	90.00	730.00	309.16
		Change		-301.86	-275.00	-547.00	-60.00	236.15
	Increase	Prior	99	43.63	30.00	7.00	90.00	55.78
		Change		102.30	60.00	23.00	275.00	131.41
Notice (days)	Decrease	Prior	161	65.45	60.00	20.00	95.00	52.31
		Change		-31.71	-23.00	-60.00	-5.00	41.96
	Increase	Prior	288	33.52	30.00	0.00	70.00	26.25
		Change		31.22	29.00	5.00	65.00	27.38
Minimum Investment ($MM)	Decrease	Prior	265	2.60	1.00	0.10	5.00	6.47
		Change		-2.05	-0.50	-4.00	-0.05	5.49
	Increase	Prior	299	0.44	0.25	0.01	1.00	0.83
		Change		1.93	0.50	0.05	4.00	5.90

Table 1.3: Summary statistics

This table reports the summary statistics for the hedge funds in our sample from January 2007-May 2012. *Asset_Liq* is the estimate of the fund asset liquidity level as measured by Getmansky et al. (2004). *Liq_Risk* is the estimate of the fund liquidity risk level as measured by the Pastor and Stambaugh (2003) traded liquidity factor loading. *Lockup* and *Notice* are the length of time the fund restricts capital withdrawals and the notice time the fund requires prior to a withdrawal of capital, respectively. *Redemption* is the number of days between redemption periods. *Min invest* is the initial minimum investment requirement. *Management Fee* and *Performance Fee* provide the magnitude of management and performance fees, respectively. *High-water* is an indicator variable that is equal to one when there is a high-water mark provision. *Offshore* is an indicator variable that is equal to one when the fund is domiciled offshore. *Age* is the number of months since fund inception. *AUM* is the fund's assets under management. *CAR* and *CAF* are the trailing three-month cumulative style-adjusted return and flow, respectively. *Family_CAR* and *Family_CAF* are the family weighted average trailing three-month cumulative style-adjusted return and flow, respectively. *Std(Abret)* is the trailing 12-month style-adjusted return volatility. For each variable, the number of observations, means, 10^{th}, 50^{th}, and 90^{th} percentiles, and standard deviations are presented.

Variable	Mean	Median	10%	90%	Std. Dev.
Asset_Liq	0.77	0.80	0.47	1.00	0.22
Liq_Risk	0.07	0.04	-0.25	0.44	0.41
Lockup (Day)	141.91	0.00	0.00	365.00	216.00
Notice (Day)	47.41	45.00	10.00	90.00	32.87
Redemption (Day)	89.23	90.00	30.00	90.00	111.64
Min invest ($MM)	0.89	0.50	0.05	1.00	1.77
Management fee (%)	1.43	1.50	1.00	2.00	0.46
Performance fee (%)	14.97	20.00	0.00	20.00	7.38
High-water	0.86	1.00	0.00	1.00	0.35
Offshore	0.59	1.00	0.00	1.00	0.49
Age (months)	82.04	69.00	25.00	158.00	54.71
AUM($MM)	223.08	57.82	5.98	494.96	640.95
CAR (%)	-0.16	-0.30	-6.91	6.69	7.18
CAF (%)	-0.12	-0.92	-17.20	15.53	20.40
Family_CAR (%)	-0.15	-0.28	-6.07	5.77	6.47
Family_CAF (%)	-0.55	-0.90	-13.67	11.87	15.03
Std(Abret) (%)	2.70	2.07	0.69	5.54	2.25
Number of observation			175,177		

Table 1.4: Fund characteristics and share restriction changes

Panel A compares the fund level characteristics between funds that change share restrictions and funds that do not change share restrictions. *Fund return* and *Fund flow* are the monthly fund raw returns and flows, respectively. *Survive* is an indicator variable set equal to one if the fund survives at the end of the sample period. *Annual performance fee* and *Annual management fee* is the estimated dollar value of performance fee and management fee charged by fund managers every year, respectively. *Annual total fee* is the sum of *Annual performance fee* and *Annual management fee*. *Total performance fee* and *Total management fee* is the total performance fee and management fee charged by fund managers during our sample period, respectively. *Total fee* is the sum of *Total performance fee* and *Total management fee*. All other control variables are as defined in Table 1.3. Panel A reports the mean value of each variable, except *Survive* from January 2007-May 2012. Panel B presents the difference in fund characteristics between funds that change share restrictions and the control group prior to the share restriction changes. The control group for each event fund includes all of the funds within the same style, past three-month cumulative style-adjusted returns and flow quartiles. We then compute benchmark by taking the average of the fund characteristics for each group. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Panel A: Funds with and without share restriction changes

	With change		Without change		Difference in mean	
	Mean	Std Dev	Mean	Std Dev	Difference	*p*-value
Asset_Liq	0.76	0.09	0.78	0.12	-0.02***	<.001
Liq_Risk	0.08	0.20	0.06	0.34	0.02***	0.010
Lockup (days)	151.40	221.19	137.14	211.25	14.26*	0.051
Redemption (days)	115.94	143.37	79.24	92.16	36.70***	<.001
Notice (days)	49.35	28.73	47.51	33.94	1.84*	0.063
Min invest ($MM)	1.07	2.03	0.89	1.47	0.19***	0.004
Management fee (%)	1.44	0.47	1.44	0.46	-0.01	0.610
Performance fee (%)	14.10	7.73	15.40	7.14	-1.31***	<.001
High-water	0.83	0.37	0.88	0.33	-0.05***	<.001
Log(AUM)	4.21	1.70	3.74	1.77	0.47***	<.001
Log(Age)	4.17	0.66	3.90	0.73	0.27***	<.001
Fund return (%)	0.17	0.95	-0.01	1.64	0.17***	<.001
Fund flow (%)	-0.04	3.25	-0.48	4.32	0.44***	<.001
Annual total fee ($MM)	46.81	137.06	35.46	130.35	11.35**	0.012
Annual performance fee ($MM)	3.37	36.82	2.11	28.68	1.26	0.284
Annual management fee ($MM)	43.44	112.65	33.35	111.55	10.09***	0.007
Total fee ($MM)	166.25	456.28	85.26	329.13	80.99***	<.001
Total performance fee ($MM)	10.27	80.01	4.77	50.49	5.50**	0.028
Total management fee ($MM)	155.98	416.30	80.49	301.92	75.49**	<.001
Survive	0.77	0.42	0.69	0.46	0.08***	<.001
Number of Fund	1,111		4,927			

Panel B: Fund characteristics prior share restriction changes

	Restriction Increase				Restriction Decrease			
	Mean	Matched	Difference	*p*-value	Mean	Matched	Difference	*p*-value
Asset_Liq	0.77	0.78	-0.01	0.393	0.81	0.80	0.00	0.843
Liq_Risk	0.11	0.07	0.05***	0.001	0.04	0.03	0.01	0.343
Lockup (days)	110.13	135.98	-25.85***	<.001	202.27	143.67	58.61***	<.001
Redemption (days)	78.99	95.92	-16.93***	<.001	217.08	101.59	115.50***	<.001
Notice (days)	41.56	47.51	-5.95***	<.001	54.54	49.38	5.16***	<.001
Min Invest ($MM)	0.66	0.87	-0.21***	<.001	1.65	0.97	0.68***	<.001
Management fee (%)	1.44	1.42	0.02	0.311	1.39	1.41	-0.02	0.273
Performance fee (%)	13.77	14.14	-0.36**	0.064	13.78	14.04	-0.27	0.134
High-water	0.80	0.84	-0.04***	0.010	0.83	0.84	-0.01	0.308
Log(AUM)	4.41	4.19	0.22***	0.001	4.22	4.17	0.06	0.351
Log(Age)	4.19	4.15	0.04	0.148	4.10	4.15	-0.05**	0.036
CAR (%)	1.46	1.08	0.38**	0.023	0.11	0.02	0.09	0.400
CAF (%)	1.97	1.17	0.80	0.202	2.12	1.52	0.61	0.309
Family_CAR (%)	1.48	0.81	0.66***	0.001	0.05	-0.02	0.08	0.542
Family_CAF (%)	1.55	0.18	1.37***	0.019	0.87	0.50	0.37	0.429
Number of Fund	668				717			

Table 1.5: Likelihood of a share restriction change

This table reports the determinants of share restriction changes. Panel A and Panel B provide the results for a multinomial logit model. There are three possible outcomes: 1) no change, 2) restriction increase, and 3) restriction decrease. No change is the baseline scenario and, as such, isn't reported. *Any increase* indicates that at least one share restriction increases without any other restrictions decreasing. *Any decrease* indicates that at least one share restriction decreases without any other restrictions increasing. *Origination year dummies* are the calendar year dummies of fund origination. All control variables are defined as in Table 1.3. Panel A examines the relationship between share restriction changes and fund asset liquidity level as measured by Getmansky et al. (2004). Panel B examines the relationship between share restriction changes and fund liquidity risk as measured by the Pastor and Stambaugh (2003) traded liquidity factor loading. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: Asset liquidity vs. share restriction

	(1) Any		(2) Minimum Investment		(3) lockup		(4) Notice		(5) Redemption	
	Decrease	Increase	Decrease	Increase	Decrease	Increase	Decrease	Increase	Decrease	Increase
Asset_Liq	0.9403***	0.0202	1.0868***	-0.0619	0.1771	0.5133	0.5267	-0.2488	1.4500***	0.5029
	(0.000)	(0.911)	(0.000)	(0.817)	(0.641)	(0.289)	(0.167)	(0.362)	(0.000)	(0.300)
Log(Min invest+1)	0.1151***	-0.1570***	0.4061***	-0.4095***						
	(0.000)	(0.000)	(0.000)	(0.000)						
Log(Lockup+1)	0.0265*	-0.0438***			0.6926***	-0.1361***				
	(0.062)	(0.009)			(0.000)	(0.001)				
Log(Notice+1)	-0.1062**	-0.1564***					0.7375***	-0.4627***		
	(0.021)	(0.000)					(0.000)	(0.000)		
Log(Redemption+1)	0.6637***	-0.0055							1.8055***	-0.6752***
	(0.000)	(0.911)							(0.000)	(0.000)
Family_CAR	-0.1543	2.9717***	-0.9657	2.2702	-1.5382	5.0236**	1.3589	4.6675***	1.5579	2.4093
	(0.901)	(0.004)	(0.621)	(0.117)	(0.567)	(0.024)	(0.564)	(0.003)	(0.478)	(0.362)
Family_CAF	0.0740	0.5395*	-0.2878	0.6431	-0.2359	0.0270	-0.0749	0.4590	0.2082	1.3968*
	(0.810)	(0.078)	(0.625)	(0.181)	(0.670)	(0.975)	(0.844)	(0.287)	(0.671)	(0.081)
CAR	0.5949	0.7048	0.2875	0.8912	2.1979	-0.8687	-1.2594	-0.3164	-0.4262	1.0300
	(0.602)	(0.470)	(0.870)	(0.509)	(0.376)	(0.688)	(0.561)	(0.833)	(0.836)	(0.681)
CAF	0.3559	-0.0149	-0.0888	-0.1415	0.7317*	0.0571	0.9771***	0.2227	0.6354*	-0.5674
	(0.118)	(0.954)	(0.833)	(0.739)	(0.063)	(0.933)	(0.000)	(0.531)	(0.092)	(0.432)
Std(Abret)	-6.4857***	-2.5290	-0.6551	3.8853	-3.7627	-2.3234	-7.1511	-12.1211***	-7.2672*	-7.8367
	(0.008)	(0.258)	(0.857)	(0.180)	(0.426)	(0.669)	(0.146)	(0.004)	(0.076)	(0.183)
Offshore	0.2233**	-0.4603***	0.0875	-0.8895***	0.3146*	-0.8572***	0.4262**	0.1244	0.5341***	-0.5471**
	(0.010)	(0.000)	(0.509)	(0.000)	(0.070)	(0.000)	(0.018)	(0.358)	(0.000)	(0.022)
Log(Age)	0.1543	-1.0395***	-0.1202	-0.4861	-0.3479	-0.7976	0.1115	-1.7361***	1.0092***	-0.5570
	(0.381)	(0.000)	(0.667)	(0.103)	(0.303)	(0.106)	(0.744)	(0.000)	(0.002)	(0.306)
Log(AUM)	0.0068	0.1536***	-0.0460	0.2514***	0.0575	0.1502**	-0.0270	0.1131***	0.0042	-0.0177
	(0.784)	(0.000)	(0.236)	(0.000)	(0.273)	(0.019)	(0.587)	(0.003)	(0.917)	(0.770)
Crisis	0.3583**	-0.0098	0.4318*	-0.1079	-0.2173	-0.1741	0.1808	0.1729	0.9846***	0.2883
	(0.013)	(0.937)	(0.094)	(0.556)	(0.462)	(0.597)	(0.573)	(0.356)	(0.000)	(0.440)
After_crisis	-0.1944	-0.0178	0.0862	-0.6908**	0.0329	-0.1762	-0.0945	0.5529**	0.2595	0.4349
	(0.308)	(0.920)	(0.791)	(0.011)	(0.929)	(0.702)	(0.816)	(0.039)	(0.441)	(0.365)
Intercept	-9.6225***	-0.0014	-28.7718	-15.1954	-21.5082	-31.6198	-7.9790***	-0.3396	-33.0664	-34.3420
	(0.000)	(0.999)	(0.997)	(0.998)	(0.988)	(0.989)	(0.000)	(0.830)	(0.992)	(0.996)
Origination year dummy	Yes		Yes		Yes		Yes		Yes	
Style dummy	Yes		Yes		Yes		Yes		Yes	
Pseudo R-squared	0.0432		0.0586		0.1127		0.0655		0.1577	
Observations	175,177		175,177		175,177		175,177		175,177	

Panel B: Liquidity risk vs. share restriction

	(1) Any		(2) Minimum Investment		(3) lockup		(4) Notice		(5) Redemption	
	Decrease	Increase	Decrease	Increase	Decrease	Increase	Decrease	Increase	Decrease	Increase
Liq_risk	-0.2287**	0.3470***	-0.2255	0.3167**	-0.0688	0.7256***	0.0924	0.2574	-0.5375***	0.0471
	(0.024)	(0.000)	(0.161)	(0.012)	(0.748)	(0.000)	(0.658)	(0.143)	(0.000)	(0.858)
Log(Min invest+1)	0.1137***	-0.1550***	0.4031***	-0.4087***						
	(0.000)	(0.000)	(0.000)	(0.000)						
Log(Lockup+1)	0.0253*	-0.0456***			0.6921***	-0.1435***				
	(0.074)	(0.006)			(0.000)	(0.000)				
Log(Notice+1)	-0.1150**	-0.1559***					0.7280***	-0.4607***		
	(0.012)	(0.000)					(0.000)	(0.000)		
Log(Redemption+1)	0.6630***	-0.0083							1.8183***	-0.6797***
	(0.000)	(0.866)							(0.000)	(0.000)
Family_CAR	-0.1550	2.9406***	-1.0180	2.2339	-1.5191	5.0482**	1.2893	4.7527***	1.5844	2.2533
	(0.898)	(0.005)	(0.593)	(0.126)	(0.571)	(0.030)	(0.578)	(0.003)	(0.448)	(0.383)
Family_CAF	0.0575	0.5429*	-0.3348	0.6474	-0.2364	0.0809	-0.0767	0.4569	0.2100	1.4030*
	(0.853)	(0.076)	(0.570)	(0.178)	(0.671)	(0.925)	(0.841)	(0.288)	(0.675)	(0.080)
CAR	0.6952	0.8725	0.4403	1.0454	2.1618	-0.4794	-1.0430	-0.2815	-0.0670	1.1438
	(0.531)	(0.374)	(0.796)	(0.443)	(0.384)	(0.829)	(0.624)	(0.852)	(0.973)	(0.641)
CAF	0.3541	-0.0125	-0.0958	-0.1386	0.7343*	0.0330	0.9814***	0.2276	0.6270	-0.5716
	(0.121)	(0.962)	(0.821)	(0.744)	(0.062)	(0.962)	(0.000)	(0.523)	(0.101)	(0.428)
Std(Abret)	-6.7952***	-3.8280*	-1.0496	2.8115	-3.7056	-7.3249	-7.6012	-12.6718***	-8.1104*	-8.3305
	(0.005)	(0.095)	(0.773)	(0.346)	(0.434)	(0.212)	(0.124)	(0.003)	(0.051)	(0.158)
Offshore	0.2231**	-0.4615***	0.0970	-0.8863***	0.3147*	-0.8516***	0.4283**	0.1202	0.5334***	-0.5423**
	(0.010)	(0.000)	(0.464)	(0.000)	(0.070)	(0.000)	(0.018)	(0.374)	(0.000)	(0.023)
Log(Age)	0.1178	-1.0229***	-0.1605	-0.4683	-0.3482	-0.8009	0.1031	-1.7178***	0.9735***	-0.5547
	(0.502)	(0.000)	(0.563)	(0.116)	(0.302)	(0.105)	(0.762)	(0.000)	(0.002)	(0.307)
Log(AUM)	0.0058	0.1531***	-0.0491	0.2530***	0.0568	0.1521**	-0.0288	0.1128***	0.0043	-0.0186
	(0.816)	(0.000)	(0.206)	(0.000)	(0.279)	(0.017)	(0.563)	(0.003)	(0.915)	(0.758)
Crisis	0.4557***	-0.0643	0.5460**	-0.1620	-0.1993	-0.2325	0.1949	0.1016	1.1531***	0.3123
	(0.002)	(0.605)	(0.035)	(0.376)	(0.501)	(0.478)	(0.544)	(0.590)	(0.000)	(0.405)
After_crisis	-0.0876	-0.0753	0.2098	-0.7517***	0.0503	-0.2233	-0.0768	0.4883*	0.4255	0.4500
	(0.645)	(0.670)	(0.518)	(0.006)	(0.892)	(0.627)	(0.850)	(0.069)	(0.203)	(0.349)
Intercept	-8.8053***	0.0717	-28.0828	-15.4632	-21.3848	-30.8819	-7.4739***	-0.4687	-31.8202	-33.4854
	(0.000)	(0.953)	(0.997)	(0.998)	(0.988)	(0.989)	(0.000)	(0.765)	(0.991)	(0.996)
Origination year dummy	Yes		Yes		Yes		Yes		Yes	
Style dummy	Yes		Yes		Yes		Yes		Yes	
Pseudo R-squared	0.0426		0.0579		0.1148		0.0654		0.1552	
Observations	175,177		175,177		175,177		175,177		175,177	

Table 1.6: The effect of share restriction changes on fund returns and flows

This table provides the changes in fund returns and flows following share restriction changes. Panel A presents the difference in the changes of six-month average style-adjusted returns and flow between the event funds and the matched control funds following a share restriction decrease. Panel B reports the difference in the changes of six-month average style-adjusted returns and flow between the event funds and the matched control funds following a share restriction increase. We exclude share restriction change events that contain simultaneously management fee or incentive fee changes. Large change includes events with at least one of the magnitude of lockup, redemption, notice, and minimum investment changes greater than the sample mean of the corresponding share restriction provision level. Small change includes all other events. Each event fund is matched with three untreated funds with the closest propensity score in the event month. *p*-values are presented below in parentheses.

Panel A: Share restriction decrease

		Six-Month Average Style-Adjusted Return					Six-Month Average Style-Adjusted Flow				
		Event Fund			Control Fund	Difference	Event Fund			Control Fund	Difference
	N	After	Before	Change	Change		After	Before	Change	Change	
All	520	-0.22%	0.18%	-0.40%	-0.10%	-0.30%	0.61%	0.55%	0.06%	-0.56%	0.62%
		(0.017)	(0.012)	(0.001)	(0.215)	(0.035)	(0.005)	(0.026)	(0.830)	(0.002)	(0.067)
Large	295	-0.18%	0.26%	-0.44%	-0.03%	-0.41%	0.94%	0.25%	0.69%	-0.56%	1.26%
		(0.203)	(0.005)	(0.008)	(0.744)	(0.035)	(0.000)	(0.398)	(0.034)	(0.018)	(0.001)
Small	225	-0.27%	0.08%	-0.34%	-0.19%	-0.15%	0.18%	0.94%	-0.77%	-0.55%	-0.22%
		(0.010)	(0.503)	(0.038)	(0.143)	(0.455)	(0.636)	(0.024)	(0.145)	(0.034)	(0.714)
Large - Small						-0.25%					1.47%
						(0.376)					(0.038)

Panel B: Share restriction increase

		Six-Month Average Style-Adjusted Return					Six-Month Average Style-Adjusted Flow				
		Event Fund			Control Fund	Difference	Event Fund			Control Fund	Difference
	N	After	Before	Change	Change		After	Before	Change	Change	
All	482	0.09%	0.52%	-0.43%	-0.27%	-0.16%	-0.01%	0.69%	-0.70%	-0.30%	-0.41%
		(0.304)	(<.001)	(0.001)	(<.001)	(0.276)	(0.966)	(0.005)	(0.012)	(0.130)	(0.224)
Large	188	-0.01%	0.66%	-0.67%	-0.35%	-0.32%	0.40%	0.79%	-0.39%	-0.03%	-0.36%
		(0.964)	(<.001)	(0.002)	(<.001)	(0.174)	(0.182)	(0.045)	(0.358)	(0.939)	(0.473)
Small	294	0.15%	0.43%	-0.28%	-0.23%	-0.05%	-0.27%	0.63%	-0.90%	-0.47%	-0.43%
		(0.134)	(0.001)	(0.083)	(0.006)	(0.785)	(0.347)	(0.049)	(0.015)	(0.054)	(0.328)
Large - Small						-0.28%					0.07%
						(0.349)					(0.919)

Table 1.7: Hazard model predicting failure of hedge funds

This table reports semi-parametric Cox proportional hazard models that relate the failure of hedge funds to their active liquidity risk management by adjusting the share restriction level. The models use fund-year observations from 2007-2011. The hedge fund inception date is even-time zero. *Ever change* is an indicator variable equal to one if the fund changes share restriction level during the sample period. *Ever increase* is an indicator variable equal to one if the fund increases the share restriction level during the sample period. *Ever decrease* is an indicator variable equal to one if the fund decreases the share restriction level during the sample period. *Raw fund return* and *raw fund flow* are the within-year average of monthly fund returns and flows. *Log(AUM)*, *Log(Min invest+1)*, *Log(Lockup+1)*, *Log(Notice+1)*, and *Log(Redemption+1)* are defined in Table 1.3 and measured at the beginning of each year. Panel A reports the prediction of failure of all hedge funds. Panel B reports the prediction of failure of old and new funds separately. Hazard ratios are reported in the table. A hazard ratio greater than one indicates a positive relationship between the independent variable and the probability of failure; a hazard ratio below one indicates the opposite. *p*-values under the null where the hazard ratio is equal to one is presented below in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively.

Panel A: Failure of hedge funds

	(1)	(2)	(3)	(4)	(5)	(6)
Ever change	0.5145***	0.5074***				
	(0.000)	(0.000)				
Ever increase			0.4407***	0.4316***		
			(0.000)	(0.000)		
Ever decrease					0.6368***	0.6364***
					(0.000)	(0.000)
Raw fund return	0.0004***	0.0002***	0.0003***	0.0002***	0.0003***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Raw fund flow	0.0106***	0.0106***	0.0100***	0.0099***	0.0096***	0.0091***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Size)	0.7956***	0.7938***	0.7940***	0.7917***	0.7884***	0.7880***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Minimum+1)	1.0970***	1.0989***	1.0964***	1.0986***	1.1022***	1.0998***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Lockup+1)	1.0182**	1.0304***	1.0167**	1.0288***	1.0175**	1.0289***
	(0.019)	(0.000)	(0.032)	(0.000)	(0.023)	(0.000)
Log(Notice+1)	1.1702***	1.1586***	1.1797***	1.1694***	1.1672	1.1558***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Redemption+1)	0.8131***	0.8077***	0.7895***	0.7837***	0.8212***	0.8168***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Style dummy	No	Yes	No	Yes	No	Yes
Observations	13,380	13,380	13,380	13,380	13,380	13,380

Panel B: Old vs. new funds

	Old funds		New funds	
	(1)	(2)	(3)	(4)
Ever change	0.5224***	0.5048***	0.5622***	0.5641***
	(0.000)	(0.000)	(0.000)	(0.000)
Raw fund return	0.0011***	0.0004***	0.0003***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Raw fund flow	0.0008***	0.0015***	0.023***	0.0219***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(Size)	0.8632***	0.8628***	0.7792***	0.7792***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(Minimum+1)	1.0673**	1.0632**	1.1209***	1.1137***
	(0.015)	(0.030)	(0.000)	(0.000)
Log(Lockup+1)	1.0303**	1.0577***	0.999	1.0005
	(0.036)	(0.000)	(0.917)	(0.959)
Log(Notice+1)	1.0091	0.9799	1.1422***	***1.1514
	(0.823)	(0.624)	(0.000)	(0.000)
Log(Redemption+1)	0.9013**	0.8926***	0.8737***	0.8779***
	(0.011)	(0.007)	(0.000)	(0.000)
Year dummy	Yes	Yes	Yes	Yes
Style dummy	No	Yes	No	Yes
Observations	4,745	4,745	8,635	8,635

Table 1.8: Share restriction change vs. fee, strategy, and manager change

Panel A reports the number of hedge fund fee, strategy, and manager changes in each share restriction change category from January 2007-May 2012. *Share restriction increase* indicates that at least one share restriction provision increases. *Share restriction decrease* indicates that at least one share restriction provision decreases. *Share restriction no change* indicates that share restriction does not change. *Fee change* indicates that management fee or incentive fee change. *Strategy change* indicates that a fund change one of the 12 investment-style groups listed in the paper to another. *Manager change* indicates that both manager company name and managerial principal change. Panel B provides the determinants of fee changes conditional on share restriction changes. *Restriction increase* is an indicator variable equal to one when there is a share restriction increase. *Prior mgmt fee* and *Prior perf. fee* are the management fees and performance fees prior to share restriction changes, respectively. All other control variables are defined in Table 1.3. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: Number of fee, strategy, and manager changes in each share restriction change category

Share restriction		Fee change		Strategy change		Manager change	
Category	N	N	%	N	%	N	%
Inc	668	109	16.32%	6	0.90%	3	0.45%
Dec	717	81	11.30%	2	0.28%	5	0.70%
No change	173792	335	0.19%	115	0.07%	104	0.06%

Panel B: Determinants of fee change

	(1)		(2)		(3)	
	Any		Management fee		Incentive fee	
	Decrease	Increase	Decrease	Increase	Decrease	Increase
Restriction increase	0.1928	0.4658**	0.0551	0.4510**	0.2469	0.5351
	(0.486)	(0.024)	(0.863)	(0.042)	(0.560)	(0.215)
Prior mgmt fee	0.3468	-1.6043***	0.8927***	-1.9154***	-0.6924	-0.6843
	(0.240)	(0.000)	(0.002)	(0.000)	(0.103)	(0.138)
Prior perf. fee	0.0165	0.0230	-0.0112	0.0545***	0.1070***	-0.0893***
	(0.409)	(0.114)	(0.604)	(0.001)	(0.004)	(0.003)
CAR	0.9632	0.7454	1.0546	-0.2783	-1.4746	13.4930***
	(0.636)	(0.611)	(0.627)	(0.857)	(0.698)	(0.002)
CAF	-0.7018	0.6686*	-0.9598	0.8191**	-1.5836	0.3718
	(0.338)	(0.080)	(0.265)	(0.041)	(0.184)	(0.616)
Std(Abret)	-11.8433	6.0542	-5.8545	8.3064	-30.5466**	-61.8867**
	(0.174)	(0.275)	(0.536)	(0.148)	(0.050)	(0.024)
Offshare	-0.0919	0.1244	-0.2821	0.1538	0.2229	-0.0811
	(0.746)	(0.553)	(0.387)	(0.496)	(0.611)	(0.853)
Log(Age)	-0.2607	0.0140	-0.3319	0.0742	-0.3306	-0.6539**
	(0.215)	(0.929)	(0.173)	(0.666)	(0.301)	(0.044)
Log(AUM)	-0.1022	0.0157	-0.0419	0.0480	-0.3032***	-0.0175
	(0.195)	(0.799)	(0.648)	(0.470)	(0.004)	(0.891)
Crisis	-0.1365	-0.6925**	-0.3000	-0.6212**	0.2213	-2.0067***
	(0.778)	(0.016)	(0.576)	(0.044)	(0.787)	(0.002)
After_crisis	0.6564	-0.5831*	0.5306	-0.7368**	1.1418	0.0473
	(0.158)	(0.055)	(0.301)	(0.027)	(0.144)	(0.926)
Intercept	-2.2989**	-0.6461	-2.8723**	-1.3622	-2.4787	1.8732
	(0.038)	(0.422)	(0.022)	(0.120)	(0.147)	(0.216)
Pseudo R-squared	0.0688		0.1007		0.1577	
Observations	1,371		1,371		1,371	

Table 1.9: Value of hedge fund managerial compensation as a % to AUM

Using the model developed in Goetzmann, Ingersoll, and Ross (2003) and the parameters stated in Aiken et al. (2014), this table gives the value of hedge fund managerial compensation as a % of AUM. We solve for managerial compensation using different liquidation threshold (b), total withdrawal rates (ω), excess return (α), and fund value to high-water mark ratios ($\frac{S}{H}$).

		ω = 0.10 & α = 0.00			ω = 0.05 & α = -0.01		
		b = 0.80	0.50	0.20	b = 0.80	0.50	0.20
$\frac{S}{H}$	1.0	5.46	18.43	23.94	5.43	20.89	31.58
	0.9	3.42	16.94	22.67	3.38	19.36	30.42
	0.8	0.00	15.03	21.41	0.00	17.25	29.19
	0.7	0.00	12.33	20.12	0.00	14.13	27.86
	0.6	0.00	8.03	18.78	0.00	9.08	26.35
	0.5	0.00	0.00	17.30	0.00	0.00	24.47

Table 1.10: The effect of endogenous bias in share restriction changes

Panel A reports the alphas of portfolios sorted on whether funds add lockup periods or increase any share restrictions conditional on funds with lockup periods in the last observation in the sample. The portfolio alphas are defined as the intercept of the CAPM, Carhart (1997) or Fund and Hsieh (2004) model, respectively. Panel B provides the cross-sectional regression of estimated individual fund Fung and Hsieh (2004) alphas on fund characteristics. *Lockup Dummy* is an indication variable set equal to one if funds have lockup periods at the end of the sample period. *Add Lockup* is an indicator that is equal to one if funds add lockup periods during the sample period. *Log(AUM)* is the natural log of fund's average AUM. All other control variables are measured in the last observation of each fund. *, **, and *** indicate 10%, 5%, and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: Alphas from portfolios sorted on whether funds adding lockup periods

	Add Lockup			Any Share Restriction Increase		
	Yes	No	Difference	Yes	No	Difference
CAPM	0.0027	-0.0001	0.0029***	0.0019	-0.0004	0.0022***
	(0.154)	(0.947)	(0.000)	(0.411)	(0.830)	(0.006)
Carhart (1997)	0.0018	-0.0010	0.0029***	0.0008	-0.0012	0.0020**
	(0.312)	(0.536)	(0.000)	(0.712)	(0.431)	(0.013)
Fung and Hsieh (2004)	0.0042***	0.0015	0.0026***	0.0038*	0.0012	0.0026***
	(0.010)	(0.311)	(0.001)	(0.059)	(0.395)	(0.001)

Panel B: Cross-sectional regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lockup dummy		0.1099***	0.0977***	0.0656**	0.0537*	0.0788***	0.0674**
		(0.000)	(0.000)	(0.017)	(0.052)	(0.004)	(0.015)
Add lockup			0.3923***		0.3727***		0.3489***
			(0.001)		(0.002)		(0.003)
Log(Minimum+1)				0.0727***	0.0721***	0.0648***	0.0644***
				(0.000)	(0.000)	(0.000)	(0.000)
Log(Redemption+1)				-0.0132	-0.0119	-0.0138	-0.0126
				(0.420)	(0.466)	(0.397)	(0.439)
Log(Notice+1)				-0.0163	-0.0164	-0.0208	-0.0209
				(0.262)	(0.257)	(0.151)	(0.150)
Log(AUM)						0.0422***	0.0415***
						(0.000)	(0.000)
Intercept	0.2508***	0.2118***	0.2118***	-0.5911***	-0.5879***	-0.6436***	-0.6397***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R-squared	0.0000	0.0162	0.0178	0.0161	0.0177	0.0399	0.0411
Observations	5,532	5,532	5,532	5,532	5,532	5,532	5,532

Chapter Two: Investment Restrictions and Fund Performance

1. Introduction

Mutual funds and hedge funds provide similar economic functions. Despite the fact that both pool investor capital and seek to invest in a portfolio of assets that deliver superior risk-adjusted performance, the literature typically finds that mutual funds underperform hedge funds. The typical hedge fund paper finds significant, average, gross-of-fee hedge fund alpha (Ibbotson, Chen, and Zhu, 2011), while most mutual fund studies find zero, gross-of-fee alpha (Fama and French, 2010). One explanation for the disparate performance is the difference in contracting environment between mutual funds and hedge funds.

Mutual funds and hedge funds face different investment, share liquidity, and compensation constraints. For example, in 1996 (the beginning of our sample), only 26% of mutual funds had the ability to short sell; conversely, it is generally believed that most, if not all, hedge funds have this ability. The use of leverage and derivatives for mutual funds is similarly constrained, while hedge funds typically face no such constraints. Mutual funds stand ready to redeem their shares at day's end, often maintaining excess levels of cash and liquidity to do so. Conversely, hedge funds are better able to manage liquidity risk by imposing lock-ups and intermittent withdrawal frequencies on their investors. Finally, the compensation arrangements between mutual funds and hedge funds differ markedly. While only 4% of mutual funds had performance-based compensation at the beginning of our sample, 95% of hedge funds in the BarclayHedge database had performance pay. These differences in pay not only affect managerial effort, but may embolden a flight of talented managers from the mutual fund industry to the hedge fund industry.

In this paper, we examine mutual funds that change their contracting environment to more closely resemble hedge funds. In doing so, we seek to establish an empirical link between contracting environment and performance. Regardless of the size of performance differences between mutual funds and hedge funds, the evidence in this paper diminishes the likelihood that these differences in performance are the result of differences in investment constraints, managerial compensation, or share liquidity.

Stulz (2007) speculates that the increased importance of hedge funds in the financial markets will lead to a convergence between mutual funds and hedge funds. Over our time period of study, 1996-2011, we find that the percent of funds with the ability to short sell, use leverage, use options, or invest in illiquid securities grew substantially. For example, the percentage of funds that had the ability to short sale increased from 27% to 64%. The percent of mutual funds with the ability to charge performance compensation nearly doubled, while the percent of mutual funds with the ability to charge short-term trading fees in an effort to curb liquidity costs grew fivefold.

Utilizing changes in the existing contracts, we use a difference-in-difference approach to identify the effect of contract changes on fund manager and investor behavior. We find that compensation, liquidity, and investment constraints neither prove binding for the average mutual fund nor explain the difference in performance between hedge funds and mutual funds. One likely explanation is that most funds do not implement their new found freedoms. For example, 525 funds removed the short sale constraint between 1996 and 2009.[13] However, only 6% of these funds actually shorted stocks within the 2-year period following the restriction removal. We observe similar conditional implementation rates for the ability to use leverage, options, or invest in restricted securities.

Given the low use of hedge fund-like characteristics, we focus instead on the sample of mutual funds that actually implement any of their contractual changes. We find that abnormal returns in the post-treatment group are not better and sometimes even worse. Further, the level of post change return is similar to the control group of funds that do not change their contracts. General, the investment restrictions have no effect on performance.

We next examine the compensation contract of the mutual fund. Both mutual funds and hedge funds typically charge their investors a management fee based on a percentage of the funds' assets under management (AUM). Additionally, over 95% of hedge funds charge a performance fee to their investors, yet only 4% of mutual funds charged a performance fee as of the beginning of our sample period (1996).[14] While mutual fund and hedge fund performance fees face several legal distinctions, we expect that mutual funds that add a performance-based component to their compensation arrangement are better able to affect effort or attract more skilled managers in the labor market. Over our period of study, the percent of mutual funds with the ability to charge

[13] Utilizing the mutual fund contract data from 1996-2011, we can examine whether funds actually implement their new found freedoms within the 2-year period following the restriction removal if they remove the restriction from 1996-2009.
[14] Mutual funds charge fulcrum fees rather than performance fees. Rather than charge a flat percentage of profits over the high-water mark, as a hedge fund would, the fund receives a bonus percentage of assets under management (AUM) for good performance (typically net of a benchmark), but is forced to refund a percentage of the management fee should they underperform. For a more complete analysis, see Golec (1992, 1993).

performance compensation nearly doubled. However, we find that funds that add performance compensation don't perform differently from the control group of funds that do not add a performance fee.[15]

Finally, we explore the role that funding risk plays in mutual fund performance. When funding liquidity is tight, funds may become reluctant to take on capital intensive positions (Brunnermeier and Pedersen, 2008). Open-end mutual funds stand ready at day's end to redeem shares from investors. The timing and volatility of these funding requests may be difficult to predict, forcing fund managers to hold excess cash to meet redemptions. To the extent that this excess cash limits mutual fund managers' ability to time the market, it likely has a drag on performance. Further, in periods of unexpected outflows, funds sell assets at fire-sale prices that erode performance (Coval and Stafford, 2007). In both cases, we expect this funding risk to dampen one's estimate of fund manager skill. Hedge funds are better able to manage funding risk by imposing lock-ups and infrequent withdrawal frequencies on their investors.

While open-ended mutual funds are not legally allowed to impose redemption restrictions that are directly comparable to hedge funds, we utilize the growing use of short-term trading fees on mutual fund investors as a shock to the liquidity of the mutual fund's shares.[16] However, we find no evidence that funds that enact short-term trading fees perform any better after the contract change.

Further, we examine how investors respond to funds removing investment and compensation constraints. We find no evidence that removing the constraints, or even

[15] We cannot identify whether mutual funds actually charged performance fees even if allowed.

[16] We note that many hedge funds offer both a hard and soft lock-up. In the case of the soft lock-up, the investor is able to withdraw funds while paying a penalty; nearly identical to a short-term trading fee.

actually implement the newly allowed strategies, attract investors. There is no significant change in fund net flows before and after the contract change. It is not surprising since funds fail to deliver better performance following restriction removal. Likewise, we find no changes in clientele or fees following a removal.

Our evidence is not consistent with the idea that investment constraints prevent mutual fund managers from performing at the same level as their hedge fund counterparts. Rather, our evidence is consistent with several alternative explanations about the structure of the two industries. First, it is possible that unobservable heterogeneity between mutual fund and hedge fund managers exist, such that even if given more hedge fund-like contract features, mutual fund managers are reluctant to implement these features. Agarwal, Boyson and Naik (2009) find hedged mutual funds outperform traditional mutual funds, but the superior performance is only driven by managers with hedge fund management experience. Cici and Palacios (2013) examine how mutual funds' use of options affects performance and find that using options generates, on average, no performance advantages. They argue that using options requires specialized knowledge of options markets and options pricing, which go beyond mutual fund managers' conventional skills. In short, mutual fund and hedge fund managers are different.

Second, the legal environment in the United States places heavy restrictions on mutual funds that attempt to implement hedge fund strategies. For example, we observe that 86% of the mutual funds in our sample allow the use of leverage at the end of our sample period. While this freedom allows the manager to leverage their best ideas, legal restrictions for open-ended mutual funds cap the use of margin at 33% of the funds

AUM; hedge funds do not face such a cap. Similarly, adding a performance fee for the mutual fund manager is likely to affect the fund's ability to attract top talent, but, as discussed in Golec (1992, 1993), mutual funds face symmetric performance compensation. Specifically, mutual funds implement fulcrum fees (as opposed to highwater marks) that pay a manager for outperformance, but require a manager to pay following underpeformance. The symmetric nature of the performance fee may dull the labor market response to compensation. While these legal restrictions may limit the ability of the mutual fund manager to perform equivalently to the hedge fund manager, based on the identification strategy in the paper, it is unclear why we find no evidence that mutual fund performance improves following the change.

Finally, our results are consistent with a growing body of literature pointing to the fact that mutual fund and hedge fund performance may not be as dissimilar as previously thought. Griffin and Xu (2009) compare the equity holdings of hedge funds and mutual funds and find limited evidence that the stock picking ability of mutual funds differs from hedge funds. Aiken, Clifford, and Ellis (2013) find that much of the previously studied hedge fund alpha can be explained by the selection bias in commercially available data. If hedge fund alpha is actually much smaller than previously thought, the fact that mutual fund skill is unaffected following a change in its charter may not be surprising.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 describes the unique data set used for our sample. Section 4 examines the time trend in contractual restrictions. Section 5 looks at the determinants of restriction removal. Section 6 examines the performance and flows of funds that remove restrictions. Section 7 examines other reasons for removing restrictions. Section 8 discusses the results, and Section 9 concludes.

2. Background

We use a dataset of N-SAR filings from the Securities and Exchange Commission (SEC) to get information on the levels of investment restrictions face by mutual funds. As documented in Almazan et al. (2004), mutual funds have faced fewer and fewer restrictions on the type of investments they can use over the past two decades. Almazan et al. (2004) use these restrictions to study management monitoring by fund shareholders and find that fewer restrictions on fund managers are associated with better board monitoring, peer monitoring within the family, and greater career concerns for the managers. They hypothesize that these four factors (restrictions, boards, peers, and career) can be adjusted by shareholders to reach an efficient contract with management.

We take a different approach to restrictions. Mutual funds with fewer restrictions are potentially more like hedge funds in investment and compensation constraints. Agarwal and Naik (2004), for example, motivate their performance measurement by first noting the differences between equity hedge funds and equity mutual funds come mostly from the tendency of the mutual fund industry to be buy-and-hold only, employing static trading strategies. Hedge funds, by contrast, employ dynamic strategies that may generate asymmetric payouts. Both invest in the same market, but with different risk profiles.[17] A mutual fund employing derivatives or other alternative investments should induce hedge fund-like behavior and performance.

[17] Griffin and Xu (2009) make this comparison explicit by examining the long equity positions of both hedge funds and mutual funds. They find hedge funds do only marginally better, though they do not examine the derivative and short positions.

Mutual funds do differ from hedge funds in ways that may make investment freedom less relevant. Mutual funds are more susceptible to market discipline than hedge funds because many hedge funds have share restrictions in place to prevent shareholders from withdrawing funds quickly. These share restrictions prevent market discipline for bad board monitoring or suboptimal manager contracts (Ding, Getmansky, Liang, and Wermers, 2009). "Voting with your feet" is an effective method of mutual fund governance (Qian, 2011), and Fama and Jensen (1983) go as far as to suggest that monitoring by a mutual fund board is relatively less important for mutual funds than other institutions since shareholders can always withdraw assets.[18]

Almazan et al. (2004) conducted the most related study. Almazan et al. (2004) look at a similar sample of funds and find that less constrained funds perform similarly to more restricted funds. They conclude that restrictions result from an optimal contracting environment that balances monitoring (via restrictions) and career concerns of the manager. Our paper differs from theirs in that we study funds that have made a change to their fund charter, either to improve the management oversight or to attempt to mimic the success of hedge funds. We therefore control for these monitoring effects throughout our study. Additionally, we also consider two contractual features that were not the focused on in Almazan et al. (2004): the role of performance compensation and share liquidity.

[18]There can still be variation in monitoring across mutual funds. James and Karceski (2006) find that institutional funds with high minimum investment requirements outperform other funds and claim these returns result from the superior monitoring of institutional investors. Chen, Goldstein, and Jiang (2008) claim that board monitoring is most effective when the board has large positions in the fund but the fund has mostly unsophisticated investors.

3. Data

We examine the population of actively managed, equity mutual funds from January 1996 to September 2011. Data on investment restrictions (and other mutual fund attributes) come from SEC Form N-SAR filings retrieved from EDGAR. Beginning in January, 1996, all mutual funds were required to report SEC Form N-SAR on a semi-annual basis. Unlike the typical prospectus, the form was standardized and contains information on a fund's finances, relationships, and investment practices. This study is most concerned with Question 70, "Investment practices." A fund must state with a simple yes or no whether they are permitted to perform a specific type of investing practice, and, if so, have they done the practice recently.

We combine the N-SAR filings data with the CRSP mutual fund database. For a given N-SAR filing, we match it to the most recent mutual fund summary information available in CRSP. This process is time intensive since most of the sample period has no common identifier in the two databases. Like Warner and Wu (2011), we began by matching on name and ticker algorithmically. For cases where names are similar, but not exactly the same, we verify the match using data common to both sets (e.g., TNA). All algorithmic matches are subsequently hand-verified. In cases where no algorithmic match was available, we did a manual search in N-SAR for a match. We were able to map over 90% of our CRSP universe to N-SAR filings.

Only annual reports are available in CRSP for the early part of the sample period, while quarterly reports are available in the latter part. Consequently, more than one of the early N-SAR reports could be matched to the same annual summary information in CRSP. This issue affects manager, expense ratio, turnover, and family identifier data, but not TNA and performance data. As is commonly done, we collapse the share classes in

CRSP down to one observation per file date, using the TNA weighted average of all variables.

We include a fund in our sample if, based on CRSP, the fund has at least $20 million in total net assets (TNA). In addition, we remove the first two years of a fund's performance history to mitigate incubation bias (Evans, 2010). The resulting dataset of N-SAR/CRSP matched data contains 75,214 mutual fund-half-years. We then filter the database to focus on actively managed, U.S. equity funds. Like Almazan et al. (2004), we screen out foreign funds, sector funds, index funds, variable annuities, ETFs, tax-managed products, REITs, and lifecycle funds. To further insure we are dealing with actual equity funds, we also only include a fund once its portfolio holdings reach 80 percent equity.[19] The filters shrink the sample to 36,522 fund-half-years from 3,059 funds.

4. Can mutual funds operate like hedge funds?

We focus on the investment, share liquidity and compensation contracts of actively managed equity mutual funds. Question 70 on SEC Form N-SAR includes two questions for eighteen different investment practices: "Permitted by Investment Policies?" and "If permitted by investment policies, engaged in during the reporting period?" We focus on contractual restrictions that are most likely to affect both mutual funds and hedge funds. These restrictions include:

1. Use leverage (Borrow money or use margin to purchase securities)

[19] To mitigate selection bias, once a fund reaches 80 percent equity and $20 million in TNA, it stays in the sample even if it subsequently goes below the cutoff. Occasionally, CRSP has missing data for the equity variable; we assume there has been no change from the last reported value in these cases. From December 1998 to September 2001, CRSP has missing equity data for most funds. Any equity fund created in this period without equity data will not be included until the first data was reported.

2. Short selling
3. Use of options
4. Invest in restricted securities
5. Performance fee
6. Short-term trading fee

The first four measures are the focus of Almazan et al. (2004). We expand on their measures in two ways. First, there are four different practices dealing with equity options of some sort. Considering that these derivatives can all be used either to speculate, hedge, or otherwise create non-linear payoffs, we treat them as interchangeable. Specifically, we have one category called "options" and a mutual fund is considered to be able to invest in this category if any of the following practices were answered yes: options on equities, options on stock indices, options on futures, and options on stock index futures. Second, we also consider two contractual features that were not the focused on in Almazan et al. (2004): the role of performance compensation and share liquidity. We use Question 51 on SEC Form N-SAR to measure whether funds have performance fee. Question 51 indicates whether a fund's advisory fee was based on its investment performance. We use Question 37 and 38 to measure a fund's share liquidity. Question 37 and 38 indicates whether funds are permitted to charge redemption fees other than a sales load.

The time series data on contractual restrictions are shown in Table 2.1. For each year, we report what percentage of the population is permitted to use or actually implement the hedge fund-like investment, share liquidity, and compensation strategies. Over our time period of study, we find that the percent of funds with the ability to short sell, use leverage, use options, invest in illiquid securities, charge performance fee, or charge short-term trading fee grew substantially. For example, the percentage of funds that had the ability to short sale increased from 27% to 64% and the percentage of funds that had the ability to use options increased from 69% to 89%. The percent of mutual funds with the ability to charge performance compensation nearly doubled, while the percent of mutual funds with the ability to charge short-term trading fees in an effort to curb liquidity costs grew fivefold, peaking in 2008.

Despite fewer restrictions, the conditional percentage of mutual funds actually implementing the hedge fund-like strategies has changed very little. Table 2.1 also shows the time trends for actually implementing in each category, conditional on being allowed to use. For example, while the percent of mutual funds with the ability to short sale more than doubled, the conditional percentage of funds actually using short sale remains at 6% over the sample period.

Overall, we find that the possibility to implement hedge fund-like investment, share liquidity, and compensation strategies has greatly increased for mutual funds over the sample period. Few funds, though permitted, actually follow these strategies. The next question is why mutual funds might want to remove the restrictions and be more like hedge funds.

5. Why do mutual funds want to be more like hedge funds?

The prior section shows that mutual funds have changed their investment, share liquidity, and compensation contracting environment to more closely resemble hedge funds over the past two decades. The next natural question is why mutual funds want to remove the restrictions and be more like hedge funds. In this section, we examine why funds remove restrictions.

We beginning by developing a model of the investment restriction removal decision. Almazan et al. (2004) propose that constraints serve as one way to monitor fund managers and show that lightly monitored funds have more constraints (and vice versa). They find no difference in performance between constrained and unconstrained funds and interpreted this result as an equilibrium environment where the shareholders have an efficient contract with the fund manager. Investment restrictions exist as necessary so that there is no performance advantage for shareholders when combined with other methods of monitoring.

As we model restriction removal events, we include two monitoring variables used by Almazan et al. (2004) to predict constraint levels. First, tighter constraints were associated more often with team management.[20] Second, large fund complexes have peer monitoring and the larger the complex the more this monitoring substitutes for explicit restrictions. We use the log of family size as a predictor and would expect larger families to be more likely to remove restrictions. A team management dummy and the family size variables are calculated using the most recent data available in CRSP before a change occurs.

Mutual funds may also use many of the investment areas to lower operational expenses. Liquidity requirements for redemptions increase a fund's overhead (Edelen, 1999) and some of these costs can be offset with alternative investment practices. For example, buying assets on margin, borrowing funds, or futures positions could offset the

[20] Funds with a CRSP manager name that indicates multiple managers (like "Team Managed" or "Smith & Chen") are marked as team managed.

implicit cost of holding a large cash balance. Derivatives may change alpha, but could also lower volatility by hedging or diversifying risk. These operational problems may become even more relevant as diseconomies of scale affect performance (Berk and Green, 2004). We measure the operational needs of a fund with five characteristics: TNA, expense ratio, turnover ratio, load fund identification, and fund age.[21] We also calculate a freedom score for each fund to take into account that, mechanically, lightly restricted funds cannot remove more restrictions. The freedom score counts how many of the six practices (as outlined in Section 4) a fund was allowed to use. Funds with more freedom will have higher freedom scores (to a maximum of six) and funds with less freedom will have lower scores (to a minimum of zero). Each of these variables is measured as of the last N-SAR filing prior to a restriction change occurring.

Another consideration is that prior performance and flow may influence what restrictions are placed on a manager. An exceptional performer may be granted access to more asset types so as to expand the markets over which a manager could apply his skill. Poor performance has a less well defined interpretation. On the one hand, low returns may result from the manager's inability to invest in the asset classes most likely to produce superior returns. Hence, a bad performer may be given more freedom in hope of improvement. On the other hand, a manager has a record of poor performance that may be compounded with more exotic asset types. Fund net flow also has a less well defined interpretation. While funds with high flows have more negotiating power to remove contractual restrictions, funds with low flows have more incentives to remove investment

[21] Expense ratio and turnover ratio both have outlier values that are likely data errors. To minimize their impact, both variables are winsorized at the 1 percent level.

restrictions to attract investors who like to have access to hedge fund-like investment strategies. Fund return volatility and flow volatility may also influence a fund's decision to remove restrictions. Funds with high return volatility may choose to use short sales or options to hedge performance risk. Funds with high flow volatility may choose to add short-term trading fee to manage funding risk. Both performance and flow measures are calculated prior to the period in which the restriction change occurred.

Anecdotal evidence suggests that the level of restrictions for an individual fund may also depend on the fund family's policies. For example, Vanguard announced several restriction changes in 2009 with the justification that all funds in the family should have the same policies. Further, fund boards in the same family typically share many of the same board members, and so we expect them to take similar approaches to restricting fund managers. To incorporate family policy in our model, we use the average freedom score of the family and would expect that funds within lightly restricted families are more likely to remove restrictions. The average family score is measured prior to the actual restriction change so as not to include the impact of the dependent outcome.

We model the likelihood of restriction removals using a logit model. In addition to the predictive variables for monitoring, operations, performance, and family restriction level, we include style, and year dummies. We use the last reported fund characteristics of semiannual period (t) to predict any changes in semiannual period (t+1). With these variables, plus the one year lag requirement for prior returns and flows, the sample is reduced to 28,673 fund-half-years.

The summary statistics for the sample are shown in Table 2.2. The mean freedom score is 3.37. The unconditional probability of removing a restriction in a six month period is 6 percent. Other fund characteristics are similar to what is found in prior research on mutual fund performance. The average monthly return is 0.63% with a standard deviation of 1.92%. The average monthly flow is 0.39%, but with significant variation (a standard deviation of 3.48%). Log(TNA), Expense ratio, and Turnover ratio are consistent with prior literature. The mean (median) fund has been in the CRSP database for 163 (124) months.

The results for the logit model of the likelihood of share restriction removal are given in Table 2.3. For ease of economic interpretation, the coefficient estimates have been suppressed, and we instead present the marginal effect for each coefficient. We convert all continuous independent variables to *z*-scores, meaning for each observation we subtract the sample mean and divide by the sample standard deviation. This procedure has no effect on model significance, but does give the marginal effects the intuitive interpretation as the impact of a one standard deviation change in the independent variable. Year and style dummies coefficients are excluded from the table for brevity.

Beginning with Panel A, the first column models the decision to make any changes to investment practices. Funds with good performance are more likely to remove restrictions, which suggest that contractual restriction may serve as a bargaining tool between fund managers and investors. Consistent with a marketing explanation, we also find that funds with low flows are more likely to remove restrictions. Low flow funds have more incentive to attract investors who like to have access to hedge fund-like investment strategies. A one standard deviation decrease in fund net flow increases the probability of restriction removal by 0.28%.

We also find that large funds, younger funds, and funds with high expense and turnover ratios are more likely to be given more freedom. A one standard deviation increase in the expense ratio increases the probability of restriction removal by 0.53%. Funds with more freedom are (not surprisingly) less likely to remove restriction.

Family restriction levels also matter. Funds in families with high freedom scores are more likely to remove restrictions. A one standard deviation increase in the average family score (1.09) increases the probability of an individual fund restriction removal by 1.62%. Funds adjust contractual restrictions to be in line with peers in the family.

The monitoring variables provide only modest support for the monitoring hypothesis and our results are mixed when compared to Almazan et al. (2004). Family size, as expected, has positive impact on restriction removal—peer monitoring within large family complex enables funds to remove contractual restrictions. A one standard deviation increase in family size increases the probability of restriction removal by 0.70%. Almazan et al. (2004) find that team management is associated with greater constraints. Our results for removing restrictions, however, are inconsistent, as team management increases the likelihood of restriction removal.

The remaining columns of Panel A reports the determinants of each individual contractual restriction removal conditional on that the corresponding practice not being permitted as of the prior N-SAR filing. The results are qualitatively similar to Model 1. For example, funds with low flows are more likely to remove the restrictions on short sale, using leverage, and investing in options and illiquid assets. Funds with high expense ratio are more likely to removal investment constraints and less likely to add a performance fee.

In general, Panel A shows that funds with low flows are more likely to remove restrictions and become more hedge fund-like, which is consistent with the marketing explanations. We next examine whether a fund with flows lower than expected given its past performance has more incentive to attract investors by removing restrictions in Panel B. Unexpected flow is measured as the residual from a regression of flow on lagged return, return volatility, size, age, turnover ratio, and expensive ratio and is used in place of the observed flow. We find that funds with low unexpected flows are more likely to remove contractual restrictions.

Taken together, performance, flows, family considerations and operational needs have strong predictive power. Funds with high returns have stronger negotiating power to remove the restriction. Funds with low flows have more incentive to use hedge fund-like strategies to attract investors. The family variables support our hypothesis that the restrictions faced by the funds are likely more about family policy than fund policy and if funds with less restricted peers in the family are more likely to remove contractual restrictions. Given these conclusions about why changes occur, we next explore the impact of these changes on the fund.

6. What is the impact of restriction removal?

6.1 The effect of restriction removal on fund operation and fund investor

Prior research generally suggests that the hedge fund industry has historically produced alpha (e.g., Ibbotson, Chen, and Zhu (2011)), but that the mutual fund industry has not (e.g., Fama and French (2010)). An often cited explanation for the disparate performance is the difference in contracting environment between mutual funds and hedge funds. Given the trend towards more investment freedom for mutual funds, the removal of restrictions may provide additional performance for shareholders. Alternatively, following the argument of Almazan et al. (2004), a restriction change may result because of a perceived or anticipated inefficiency in the current contract. The monitoring hypothesis would also predict a higher alpha in the period following a contract change as it leads to a more efficient contract. Agarwal et al. (2009) argue that hedged mutual funds provide access to hedge fund-like strategies with the fee structure, liquidity, and regulatory requirements of mutual funds and will plan an increasing important role in the field of investment management. One possibility that funds remove restriction is to attract fund flows. This section explores the performance and flow effects of removing contractual restrictions.

We examine changes in fund performance and flows around contractual restriction removals. Our tests use both pre-change and post-change returns over a 30 month period. Specifically, when a change is reported on an N-SAR filing, we know the change actually occurred sometime in the preceding six months. To avoid any overlap with the changing period, we use twelve months of returns starting eighteen months before the N-SAR report date for pre-change returns. We use the twelve months following the report date for the post-change returns for a total of 24 months of returns containing a six month gap in the middle. We use fund style-adjusted return to measure risk-adjusted returns. We assign funds to one of seven style categories based on stated fund strategy. Because there are multiple objective code sources in CRSP, we assign a style category based on values from the following sources, listed in terms of priority: Wiesenberger, Strategic Insight, and Lipper. We compute benchmark returns for each style by taking the asset-weighted average of monthly returns. Then for each fund, we calculate the style-adjusted return as the excess return relative to the benchmark return and estimate the following model:

$$Style-adj\ ret = \alpha_0 + \alpha_1 * Post + \beta_1 * Fund\ characteristics \tag{1}$$

where *Style-adj ret* is the fund's style-adjust return; *Post* is a dummy variable equal to one if the return is in the twelve months after the contract restriction removal and zero otherwise; and *Fund characteristics* include the trailing 3-month average style-adjusted return, age, size, turnover ratio, and expense ratio. We also include style, and year dummies.

The results of the regression are given in Table 2.4. Column 1 of Panel A shows that the coefficient on *Post* is not significant, suggesting that contract restriction removal has no significant effect on performance. We recognize, of course, that funds changing one specific constraint may differ systematically depending on the constraint. Column 2-7 report the performance changes following each restriction removal. Performance following any of the six contractual restriction removal is not better (sometimes even worse). For example, a fund's monthly style-adjusted return decreases by 0.15% following leverage restriction removal.

To further test the effect of contractual restriction removal on fund manager's operation, we add back fund expense ratio and use monthly gross returns in Panel B. We define fund monthly gross return as fund monthly net return reported in CRSP plus one-twelfth of its annual expense ratio. Panel B shows that restriction removal has no significant effect on fund gross return.

While fund investors would like the fund manager to maximize risk-adjusted fund returns, a fund manager has an incentive to take actions that increase fund flows

(Chevalier and Ellison, 1997). Next, we examine the effect of contractual restriction removal on fund flows. We use the following piecewise linear specification for performance to capture the previously documented nonlinear flow-performance relation (Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998)):

$$\begin{aligned} Flow = {} & \alpha_0 + \alpha_1 * Post + \alpha_2 * Post * Low + \alpha_3 * Post * Mid + \alpha_4 * Post * High \\ & + \beta * Fund\ Characteristics \end{aligned} \tag{2}$$

where *flow* is the fund's net flow; *Post* is a dummy variable equal to one if the flow is in the twelve months after the contract restriction removal and zero otherwise; and *Fund characteristics* include the trailing 3-month average style-adjusted return, age, size, turnover ratio, and expense ratio. We include style and year dummies. Following Sirri and Tufano (1998), each month we calculate a fractional rank (Rank) ranging from 0 to 1 for each fund based on the fund's previous month return. The variable Low is defined as Min(0.2, Rank); Mid is defined as Min(Rank – Low, 0.6); and High is defined as (Rank – Low – Mid). We also use the interaction between *Post* and return rank variables, *Low*, *Mid*, and *High*, to examine whether fund flow-performance sensitivity changes following contractual restriction removal.

We provide the estimates of Eq. (2) in Table 2.5. We see that the *Post* dummy variable is at no point significant and restriction removal has no significant effect on flows. Funds cannot attract more flows by being more hedge fund-like. Given the lack of increased performance documented in Table 2.4, it is perhaps not surprising that removing contractual restrictions does not attract investors.

One issue with the above tests is the inability to identify a correct benchmark for comparing the fund. Comparing a fund to its own prior returns and flows misses the possibility that non-event funds all changed while the event fund stayed the same because of the event. We address this by conducting a difference-in-difference analysis using the propensity score matching approach (PSM) to control for factors that simultaneously affect a fund's decision to remove restrictions and its future performance and flows. We first use the logit model specified in Panel A of Table 2.3 to create a propensity score that indicates the probability of each contractual restriction removal, respectively. We match each restriction removal fund at its event date with 10 funds that do not remove restrictions but have the closest propensity score in the same calendar quarter.

We present the results of the PSM analysis in Table 2.6. Panel A of Table 2.6 reports the mean of monthly return and flow across both groups and we find no evidence that restriction removal funds perform better than the control funds. Following contractual restriction removal, event funds have an average of 0.17% decrease in monthly return and 0.81% decrease in monthly flow, the control funds have an average of 0.17% decrease in monthly return and 0.75% decrease in monthly flow. The resulting differences in returns and flows are not statistically significant.

We demonstrate that more freedom does not help a fund improve performance and attract flows. However, freedom may allow managers to better manage their portfolio exposures and we next examine whether more freedom can help funds manage risk. Hedge fund-like strategies, including short sales and using options, enable funds to generate returns under any market condition. We test for this risk management behavior by looking at the changes in fund return volatility and Sharpe ratio following restriction removal. Panel A shows that restriction removal cannot help funds hedge risk and improve Sharpe ratio. Allowing funds to invest in restricted securities will increase the fund return volatility.

We also examine the effect of restriction removal on fund expense ratio, fund clientele, and cash holding. We find that fund expense ratio decreases following investment and share liquidity restriction removals and increases following performance fee enacting. However, the change in the fund expense ratio is not economically significant. Of the different contractual restriction removal, allowing performance fee changes expense ratio most. Annual expense ratio increases by 0.09% following performance fee enacting. Panel B of Table 2.6 also shows that restriction removal has no strong effect on fund clientele. Only allowing short sales and using leverage decreases the flow-performance sensitivity and only allowing short-term fee will decrease the number of shareholder accounts. Enacting a short-term trading fee should allow funds to decrease cash holdings, but we find no evidence of that.

Taken together, we find no evidence that the difference in contractual constraints can explain the difference in returns between mutual funds and hedge funds. Our results imply that greater freedom cannot improve (and sometimes actually hurts) fund performance. We also find no evidence that funds can attract more flows by being more hedge fund-like. Removing the contractual restriction also has no significant effect on fund fees, cash holdings, and fund clientele.

6.2 Are funds actually implementing newly allowed strategies?

In Table 2.1, we show that the possibility to implement hedge fund-like investment, share liquidity, and compensation strategies has greatly increased for mutual funds over the sample period. Few funds, though permitted, actually follow these strategies. For example, only 6% of funds that are allowed to use short sale actually used it over the sample period. We examine whether funds are more likely to actually implement hedge fund-like strategies if they are newly allowed. Table 2.7 reports the proportion of funds that remove the restriction actually implement the strategy within two years. We find that even if funds just removed the restriction, they are not likely to implement the strategy. For example, 525 funds removed the short sale constraint and 297 funds removed the options constraint during 1996-2009. However, only 6% of funds actually used short sales and 17% of funds actually used options within two years following restriction removal.

So far, we have shown that removing the contractual restriction, on average, has no significant effect on performance, flows, fund fees, cash holdings, and fund clientele. Given the low use of hedge fund-like strategies following restriction removal, we now focus instead on the sample of mutual funds that removal contractual restrictions and actually implement any of their contractual changes.

Conditional on funds that remove restrictions, we repeat the difference-in-difference analysis using the propensity score matching approach (PSM) specified in Table 2.6 for funds that actually implement and do not implement the strategies separately. Table 2.8 shows that funds remove contractual restriction and implement those strategies generally have no better (and sometimes even worse) performance. For example, funds newly allow trading in restricted securities and then actually do invest in restricted securities show the worst decrease in returns and Sharpe ratio. Funds lower fees following removing contractual restrictions and implementing those strategies, but the change in expense ratio is economically insignificant. Funds that remove restriction and then actually invest in restricted securities have a lower flow-performance sensitivity. But generally, Table 2.8 also shows that removing constraints and actually implementing those strategies has no significant effect on fund flows, return volatility, cash holding, and number of shareholder accounts.

Overall, we find no evidence that the funds that have more freedom and actually implement hedge fund-like strategies have better performance and flows. Being more like a hedge fund does not appear to help mutual fund to increase performance and flows. We also find no evidence that being more like a hedge fund have significant effects on fund fees, return volatility, cash holding, and fund investor clientele.

7. Other reasons for removing restrictions

The prior sections demonstrate no impact from additional investment freedom. If not to increase performance, attract flows, or hedge downside risk, why do mutual funds remove restrictions on investment, share liquidity and compensations? In this section, we test several explanations for why funds remove contractual restrictions.

7.1 Retain or attract fund managers

One aspect of contractual restrictions not yet considered is their use to retain or attract fund managers. A manager may find fewer restrictions attractive, allowing him or her to invest with more autonomy. We consider the possibility that contract restriction removal may precede management changes. Panel A of Table 2.9 models the likelihood of any change in a fund’s management using a logit model. Management changes include changes from single manager to single manager, single manager to team management, and team management to single management. All continuous independent variables have been converted to *z*-scores and marginal effects are reported as in Table 2.9.

Panel A of Table 2.9 shows that the probability of a management change increases by 2.33% following the removal of a restriction. The unconditional probability of management change in a six-month period is 8.47%, which suggests that contractual restriction removal has a large impact on manager turnover. Consistent with Khorana (1996), we find that funds with low flow and high turnover ratio are more likely to replace managers.

While these results do not support the idea of retaining managers, the data suggest three possible scenarios. First, managers in funds given more freedom are more likely to get recruited elsewhere. Second, managers in funds given more freedom are more likely to get fired. Third, investment freedom may be relevant in attracting a new manager. Without more information on why a manager has left, we cannot distinguish between these scenarios. We can conclude, however, that individual fund restrictions play a role in management transitions, if not performance improvement.[22]

We also consider the possibility that management changes may precede contract restriction removals. New fund managers may be more likely to remove contractual restrictions. Panel B shows that fund manager change has no significant effect on contractual restriction removal.

7.2 Bad-performing funds roll the dice

When a mutual fund begins using hedge fund-like strategies, it can be a sign that funds start to "roll the dice."[23] Specifically, a bad fund may engage in lottery-like

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[22] We also confirm that the lack of performance changes noted earlier following restriction changes still exist when excluding funds with a simultaneous manager change. We did not perform a test of funds with restriction changes and a manager change because the sample was too small to deliver meaningful statistics.

[23] "Mutual Funds Adopt Hedge-Fund Tactics", Wall Street Journal 2/21/2006.

investments in the hope of achieving outperformance. If that is the case, bad-performing funds have more incentive to actually implement the hedge fund-like strategies than good-performing funds.

In Panel A of Table 2.10, we compare the probability of implementing the newly allowed strategies between bad and good performing funds. We define bad performing funds as funds that underperform the style average. Conditional on restriction removal, we find that bad performing funds are not more likely (and sometimes less likely) to implement the newly allowed strategies than good-performing funds. For example, 10.00% of bad-performing funds and 16.85% of good-performing funds that remove the restriction in investing restricted securities actually implement that within 6-month period, the resulting difference of 6.85% in the implement ratio is statistically significant in 10% level.

Next, we compare the fund characteristics between funds that implement and don't implement the newly allowed strategies. Panel B shows that, conditional on restriction removal, funds with good performance, high flows, high expense ratio, and high turnover ratio are more likely to implement the newly allowed strategies. Overall, we find no evidence that funds use hedge fund-like strategies to roll the dice.

8. Discussion

We confirm a prediction of Stulz (2007) that mutual funds and hedge funds increasingly face similar investment restrictions over time. The result of these changes, however, suggests little benefit (and some harm) to mutual fund performance. Given the relative rarity of funds implementing dynamic strategies, why do funds so frequently give managers this freedom when it does little good? We discuss several potential barriers preventing fund managers from fully taking advantage of their new freedoms.

The first barrier is transparency and regulatory requirements. Individual mutual fund holdings are available from the SEC and allow for copy-cat trading, an additional risk for any investment. Hedge funds, however, file their holdings at the aggregate advisor level, allowing individual funds to better mask their trades. Further, mutual funds are prohibited from taking on more than 33.33% leverage in their fund, while hedge funds face no leverage restrictions.

Second, mutual fund liquidity needs may serve as a barrier to implementation. While there is an increasing trend in imposing early redemption penalties, most mutual fund investors have daily liquidity in their shares. Hedge fund investors, on the other hand, may be locked in to their shares for years and, in some cases, the hedge fund manager can “side pocket” funds tied up in an illiquid trade, preventing any redemption at all (Aiken, Clifford, Ellis, 2014). Maintaining liquidity is a significant cost for a mutual fund (Edelen, 1999), and funds may avoid restricted assets and other illiquid assets even if they are allowed to buy them.

The third possibility is that mutual fund managers lack the experience to implement these strategies. Agarwal, Boyson and Naik (2009) find hedged mutual funds outperform traditional mutual funds, but the superior performance is driven by managers with hedge fund management experience. Cici and Palacios (2013) find that using options generates, on average, no performance advantages for mutual funds. They argue that using options requires specialized knowledge of options markets and options pricing, which go beyond mutual fund managers’ conventional skills.

These barriers may decrease the incentive for managers to short, leverage, and implement other dynamic trading strategies. Put another way, the required payoff for implementing these strategies will have to be much higher to tempt a mutual fund manager into investing. Until mutual fund shareholders reward funds using these strategies, any convergence of the mutual fund and hedge fund industries will be significantly delayed.

9. Conclusion

The literature typically finds that mutual funds underperform hedge funds. An often cited explanation for the disparate performance is the difference in contracting environment between mutual funds and hedge funds. Mutual funds show a distinct trend towards more freedom in investment, share liquidity, and compensation over the past 15 years, making the average mutual fund more like a hedge fund.

We examine the motivation for changes in restrictions, we find that funds that have lower than expected flows given their past performance are more likely to remove contractual restrictions, likely with the hope of attracting more cash flow looking for hedge fund behavior in mutual funds. Funds with good performance are more likely to remove restrictions, which suggest that contractual restrictions may serve as a bargaining tool between fund managers and investors. Family considerations also have strong predictive power. Funds with less restricted peers in the family are more likely to remove the contractual restrictions, suggesting that the restrictions faced by the fund are likely more about family policy than fund policy.

When we examine the impact of investment restrictions on mutual funds, we find no evidence that general increase in freedom has a positive impact on fund performance.

Funds do not perform better (and sometimes perform worse) following contractual restriction removal. The impact of emulating the greater freedom enjoyed by hedge funds has not paid off for fund investors, though so few funds do each investment activity. The results suggest that compensation, liquidity, and investment constraints are unlikely to be binding for the average mutual fund and unlikely to explain the difference in performance between hedge funds and mutual funds.

Table 2.1: Fund freedom through time

This table provides summary statistics on the mutual fund freedom through time in the sample of domestic equity funds. Using the last observation for each fund in every year, the table shows the proportion of funds that reported they were permitted to implement in the practices listed in the column heads and proportion of funds that actually, conditional on permitted to, implement in the practices listed in the column heads. Short refers to short sale. Option refers to writing or investing in options on equities, stock indices, futures, or stock index futures. Leverage refers to borrowing money or margin purchases. Restricted refers to holding of restricted securities. Short-term trading fee refers to a redemption fee other than a deferred or contingent sales load. Performance fee refers to the advisory fee based in whole or in part of fund's investment performance.

Year	Short		Option		Leverage		Restricted		Short-term fee		Performance fee
	Can	Did	Can	Did	Can	Did	Can	Did	Can	Did	Can
1996	27%	6%	69%	14%	72%	8%	73%	29%	4%	65%	4%
1997	28%	7%	74%	12%	75%	7%	79%	28%	3%	78%	5%
1998	28%	8%	76%	16%	74%	11%	83%	22%	6%	78%	5%
1999	33%	8%	78%	13%	77%	12%	85%	21%	7%	89%	5%
2000	35%	7%	80%	12%	79%	13%	86%	22%	8%	85%	4%
2001	38%	8%	81%	11%	79%	12%	87%	20%	11%	85%	5%
2002	48%	7%	84%	13%	83%	12%	90%	21%	14%	83%	5%
2003	52%	6%	87%	11%	82%	9%	92%	17%	15%	75%	5%
2004	54%	5%	88%	9%	83%	8%	92%	16%	24%	71%	5%
2005	57%	5%	89%	10%	84%	10%	92%	18%	29%	72%	6%
2006	59%	5%	89%	9%	84%	11%	93%	18%	29%	77%	7%
2007	61%	5%	89%	10%	85%	12%	92%	18%	30%	74%	6%
2008	63%	6%	89%	11%	85%	12%	92%	18%	30%	75%	6%
2009	62%	8%	90%	12%	87%	12%	92%	17%	26%	72%	7%
2010	60%	7%	88%	11%	84%	13%	91%	18%	24%	75%	6%
2011	64%	6%	89%	9%	85%	10%	92%	17%	22%	76%	7%
1996-2003	38%	7%	80%	13%	79%	11%	86%	21%	9%	80%	5%
2004-2011	60%	6%	89%	10%	85%	11%	92%	17%	27%	74%	6%
Overall	52%	6%	86%	11%	82%	11%	90%	19%	20%	75%	6%

Table 2.2: Summary statistics

This table shows summary statistics for variables used in Table 2.3. *Restriction removal* is a dummy which equals to 1 if the fund removes a restriction. *Fund score* is a score ranging from zero to six that measures the amount of freedom a fund has to use hedge fund-like strategies as of the prior N-SAR report date. *Family score* is the equally weighted average of scores for all funds in a family in the sample as of the prior N-SAR report date. *Prior 12 month average return* is the average monthly return using 12 months of returns ending at the last N-SAR report date. *Prior 12 month return volatility* is the standard deviation of monthly returns over the same time frame. *Prior 12 month average flow* is the average monthly flow using 12 months of flows ending at the last N-SAR report date. *Prior 12 month flow volatility* is the standard deviation of monthly flows over the same time frame. *Prior 12 month average unexpected flow* is the average monthly unexpected flows using 12 months of flows ending at the last N-SAR report date. *Prior 12 month unexpected flow volatility* is the standard deviation of monthly unexpected flows over the same time frame. Unexpected flow is the residual from regressing flow on lag of return, return volatility, turnover ratio, expense ratio, natural log of fund age, natural log of TNA, style dummies, and year dummies. *Log (TNA)* is the natural log of the fund's TNA. *Log (Fund age)* is the natural log of the total number of months the fund is present in CRSP. *Expense ratio* is the reported expense ratio for the fund. *Turnover ratio* is the percentage of the fund traded using the SEC definition of turnover and reported in CRSP. *Load* is a dummy which equals to 1 if the fund has a front or a back-end load. *Log(Family TNA)* is the natural log of family TNA. *Team managed* is a dummy variable indicating that the fund was team managed as of the last N-SAR report date. *Log (TNA)*, *Log (Fund age)*, *Expense ratio*, *Turnover Ratio*, *Load*, *Log(Family TNA)*, and *Team managed* are all as of the prior N-SAR report date. For each variable, the number of observations, mean, 10th, 50th, and 90th percentiles, and standard deviation are presented.

Variable	N	Mean	10th percentile	Median	90th percentile	Std Dev
Restriction removal	28,673	0.06	0.00	0.00	0.00	0.24
Fund score	28,673	3.37	2.00	4.00	5.00	1.18
Family score	28,673	3.37	2.00	3.50	4.85	1.09
Prior 12 month average return (%)	28,673	0.63	-2.10	0.95	2.60	1.92
Prior 12 month return volatility (%)	28,673	5.03	2.36	4.55	8.29	2.55
Prior 12 month average flow (%)	28,673	0.39	-2.46	-0.26	3.92	3.48
Prior 12 month average flow volatility (%)	28,673	3.64	0.54	1.85	7.92	5.73
Prior 12 month average unexpected return (%)	28,673	-0.01	-2.98	-0.38	3.18	3.31
Prior 12 month return unexpected volatility (%)	28,673	3.70	0.72	1.92	7.88	5.68
Log(TNA)	28,673	5.66	3.42	5.56	8.00	1.77
Fund age	28,673	162.81	48.00	124.00	362.00	125.02
Expense ratio	28,673	0.01	0.01	0.01	0.02	0.00
Turnover ratio	28,673	0.89	0.19	0.69	1.80	0.75
Load	28,673	0.51	0.00	1.00	1.00	0.50
Log(Family TNA)	28,673	9.15	5.49	9.30	12.36	2.61
Team managed	28,673	0.58	0.00	1.00	1.00	0.49

Table 2.3: Likelihood of a restriction removal

This table shows the marginal effect of a logit regression of a restriction removal. There are six possible restriction removals: *Short*, *Option*, *Leverage*, *Restricted*, *Short-term fee*, and *Performance fee*. *Short* indicates that short sale was newly allowed. *Option* indicates the writing or investing in options on equities, stock indices, futures, or stock index futures was newly allowed. *Leverage* indicates borrowing money or margin purchases was newly allowed. *Restricted* indicates holding of restricted securities was newly allowed. *Short-term fee* indicates charging short-term trading fee was newly allowed. *Performance fee* indicates charging performance fee was newly allowed. *Any* indicates any of the above six strategies was newly allowed. All other variables are described in Table 2.2. All continuous variables have been converted to z-score, meaning we subtract out the variable's mean and divide by the standard deviation for each observation. Each regression includes the observations with the corresponding strategy not allowed as of the prior N-SAR report date. Coefficients have been suppressed and replaced with marginal effect. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: Restriction removal and fund flow

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Prior 12 month average return	0.0046***	0.0048**	0.0076	-0.0004	0.0014	0.0023**	0.0002
	(0.007)	(0.011)	(0.152)	(0.945)	(0.852)	(0.040)	(0.462)
Prior 12 month return volatility	-0.0000	-0.0004	0.0016	0.0025	0.0096	-0.0009	0.0004**
	(1.000)	(0.850)	(0.744)	(0.631)	(0.171)	(0.391)	(0.040)
Prior 12 month average flow	-0.0028**	-0.0028*	-0.0095**	-0.0175***	-0.0123**	0.0002	0.0003
	(0.042)	(0.093)	(0.023)	(0.000)	(0.021)	(0.788)	(0.177)
Prior 12 month flow volatility	0.0031**	0.0036**	0.0103***	0.0170***	0.0139***	0.0004	-0.0002
	(0.018)	(0.018)	(0.006)	(0.000)	(0.006)	(0.589)	(0.460)
Log(TNA)	0.0045***	0.0056***	0.0045	0.0080	0.0048	-0.0002	-0.0004
	(0.007)	(0.004)	(0.380)	(0.118)	(0.490)	(0.887)	(0.162)
Log(Fund age)	-0.0069***	-0.0076***	-0.0101**	-0.0136***	-0.0033	-0.0007	0.0001
	(0.000)	(0.000)	(0.011)	(0.001)	(0.532)	(0.389)	(0.640)
Expense ratio	0.0053***	0.0088***	0.0127***	0.0048	0.0187***	0.0012	-0.0005**
	(0.000)	(0.000)	(0.002)	(0.258)	(0.001)	(0.146)	(0.036)
Turnover ratio	0.0034***	0.0043***	0.0085**	0.0033	0.0034	0.0004	0.0007***
	(0.004)	(0.003)	(0.026)	(0.413)	(0.522)	(0.535)	(0.000)
Load dummy	0.0056**	-0.0068**	-0.0107	0.0140*	0.0374***	0.0069***	-0.0015***
	(0.032)	(0.027)	(0.181)	(0.093)	(0.002)	(0.000)	(0.003)
Fund score	-0.0422***	-0.0143***	-0.0444***	-0.0497***	-0.0353***	-0.0058***	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.474)
Family score	0.0149***	0.0086***	0.0197***	0.0196***	0.0058	0.0070***	0.0013***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.409)	(0.000)	(0.008)
Team	0.0042*	0.0079***	-0.0162**	-0.0065	0.0044	0.0018	-0.0003
	(0.071)	(0.004)	(0.044)	(0.391)	(0.669)	(0.209)	(0.486)
Log(Family size)	0.0070***	0.0175***	0.0271***	0.0200***	0.0548***	-0.0060***	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.039)
Style dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1111	0.0881	0.1081	0.1115	0.1583	0.0921	0.0964
Observations	28,404	13,982	4,071	4,924	2,820	21,907	25,822

Panel B: Restriction removal and unexpected fund flow

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Prior 12 month average return	0.0044***	0.0046**	0.0068	-0.0017	0.0005	0.0024**	0.0002
	(0.010)	(0.016)	(0.196)	(0.761)	(0.945)	(0.036)	(0.419)
Prior 12 month return volatility	0.0000	-0.0003	0.0017	0.0027	0.0096	-0.0009	0.0004**
	(0.984)	(0.856)	(0.724)	(0.612)	(0.168)	(0.396)	(0.042)
Prior 12 month unexpected average flow	-0.0024*	-0.0022	-0.0087**	-0.0163***	-0.0120**	0.0002	0.0003
	(0.076)	(0.167)	(0.032)	(0.000)	(0.020)	(0.768)	(0.154)
Prior 12 month unexpected flow volatility	0.0028**	0.0033**	0.0098***	0.0163***	0.0138***	0.0003	-0.0002
	(0.034)	(0.028)	(0.009)	(0.000)	(0.006)	(0.696)	(0.430)
Log(TNA)	0.0044***	0.0055***	0.0044	0.0081	0.0050	-0.0002	-0.0004
	(0.009)	(0.005)	(0.391)	(0.116)	(0.469)	(0.863)	(0.151)
Log(Fund age)	-0.0062***	-0.0068***	-0.0077*	-0.0091**	-0.0001	-0.0008	0.0000
	(0.000)	(0.000)	(0.051)	(0.020)	(0.989)	(0.322)	(0.898)
Expense ratio	0.0054***	0.0088***	0.0128***	0.0050	0.0190***	0.0012	-0.0005**
	(0.000)	(0.000)	(0.002)	(0.234)	(0.001)	(0.154)	(0.034)
Turnover ratio	0.0035***	0.0043***	0.0087**	0.0037	0.0036	0.0005	0.0007***
	(0.003)	(0.002)	(0.022)	(0.355)	(0.496)	(0.524)	(0.000)
Load dummy	0.0056**	-0.0068**	-0.0106	0.0139*	0.0374***	0.0069***	-0.0015***
	(0.032)	(0.027)	(0.182)	(0.096)	(0.002)	(0.000)	(0.003)
Fund score	-0.0421***	-0.0143***	-0.0444***	-0.0497***	-0.0353***	-0.0058***	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.475)
Family score	0.0149***	0.0086***	0.0197***	0.0196***	0.0058	0.0070***	0.0013***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.405)	(0.000)	(0.008)
Team	0.0042*	0.0079***	-0.0161**	-0.0064	0.0043	0.0018	-0.0003
	(0.069)	(0.004)	(0.045)	(0.396)	(0.674)	(0.206)	(0.484)
Log(Family size)	0.0071***	0.0176***	0.0272***	0.0201***	0.0548***	-0.0060***	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.039)
Style dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1110	0.0879	0.1077	0.1109	0.1583	0.0921	0.0966
Observations	28,404	13,982	4,071	4,924	2,820	21,907	25,822

Table 2.4: The effect of restriction removal on fund performance

This table shows the changes in fund performance around contract restriction removals. The definition of contract restriction removal is as described in Table 2.3. The tests use twelve months of returns starting eighteen months before the N-SAR report date for pre-change returns and twelve months following the report date for the post-change returns. Dependent variable is the style-adjusted return. *Post* is a dummy variable equal to one if the return is in the twelve months after the contract change and zero otherwise. *Average style-adj ret*$_{(t-3,t-1)}$ is the trailing three-month average style-adjusted return. *Average style-adj gret*$_{(t-3,t-1)}$ is the trailing three-month average style-adjusted gross-of-expenses return. The remaining variables are as described in Table 2.2. Panel A uses the CRSP fund monthly net return. Panel B uses "gross-of-expenses" returns calculated as net return plus 1/12 of the annual expense ratio. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: The changes in fund net return around contract restriction changes

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Post	-0.0003	-0.0008	-0.0011	-0.0015**	-0.0010	0.0006	0.0016
	(0.315)	(0.194)	(0.144)	(0.029)	(0.156)	(0.268)	(0.318)
Log (Fund age)	0.0000	-0.0003	0.0005	0.0007	0.0008	-0.0001	-0.0028*
	(0.961)	(0.474)	(0.321)	(0.160)	(0.152)	(0.845)	(0.094)
Log (TNA)	-0.0004***	-0.0005***	-0.0005**	-0.0006***	-0.0005*	-0.0005**	-0.0004
	(0.000)	(0.004)	(0.016)	(0.002)	(0.096)	(0.017)	(0.373)
Turnover Ratio	-0.0001	-0.0000	-0.0005	-0.0001	0.0002	-0.0005	-0.0004
	(0.662)	(0.980)	(0.364)	(0.867)	(0.783)	(0.176)	(0.735)
Expense ratio	0.0108	0.0069	0.1606	-0.0425	-0.0774	0.0101	-0.1412
	(0.868)	(0.944)	(0.139)	(0.726)	(0.584)	(0.908)	(0.519)
Average style-adj ret$_{(t-3,t-1)}$	0.0717***	0.0145	0.1524***	0.0484	0.1272***	0.0766***	0.0255
	(0.000)	(0.703)	(0.000)	(0.114)	(0.000)	(0.002)	(0.671)
Intercept	0.0040	0.0153***	0.0131**	0.0116***	0.0036	0.0058	0.0410***
	(0.240)	(0.001)	(0.013)	(0.003)	(0.389)	(0.431)	(0.000)
Style dummy	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y
R-squared	0.01	0.01	0.03	0.01	0.02	0.02	0.03
Observations	39,277	12,813	7,107	10,068	6,610	11,916	2,096

Panel B: The changes in fund gross-of-expenses return around contract restriction changes

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Post	-0.0002	-0.0007	-0.0010	0.0017	-0.0009	0.0007	0.0017
	(0.472)	(0.277)	(0.186)	(0.292)	(0.184)	(0.190)	(0.292)
Log (Fund age)	-0.0000	-0.0004	0.0005	-0.0029*	0.0008	-0.0001	-0.0029*
	(0.937)	(0.404)	(0.319)	(0.084)	(0.140)	(0.824)	(0.084)
Log (TNA)	-0.0004***	-0.0005***	-0.0005**	-0.0004	-0.0004	-0.0005**	-0.0004
	(0.000)	(0.004)	(0.021)	(0.433)	(0.104)	(0.014)	(0.433)
Turnover Ratio	-0.0001	-0.0001	-0.0005	-0.0004	0.0001	-0.0005	-0.0004
	(0.617)	(0.921)	(0.386)	(0.737)	(0.824)	(0.173)	(0.737)
Expense ratio	0.0842	0.0906	0.2286**	-0.0768	0.0036	0.0890	-0.0768
	(0.194)	(0.357)	(0.037)	(0.731)	(0.980)	(0.308)	(0.731)
Average style-adj ret$_{(t-3,t-1)}$	0.0690***	0.0092	0.1493***	0.0216	0.1245***	0.0739***	0.0216
	(0.000)	(0.806)	(0.000)	(0.712)	(0.000)	(0.003)	(0.712)
Intercept	0.0030	0.0152***	0.0159***	0.0773***	0.0015	-0.0051**	0.0773***
	(0.187)	(0.001)	(0.002)	(0.003)	(0.715)	(0.012)	(0.003)
Style dummy	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y
R-squared	0.01	0.01	0.03	0.04	0.02	0.03	0.04
Observations	39,259	12,808	7,101	2,095	6,608	11,913	2,095

Table 2.5: The effect of restriction removal on fund flows

This table shows the changes in fund flows around contract restriction removals. The definition of contract restriction removal is as described in Table 2.3. The tests use twelve months of flows starting eighteen months before the N-SAR report date for pre-change flows and twelve months following the report date for the post-change flows. Dependent variable is mutual fund flow. *Post* is a dummy variable equal to one if the flow is in the twelve months after the contract change and zero otherwise. Following Sirri and Tufano (1998), we use a piecewise linear relationship between current flows and past returns. *Low* = min(*Rank*, 0.2); *Mid* = min(*Rank* - *Low*, 0.6); and *High*= (*Rank* – *Low* - *Mid*). *Rank* is the percentile performance rank across all funds in the sample during each month. Return volatility is the standard deviation of trailing 12-month returns. The remaining variables are as described in Table 2.2. *Rank, Log (Fund age)*, *Log (TNA)*, *Turnover ratio,* and *Expense ratio* are all as of the month t-1. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively. *p*-values are presented below in parentheses.

	Any	Short	Option	Leverage	Restricted	Short-term fee	Performance fee
Post	0.0008	-0.0011	-0.0002	-0.0004	0.0037	0.0037	0.0020
	(0.774)	(0.799)	(0.970)	(0.938)	(0.730)	(0.545)	(0.861)
Post*High	0.0005	0.0511*	0.0049	-0.0567	-0.0953	-0.0222	0.0550
	(0.981)	(0.099)	(0.911)	(0.149)	(0.104)	(0.560)	(0.475)
Post*Mid	-0.0018	-0.0059	0.0041	0.0054	0.0160**	-0.0013	0.0042
	(0.604)	(0.274)	(0.653)	(0.370)	(0.026)	(0.836)	(0.873)
Post*Low	-0.0138	0.0030	-0.0009	-0.0150	-0.0340	-0.0421	-0.0202
	(0.405)	(0.903)	(0.982)	(0.566)	(0.565)	(0.197)	(0.826)
High	0.0839***	0.0418	0.0948***	0.1064***	0.1168***	0.1260***	0.0350
	(0.000)	(0.127)	(0.009)	(0.000)	(0.007)	(0.000)	(0.546)
Mid	0.0141***	0.0214***	0.0105	0.0071*	0.0086*	0.0118**	0.0153
	(0.000)	(0.000)	(0.154)	(0.086)	(0.076)	(0.032)	(0.407)
Low	0.0129	-0.0186	0.0112	0.0403**	-0.0144	0.0278	0.0058
	(0.337)	(0.327)	(0.721)	(0.040)	(0.712)	(0.232)	(0.942)
Return volatility	-0.0665*	-0.0310	0.0311	-0.0308	-0.2175***	-0.0218	0.0560
	(0.064)	(0.477)	(0.641)	(0.580)	(0.008)	(0.779)	(0.687)
Log (Fund age)	-0.0075***	-0.0074***	-0.0066***	-0.0033**	-0.0050**	-0.0112***	-0.0191***
	(0.000)	(0.000)	(0.001)	(0.027)	(0.016)	(0.000)	(0.003)
Log (TNA)	0.0012***	0.0010*	0.0025***	0.0013**	0.0025***	0.0006	-0.0002
	(0.002)	(0.099)	(0.001)	(0.046)	(0.004)	(0.415)	(0.904)
Turnover ratio	-0.0006	0.0005	-0.0032*	-0.0033*	0.0005	-0.0000	-0.0034
	(0.566)	(0.784)	(0.054)	(0.079)	(0.835)	(0.998)	(0.385)
Expense ratio	0.1270	0.2829	0.9154***	0.1098	0.1630	0.1681	-0.4318
	(0.498)	(0.324)	(0.008)	(0.745)	(0.639)	(0.652)	(0.630)
Intercept	0.0323**	0.0378***	-0.0182	-0.0147	0.0262	0.0298	0.0783**
	(0.039)	(0.006)	(0.445)	(0.286)	(0.331)	(0.547)	(0.022)
Style dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.02	0.03	0.04	0.02	0.03	0.03	0.04
Observations	39,288	12,826	7,089	10,071	6,612	11,910	2,114

Table 2.6: Matched sample analysis of the changes in fund characteristics

This table shows the effect of restriction removal based on 1-to-10 propensity score matching. The definition of contract restriction removal is as described in Table 2.3. Panel A compares the changes in the 12-month average return, flow, return volatility, and Sharpe ratio before and after the restriction removal between funds with restriction removal and matched funds without restriction changes. Panel B compares the changes in fund other characteristics, including expense ratio, flow sensitivity, number of shareholder accounts, and cash ratio. Flow sensitivity is the regression coefficient of flow on lagged style-adjusted return. We construct the matched sample by matching funds on the propensity score estimated from the results of the logistic regression in Panel A of Table 2.3. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively.

Panel A: Fund return and flow changes

		Before	After	Change	Matched	Difference	*p*-value
Monthly return	Any	0.84%	0.67%	-0.17%	-0.17%	0.00%	0.904
	Short	0.88%	0.67%	-0.21%	-0.14%	-0.06%	0.372
	Option	0.87%	0.68%	-0.20%	-0.10%	-0.10%	0.311
	Leverage	0.69%	0.76%	0.07%	0.17%	-0.10%	0.160
	Restricted	0.70%	0.92%	0.21%	0.28%	-0.07%	0.426
	Short-term fee	0.92%	0.62%	-0.31%	-0.32%	0.01%	0.854
	Performance fee	0.41%	0.99%	0.58%	0.45%	0.14%	0.491
Monthly flow	Any	0.76%	-0.05%	-0.81%	-0.75%	-0.06%	0.566
	Short	0.88%	-0.06%	-0.94%	-0.69%	-0.25%	0.161
	Option	0.62%	0.12%	-0.50%	-0.50%	0.00%	0.987
	Leverage	0.68%	-0.15%	-0.84%	-0.46%	-0.38%**	0.047
	Restricted	0.97%	-0.02%	-0.99%	-0.83%	-0.16%	0.571
	Short-term fee	0.69%	-0.13%	-0.83%	-0.81%	-0.02%	0.929
	Performance fee	0.97%	0.48%	-0.49%	-0.16%	-0.33%	0.603
Return volatility	Any	5.06%	5.04%	-0.02%	-0.06%	0.04%	0.306
	Short	5.32%	5.24%	-0.08%	-0.04%	-0.04%	0.599
	Option	5.13%	5.27%	0.14%	0.14%	0.00%	0.987
	Leverage	5.04%	5.32%	0.28%	0.17%	0.12%	0.141
	Restricted	5.01%	5.19%	0.18%	0.03%	0.15%*	0.082
	Short-term fee	4.81%	4.49%	-0.32%	-0.36%	0.04%	0.594
	Performance fee	5.42%	5.33%	-0.09%	0.07%	-0.17%	0.502
Sharpe ratio	Any	-1.15%	-4.12%	-2.97%	-2.87%	-0.09%	0.940
	Short	-0.96%	-5.04%	-4.08%	-1.71%	-2.37%	0.262
	Option	-2.21%	-6.35%	-4.13%	-0.93%	-3.21%	0.297
	Leverage	-5.32%	-7.84%	-2.52%	0.04%	-2.56%	0.293
	Restricted	-4.64%	-8.00%	-3.36%	-1.20%	-2.16%	0.455
	Short-term fee	2.64%	-0.01%	-2.65%	-2.55%	-0.10%	0.964
	Performance fee	-1.44%	4.23%	5.67%	-3.45%	9.12%	0.115

Panel B: Fund other characteristics change

		Before	After	Change	Matched	Difference	*p*-value
Expense ratio	Any	1.31%	1.29%	-0.02%	-0.01%	0.00%	0.274
	Short	1.29%	1.27%	-0.02%	-0.02%	0.00%	0.984
	Option	1.28%	1.26%	-0.02%	0.00%	-0.02%**	0.042
	Leverage	1.31%	1.28%	-0.02%	0.00%	-0.03%***	0.000
	Restricted	1.31%	1.30%	-0.01%	0.01%	-0.02%***	0.005
	Short-term fee	1.39%	1.35%	-0.04%	-0.02%	-0.02%**	0.023
	Performance fee	1.17%	1.19%	0.02%	-0.07%	0.09%***	0.001
Flow sensitivity	Any	16.28%	10.55%	-5.73%	-0.68%	-5.05%	0.321
	Short	17.58%	6.21%	-11.37%	5.18%	-16.55%*	0.086
	Option	21.14%	18.83%	-2.31%	0.86%	-3.17%	0.781
	Leverage	29.91%	8.57%	-21.34%	4.41%	-25.75%**	0.015
	Restricted	22.25%	5.64%	-16.61%	3.21%	-19.82%	0.106
	Short-term fee	14.81%	7.46%	-7.35%	-11.83%	4.48%	0.650
	Performance fee	-0.63%	11.85%	12.47%	6.84%	5.63%	0.843
Cash ratio	Any	0.38%	0.25%	-0.12%	-0.01%	-0.12%**	0.018
	Short	0.32%	0.32%	0.00%	-0.03%	0.03%	0.700
	Option	0.25%	0.19%	-0.06%	0.08%	-0.14%	0.276
	Leverage	0.33%	0.20%	-0.13%	-0.10%	-0.03%	0.661
	Restricted	0.57%	0.40%	-0.17%	-0.09%	-0.09%	0.579
	Short-term fee	0.35%	0.27%	-0.07%	-0.12%	0.05%	0.376
	Performance fee	0.80%	0.03%	-0.78%	0.17%	-0.95%**	0.027
Shareholder accounts	Any	17196	17440	244	199	45	0.905
	Short	20130	19785	-345	-57	-288	0.690
	Option	16144	16737	594	478	116	0.907
	Leverage	17570	17904	334	528	-194	0.787
	Restricted	14651	16448	1797	342	1454	0.165
	Short-term fee	14003	13773	-230	594	-823*	0.090
	Performance fee	18787	20237	1450	-351	1801	0.404

Table 2.7: Fund restriction removals through time

This table provides summary statistics on the mutual fund contract restriction removals through time in the sample of domestic equity funds. Column (a) shows the number of funds removing the restriction listed in the column heads. Column (b) shows the proportion of funds that remove the restriction in the column heads actually implement the strategy within two years following the restriction removal. The definition of contract restriction removal is as described in Table 2.3.

Year	Short		Option		Leverage		Restricted		Short-term fee		Performance fee
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)
1996	9	11%	8	50%	13	23%	13	46%	1	100%	0
1997	17	12%	23	22%	35	6%	35	31%	0		2
1998	17	12%	21	33%	21	52%	24	21%	9	33%	2
1999	38	8%	24	21%	47	26%	23	48%	8	88%	5
2000	34	3%	19	16%	18	33%	22	32%	13	69%	1
2001	26	12%	20	40%	22	9%	14	29%	35	86%	9
2002	120	3%	49	10%	93	25%	44	16%	50	68%	6
2003	36	0%	13	15%	21	10%	19	21%	36	72%	7
2004	46	0%	22	14%	32	9%	16	13%	159	76%	1
2005	44	7%	24	8%	24	33%	18	17%	76	70%	15
2006	33	12%	16	6%	21	14%	22	27%	33	45%	6
2007	48	8%	15	13%	36	22%	14	0%	56	63%	8
2008	35	3%	27	4%	28	7%	13	15%	31	81%	14
2009	22	14%	16	19%	29	83%	15	33%	31	35%	7
2010	41		38		22		30		17		7
2011	57		25		36		22		11		7
1996-2009	525	6%	297	17%	440	25%	292	25%	538	69%	97

Table 2.8: The changes in fund characteristics for funds that implement and do not implement the newly allowed strategy

This table shows the effect of restriction removal based on 1-to-10 propensity score matching for funds that implement or do not implement the newly allowed strategy separately. Panel A compares the change in the 12-month average return, flow, return volatility, and Sharpe ratio before and after the restriction removal between funds with restriction removal and matched funds without restriction changes. Panel B compares the changes in fund other characteristics, including expense ratio, flow sensitivity, number of shareholder accounts, and cash ratio. Flow sensitivity is the regression coefficient of flow on lagged style-adjusted return. We construct the matched sample by matching funds on the propensity score estimated from the results of the logistic regression in Panel A of Table 2.3. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively.

Panel A: Fund return and flow changes

		Remove & Implement				Remove & Don't implement			
		Change	Matched	Difference	*p*-value	Change	Matched	Difference	*p*-value
Monthly return	Any	-0.38%	-0.24%	-0.14%	0.102	-0.15%	-0.17%	0.02%	0.733
	Short	-0.57%	-0.66%	0.09%	0.752	-0.19%	-0.12%	-0.07%	0.334
	Option	-0.31%	-0.19%	-0.11%	0.695	-0.18%	-0.09%	-0.10%	0.350
	Leverage	0.16%	0.48%	-0.33%*	0.064	0.05%	0.12%	-0.06%	0.417
	Restricted	-0.99%	-0.19%	-0.80%**	0.017	0.39%	0.35%	0.04%	0.637
	Short-term fee	-0.39%	-0.32%	-0.07%	0.558	-0.23%	-0.32%	0.09%	0.246
Monthly flow	Any	-1.00%	-0.83%	-0.16%	0.528	-0.77%	-0.62%	-0.16%	0.192
	Short	-0.87%	-0.94%	0.08%	0.917	-0.94%	-0.68%	-0.26%	0.149
	Option	-0.53%	-0.69%	0.16%	0.822	-0.49%	-0.48%	-0.02%	0.946
	Leverage	-0.79%	-0.17%	-0.61%	0.301	-0.84%	-0.51%	-0.34%*	0.090
	Restricted	-2.11%	-0.71%	-1.40%	0.353	-0.83%	-0.85%	0.02%	0.926
	Short-term fee	-0.82%	-0.80%	-0.02%	0.946	-0.83%	-0.81%	-0.02%	0.954
Return volatility	Any	-0.13%	-0.25%	0.12%	0.148	0.02%	0.01%	0.01%	0.900
	Short	0.42%	0.01%	0.41%	0.266	-0.10%	-0.04%	-0.06%	0.441
	Option	-0.27%	-0.14%	-0.13%	0.629	0.19%	0.17%	0.01%	0.901
	Leverage	0.03%	-0.19%	0.23%	0.260	0.32%	0.22%	0.10%	0.248
	Restricted	0.86%	0.52%	0.34%	0.185	0.08%	-0.05%	0.13%	0.178
	Short-term fee	-0.34%	-0.32%	-0.02%	0.839	-0.31%	-0.40%	0.10%	0.279
Sharpe ratio	Any	-5.80%	-2.37%	-3.43%	0.198	-2.56%	-2.23%	-0.33%	0.824
	Short	-6.07%	-7.93%	1.86%	0.867	-3.99%	-1.42%	-2.56%	0.234
	Option	-3.14%	-1.86%	-1.28%	0.905	-4.25%	-0.82%	-3.44%	0.283
	Leverage	-3.78%	4.37%	-8.15%	0.191	-2.31%	-0.65%	-1.66%	0.530
	Restricted	-14.36%	7.23%	-21.59%**	0.027	-1.75%	-2.47%	0.73%	0.808
	Short-term fee	-5.99%	-1.79%	-4.20%	0.181	0.54%	-3.27%	3.81%	0.224

Panel B: Fund other characteristics change

		Remove & Implement				Remove & Don't implement			
		Change	Matched	Difference	*p*-value	Change	Matched	Difference	*p*-value
Expense ratio	Any	-0.04%	0.00%	-0.04%***	<.001	-0.02%	-0.01%	0.00%	0.825
	Short	-0.05%	-0.05%	0.00%	0.974	-0.02%	-0.02%	0.00%	0.973
	Option	-0.01%	-0.01%	-0.01%	0.680	-0.02%	0.00%	-0.02%**	0.046
	Leverage	-0.04%	0.02%	-0.06%**	0.016	-0.02%	0.00%	-0.02%***	0.003
	Restricted	-0.03%	-0.01%	-0.02%	0.400	-0.01%	0.01%	-0.02%***	0.007
	Short-term fee	-0.05%	-0.01%	-0.03%***	0.006	-0.04%	-0.03%	-0.01%	0.473
Flow sensitivity	Any	-5.52%	-4.81%	-0.71%	0.935	-7.25%	1.95%	-9.19%	0.138
	Short	20.91%	-9.46%	30.37%	0.352	-12.84%	5.85%	-18.69%**	0.061
	Option	6.26%	5.93%	0.34%	0.982	-3.35%	0.24%	-3.59%	0.776
	Leverage	-15.56%	1.10%	-16.65%	0.512	-22.27%	4.95%	-27.22%**	0.019
	Restricted	-35.46%	13.99%	-49.46%**	0.033	-13.85%	1.73%	-15.57%	0.254
	Short-term fee	0.45%	-14.60%	15.04%	0.180	-14.78%	-9.20%	-5.59%	0.728
Cash ratio	Any	-0.08%	-0.04%	-0.04%	0.478	-0.09%	-0.03%	-0.06%	0.280
	Short	0.09%	0.03%	0.05%	0.900	-0.01%	-0.03%	0.02%	0.719
	Option	-0.09%	-0.24%	0.14%	0.599	-0.05%	0.12%	-0.17%	0.218
	Leverage	-0.18%	0.00%	-0.18%	0.289	-0.12%	-0.11%	-0.01%	0.874
	Restricted	-0.17%	0.07%	-0.24%	0.384	-0.18%	-0.12%	-0.06%	0.752
	Short-term fee	-0.07%	-0.12%	0.05%	0.430	-0.07%	-0.13%	0.05%	0.586
Shareholder accounts	Any	-384	281	-665	0.375	347	495	-148	0.734
	Short	-3701	-1316	-2385	0.407	-164	10	-174	0.815
	Option	-151	281	-432	0.911	677	500	178	0.862
	Leverage	-2006	-329	-1677	0.554	644	636	7	0.992
	Restricted	349	1369	-1020	0.579	2030	195	1835	0.120
	Short-term fee	-88	333	-421	0.611	-365	847	-1212**	0.022

Table 2.9: Manager turnover and restriction removal

This table shows the relation between manager turnover and restriction removal. Panel A are the results for a logit model of the likelihood of manager change. The dependent variable is equal to one if there is a change in management during month t to t+6 and zero otherwise. Management changes include changes from single manager to single manager, single manager to team management, and team management to single management. *Restriction removal* is equal to one if the restriction listed in the column heads was removed during month t-6 to t. Panel B are the results for a logit model of the likelihood of restriction removal. The dependent variable is equal to one if the restriction listed in the column heads was removed during month t to t+6 and zero otherwise. Manager turnover is equal to one if there is a change in management during month t-6 to t and zero otherwise. All other independent variables are as described in Table 2.2 and measured at month t. The marginal effects are presented. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively. *p*-values are presented below in parentheses.

Panel A: A logit model of the likelihood of manager change

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Restriction removal	0.0233***	0.0062	0.0256	0.0346**	0.0116	0.0128	-0.0055
	(0.002)	(0.601)	(0.140)	(0.031)	(0.548)	(0.310)	(0.820)
Prior 12 month average return	0.0792	0.2600	0.0795	0.1899	0.1684	0.0448	0.0921
	(0.520)	(0.134)	(0.770)	(0.532)	(0.689)	(0.749)	(0.461)
Prior 12 month return volatility	-0.1676*	-0.3322***	-0.2925	-0.1712	-0.4953	-0.2211**	-0.1824**
	(0.056)	(0.009)	(0.131)	(0.438)	(0.103)	(0.028)	(0.042)
Prior 12 month average flow	-0.2684***	-0.3375***	-0.2114	-0.3455**	-0.0276	-0.2719***	-0.2923***
	(0.000)	(0.000)	(0.130)	(0.014)	(0.883)	(0.000)	(0.000)
Prior 12 month flow volatility	0.0514	0.0213	0.0279	0.0607	-0.0462	0.0821**	0.0451
	(0.123)	(0.692)	(0.731)	(0.490)	(0.700)	(0.031)	(0.183)
Log(TNA)	-0.0053***	-0.0072***	-0.0038	-0.0068**	-0.0071	-0.0054***	-0.0050***
	(0.000)	(0.000)	(0.178)	(0.019)	(0.110)	(0.000)	(0.000)
Log(Fund age)	0.0038	0.0017	0.0033	-0.0058	-0.0011	0.0018	0.0041
	(0.146)	(0.658)	(0.528)	(0.310)	(0.890)	(0.541)	(0.126)
Expense ratio	0.0001	-0.3076	1.7566*	0.9563	-0.1410	-0.2465	0.0230
	(1.000)	(0.639)	(0.066)	(0.383)	(0.924)	(0.640)	(0.961)
Turnover ratio	0.0138***	0.0164***	0.0111**	0.0137***	0.0187***	0.0141***	0.0145***
	(0.000)	(0.000)	(0.013)	(0.006)	(0.005)	(0.000)	(0.000)
Load dummy	0.0128***	0.0097*	0.0133	-0.0066	0.0219	0.0130***	0.0125***
	(0.001)	(0.050)	(0.125)	(0.452)	(0.108)	(0.001)	(0.001)
Fund score	0.0019	0.0121**	-0.0005	0.0085	0.0182*	0.0045	0.0054
	(0.591)	(0.022)	(0.943)	(0.223)	(0.078)	(0.261)	(0.148)
Family score	-0.0033	-0.0100*	-0.0025	-0.0104	-0.0121	-0.0057	-0.0054
	(0.395)	(0.069)	(0.704)	(0.177)	(0.238)	(0.193)	(0.177)
Team	-0.0849***	-0.0851***	-0.0805***	-0.0927***	-0.0582***	-0.0903***	-0.0849***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(Family TNA)	0.0040***	0.0048***	0.0029	0.0114***	0.0039	0.0038***	0.0042***
	(0.000)	(0.000)	(0.135)	(0.000)	(0.202)	(0.000)	(0.000)
Style dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.0830	0.0800	0.1043	0.1054	0.0879	0.0770	0.0848
Observations	23,318	11,381	3,285	4,016	2,251	18,502	22,013

Panel B: A logit model of the likelihood of restriction removal

	(1) Any	(2) Short	(3) Option	(4) Leverage	(5) Restricted	(6) Short-term fee	(7) Performance fee
Manager turnover	0.0002	-0.0040	0.0110	0.0041	0.0073	0.0009	0.0005
	(0.970)	(0.373)	(0.450)	(0.758)	(0.675)	(0.732)	(0.534)
Prior 12 month average return	0.0047***	0.0049**	0.0080	-0.0004	0.0023	0.0023**	0.0002
	(0.006)	(0.011)	(0.125)	(0.942)	(0.762)	(0.039)	(0.472)
Prior 12 month return volatility	-0.0000	-0.0004	0.0013	0.0026	0.0092	-0.0009	0.0004**
	(0.984)	(0.847)	(0.792)	(0.628)	(0.185)	(0.389)	(0.041)
Prior 12 month average flow	-0.0029**	-0.0028*	-0.0100**	-0.0175***	-0.0129**	0.0002	0.0003
	(0.037)	(0.090)	(0.017)	(0.000)	(0.015)	(0.785)	(0.172)
Prior 12 month flow volatility	0.0031**	0.0036**	0.0105***	0.0170***	0.0141***	0.0004	-0.0002
	(0.017)	(0.017)	(0.004)	(0.000)	(0.004)	(0.600)	(0.449)
Log(TNA)	0.0045***	0.0056***	0.0045	0.0081	0.0050	-0.0001	-0.0004
	(0.007)	(0.005)	(0.367)	(0.115)	(0.463)	(0.894)	(0.174)
Log(Fund age)	-0.0068***	-0.0076***	-0.0093**	-0.0135***	-0.0024	-0.0007	0.0001
	(0.000)	(0.000)	(0.019)	(0.001)	(0.643)	(0.378)	(0.653)
Expense ratio	0.0054***	0.0088***	0.0127***	0.0048	0.0189***	0.0012	-0.0005**
	(0.000)	(0.000)	(0.002)	(0.259)	(0.001)	(0.140)	(0.036)
Turnover ratio	0.0035***	0.0043***	0.0089**	0.0033	0.0041	0.0004	0.0007***
	(0.004)	(0.003)	(0.018)	(0.423)	(0.435)	(0.542)	(0.000)
Load dummy	0.0056**	-0.0068**	-0.0101	0.0139*	0.0384***	0.0069***	-0.0015***
	(0.030)	(0.027)	(0.199)	(0.093)	(0.002)	(0.000)	(0.003)
Fund score	-0.0422***	-0.0143***	-0.0440***	-0.0497***	-0.0354***	-0.0058***	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.474)
Family score	0.0150***	0.0086***	0.0199***	0.0197***	0.0063	0.0070***	0.0013***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.365)	(0.000)	(0.008)
Team	0.0042*	0.0078***	-0.0164**	-0.0064	0.0033	0.0019	-0.0003
	(0.075)	(0.005)	(0.040)	(0.399)	(0.745)	(0.197)	(0.529)
Log(Family TNA)	0.0070***	0.0176***	0.0269***	0.0200***	0.0543***	-0.0060***	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.043)
Style dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.1111	0.0882	0.1111	0.1115	0.1606	0.0923	0.0968
Observations	28,398	13,976	4,069	4,924	2,818	21,902	25,816

Table 2.10: Fund characteristics and the probability of implementing the newly allowed strategies

This table shows the relation between fund characteristics and the probability of implementing the newly allowed strategy listed in the first column. Panel A reports the probability of actually implementing the newly allowed strategy when funds remove the restriction and within 24-month following funds removing restrictions. Good performing funds are the funds that perform better than style average during the past 12 months. Other funds are bad performing funds. Panel B reports the difference in the fund characteristics between funds that implement and that do not implement the newly allowed strategy. Fund characteristics are measured before the restriction removal. There are five possible restriction removals: *Short*, *Option*, *Leverage*, *Restricted*, and *Short-term fee*. *Short* indicates short sale was newly allowed. *Option* indicates writing or investing in options on equities, stock indices, futures, or stock index futures was newly allowed. *Leverage* indicates borrowing money or margin purchases was newly allowed. *Restricted* indicates holding of restricted securities was newly allowed. *Short-term fee* indicates charging short-term trading fee was newly allowed. *Any* indicates any of the above five strategies was newly allowed. Fund characteristic variables are as described in Table 2.2. *, **, and *** indicate 10%, 5% and 1% significance levels, respectively.

Panel A: Good vs. bad performing funds

	Implement at t				Implement at (t, t+24)			
	Good performing	Bad performing	Good - Bad	*p*-value	Good performing	Bad performing	Good - Bad	*p*-value
Any	25.47%	22.28%	3.19%	0.119	29.37%	27.32%	2.05%	0.370
Short-term fee	51.03%	44.14%	6.89%	0.108	73.50%	64.44%	9.06%**	0.025
Leverage	14.59%	13.31%	1.29%	0.685	26.83%	24.22%	2.61%	0.536
Short	4.25%	4.67%	-0.42%	0.803	6.59%	5.08%	1.51%	0.466
Option	10.86%	12.18%	-1.32%	0.707	17.57%	17.56%	0.01%	0.998
Restricted securities	16.85%	10.00%	6.85%*	0.068	27.92%	21.60%	6.32%	0.227

Panel B: Implement vs. do not implement the newly allowed strategy

	Implement at t				Implement at t to t+24			
	Did	Didn’t	Did - Didn't	*p*-value	Did	Didn’t	Did - Didn't	*p*-value
Prior 12 month average return	0.0102	0.0067	0.0034***	0.001	0.0085	0.0056	0.0030***	0.005
Prior 12 month return volatility	0.0505	0.0499	0.0006	0.675	0.0504	0.0488	0.0016	0.256
Log(TNA)	5.6822	5.6152	0.0669	0.471	5.7409	5.5215	0.2194**	0.016
Log(Fund age)	4.7968	4.7981	-0.0013	0.972	4.7943	4.7816	0.0127	0.734
Expense ratio	0.0134	0.0130	0.0004*	0.082	0.0138	0.0133	0.0005**	0.020
Turnover ratio	1.0069	0.8450	0.1619***	0.000	0.9844	0.8554	0.1291***	0.002
Prior 12 month average flow	0.0086	0.0044	0.0042*	0.080	0.0087	0.0039	0.0047**	0.035
Prior 12 month flow volatility	0.0394	0.0366	0.0028	0.385	0.0375	0.0368	0.0008	0.801
Load dummy	0.5276	0.5789	-0.0513*	0.065	0.5551	0.5784	-0.0234	0.399
Fund score	2.4460	2.4279	0.0181	0.819	2.5371	2.4127	0.1244*	0.096
Family score	2.6693	2.6427	0.0265	0.705	2.6968	2.6281	0.0687	0.312
Log(Family TNA)	8.7996	9.0749	-0.2753*	0.051	8.8066	8.8658	-0.0591	0.663
Team	0.5707	0.6196	-0.0489*	0.075	0.5663	0.6043	-0.038	0.168

Chapter Three: Industry Information and the 52-Week High Effect

1. Introduction

The "52-week high effect" was first documented by George and Hwang (2004), who find that stocks with prices close to their 52-week highs have better subsequent returns than stocks with prices far from their 52-week highs. George and Hwang (2004) argue that investors use the 52-week high as an "anchor" against which they value stocks. When stock prices are near the 52-week highs, investors are unwilling to bid the price all the way to the fundamental value. As a result, investors underreact when stock prices approach their 52-week highs, and this creates the 52-week high effect. Li and Yu (2012) find that there is also a 52-week high effect on the market index.

In this paper, we show that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. Specifically, we design an idiosyncratic 52-week high strategy and an industry 52-week high strategy based on the original 52-week high trading strategy proposed by George and Hwang (2004), which we call the individual 52-week high strategy. The idiosyncratic 52-week high trading strategy involves buying stocks whose prices are close to their 52-week highs and shorting the same dollar amount of stocks in the same industry whose prices are far away from their 52-week highs. This strategy is thus industry-neutral, and the profit associated with it is mainly driven by firm-specific information. In contrast, the industry 52-week high strategy involves buying stocks in industries whose total market capitalizations are close to their 52-week highs and shorting stocks in industries whose total market capitalizations are far from their 52-week highs. Because we buy and short whole industries in this strategy, the profit associated with it is mainly driven by industry information. We find that the industry 52-week high strategy is more profitable than the idiosyncratic 52-week high strategy, suggesting that the 52-week high effect may be mainly driven by investor underreaction to industry instead of firm-specific information. We also find that the industry 52-week high strategy is slightly more profitable than the individual 52-week high trading strategy proposed by George and Hwang (2004). Using all stocks listed on NYSE, AMEX, and NASDAQ from 1963 to 2009, the industry 52-week high strategy generates a monthly return of 0.46%, higher than 0.32% from the idiosyncratic 52-week high strategy, and is also slightly higher than the 0.43% from the individual 52-week high strategy in the same period.

While anchoring bias could be the reason behind the 52-week high effect, an alternative explanation is that stocks with prices close to 52-week highs are more risky than other stocks. To illustrate why risk factors can potentially cause the 52-week high effect, suppose that the market beta is the only risk factor. If the market return is high, high-beta stocks will have higher returns than other stocks and their prices will be closer to their 52-week highs. These stocks tend to have higher subsequent returns because market returns are positively correlated over time (see, e.g., Lo and MacKinlay, 1990). Conversely, if the market return is low, high-beta stocks will have lower returns and their prices will be farther from their 52-week highs. These stocks tend to have lower subsequent returns. Therefore, we could observe that stocks with prices close to their 52-week highs have higher subsequent returns than stocks with prices far from their 52-week highs, i.e., a 52-week high effect.

If the 52-week high effect is indeed caused by anchoring bias, then we would expect more sophisticated investors to suffer less from this bias and buy (sell) stocks whose prices are close to (far from) the 52-week highs. In contrast, less sophisticated investors should suffer more from this bias and trade in the opposite direction. On the other hand, if the 52-week high effect is driven by risk factors, then the trading strategy is no longer profitable after we properly control for different risks. Further, sophisticated investors should not buy (sell) stocks whose prices are close to (far from) the 52-week highs because the higher return is simply the compensation for higher risks associated with the trading strategy, and there is no risk-adjusted abnormal return.

Many previous studies find that institutional investors are more sophisticated than individual investors (Gompers and Metrick, 2001; Cohen, Gompers, and Vuolteenaho, 2002; Sias, Starks, and Titman, 2006; Amihud and Li, 2006). Therefore, we use institutional investors to proxy for sophisticated investors. We find that institutional investors buy (sell) stocks whose prices are close to (far from) the 52-week highs. We also use a stock's mean return to control for potential risks associated with the 52-week high strategy, and we find that the 52-week high effect still exists. Thus, the evidence is more consistent with the underreaction explanation than the risk-based explanation.

We then go one step further in trying to understand what type of information investors underreact to. Is it true that investors underreact mainly to industry instead of firm-specific information? Do investors underreact to positive or negative information? How can one design a better investment strategy based on the answers to these questions? What are the implications of these findings for the efficient market hypothesis?

We find further evidence that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. The individual 52-week high strategy used by George and Hwang (2004) works best among stocks with high factor model R-squares and high industry betas (i.e., stocks whose values are more affected by industry factors and less affected by firm-specific information) and does not work among stocks with low factor model R-squares and low industry betas. We also find that investor underreaction to positive news accounts more for the profits associated with the 52-week high strategy than investor underreaction to negative news. Given that it is positive news that pushes stock prices to their 52-week highs, the finding is not surprising. The Daniel, Grinblatt, Titman, and Wermers (1997; DGTW hereafter) benchmark-adjusted return for stocks in industries in which market values are close to 52-week highs is 0.24% per month, much larger than the 0.07% per month from shorting stocks in industries in which market values are far from 52-week highs. These returns imply that the industry 52-week high strategy is not highly affected by costs associated with short-selling: the buy-only portfolio accounts for most of the profits. Our finding also casts doubt on market efficiency. Given that the trading strategy is based on publicly available information and does not require extensive short-selling, why do prices not adjust to the information and eliminate the trading profits?

Our results may also offer insights on how to design better investment strategies based on 52-week highs. First, our results indicate that the individual 52-week high strategy proposed by George and Hwang (2004) is more profitable for stocks with high industry betas and high factor model R-squares. Second, investors can earn higher profits if they buy (short) all stocks in industries in which the total market capitalizations are close to (far from) 52-week highs instead of trading on individual stocks based on the 52-week high effect.

To provide further evidence that our industry 52-week high strategy is consistent with investor underreaction to public information due to anchoring bias, we divide firms into different groups based on how informative the firm's stock price is. We would expect investors to suffer more anchoring bias when the firm is hard to value and when the stock price is less informative. We use five measures of price informativeness widely recognized in the literature: firm size, firm age, price impact, analyst coverage, and institutional ownership. Our industry 52-week high effect is more pronounced among firms whose stock prices are hard to value, namely, small firms, young firms, firms with large price impacts, firms with no analyst coverage, and firms with relatively low institutional ownership.

Following the prior literature (e.g., George and Hwang, 2004; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999), we form equal-weighted portfolios when designing our industry 52-week high strategy. One criticism is that since we hold our portfolios for six months, we need to rebalance our portfolios at the end of each month in order to keep it equal-weighted. The rebalancing can be potentially costly if the transaction cost is high. We address this issue by considering two variations in our strategy. First, we consider a modified industry 52-week high strategy in which we form an equal-weighted portfolio at the end of each month *t*, but do not rebalance in the next six months; i.e., we calculate the buy-and-hold return of the portfolio. Second, since we have shown that the industry 52-week high strategy is more profitable among small firms, investors can always implement the industry 52-week high strategy using only small stocks and form value-weighted portfolios. This way, investors do not have to worry about portfolio rebalancing, either. We find that the industry 52-week high strategy is still highly profitable using either of the above two modifications, so portfolio rebalancing is not necessary.

The rest of the paper is structured as follows. In section 2, we discuss related literature. In section 3, we describe data and sample selection and report some baseline results. Section 4 presents results on what drives the 52-week high effect. Section 5 reports some robustness tests, and Section 6 concludes.

2. Related literature

Several recent studies have documented that the 52-week high has predictive ability for stock returns. George and Hwang (2004) find that the average monthly return for the 52-week high strategy is 0.45% from 1963 to 2001, and the return does not reverse in the long run. Li and Yu (2012) examine the 52-week high effect on the aggregate market return. They use the nearness to the 52-week high and the nearness to the historical high as proxies for the degree of good news that traders have underreacted and overreacted to in the past. For the aggregate market returns, they find their nearness to the 52-week high positively predicts future market return, while the nearness to the historical high negatively predicts future returns. They also find that the predictive power from these proxies is stronger than traditional macro variables. Liu, Liu, and Ma (2011) find that the 52-week high effect also exists in the international stock markets.

The 52-week high can not only predict future stock returns, it also affects mergers and acquisitions, the exercise of options, mutual fund returns and flows, stock betas, returns, volatility, and trading volume. Baker, Pan, and Wurgler (2009) examine the 52-week high effect on mergers and acquisitions. They find that mergers and acquisitions offer prices are biased toward the 52-week high, a largely irrelevant past price, and the modal offer price is exactly that reference price. They also find that an offer's probability of acceptance discontinuously increases when the offer exceeds that 52-week high; conversely, bidder shareholders react increasingly negatively as the offer price is pulled upward toward that price.

The 52-week high price is not only a reference point for mergers and acquisitions, but also a reference point for the exercise of options. Heath, Huddart, and Lang (1999) investigate stock option exercise decisions by more than 50,000 employees at seven corporations. They find that employee exercise activity roughly doubles when the stock price exceeds the maximum price attained during the previous year. They interpret this behavior as evidence that individual option-holders set a reference point based on the maximum stock price that was achieved within the previous year, and option-holders are more likely to exercise when subsequent price movements move past that reference point.

Sapp (2011) documents a 52-week high effect for mutual fund returns and cash flows. He examines the performance of trading strategies for mutual funds based on an analogous one-year high measure for the net asset value of fund shares, prior extreme returns, and fund sensitivity to stock return momentum. He finds all three measures have significant, independent predictive power for fund returns, whether measured in raw or risk-adjusted returns. He also finds that nearness to the one-year high is a significant predictor of fund monthly cash flows.

Driessen, Lin, and Hemert (2010) examine stock betas, return volatilities, and option-implied volatility changes when stock prices approach their 52-week highs and also when stock prices break through those highs. They find that betas and volatilities decrease when stock prices approach 52-week highs, and volatilities increase after breakthroughs. The effects are economically large and significant and consistent across stock and stock option markets.

Huddart, Lang, and Yetman (2008) examine the volume and price patterns around 52-week highs and lows. Based on a random sample of 2,000 firms drawn from the CRSP in the period from November 1, 1982, to December 31, 2006, they find that volume is strikingly higher, in both economic and statistical terms, when the stock price crosses either the 52-week high or low. And this increase in volume is more pronounced the longer the time since the stock price last achieved the price extreme, the smaller the firm, and the higher the individual investor interest in the stock.

Tversky and Kahneman (1974) discuss the concept of *anchoring*, which describes the common human tendency to rely too heavily on one piece of information when making decisions. George and Hwang (2004) argue that investors use the 52-week high as an anchor when they evaluate new information. Burghof and Prothmann (2009) test George and Hwang's (2004) anchoring bias hypothesis. Motivated by a result from the literature that behavioral biases increase under uncertainty (Daniel, Hirshleifer, and Subrahmanyam, 1998 and 2001; Hirshleifer, 2001), they examine whether the 52-week high price has more predictive power in cases of larger information uncertainty. Using firm size (market value), book-to-market ratio, nearness to the 52-week high price, stock price volatility, firm age, and cash flow volatility as proxies for information uncertainty, they find that 52-week high strategy profits are increasing in uncertainty measures, which means that the anchoring bias hypothesis cannot be rejected.

3. Data, methods, and baseline results

To test whether the profits from the 52-week high strategy documented in George and Hwang (2004) are mainly driven by industry or firm-specific information, we design an industry 52-week high strategy and an idiosyncratic 52-week high strategy. For convenience, we call the 52-week high strategy in George and Hwang (2004) the individual 52-week high strategy. We first define $PRILAG_{i,t}$ as

$$PRILAG_{i,t} = \frac{Price_{i,t}}{52weekhigh_{i,t}} \quad (1)$$

where $Price_{i,t}$ is stock *i*'s price at the end of month *t*, and $52weekhigh_{i,t}$ is the highest price for stock *i* during the 12-month period that ends on the last day of month *t*.[24] Price information is obtained from CRSP. The individual 52-week high strategy involves buying stocks in the winner portfolio and shorting stocks in the losing portfolio at the end of each month *t*, where the winner (loser) portfolio consists of the 30% of stocks with the highest (lowest) value of $PRILAG_{i,t}$. We hold the portfolio for six months. To construct the idiosyncratic 52-week high strategy, we first use two-digit SIC codes to form 20 industries following Moskowitz and Grinblatt (1999).[25] In each month *t*, we define the winner (loser) portfolio as the 30% of stocks with the highest (lowest) value of $PRILAG_{i,t}$ in each industry. In the idiosyncratic 52-week high strategy, we buy stocks in the winner portfolio and short stocks in the loser portfolio and hold them for six months. Since we buy and short equal dollar amont of stocks in each industry, the industry information in these stocks will more or less cancel out. Therefore, the profit produced by the idiosyncratic 52-week high strategy is mainly driven by firm-specific information instead of industry information.

To construct the industry 52-week high strategy, we first define $MKTVLAG_{j,t}$ as

$$MKTVLAG_{j,t} = \frac{MktValue_{j,t}}{52weekhigh_{j,t}} \quad (2)$$

[24] Consistent with George and Hwang (2004), we find that a strategy based on 52-week lows is not profitable. George and Hwang (2004) conjecture that this is possibly due to the tax distortion associated with the strategy (page 2170).

[25] See Table I in Moskowitz and Grinblatt (1999) for a description of the 20 industries.

where $MktValue_{j,t}$ is industry j's market value at the end of month t, measured as the sum of the market values of all stocks in industry j. $52weekhigh_{j,t}$ is the highest value of $MktValue_{j,t}$ during the 12-month period that ends on the last day of month t.[26] The industry 52-week high strategy involves buying stocks in the six industries with the highest value of $MKTVLAG_{j,t}$ and shorting stocks in the six industries with the lowest value of $MKTVLAG_{j,t}$. Since we buy and short the entire industries, the idiosyncratic information in these portfolios is more or less diversified away. Therefore, the profit produced by the industry 52-week high strategy is mainly driven by industry instead of firm-specific information.

For all the above three strategies, we hold the portfolios for six months. The return on the winner (loser) portfolio in month $t+k$ is the equal-weighted return of all stocks in the portfolio, where k=1, …, 6. Stock returns are obtained from CRSP, and we use the corrections suggested in Shumway (1997).[27] We compute the average monthly returns from July 1963 to December 2009. Results are reported in Table 3.1.

Panel A in Table 3.1 shows that the individual 52-week high strategy generates an average monthly return of 0.43% in our sample period, close to the 0.45% documented in George and Hwang (2004) from July 1963 to December 2001. The industry 52-week high strategy generates a monthly return of 0.46%,

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[26] In an earlier version of this paper, we define $MktValue_{j,t}$ as the value weighted average of individual stock's $PRILAG_{i,t}$ in the industry and we find qualitatively similar results. We choose this measure because intuitively, the market value of an industry is a better heuristic for investors to anchor their beliefs.

[27] Specifically, if a stock is delisted for performance reasons and the delist return is missing in CRSP, we set the delist return to -0.30 for NYSE/AMEX stocks and -0.55 for NASDAQ stocks. We obtain very similar results when we use only CRSP delist returns without filling missing performance-related delist returns.

and the profit is statistically different from zero at any conventional level (t=4.72). In contrast, the idiosyncratic 52-week high strategy generates a monthly return of 0.32%, and the profit is not statistically different from zero.

The returns to the three 52-week high strategies may be driven by certain firm characteristics. In particular, firms with prices close to their 52-week highs most likely have experienced high returns in the past several months, and the profits could be due to the return momentum effect. To test whether this is the case, we use the DGTW benchmark-adjusted returns instead of raw returns. Specifically, we group stocks into 125 portfolios (quintiles based on size, book-to-market, and return momentum) and calculate the DGTW benchmark-adjusted return for a stock as its raw return minus the value-weighted average return of the portfolio to which it belongs.

The last three columns in Panel A of Table 3.1 show that size, book-to-market ratio, and return momentum can indeed explain part of the profits generated by the three strategies. The average monthly profit of the individual 52-week high strategy is reduced to 0.08% and not statistically different from zero. In contrast, we still have a sizeable 0.31% average monthly abnormal return associated with the industry 52-week high strategy, which remains highly significant statistically and economically. The average monthly profit of the idiosyncratic 52-week high strategy is 0.04% and not statistically different from zero. Further, the differences between the profits associated with the industry 52-week high strategy and the other two strategies are statistically significant: it outperforms the idiosyncratic 52-week high strategy by 0.27% per month and the individual 52-week high strategy by 0.23% per month. Therefore, the results seem to indicate that the 52-week high effect is mainly driven by industry instead of firm-specific information.

Most of the profits from the industry 52-week high strategy come from the buy portfolio. Buying stocks in the six industries with the highest $MKTVLAG_{j,t}$ produces an average monthly DGTW benchmark-adjusted return of 0.24%. In contrast, the profit from shorting stocks in the six industries with the lowest $MKTVLAG_{j,t}$ is only 0.07%. Therefore, close to 80% of the DGTW-adjusted profits from the industry 52-week high strategy is generated by the buy portfolio. As a result, the industry 52-week high strategy is highly implementable because most of the profits do not require shorting, which can be costly to implement.

George and Hwang (2004) document that the return to the individual 52-week high strategy is actually negative in January because loser stocks tend to rebound in January. Jegadeesh and Titman (1993) also document a negative return to the individual momentum strategy in January for the same reason. To examine whether the industry 52-week high strategy loses money in January, we exclude returns in January and repeat our analyses. Panel B of Table 3.1 shows that after excluding January, the profits to the individual 52-week high strategy and the idiosyncratic 52-week high strategy increase dramatically, whereas the profits to the industry 52-week high strategy increase only slightly, especially for the DGTW benchmark-adjusted return. The results imply that the returns to the individual 52-week high strategy and the idiosyncratic 52-week high strategy are highly negative in January, whereas the profit to the industry 52-week high strategy is near zero in January. The pattern is clearly borne out in Panel C, where we report the returns in January only. The profit to the individual 52-week high strategy is -7.62% (-1.90% based on DGTW benchmark-adjusted return), and the profit to the idiosyncratic 52-week high strategy is -7.04% (-1.70% based on DGTW benchmark-adjusted return) in January. The profit to the industry 52-week high strategy is -0.87% in January and it becomes positive (though not significantly different from zero) based on DGTW benchmark-adjusted return.

To summarize, we find that the industry 52-week high strategy is significantly more profitable than the individual 52-week high strategy or the idiosyncratic 52-week high strategy, both economically and statistically. Further, the profit of the industry 52-week high strategy stems mainly from the buy portfolio.

4. What drives the 52-week high effect?

4.1. Can risk factors explain the industry 52-week high effect?

While results in Tables 3.1 control for size, book-to-market ratio, and momentum effects, there are potentially other risk factors that we do not control, and they could be related to the 52-week high strategy. To alleviate this concern, we use the mean monthly return of the stock in the sample period as the expected return on the stock. We define the mean-adjusted abnormal return on stock *i* in month *t* as the raw return minus the mean return on the stock from 1963 to 2009. Panel A of Table 3.2 shows that the individual 52-week high strategy is no longer profitable, whereas the industry 52-week high strategy generates a monthly mean-adjusted abnormal return of 0.39%, which is highly significant economically and statistically (t=3.19).[28] In Panel B of Table 3.2, we exclude January returns, and find that all three strategies are profitable: while the average monthly returns to the individual and the industry 52-week high strategies are similar (both at 0.50%), the average monthly return to the individual 52-week high strategy is slightly lower at 0.45%. Panel C reports profits in January only. The individual and idiosyncratic 52-week high strategies lose 8.08% and 7.56% per month in Januarys, respectively, whereas the loss to the industry 52-week high strategy is only 0.94%.

To summarize, results in Tables 3.1 and 3.2 seems to indicate that risk factors cannot explain the profits associated with the 52-week high effects. Thus, the 52-week high effect is unlikely to be caused by higher risks associated with the three trading strategies.

4.2. Institutional demand and the 52-week high strategy

To further test whether the 52-week high effect is driven by anchoring bias or risk factors, we examine the relation between institutional demand and the 52-week high effect. By definition, shares not held by institutional investors (more sophisticated) are held by individual investors (less sophisticated). While the anchoring bias hypothesis predicts that institutional investors buy (sell) stocks whose prices are close to (far from) 52-week highs, the risk factor hypothesis predicts no difference in institutional demand between the two groups of stocks.

[28] In unreported results, we also use a stock's average return in the past 60 months as the expected return on the stock and find qualitatively similar results.

We use two measures of institutional demand from Thomson Financial's CDA/Spectrum 13F filings: the change in the fraction of shares held by institutional investors and the change in the number of institutions holding the stock. Because 13F filings report institutional holdings at the end of each calendar quarter, we look at institutional demand change from quarter to quarter. In Table 3.3, we rank stocks based on their closeness to the 52-week high (i.e., based on the value of $PRILAG_{i,t}$) at the end of quarter t and examine the average value of institutional demand changes for firms in each group in the next four quarters.

Table 3.3 shows that, from quarter t to $t+1$, institutional investors increase their holdings of stocks whose prices are close to 52-week highs by 0.47% of shares outstanding. In contrast, they decrease their holdings of stocks whose prices are far from 52-week highs by 0.33%. The difference between the winner and loser groups is 0.80% and highly statistically significant (with t=9.45). In the second subsequent quarter (from quarter $t+1$ to $t+2$), we find a similar pattern, though the magnitude is smaller, with a 0.55% difference between the winner and loser groups. The magnitude becomes even smaller in the third and fourth quarters, but there are still significant differences in institutional demand change between the winner and loser groups.

The change in the number of institutions holding the firm's stocks shows a similar pattern. In quarter $t+1$, the number of institutional investors increases by 2.06 for stocks whose prices are close to 52-week highs. In contrast, the number decreases by 0.61 for stocks whose prices are far from 52-week highs. The difference between the winner and loser groups is highly statistically significant.

In the next three quarters, we find a similar pattern, though the magnitude becomes smaller.

To summarize, we find that institutional investors generally increase their holdings of stocks whose prices are close to 52-week highs and decrease their holding of stocks whose prices are far from 52-week highs. This result is consistent with the anchoring bias hypothesis.

4.3. Can return momentum explain the industry 52-week high strategy?

Because there is a positive correlation between past returns and closeness to the 52-week high, one may wonder whether the profit from the industry 52-week high strategy is caused by the momentum in stock returns. To test this, we construct the momentum strategy proposed by Jegadeesh and Titman (1993). The winners (losers) in the momentum strategy are the 30% of stocks with the highest (lowest) returns in the past six months. In the momentum strategy, we buy stocks in the winner portfolio and short stocks in the loser portfolio and hold them for six months. The return on the winner (loser) portfolio in month t is the equal-weighted return of all stocks in the portfolio.

We first perform a pairwise comparison between the momentum strategy and the industry 52-week high strategy. In Panel A of Table 3.4, we first group firms into winners, losers, and the middle group (the rest) based on the momentum strategy. Then within each group, we perform the industry 52-week high strategy by buying (shorting) stocks in the six industries with the highest (lowest) value of $MKTVLAG_{j,t}$. We can see that the industry 52-week high strategy is profitable in each group. In contrast, when we first group firms into winners, losers, and the middle group based on the industry 52-week high strategy in Panel B, the momentum strategy is not always profitable. In particular, the strategy is not profitable in the winner or middle group based on DGTW benchmark-adjusted returns.

Results in Panels A and B of Table 3.4 show that the industry 52-week high strategy is not subsumed by the return momentum effect. We also perform a pairwise comparison between individual and industry 52-week high strategies. Panels C and D report results. If we group firms into winners, losers, and the middle group based on individual 52-week high strategy, the industry 52-week high strategy is profitable in each group. When we group firms into winners, losers, and the middle group based on the industry 52-week high strategy, the individual 52-week high strategy is not always profitable. The results show that the industry 52-week high strategy is not subsumed by the individual 52-week high effect.

4.4. Comparing the five strategies simultaneously

Following Fama and MacBeth (1973) and George and Hwang (2004), we run the following regression to compare the five strategies simultaneously, while controlling for the effects of firm size and bid-ask bounce:

$$R_{i,t} = b_{0jt} + b_{1jt} R_{i,t-1} + b_{2jt} SIZE_{i,t-1} + b_{3jt} JH_{i,t-j} + b_{4jt} JL_{i,t-j} + b_{5jt} MH_{i,t-j} + b_{6jt} ML_{i,t-j} + b_{7jt} GH_{i,t-j} + b_{8jt} GL_{i,t-j} + b_{9jt} IdioH_{i,t-j} + b_{10jt} IdioL_{i,t-j} + b_{11jt} IndH_{i,t-j} + b_{12jt} IndL_{i,t-j} + e_{p,t}. \quad (3)$$

The dependent variable, $R_{i,t}$, is the return to stock i in month t. We skip one month between the portfolio-forming month and holding period and include the month $t-1$ return $R_{i,t-1}$ in the regression to control for the effect of bid-ask bounce. Because we form a portfolio every month and hold the portfolio for six months, the profit from a winner or loser portfolio in month t can be calculated as the sum of returns to six portfolios, each formed in one of the six past successive months t-j, where j=2, 3, …,7 (we skip one month between portfolio formation and holding). $JH_{i,t-j}$ is a dummy variable with value 1 if stock i is included in the Jegadeesh and Titman (1993) winner portfolio in month t-j (i.e., if the stock is in the top 30% based on returns from month t-j-6 to month t-j); and 0 otherwise. Similarly, $JL_{i,t-j}$ is a dummy variable indicating whether stock i is included in the Jegadeesh and Titman (1993) loser portfolio in month t-j. $MH_{i,t-j}$ and $ML_{i,t-j}$ are dummy variables for Moskowitz and Grinblatt (1999) industry momentum winner and loser portfolios, and $GH_{i,t-j}$ and $GL_{i,t-j}$ are dummy variables for George and Hwang (2004) individual 52-week high winner and loser portfolios. For our idiosyncratic and industry 52-week high winner and loser portfolios, we create four dummies, $IdioH_{i,t-j}$, $IdioL_{i,t-j}$, $IndH_{i,t-j}$, and $IndL_{i,t-j}$.

Following George and Hwang (2004), we first run separate cross-sectional regressions of equation (3) for each j=2, …, 7. Then the total return in month t of a portfolio is the average over j=2, …, 7. For example, the month t return to the Jegadeesh and Titman (1993) individual momentum winner portfolio is $\frac{1}{6}\sum_{j=2}^{7} b_{3jt}$. We then report in Table 3.5 the time-series averages of these values and the associated t-statistics when either the raw return or the DGTW benchmark-adjusted return is the dependent variable. Profits from the five investment strategies are reported in the bottom panel. We also run regressions excluding Januarys and in Januarys only.

When we use raw return as the dependent variable, the industry 52-week high strategy generates a return of 0.20% after controlling for the other four investing strategies, indicating that the profits from the industry 52-week high are above and beyond those from the other four strategies. Results excluding Januarys are similar. The third column shows that, in Januarys, while the individual 52-week high strategy loses money, the industry or the idiosyncratic 52-week high strategy generates essentially zero profit. The results using DGTW benchmark-adjusted returns are similar.

4.5. Is the 52-week high effect driven by industry or firm-specific information?

So far, our results show that the industry 52-week high strategy is more profitable than the idiosyncratic 52-week high strategy. This suggests that the 52-week high effect is mainly driven by investor underreaction to industry instead of firm-specific information. If this is true, then the 52-week high effect documented by George and Hwang (2004) should be more pronounced among firms whose values are influenced more by industry information and less by firm-specific information, i.e., stocks with high industry betas and high factor model R-squares.

To estimate industry beta and R-square, we run the following regression for each stock *i* using daily stock return data in the past 12 months:

$$R_{i,t} = a_i + \beta_{mkt,i} R_{m,t} + \beta_{ind,i} R_{ind,t} + e_{i,t}, \qquad (4)$$

where $R_{m,t}$ is the market return at day *t*, and $R_{ind,t}$ is the value-weighted return of all stocks in stock *i*'s industry at day *t*. The industry portfolio is constructed without stock *i*. Industry beta is the estimated value of $\beta_{ind,i}$, and R-square is the adjusted R-square from the regression. At the end of each month, we repeat the regression and rank stocks based on industry beta and R-square. We then examine the profits to the individual 52-week high strategy in each industry beta tercile and R-square tercile.

Panel A of Table 3.6 shows that the profit to the individual 52-week high strategy is 0.32% per month among firms with the lowest industry betas. The profit increases to 0.40% in the middle group and 0.51% among firms with the highest industry betas. Results based on DGTW benchmark-adjusted returns show a similar pattern. The 52-week high effect is strongest among high industry beta firms and weakest among low industry beta firms, although the profits are statistically insignificant in all three terciles (which is consistent with the finding in Table 3.1 that the individual 52-week high strategy does not generate significant DGTW benchmark-adjusted returns).

Panel B of Table 3.6 shows that the profit to the individual 52-week high strategy increases with a firm's R-square. The profit among firms in the lowest tercile of R-square is -0.05% per month, though not statistically significant. The profit increases to 0.56% in the middle group and 0.80% among firms with the highest R-squares. If we use DGTW benchmark-adjusted returns, the individual 52-week high strategy actually loses 0.27% per month among firms with the lowest R-squares, and the negative profit is statistically different from zero at the 5% level. The profit is 0.16% in the middle group and 0.33% among firms with the highest R-squares.

To summarize, results in Table 3.6 indicate that the 52-week high effect is mainly driven by industry information instead of firm-specific information. The

52-week high effect documented by George and Hwang (2004) is more pronounced among firms with high industry betas and high R-squares.

4.6. Price informativeness and the industry 52-week high effect

If the profits from the industry 52-week high strategy are indeed driven by the anchoring bias of investors, we would expect the bias to be stronger among firms whose valuations are harder to determine. Therefore, the industry 52-week high effect should be more (less) pronounced among firms with less (more) informative prices. To test this, we use five price informativeness measures that are widely recognized in the literature. The five measures are as follows:

1. Firm size, defined as the firm's market capitalization at the end of the month of the portfolio formation. It is well known that large firms have more informative prices than small firms (e.g., Fama and French, 1993).
2. Firm age, measured as the number of months since the stock is publicly traded. Availability of public trading history may reduce the information asymmetry between the firm and outside investors (e.g., Stambaugh, 1997). Therefore, older firms should have more informative prices than younger firms.
3. Price impact, measured by the absolute daily return divided by the daily dollar volume of trade (in millions), averaged over the past twelve months, similar to the definition in Amihud (2002). It measures how easily investors can liquidate a stock without severely affecting the price. Firms with less informative prices generally have high price impacts (e.g., Amihud, 2002).

4. Analyst coverage, defined as the number of analysts following the firm. Firms with more analyst coverage should have more informative prices (e.g., Womack, 1996).
5. Institutional ownership, defined as the fraction of shares held by institutions who file the 13F form with the Securities and Exchange Commission. Firms with more institutional ownership may have less information asymmetry (Gompers and Metrick, 2001).

We divide firms into three groups based on each of the above measures and evaluate the profits to the industry 52-week high strategy in each group. Table 3.7 reports the results.

Panel A of Table 3.7 shows that the profit to the industry 52-week high strategy is 0.62% per month among small firms (the bottom 1/3 of firms based on firm size). In contrast, the profit is 0.47% among mid-sized firms and 0.29% among large firms. Results based on DGTW benchmark-adjusted returns show a similar pattern.

Panel B of Table 3.7 shows that the profit to the industry 52-week high strategy decreases with a firm's age. The profit among firms in the bottom tercile is 0.60% per month. It is 0.55% in the middle tercile and 0.25% in the top tercile. If we use DGTW benchmark-adjusted returns, the profit is 0.37% per month among young firms and 0.21% among old firms.

Panels C, D, and E, report results based on price impact, analyst coverage, and institutional ownership, respectively. They all show the same pattern. The industry 52-week high strategy is more profitable among firms with high information asymmetry (firms with high price impact, no analyst coverage, and low institutional ownership). The results in Table 3.7 are consistent with the notion that the industry 52-week high effect is driven by investors' anchoring bias.

4.7. Portfolio rebalancing and the industry 52-week high strategy

So far, we have followed the prior literature (e.g., George and Hwang, 2004; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999) and formed equal-weighted portfolios when designing our strategies. One criticism is that since we hold our portfolios for six months, we need to rebalance our portfolios at the end of each month in order to keep them equal-weighted. The rebalancing can be potentially costly if the transaction costs are high, and it is not clear whether our strategies are still profitable after transaction costs. We address the implementability of the industry 52-week high strategy related to the rebalancing of the portfolio in this subsection.

First, we consider a modified industry 52-week high strategy that does not require monthly portfolio rebalancing. Specifically, at the end of each month t, we buy an equal-weighted portfolio of stocks in the six industries with the highest value of $MKTVLAG_{j,t}$, and short the same dollar amount of an equal-weighted portfolio of stocks in the six industries with the lowest value of $MKTVLAG_{j,t}$. We then hold the portfolio for six months without rebalancing. Therefore, at the end of each month, the portfolio is neither equal-weighted nor value-weighted. To calculate the average monthly return of such a strategy, we first calculate the six-month cumulative buy-and-hold raw return of each stock in each portfolio. The cumulative profit of the modified industry 52-week high strategy (*CRET*) is the mean cumulative return of all stocks in the long portfolio minus that of all stocks in the short portfolio. The monthly profit of the modified industry 52-week high strategy is then $(1+CRET)^{1/6}-1$.

To calculate the abnormal return of the modified industry 52-week high strategy, we form 125 portfolios at the end of month *t* based on size, book-to-market ratio, and momentum. The six-month cumulative abnormal return of each stock is the cumulative raw return minus the cumulative return on the portfolio to which the stock belongs. The cumulative abnormal return of the modified industry 52-week high strategy (*ACRET*) is the mean abnormal cumulative return of all stocks in the long portfolio minus that of all stocks in the short portfolio. The monthly abnormal return of the modified industry 52-week high strategy is then $(1+ACRET)^{1/6}-1$. The modified individual and idiosyncratic 52-week high strategies are similarly defined.

Panel A of Table 3.8 shows that the modified industry 52-week high strategy that does not require monthly rebalancing is still profitable, with an average monthly return of 0.53%. The average DGTW benchmark-adjusted abnormal return of the strategy is 0.33% per month, which is greater than the abnormal returns on the modified individual or idiosyncratic 52-week high strategy.

We now consider a second way to address the rebalancing concern. In Table 3.7, we have seen that the industry 52-week high strategy is more profitable among small firms. If investors want to implement the industry 52-week high strategy, they can always focus on small stocks and form value-weighted portfolios. This way, investors do not have to worry about portfolio rebalancing. To see if such a strategy is still profitable, we buy a value-weighted portfolio of small stocks in the six industries with the highest values of $MKTVLAG_{j,t}$ and short the same dollar amount of a value-weighted portfolio of small stocks in the six industries with the lowest values of $MKTVLAG_{j,t}$. Small stocks are defined as the 25% of stocks with the lowest values of market capitalization at the end of month t. Similarly, we calculate the profit of the individual and idiosyncratic 52-week high strategies among small stocks using value-weighted portfolios.

Panel B of Table 3.8 shows that the industry 52-week high strategy is still profitable if we focus on small stocks and use value-weighted portfolios, with an average monthly return of 0.70%. The average DGTW benchmark adjusted abnormal return of the strategy is 0.38% per month. Both the idiosyncratic and individual 52-week high strategies produce similar magnitudes of profits compared to the industry 52-week high strategy among small stocks.

To summarize, even though we follow the literature and form equal-weighted portfolios in our industry 52-week high strategy, which requires monthly rebalancing of the portfolio, our results still hold if we modify our strategy so that portfolio rebalancing is not necessary.

5. Additional robustness tests

In this section, we perform some additional robustness tests regarding our main findings.

5.1. Sample periods

To test if our results hold over different time periods, we divide our sample period into three sub-periods: July 1963 to December 1978, January 1979 to December 1994, and January 1995 to December 2009, so that each sub-period has roughly the same length. We compare the profits to the three 52-week high strategies in each sub-period, using both raw returns and DGTW benchmark-adjusted returns.

Table 3.9 shows that from July 1963 to December 1978, the individual and idiosyncratic 52-week high strategies generate 0.08% and 0.06% per month, which are both insignificantly different from zero. In contrast, the industry 52-week high strategy generates 0.33% per month, which is statistically significantly different from zero at the 5% level. When we use DGTW benchmark-adjusted returns, both the industry and idiosyncratic 52-week high strategies generate significant profits, whereas the profit to the individual 52-week high strategy is not statistically significant.

From January 1979 to December 1994, when we use raw returns, all three 52-week high strategies generate significant profits. However, when we use DGTW benchmark-adjusted returns, only the industry 52-week high strategy generates significant profits. From January 1995 to December 2009, the industry 52-week high strategy generates significant profits based on DGTW benchmark-adjusted return, though the profit based on raw returns is not statistically significant (t-value=1.60). In contrast, the idiosyncratic and individual 52-week high strategies generate no significant profits when we use either raw returns or the DGTW benchmark-adjusted returns.

The above results show that in each sub-period, the industry 52-week high strategy generates more profits than the idiosyncratic 52-week high strategy. We also explore whether our results are driven by the extreme market conditions. Specifically, during the Internet bubble period, many stocks had very high stock prices and prices at or close to their 52-week highs. In contrast, during the recent financial crisis, many stocks have very low prices that are far from their 52-week highs. We test if our results are robust to the exclusion of the following two periods: 1998-2000 and 2008-2009.

Results at the bottom of Table 3.9 show that our results hold even after excluding the Internet bubble period and the recent financial crisis period. When we use raw returns, all three 52-week high strategies generate significant profits. When we use DGTW benchmark-adjusted returns, the industry 52-week high strategy continue to generate significant profits, whereas the profits associated with the other two strategies are not statistically significant.

5.2. Changing the holding period to three or twelve months

In all previous tests, we follow George and Hwang (2004) and hold the portfolios for six months after forming the winner and loser portfolios. In this subsection, we examine whether our results hold if we hold the portfolio for three or twelve months. Results are reported in Table 3.10.

Panel A of Table 3.10 shows that if we hold the portfolios for three months instead of six months, the individual 52-week high strategy generates

0.44% per month, whereas the industry 52-week high strategy generates 0.67% per month. The idiosyncratic 52-week high strategy does not generate significant profits. When we use DGTW benchmark-adjusted returns, the industry 52-week high strategy generates significant profits, whereas the other two strategies do not. By looking at profits excluding Januarys and in Januarys only, we can see that there are large negative returns for the individual and the idiosyncratic 52-week high strategies in Januarys, whereas the profits to the industry 52-week high are insignificantly different from zero in Januarys.

Panel B of Table 3.10 shows that if we hold the portfolios for twelve months, the results are qualitatively similar to those in Panel A of Table 3.10 and those in Table 3.1. Overall, Table 3.10 shows that if we hold our portfolios for three or twelve months instead of six months, our main results are unchanged.

6. Conclusion

In this paper, we find that the 52-week high effect (George and Hwang, 2004) cannot be explained by risk factors. We find that the effect is more consistent with investor underreaction caused by anchoring bias: the presumably more sophisticated institutional investors suffer less from this bias and buy (sell) stocks close to (far from) their 52-week highs. Further, the 52-week high effect is mainly driven by investor underreaction to industry information. The extent of underreaction is more for positive than for negative industry information. We also find that the 52-week high strategy works best among stocks with high factor model R-squares and high industry betas (i.e., stocks whose values are most affected by industry factors and least affected by firm-specific information).

We design an idiosyncratic 52-week high trading strategy to buy stocks with prices close to their 52-week highs and short the same dollar amount of stocks in the same industry with prices far from their 52-week highs. We also design an industry 52-week high trading strategy to buy stocks in industries whose total market capitalizations are close to their 52-week highs and short stocks in industries whose total market capitalizations are far from their 52-week highs. We find that the industry 52-week high strategy generates a monthly return of 0.46% from 1963 to 2009, higher than the 0.32% from the idiosyncratic 52-week high strategy, and also slightly higher than the profit generated from the individual 52-week high strategy proposed by George and Hwang (2004) in the same period.

Also consistent with the anchoring bias effect, our industry 52-week high trading strategy is most profitable among firms whose stock prices are hard to value, namely, small firms, young firms, firms with large price impacts, firms with no analyst coverage, and firms with relatively low institutional ownership. Our results hold after controlling for individual and industry momentum effects.

Table 3.1: Profits from individual, idiosyncratic, and industry 52-week high strategies

This table reports the average monthly portfolio returns from July 1963 through December 2009 for individual, idiosyncratic, and industry 52-week high strategies. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks in CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: All months included

	Raw return			DGTW return		
	Winner	Loser	W - L	Winner	Loser	W - L
Individual	1.35%	0.92%	0.43%	0.11%	0.03%	0.08%
	(6.41)	(2.88)	(1.74)	(3.53)	(0.50)	(0.94)
Industry	1.39%	0.93%	0.46%	0.24%	-0.07%	0.31%
	(5.00)	(3.13)	(3.67)	(5.30)	(-1.35)	(3.74)
Idiosyncratic	1.31%	0.99%	0.32%	0.10%	0.05%	0.04%
	(5.91)	(2.63)	(1.60)	(4.02)	(1.20)	(0.67)
Industry - Idio			0.14%			0.27%
			(0.67)			(2.35)
Idio - Individual			-0.11%			-0.04%
			(-1.68)			(-0.95)
Industry - Individual			0.03%			0.23%
			(0.11)			(2.00)

Panel B: Excluding January

	Raw return			DGTW return		
	Winner	Loser	W-L	Winner	Loser	W-L
Individual	1.21%	0.05%	1.16%	0.16%	-0.10%	0.26%
	(5.63)	(0.12)	(4.51)	(5.17)	(-1.75)	(3.08)
Industry	1.02%	0.44%	0.58%	0.22%	-0.11%	0.33%
	(3.66)	(1.48)	(4.14)	(5.05)	(-1.98)	(3.86)
Idiosyncratic	1.16%	0.17%	0.98%	0.14%	-0.06%	0.20%
	(5.13)	(0.47)	(5.00)	(6.06)	(-1.40)	(3.35)
Industry - Idio			-0.40%			0.13%
			(-2.05)			(1.20)
Idio - Individual			-0.17%			-0.06%
			(-2.30)			(-1.41)
Industry - Individual			-0.58%			0.08%
			(-2.49)			(0.69)

Panel C: January only

	Raw return			DGTW return		
	Winner	Loser	W-L	Winner	Loser	W-L
Individual	2.95%	10.57%	-7.62%	-0.45%	1.45%	-1.90%
	(4.09)	(6.42)	(-5.63)	(-3.84)	(4.71)	(-4.84)
Industry	5.57%	6.44%	-0.87%	0.43%	0.35%	0.08%
	(6.23)	(5.54)	(-1.90)	(3.08)	(2.60)	(0.39)
Idiosyncratic	3.04%	10.08%	-7.04%	-0.42%	1.29%	-1.70%
	(4.12)	(6.54)	(-5.98)	(-3.70)	(4.83)	(-4.84)
Industry - Idio			6.17%			1.78%
			(6.67)			(3.95)
Idio - Individual			0.58%			0.20%
			(2.63)			(1.97)
Industry - Individual			6.75%			1.98%
			(6.26)			(4.13)

Table 3.2: Mean-adjusted returns for individual, idiosyncratic, and industry 52-week high strategies

This table reports the average monthly portfolio mean-adjusted returns from July 1963 through December 2009 for individual, idiosyncratic, and industry 52-week high strategies. The mean-adjusted return of stock *i* at month *t* is defined as the raw return of stock *i* in month *t* minus the average monthly return of stock *i* from 1963 to 2009. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks in CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: All months included

	Mean-adjusted return		
	Winner	Loser	Winner-Loser
Individual	0.03%	0.08%	-0.05%
	(0.15)	(0.20)	(-0.20)
Industry	0.21%	-0.18%	0.39%
	(076)	(-0.60)	(3.19)
Idiosyncratic	-0.04%	0.17%	-0.21%
	(-0.20)	(0.46)	(-1.07)
Industry - Idio			0.60%
			(2.95)
Idio - Individual			-0.17%
			(-2.58)
Industry - Individual			0.43%
			(1.85)

Panel B: Excluding January

	Mean-adjusted return		
	Winner	Loser	Winner-Loser
Individual	-0.11%	-0.79%	0.50%
	(-0.53)	(-2.01)	(2.72)
Industry	-0.17%	-0.67%	0.50%
	(-0.60)	(-2.31)	(3.77)
Idiosyncratic	-0.20%	-0.65%	0.45%
	(-0.89)	(-1.78)	(2.33)
Industry - Idio			0.06%
			(0.30)
Idio - Individual			-0.23%
			(-3.12)
Industry - Individual			-0.17%
			(-0.75)

Panel C: January only

	Mean-adjusted return		
	Winner	Loser	Winner-Loser
Individual	1.63%	9.71%	-8.08%
	(2.31)	(5.87)	(-5.88)
Industry	4.38%	5.32%	-0.94%
	(4.99)	(4.55)	(-1.97)
Idiosyncratic	1.68%	9.24%	-7.56%
	(2.30)	(6.01)	(-6.35)
Industry - Idio			6.63%
			(7.16)
Idio - Individual			0.52%
			(2.32)
Industry - Individual			7.14%
			(6.59)

Table 3.3: Institutional demand in individual 52-week high portfolios

This table reports quarterly changes in total institutional holding and changes in the number of total institutional investors holding the stocks in individual 52-week high portfolios. Total institutional holding of a stock in a quarter is defined as the number of shares held by all institutional investors at the end of that quarter divided by the number of shares outstanding. For each quarter t, we group all stocks into three individual 52-week high portfolios. The individual 52-week high winner (loser) portfolio is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The individual 52-week high middle portfolio is the equally weighted portfolios of stocks that are neither individual 52-week high winners nor losers. For each portfolio, we report quarterly equal-weighted average of change in institutional holding and change in the number of institutions holding the stock for quarters *t+1* to *t+4*. *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

	Change in institutional holding				Change in investor number			
	Loser	Middle	Winner	W – L	Loser	Middle	Winner	W - L
t + 1	-0.33%	0.45%	0.47%	0.80%	-0.61	0.81	2.06	2.67
	(-3.16)	(5.50)	(7.41)	(9.45)	(-3.77)	(4.97)	(9.52)	(10.52)
t + 2	-0.17%	0.31%	0.39%	0.55%	-0.18	0.81	1.57	1.75
	(-1.71)	(3.78)	(5.74)	(7.60)	(-1.22)	(5.15)	(8.27)	(10.19)
t + 3	-0.06%	0.24%	0.30%	0.35%	0.01	0.77	1.35	1.34
	(-0.60)	(2.94)	(3.89)	(4.59)	(0.06)	(4.87)	(7.72)	(9.62)
t + 4	0.02%	0.21%	0.19%	0.17%	0.15	0.75	1.19	1.04
	(0.22)	(2.61)	(2.50)	(2.26)	(1.07)	(4.75)	(6.59)	(8.24)

Table 3.4: Pairwise comparison of the 52-week high and momentum strategies

This table reports the average monthly returns from July 1963 through December 2009 for equally weighted portfolios. Stocks are sorted independently by past 6-month return and by the 52-week high measure. Individual momentum winners (losers) are the 30% of stocks with the highest (lowest) past 6-month return. Individual 52-week high winners (losers) are the 30% stocks with the highest (lowest) ratio of current price to 52-week high. Industry 52-week high winners (losers) are stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. All portfolios are held for 6 months. *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A

Individual Momentum	Industry 52-Week High	Raw return	DGTW return
Winner	Winner	1.59%	0.22%
	Loser	1.17%	-0.03%
	Winner - Loser	0.42% (3.58)	0.25% (2.79)
Middle	Winner	1.32%	0.22%
	Loser	1.01%	-0.03%
	Winner - Loser	0.31% (3.22)	0.25% (3.45)
Loser	Winner	1.31%	0.30%
	Loser	0.75%	-0.15%
	Winner - Loser	0.57% (3.85)	0.45% (3.77)

Panel B

Industry 52-Week High	Individual Momentum	Raw return	DGTW return
Winner	Winner	1.59%	0.22%
	Loser	1.31%	0.30%
	Winner - Loser	0.28% (1.43)	-0.08% (-1.15)
Middle	Winner	1.42%	0.13%
	Loser	0.98%	0.09%
	Winner - Loser	0.44% (2.72)	0.04% (0.82)
Loser	Winner	1.17%	-0.03%
	Loser	0.75%	-0.15%
	Winner - Loser	0.43% (2.51)	0.12% (1.83)

Panel C

Individual 52-Week High	Industry 52-Week High	Raw return	DGTW return
Winner	Winner	1.43%	0.15%
	Loser	1.25%	0.02%
	Winner - Loser	0.18% (1.94)	0.12% (1.89)
Middle	Winner	1.40%	0.26%
	Loser	1.04%	0.01%
	Winner - Loser	0.37% (3.64)	0.26% (3.27)
Loser	Winner	1.32%	0.32%
	Loser	0.64%	-0.22%
	Winner - Loser	0.68% (4.32)	0.54% (4.21)

Panel D

Industry 52-Week High	Individual 52-Week High	Raw return	DGTW return
Winner	Winner	1.43%	0.15%
	Loser	1.32%	0.32%
	Winner - Loser	0.11% (0.43)	-0.17% (-1.67)
Middle	Winner	1.35%	0.11%
	Loser	0.96%	0.06%
	Winner - Loser	0.39% (1.71)	0.06% (0.68)
Loser	Winner	1.25%	0.02%
	Loser	0.64%	-0.22%
	Winner - Loser	0.61% (2.74)	0.25% (2.74)

Table 3.5: Comparison of JT, MG, individual, idiosyncratic, and industry 52-week high strategies

Each month between July 1963 and December 2009, the following cross-sectional regressions are estimated:

$R_{it} = b_{0jt} + b_{1jt}R_{i,t-1} + b_{2jt}SIZE_{i,t-1} + b_{3jt}JH_{i,t-j} + b_{4jt}JL_{i,t-j} + b_{5jt}MH_{i,t-j} + b_{6jt}ML_{i,t-j} + b_{7jt}GH_{i,t-j} + b_{8jt}GL_{i,t-j} + b_{9jt}IdioH_{i,t-j} + b_{10jt}IdioL_{i,t-j} + b_{11jt}IndH_{i,t-j} + b_{12jt}IndL_{i,t-j} + e_{it}$

where $R_{i,t}$ and $SIZE_{i,t}$ are the return and the market capitalization of stock i in month t. $IndH_{i,t-j}$ ($IndL_{i,t-j}$) is the industry 52-week high winner (loser) dummy that takes the value of 1 if the ratio of industry total capitalization in month t-j to the maximum industry total capitalization achieved in months t-j-12 to t-j for stock i is ranked in the top (bottom) 30%, and is zero otherwise. $GH_{i,t-j}$ ($GL_{i,t-j}$) is the individual 52-week high winner (loser) dummy that takes the value of 1 if the ratio of price level in month t-j to the maximum price achieved in months t-j-12 to t-j for stock i is ranked in the top (bottom) 30%, and is zero otherwise. $IdioH_{i,t-j}$ ($IdioL_{i,t-j}$) is the idiosyncratic 52-week high winner (loser) dummy that takes the value of 1 if the ratio of price level in month t-j to the maximum price achieved in months t-j-12 to t-j for stock i is ranked in the top (bottom) 30% within each industry, and is zero otherwise. $JH_{i,t-j}$ ($JL_{i,t-j}$) equals to one if stock i's return over the 6-month period (t-j-6, t-j) is in the top (bottom) 30%, and is zero otherwise; $MH_{i,t-j}$ ($ML_{i,t-j}$) equals to one if stock i's valued-weighted industry return over the 6-month period (t-j-6, t-j) is in the top (bottom) 30%, and is zero otherwise. This table reports the average of the month-by-month estimates of $\frac{1}{6}\sum_{j=2}^{7} b_{3jt}, \ldots, \frac{1}{6}\sum_{j=2}^{7} b_{12jt}$. t-statistics in parentheses are based on Newey–West standard errors with three lags.

	Raw return			DGTW return		
	Whole	Jan. Excl.	Jan. Only	Whole	Jan. Excl.	Jan. Only
Intercept	0.0205	0.0127	0.1073	0.0062	0.0064	0.0039
	(5.72)	(3.69)	(9.37)	(8.70)	(8.61)	(1.58)
Ri,t-1	-0.0561	-0.0469	-0.1581	-0.0624	-0.0578	-0.1134
	(-13.51)	(-12.47)	(-7.53)	(-18.38)	(-17.76)	(-7.13)
Size	-0.0018	-0.0007	-0.0136	-0.0009	-0.0010	-0.0005
	(-4.82)	(-2.10)	(-7.80)	(-7.23)	(-7.40)	(-0.92)
JT winner	0.0018	0.0016	0.0041	0.0000	-0.0006	0.0068
	(2.12)	(1.85)	(1.69)	(0.04)	(-1.51)	(4.79)
JT loser	-0.0023	-0.0029	0.0045	-0.0013	-0.0010	-0.0041
	(-4.46)	(-5.39)	(1.79)	(-4.56)	(-3.58)	(-5.21)
MG winner	0.0018	0.0016	0.0033	0.0014	0.0014	0.0022
	(2.35)	(2.05)	(1.37)	(2.19)	(1.98)	(1.19)
MG loser	-0.0006	-0.0004	-0.0030	-0.0009	-0.0007	-0.0026
	(-0.93)	(-0.58)	(-1.38)	(-1.57)	(-1.21)	(-1.29)
Individual 52-week high winner	0.0014	0.0023	-0.0096	0.0003	0.0010	-0.0076
	(1.82)	(3.17)	(-3.42)	(0.62)	(2.13)	(-4.54)
Individual 52-week high loser	-0.0040	-0.0070	0.0300	-0.0018	-0.0032	0.0141
	(-2.87)	(-4.97)	(5.50)	(-2.29)	(-4.21)	(5.01)
Idiosyncratic 52-week high winner	0.0001	0.0001	-0.0003	-0.0001	-0.0001	-0.0004
	(0.53)	(0.73)	(-0.79)	(-0.86)	(-0.67)	(-1.08)
Idiosyncratic 52-week high loser	-0.0003	-0.0002	-0.0005	-0.0003	-0.0003	-0.0003
	(-1.69)	(-1.51)	(-1.04)	(-1.73)	(-1.66)	(-0.46)
Industry 52-week high winner	0.0008	0.0007	0.0023	0.0002	0.0001	0.0012
	(1.42)	(1.25)	(1.01)	(0.47)	(0.30)	(0.64)
Industry 52-week high loser	-0.0012	-0.0015	0.0023	-0.0009	-0.0011	0.0007
	(-1.90)	(-2.35)	(1.26)	(-1.57)	(-1.79)	(0.52)
JT winner -	0.0040	0.0044	-0.0004	0.0013	0.0004	0.0109
JT loser	(3.74)	(4.03)	(-0.13)	(2.19)	(0.73)	(6.34)
MG winner -	0.0024	0.0021	0.0063	0.0023	0.0021	0.0048
MG loser	(2.19)	(1.73)	(2.19)	(2.54)	(2.12)	(1.98)
Individual 52-week high winner -	0.0053	0.0094	-0.0396	0.0021	0.0042	-0.0217
Individual 52-week high loser	(2.63)	(4.60)	(-5.43)	(1.75)	(3.64)	(-5.45)
Idiosyncratic 52-week high winner -	0.0003	0.0003	0.0002	0.0002	0.0002	-0.0001
Idiosyncratic 52-week high loser	(1.76)	(1.65)	(0.42)	(0.84)	(0.88)	(-0.09)
Industry 52-week high winner -	0.0020	0.0022	-0.0001	0.0011	0.0012	0.0005
Industry 52-week high loser	(2.47)	(2.64)	(-0.02)	(1.60)	(1.64)	(0.22)

Table 3.6: Profits of the individual 52-week high strategy of firms with different industry betas and R-squares

This table reports the average monthly portfolio returns for individual 52-week high strategy for each tercile which is ranked by the R-square or industry beta ($\beta_{ind,i}$) from the regression $R_{i,t} = a_i + \beta_{mkt,i} R_{m,t} + \beta_{ind,i} R_{ind,t} + e_{i,t}$, where $R_{i,t}$ is the return of stock *i* on day *t*, $R_{m,t}$ is the market return on day *t*, and $R_{ind,t}$ is the value-weighted stock return of stock *i*'s industry. We run this regression at the end of each month for each stock, using returns in the past year. Each month, stocks are sorted by R-square or industry beta ($\beta_{ind,i}$) from this regression. Individual 52-week high winner (loser) portfolio is the equal-weighted portfolio of the 30% of stocks with the highest (lowest) ratio of current price to 52-week high. The monthly returns are from July 1963 to December 2009. *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: Rank by industry beta

	Raw return			DGTW return		
	T1-Low	T2	T3-High	T1-Low	T2	T3-High
Winner	1.39%	1.32%	1.32%	0.13%	0.08%	0.11%
	(6.47)	(6.72)	(5.64)	(3.19)	(1.85)	(3.28)
Loser	1.07%	0.92%	0.81%	0.12%	-0.01%	-0.03%
	(2.64)	(2.64)	(1.81)	(1.78)	(-0.23)	(-0.35)
Winner-Loser	0.32%	0.40%	0.51%	0.01%	0.09%	0.15%
	(1.32)	(1.93)	(1.80)	(0.07)	(1.24)	(1.32)

Panel B: Rank by R-square

	Raw return			DGTW return		
	T1-Low	T2	T3-High	T1-Low	T2	T3-High
Winner	1.39%	1.37%	1.28%	0.08%	0.12%	0.11%
	(7.07)	(6.23)	(5.6)	(1.14)	(3.18)	(3.39)
Loser	1.44%	0.81%	0.48%	0.35%	-0.05%	-0.21%
	(3.29)	(1.96)	(1.28)	(4.06)	(-0.73)	(-2.58)
Winner-Loser	-0.05%	0.56%	0.80%	-0.27%	0.16%	0.33%
	(-0.17)	(2.21)	(3.59)	(-2.04)	(1.82)	(3.64)

Table 3.7: Profits of the industry 52-week high strategy for firms with different price informativeness measures

This table reports the average monthly portfolio returns for the industry 52-week high strategy for each group which is ranked by the price informativeness measures: size, age, price impact, analyst coverage, and institutional ownership. Industry 52-week high winners (losers) are stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. Each month, within each industry, stocks are sorted into three groups by size, age, price impact, analyst coverage, and institutional ownership. All portfolios are held for 6 months. *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: Size and industry 52-week High (July 1963 - December 2009)

Size	Raw return			DGTW return		
	Winner	Loser	W-L	Winner	Loser	W-L
T1 - Small	1.77%	1.16%	0.62%	0.45%	-0.02%	0.46%
	(5.07)	(3.34)	(4.23)	(5.85)	(-0.20)	(3.96)
T2	1.26%	0.78%	0.47%	0.16%	-0.14%	0.30%
	(4.46)	(2.55)	(3.43)	(3.34)	(-2.28)	(3.20)
T3 - Large	1.16%	0.87%	0.29%	0.13%	-0.06%	0.18%
	(5.05)	(3.27)	(2.31)	(3.21)	(-0.89)	(2.31)

Panel B: Age and industry 52-week high (July 1963 - December 2009)

Age	Raw return			DGTW return		
	Winner	Loser	W-L	Winner	Loser	W-L
T1 - Small	1.35%	0.76%	0.60%	0.23%	-0.14%	0.37%
	(4.33)	(2.25)	(3.73)	(3.13)	(-1.65)	(3.14)
T2	1.50%	0.95%	0.55%	0.29%	-0.11%	0.40%
	(5.07)	(3.05)	(3.96)	(4.88)	(-1.77)	(4.18)
T3 - Large	1.32%	1.07%	0.25%	0.20%	-0.01%	0.21%
	(5.56)	(4.1)	(2.38)	(4.75)	(-0.22)	(2.76)

Panel C: Price impact and industry 52-week high (July 1963 - December 2009)

Price impact	Raw return			DGTW return		
	Winner	Loser	W-L	Winner	Loser	W-L
T1 - Small	1.06%	0.80%	0.25%	0.11%	-0.07%	0.18%
	(4.47)	(2.91)	(1.86)	(2.41)	(-1.00)	(2.07)
T2	1.23%	0.84%	0.39%	0.14%	-0.15%	0.29%
	(4.35)	(2.72)	(2.88)	(2.80)	(-2.47)	(3.13)
T3 - Large	1.80%	1.24%	0.57%	0.49%	0.06%	0.43%
	(5.40)	(3.68)	(4.20)	(6.96)	(0.86)	(3.95)

Panel D: Analyst coverage and industry 52-week high (January 1984 - December 2009)

Analyst	Raw ret			DGTW ret		
	Winner	Loser	W-L	Winner	Loser	W-L
No	1.26%	0.83%	0.43%	0.36%	-0.02%	0.38%
	(3.00)	(1.99)	(1.89)	(3.50)	(-0.16)	(2.44)
Small	1.34%	0.90%	0.44%	0.25%	-0.10%	0.35%
	(3.29)	(2.11)	(2.25)	(3.35)	(-1.09)	(2.49)
Large	1.19%	1.03%	0.16%	0.17%	0.01%	0.16%
	(3.62)	(2.56)	(0.78)	(2.41)	(0.11)	(1.19)

Panel E: Institutional ownership and industry 52-week high (January 1980 - December 2009)

IO	Raw ret			DGTW ret		
	Winner	Loser	W-L	Winner	Loser	W-L
T1 - Small	1.33%	0.80%	0.53%	0.40%	-0.09%	0.48%
	(3.29)	(1.97)	(2.53)	(3.88)	(-0.88)	(3.44)
T2	1.44%	0.83%	0.61%	0.28%	-0.15%	0.43%
	(3.94)	(3.14)	(2.13)	(3.92)	(-1.69)	(3.22)
T3 - Large	1.32%	0.95%	0.37%	0.14%	-0.07%	0.21%
	(4.24)	(2.74)	(2.23)	(2.40)	(-0.80)	(1.83)

Table 3.8: Portfolio rebalancing and individual, idiosyncratic, and industry 52-week high strategies

Panel A reports returns to individual, idiosyncratic, and industry 52-week high strategies if we do not rebalance the portfolio. Each month, we form portfolios based on individual, idiosyncratic, and industry 52-week high measures and hold the portfolios for six months without rebalancing. Then we calculate the buy and hold six-month cumulative raw return and the buy and hold six-month cumulative abnormal return, where the abnormal return is the six-month cumulative raw return minus the six month cumulative raw return on the size/book-to-market ratio/momentum portfolio. Panel B reports monthly value-weighted average portfolio returns for small stocks. Each month, we form portfolios based on the 52-week high measures and then calculate monthly value-weighted average small stock returns for each portfolio. Small stocks are stocks with size below 25 percentile of all stocks. All portfolios are held for 6 months. The sample includes all stocks on CRSP from July 1963 through December 2009; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: Monthly returns without rebalancing

	Raw return			DGTW return		
	Winner	Loser	Winner-Loser	Winner	Loser	Winner-Loser
Individual	1.27%	0.43%	0.84%	0.08%	-0.01%	0.09%
	(7.85)	(1.46)	(4.81)	(3.64)	(-0.13)	(1.51)
Idiosyncratic	1.23%	0.55%	0.67%	0.08%	0.02%	0.05%
	(7.25)	(2.01)	(4.94)	(4.17)	(0.77)	(1.26)
Industry	1.20%	0.67%	0.53%	0.20%	-0.12%	0.33%
	(5.69)	(3.06)	(5.69)	(5.34)	(-2.45)	(4.39)

Panel B: Monthly value-weighted average portfolio return among small stocks (Size <= 25 percentile)

	Raw return			DGTW return		
	Winner	Loser	Winner-Loser	Winner	Loser	Winner-Loser
Individual	1.58%	0.69%	0.89%	0.06%	-0.27%	0.33%
	(6.48)	(1.64)	(3.66)	(1.33)	(-5.1)	(3.76)
Idiosyncratic	1.50%	0.76%	0.74%	0.04%	-0.25%	0.30%
	(5.95)	(1.87)	(3.60)	(1.02)	(-5.70)	(3.90)
Industry	1.41%	0.71%	0.70%	0.05%	-0.33%	0.38%
	(3.90)	(2.07)	(4.61)	(0.90)	(-5.53)	(4.10)

Table 3.9: Individual, idiosyncratic, and industry 52-week high strategies in different time periods

This table reports the average monthly portfolio returns for individual, idiosyncratic, and industry 52-week high strategies in four time periods. All portfolios are held for 6 months. The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks on CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

		Raw return			DGTW return		
		Winner	Loser	W-L	Winner	Loser	W-L
July 63 - Dec 78	Individual	1.16%	1.09%	0.08%	0.07%	-0.06%	0.13%
		(2.86)	(1.58)	(0.23)	(1.80)	(-0.78)	(1.21)
	Idiosyncratic	1.17%	1.11%	0.06%	0.09%	-0.06%	0.15%
		(2.75)	(1.67)	(0.21)	(2.64)	(-0.98)	(1.75)
	Industry	1.36%	1.03%	0.33%	0.17%	0.00%	0.18%
		(2.78)	(1.91)	(2.12)	(2.82)	(-0.03)	(1.65)
Jan 79 - Dec 94	Individual	1.65%	0.78%	0.87%	0.14%	0.05%	0.09%
		(4.68)	(1.36)	(2.85)	(3.61)	(0.71)	(0.89)
	Idiosyncratic	1.56%	0.92%	0.64%	0.11%	0.10%	0.00%
		(4.29)	(1.65)	(2.44)	(3.17)	(1.51)	(0.05)
	Industry	1.48%	0.92%	0.55%	0.22%	-0.09%	0.31%
		(3.44)	(2.1)	(3.42)	(4.59)	(-1.18)	(2.93)
Jan 95 - Dec 09	Individual	1.22%	0.89%	0.34%	0.11%	0.10%	0.01%
		(3.71)	(1.07)	(0.55)	(1.46)	(0.68)	(0.05)
	Idiosyncratic	1.20%	0.95%	0.25%	0.09%	0.11%	-0.03%
		(3.29)	(1.28)	(0.53)	(1.63)	(1.13)	(-0.18)
	Industry	1.34%	0.85%	0.50%	0.33%	-0.13%	0.45%
		(2.50)	(1.47)	(1.60)	(2.90)	(-0.95)	(2.22)
Exclude 98 99 00 08 09	Individual	1.46%	0.99%	0.47%	0.11%	0.01%	0.10%
		(6.82)	(2.54)	(2.07)	(4.13)	(0.26)	(1.40)
	Idiosyncratic	1.42%	1.06%	0.36%	0.10%	0.03%	0.07%
		(6.30)	(2.90)	(1.93)	(5.03)	(0.85)	(1.25)
	Industry	1.42%	1.06%	0.36%	0.18%	-0.03%	0.22%
		(5.45)	(3.56)	(3.19)	(5.49)	(-0.71)	(3.17)

Table 3.10: Individual, idiosyncratic, and industry 52-week high strategies with alternative holding periods

This table reports the average monthly portfolio returns for individual, idiosyncratic, and industry 52-week high strategies. The portfolios are held for 3 months (Panel A) or 12 months (Panel B). The winner (loser) portfolio in the individual 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high. The winner (loser) portfolio in the idiosyncratic 52-week high strategy is the equally weighted portfolio of the 30% stocks with the highest (lowest) ratio of current price to 52-week high within each industry. The winner (loser) portfolio in the industry 52-week high strategy is the equally weighted portfolio of stocks in the top (bottom) 6 industries ranked by the ratio of industry total capitalization to the industry 52-week high capitalization. The sample includes all stocks on CRSP; *t*-statistics in parentheses are based on Newey–West standard errors with three lags.

Panel A: Hold the portfolio for 3 months

		Raw return			DGTW return		
		Winner	Loser	W - L	Winner	Loser	W - L
whole	Individual	1.35%	0.91%	0.44%	0.09%	0.04%	0.05%
		(6.43)	(2.24)	(1.74)	(2.86)	(0.81)	(0.57)
	Idiosyncratic	1.30%	1.02%	0.28%	0.07%	0.10%	-0.04%
		(5.88)	(2.68)	(1.35)	(2.61)	(2.37)	(-0.57)
	Industry	1.49%	0.82%	0.67%	0.32%	-0.14%	0.46%
		(5.33)	(2.76)	(5.33)	(6.39)	(-2.39)	(4.97)
Jan excluded	Individual	1.22%	0.03%	1.19%	0.14%	-0.08%	0.23%
		(5.70)	(0.07)	(4.54)	(4.63)	(-1.55)	(2.83)
	Idiosyncratic	1.16%	0.19%	0.97%	0.12%	-0.01%	0.13%
		(5.16)	(0.50)	(4.74)	(4.81)	(-0.31)	(2.22)
	Industry	1.12%	0.32%	0.80%	0.30%	-0.19%	0.49%
		(4.01)	(1.07)	(5.19)	(6.18)	(-3.06)	(5.11)
Jan only	Individual	2.80%	10.67%	-7.87%	-0.53%	1.47%	-1.99%
		(3.99)	(6.38)	(-5.68)	(-4.30)	(4.82)	(-5.08)
	Idiosyncratic	2.88%	10.26%	-7.38%	-0.50%	1.35%	-1.85%
		(4.01)	(6.52)	(-6.01)	(-3.85)	(5.26)	(-5.21)
	Industry	5.69%	6.44%	-0.75%	0.49%	0.40%	0.10%
		(6.03)	(5.58)	(-1.47)	(3.16)	(2.42)	(0.40)

Panel B: Hold the portfolio for 12 months

		Raw return			DGTW return		
		Winner	Loser	W - L	Winner	Loser	W - L
whole	Individual	1.29%	1.04%	0.25%	0.09%	0.10%	-0.01%
		(6.09)	(2.63)	(1.08)	(2.88)	(1.54)	(-0.11)
	Idiosyncratic	1.27%	1.08%	0.19%	0.09%	0.09%	-0.01%
		(5.65)	(2.92)	(1.02)	(3.64)	(1.92)	(-0.13)
	Industry	1.33%	1.01%	0.32%	0.18%	-0.03%	0.21%
		(4.83)	(3.40)	(2.90)	(4.76)	(-0.57)	(2.86)
Jan excluded	Individual	1.13%	0.19%	0.94%	0.14%	-0.04%	0.18%
		(5.24)	(0.49)	(4.02)	(4.48)	(-0.73)	(2.1)
	Idiosyncratic	1.09%	0.28%	0.81%	0.13%	-0.03%	0.16%
		(4.80)	(0.78)	(4.62)	(5.68)	(-0.62)	(2.54)
	Industry	0.94%	0.53%	0.41%	0.16%	-0.06%	0.22%
		(3.41)	(1.80)	(3.54)	(4.4)	(-1.24)	(3.01)
Jan only	Individual	3.11%	10.48%	-7.37%	-0.47%	1.67%	-2.14%
		(4.23)	(6.62)	(-6.02)	(-4.49)	(5.4)	(-5.53)
	Idiosyncratic	3.23%	9.95%	-6.72%	-0.45%	1.46%	-1.91%
		(4.23)	(6.67)	(-6.36)	(-4.7)	(5.43)	(-5.55)
	Industry	5.65%	6.37%	-0.72%	0.40%	0.36%	0.04%
		(6.45)	(5.59)	(-1.88)	(2.89)	(4.34)	(0.23)

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