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Essays in Behavioral Economics

by

Sheng Li

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Economics in the Graduate Division of the University of California, Berkeley

Committee in charge:

Professor Stefano DellaVigna, Chair
Professor Ulrike Malmendier
Assistant Professor Benjamin R. Handel
Professor Terrance T. Odean

Spring 2015
Essays in Behavioral Economics

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Sheng Li
Abstract

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Doctor of Philosophy in Economics

University of California, Berkeley

Professor Stefano DellaVigna, Chair

This dissertation consists of two chapters on behavioral economics.

Chapter one analyzes mutual fund flows from 1999 to 2012 to provide evidence that financial advisers exploit their clients’ extrapolative beliefs to sell funds that pay high commissions. Utilizing comparisons between twin retail mutual fund share classes that differ only in commissions, I find a strong positive correlation between commission levels and return chasing. Fund flows from high commission shares show increased purchases of past winners, but no increased redemptions of past losers. This pattern is consistent with the incentives from 12b-1 commissions, which pay advisers to keep clients invested in high commission funds, but is hard to reconcile with alternative explanations such as advisers reducing search costs for quality funds, or return chasers self-selecting into high commission advisers. My findings support the SEC’s recent efforts at restructuring 12b-1 commissions, as well as the White House’s recent push to require fiduciary duty from all retirement advisers.

Chapter two attempts to isolate the effects of violent video game sales on crime using a novel data set of state-level game sales from 2006 to 2010. The panel database, constructed using NPD group publications and state-level sales weights computed from Google Trends search data, overcomes the time-series data restrictions faced by previous works. However, the state-level variation in this panel data was not enough to disentangle the impact of game sales from time trends because video game sales are highly correlated across states. I document the methodology used to reconstruct the panel data using Google Trends, as this could prove useful in other situations where panel data is difficult or expensive to obtain.


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I have benefited immensely from other faculty members, seminar and conference audiences, and my colleagues at Berkeley. Among my dear friends at Berkeley, I would especially like to thank Takeshi Murooka, Yury Yatsynovich, and Minah Jung for their insightful discussions and for being there for me when times were tough.

I dedicate this dissertation to my parents. This would not have been possible without their unwavering support.
Chapter 1

Influence of Financial Advisers on Return Chasing

1.1 Introduction

How do commission payments influence financial advisers? Mutual fund investors often rely on financial advisers to make investment decisions, but the same advisers also receive billions of dollars each year in sales commissions from mutual fund companies\(^1\). The conflicts of interests created by these commissions are the subject of ongoing regulatory debate at the Security and Exchanges Commission (SEC). In a 2010 statement, the SEC Chairman Mary L. Shapiro expressed concerns that “despite paying billions of dollars, many investors do not understand what 12b-1 fees are, and it’s likely that some don’t even know that these fees are being deducted from their funds or who they are ultimately compensating”.

Advisers are incentivized to upsell expensive commission paying funds. But to do so, they may need to justify the expense to their clients. Extrapolating favorable past performance is an easy way to sell expensive funds, and indeed this is what was found by recent studies. Mullainathan, Noeth, and Schoar (2012) sent undercover auditors to financial advisers, and found that advisers reinforce biases that are in their interests, encouraging return chasing and push for high-fee actively managed funds. Chalmers and Reuter (2013) compared the portfolios of commission based broker clients against those of self directed investors within the Oregon University System’s defined contribution plan, and found higher return chasing among the broker clients. Foerster et al. (2014), using account-level data from Canadian, found that advised portfolios relying on conflicted advice pay higher fees and receive lower risk-adjusted returns than a passive index. My empirical approach allows me to go one step further and ask whether misaligned adviser incentives matter in the aggregate.

In this paper, I use mutual fund flows data from Center for Research in Security Prices

(CRSP) to provide market level evidence that retail financial advisers exploit their clients’ extrapolative beliefs about future returns to sell high commission funds.

I measure commission payments using 12b-1 distribution fees, which are a form of annual fees paid out of mutual funds’ assets. Unlike management fees, which are used to pay fund managers, 12b-1 fees are used to pay streams of sales commissions to brokers. 12b-1 commissions are reported within SEC filings, but they are not salient to retail investors. Previous work by Sirri and Tufano (1998) found return chasing to be stronger in high-fee funds. They suggested increased marketing by high-fee funds as a plausible channel, but they were not able to separate the effects of marketing and non-marketing expenditures due to data limitations. I isolate the distortions created by commissions by explicitly comparing the effect of 12b-1 fees on fund flows versus the effect of management fees. Plots of fund flows against excess returns show that return chasing is strongly correlated with 12b-1 commissions (figure 1.1), but not management fees (figure 1.2). Panel regressions using 3,438 actively managed US fund shares from 1999 to 2012 confirm this pattern is statistically significant. Given that retail investors generally do not know the difference between the 12b-1 and management fees and that both fees contribute additively to the annual expense, the differential effect with 12b-1 fees is unlikely to be driven by investor demand. Distorted advice from commission based advisers is the more likely culprit.

An empirical concern for interpreting the results from the panel regressions is the lack of exogenous variation in commissions. Commission levels are set at the fund share class level, and remain mostly constant throughout the fund’s life cycle. The correlation between 12b-1 commissions and return chasing could be generated by alternative explanations such as investor self-selection or advisers reducing search costs for quality funds. I address these issues directly using three tests. First, I use comparisons between twin share classes to control for investor self-selection. These twin shares are issued from the same funds, invest in the same underlying portfolios, are available in the same retail markets, and differ only in commissions. This allows me to control for investor self-selection based on portfolio, fund manager, and branding using fund fixed effects. Using this method, I find return chasing to be significantly stronger in the high commission shares.

Second, I use the asymmetric responses of fund flows to positive and negative past performance to disentangle the conflict of interests and extrapolation explanation from alternatives based on search costs or self-selection of return chasers. If past performance signaled fund quality and advisers reduced search costs for quality funds, then high commission shares would show increased sensitivity to both positive and negative excess returns. Similarly, if return chasers were self-selecting into accounts managed by high commission advisers, those accounts would exhibit increased sensitivity to both positive and negative excess returns. However, in the data, high commission fund flows show only increased purchases of past winners, but no increased redemptions of past losers. This is hard to reconcile with explanations based on search costs or investor self-selection, but it is consistent with advisers’ incentives for commissions. 12b-1 commission payments are based on holding length, which encourages advisers to steer clients into high commission funds, and to keep them in.

Third, I compare return chasing between retail and institutional shares to further test
Figure 1.1: Comparison of return chasing by 12b-1 fees. The graph plots monthly net flows (measured as percentage of total net assets) in month t against excess returns in the previous 12 months from t-1 to t-12. The unit of observation is at the fund share-class level (ex. Black Rock Large Cap Value fund - class A). The funds are sorted into three groups based on 12b-1 fee levels, 12b-1 fees <25bp roughly correspond with the bottom quartile, 12b-1 between 25-75bp roughly correspond to the middle two quartiles, and 12b-1 fees >75bp correspond to the top quartile. 12 month excess returns are Winsorized at the 1st and 99th percentiles.
Figure 1.2: Comparison of return chasing by management fees. The graph plots monthly net flows (measured as percentage of total net assets) in month t against excess returns in the previous 12 months from t-1 to t-12. The unit of observation is at the fund share-class level (ex. Black Rock Large Cap Value fund - class A). The funds are sorted into three groups based on management fee levels, management fees <50bp roughly correspond with the bottom quartile, management between 50-100bp roughly correspond to the middle two quartiles, and management >100bp correspond to the top quartile. 12 month excess returns are Winsorized at the 1st and 99th percentiles.
alternative explanations based on search costs. Mutual funds often issue institutional shares with reduced management fees and high minimum investment requirements (>\$100,000) to target small institutional investors. It is possible that some fund managers are able to generate excess returns, like those described by Berk and Green (2004), and that commission based advisers help clients by reducing search costs for quality managers. But the retail advisers’ search costs should not be lower than those of institutional investors. Thus, if sensitivity of fund flows to excess returns is driven by search costs, then adviser sold shares should not be more sensitive than institutional shares. The data shows the opposite. High commission retail shares exhibit more return chasing than both low commission retail shares and institutional shares. Search costs for quality funds cannot be an explanation.

My paper builds upon a large body of work on extrapolative expectations and returns chasing (e.g. Gruber 1996; Sirri and Tufano 1998; Bailey, Kumar, and Ng 2011; Barberis et. al. 2013; Beshears et. al. 2013; Greenwood and Shleifer 2013; Berk and van Binsbergen 2013; Barber, Odean, and Huang 2014; Yagan 2014, among many others). My analysis using twin mutual funds share classes compliments works by Nanda, Wang, and Zheng (2009) and Kahraman (2011) which examined how different fees structures of fund share classes impacted fund flows and investor holding periods. Earlier works on return chasing have focused on analyzing the phenomenon as an investor-side demand bias. My contribution to this literature is that I analyze the supply side of return chasing. That is, how do professional financial advisers react to return chasing investors? Do they de-bias their clients, or do they encourage return chasing to make more money? With regards to the adviser conflict of interests literature, recent findings by Bergstresser, Chalmers, and Tufano (2009) and Christoffersen, Evans, and Musto (2013) suggest that commission based brokers are steering clients into worse funds. However, the mechanisms used by advisers to steer their clients have remained a black box. I provide a window into this black box by examining how advisers exploit clients’ extrapolative beliefs to sell high commission funds. My results are also complementary to the work of Del Guercio and Reuter (2014) who document that fund flows from broker advised investors are more responsive to short term raw returns, while fund flow from direct retail investors are more responsive to longer term risk adjusted returns.

My findings, that commission payments distort advice and harm investors, support the SEC’s recent efforts at restructuring 12b-1 commissions as well as the White House’s recent push for requiring fiduciary duty from all retirement advisers. At present, financial advisers can be either fiduciaries, who are legally obligated to make recommendations that are in their clients’ best interests, or broker-dealers, who do not have such obligations. Broker dealers are the main channel for high commission fund sales. Fiduciaries can and do get sued for steering clients into high commission fund shares2. The SEC Investor Advisory Committee issued a recommendation in 2013 to impose fiduciary duties on all broker-dealers who provide advisory service, but it was met with strong resistance from the industry. More

2In 2011, Wal-Mart and Merrill Lynch paid $13.5 million in a class-action lawsuit for violating fiduciary duties by placing funds with excessive investment fees (including 12b-1 fees) in the 401(k) plan. In a similar case in 2010, Caterpillar Inc. paid $16.5 million for violating fiduciary duty by offering investment options with excessive management and other fees in their 401(k) plan.
recently, in 2015, the Council of Economic Advisers from the White House issued an official report condemning back-door commission payments in the mutual fund industry, including those through the 12b-1 fee channel. In addition, it proposed new regulation that would hold all retirement advisers fiduciary standards\(^3\). My findings speak directly to this issue and suggests that there is a role for regulatory involvement to protect investors.

The remainder of the paper is structured as follows. Section 1.2 provides background on mutual fund commissions as well as the multiple share class structure of funds. Section 1.3 outlines my main hypotheses. Section 1.4 describes the data. Section 1.5 tests the hypotheses and quantifies the impact of broker commissions on return chasing. Section 1.6 concludes.

### 1.2 Background

#### Mutual fund fees

Annual expenses charged by mutual funds are divided into three categories: management fees, 12b-1 distribution and service fees, and other fees. Management fees pay for each fund’s portfolio managers as well as administrative expenses. This is the annual cost of active management. 12b-1 fees are defined by the SEC as fees paid out of fund assets to “cover distribution expenses and sometimes shareholder services” and they are capped at 100 basis points.

Introduced in 1980 as a way to allow small self-distributing funds to pay for marketing expenses\(^4\), industry-wide 12b-1 fees totaled just a few million dollars at the time of its inception, but they had ballooned to $9.5 billion by 2009\(^5\). According to a 2005 report by the Investment Company Institute, 92% of 12b-1 fees are paid out to financial advisers for “ongoing shareholder services” or “compensation for initial assistance” (see figure 1.3 for a breakdown of the how 12b-1 fees are used), only 2% is used for actual advertising. 12b1 fees are in effect, annual commission payments to advisers for selling the fund.

Although management fees and 12b-1 fees are reported separately in each funds’ SEC filings, retail investors often only see their sum in the form of the total annual expense. Popular retail investment websites such as Morningstar and Fidelity only show total expense in their fund summaries. Even in fund prospectuses, they are simply shown as ”12b-1 distribution fees” with no explanation of their underlying purpose. The SEC has raised concerns about the opacity of 12b-1 services charges in a 2010 proposal to limit service charges and improve their disclosure.

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\(^3\)http://www.whitehouse.gov/sites/default/files/docs/cea_coi_report_final.pdf


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Figure 1.3: 12b-1 fees are payments to advisers. The graph is taken directly from the ICI’s 2005 report "How Mutual Funds Use 12b-1 Fees". Both "Ongoing Shareholder Services" and "Compensation to Financial Advisers for Initial Assistance" are payments to financial advisers after selling the 12b-1 fee carrying fund share class.

Share classes

Many mutual funds offer multiple share classes of the same portfolios. All share classes of the same fund invest in the same underlying portfolio, so they have the same gross returns. However, each share class has different fees and expenses as well as distribution and commission arrangements. The trend towards multiple share classes started in the mid 1990s after the passing of Rule 18f-3 by the SEC. The justification given for allowing multiple share classes is that they cater to different categories of investors. In practice, this means that funds often have high commission share classes for retail adviser-assisted sales, low commission share classes for direct retail sales, and institutional share classes for large volume sales.

In my analysis, I organize the share classes into two groups: retail share classes that target individual investors, and institutional share classes that target large scale investors.

Retail shares are characterized by low minimum investment requirements (usually not more than $5,000), and higher annual expenses compared to institutional shares, including higher 12b-1 marketing fees. Even within the retail category, funds often offer multiple share classes which differ in commission structures. Figure 1.4 shows an example of a fund that offers three non-institutional share classes. The class A and C shares are high commission...
CHAPTER 1. INFLUENCE OF FINANCIAL ADVISERS ON RETURN CHASING

Figure 1.4: Example of multiple share classes

The Service class share is a low fee share that targets wealth managers. Class A and class C are the most common retail share classes\textsuperscript{6} and they form the basis of my twin shares comparisons in section 1.5. Class A shares were the standard retail shares before the multiple-class era and they account for over $2.6 trillion in assets under management as of 2013\textsuperscript{7}. They typically carried front end sales loads of around 5% (a one-time charge) and annual 12b-1 fees of around 25 basis points. The front end sales loads were used to pay advisers one-time commissions at the time of sale. Class C shares feature no front loads, but high annual 12b-1 fees (usually set at 100 basis points). They were introduced as alternatives to class A for providing advisers with steady streams of income. Within my sample period of 1999-2012, approximately 80% of class A shares were sold without their front end sales loads\textsuperscript{8}. This makes class A shares a good control group for studying the distortions caused by 12b-1 commissions.

Institutional share classes are characterized by reduced management fees, little or no 12b-1 fees, and high minimum investment requirements (often in the $millions). A share class is labeled as institutional if it is classified as such by either CRSP or Morningstar or if it is explicitly labeled as an “institutional share” by the fund company. The target audience for institutional shares are managers of retirement funds and wealth managers of high net

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|c|}
\hline
\textbf{Fund Name} & \textbf{Front Load} & \textbf{Deferred Load} & \textbf{Expense Ratio} & \textbf{Min. Init. Purchase} & \textbf{12b-1 Actual} \\
\hline
BlackRock Large Cap Value Instl & - & - & 0.94 & 2.0 Mil & - \\
\hline
BlackRock Large Cap Value Inv A & 5.25 & - & 1.21 & 1,000 & 0.25 \\
\hline
BlackRock Large Cap Value Inv C & - & 1.00 & 2.02 & 1,000 & 1.00 \\
\hline
BlackRock Large Cap Value Svc & - & - & 1.18 & 5,000 & 0.25 \\
\hline
\end{tabular}
\caption{Example of multiple share classes}
\end{table}

\textsuperscript{6}Class B shares, characterized by no front loads, high rear loads and 12b-1 fees were also popular in the 90’s. Class B shares are often dominated by either class A or C shares in terms of cost for any investment horizon. Kahraman (2011) investigates the naïve behavior of class B investors. Both investors and fund companies began to abandon B shares after 2002 when NASD brought enforcement action against brokers for selling class B shares to clients who would be better off with class A. I drop class B shares from my sample to avoid confounding results with liquidations of class B shares following the NASD investigations.

\textsuperscript{7}Based on ICI’s accounting of Front-end load and level load funds in figure 5.11 of the 2014 Investment Company Factbook.

\textsuperscript{8}As of 2014, class A shares are commonly listed with front load waivers with discount brokerages such as Fidelity and Schwab. See appendix for more detail.
worth individuals (usually Registered Investment Advisers). Comparing the fund flows of institutional and retail shares allow me to benchmark the behavior of individual investors and retail advisers against institutional money managers.

1.3 Testable hypotheses

In this section, I outline testable implications of the fund flow distortions caused by 12b-1 commissions. The underlying assumptions are that 1) advisers are trying to maximize sales commissions, 2) retail investors are aware of total fund expenses, but are 3) at least partially naive regarding agency problems caused by 12b-1 commissions and 4) have extrapolative beliefs about future fund returns. I measure return chasing as the sensitivity of fund flows to past excess returns.

If commissions do not distort advice, then 12b-1 fees should have the same effect on fund flows as any other annual expense. There may be correlation between total fund expense and return chasing behavior, if for example return chasers are more likely to be inattentive to fees. However, such correlations should be the same whether the expenses are coming from 12b-1 fees or management fees, because both contribute additively to total annual expense. On the other hand, if advisers are using favorable past returns to upsell high commission funds, then return chasing would be increasing in commission fees but not management fees. Advisers have no incentives to upsell high management fee funds that do not pay commissions.

**Hypothesis 1.** Conditional on total annual expenses, fund shares with higher 12b-1 commissions will exhibit more return chasing.

Plots of fund flows against excess returns support the above hypothesis. Figure 1.1 separates fund shares into high, mid, and low 12b-1 fee groups using the 25th and 75 percentile values of 12b-1 fees. The degree of return chasing, as measured in the responsiveness of fund flows to excess returns (the slope of the graphs) is monotonically increasing in the 12b-1 fee level. Figure 1.2 repeats the exercise using management fees. Return chasing is not increasing in management fees. I quantify these relationships using panel regressions in section 1.5 and section 1.5.

12b-1 commission payments incentivize advisers to steer clients into high commission funds, and to keep them in. Advisers receive annual 12b-1 commissions based on the amount of money their clients invested, and the payments continue indefinitely so long as the clients stay in the fund. Therefore, advisers are likely to highlight good past returns to increase fund purchases, but down-play or hide poor past returns to minimize redemptions.

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9That is, investors are either unaware that 12b-1 fees are commission payments for advisers, or fail to account for advisers’ incentives to distort recommendations. This is similar to the investor naivete investigated by Inderst and Ottaviani (2012a; 2012b), Malmendier and Shanthikumar (2007), Murooka (2014), and the cursed equilibrium framework proposed by Eyster and Rabin (2005).
Hypothesis 2. Relative to low 12b-1 commission fund shares, high 12b-1 commission fund shares will exhibit increased purchases after positive excess returns, but no increased redemptions after negative excess returns.

Hypothesis 2 lies in sharp contrast to predictions from two competing explanations of the 12b-1 fees and return chasing correlation. The first is that investors who go to high commission advisers are more likely to be return chasers. Naivete about commissions may be correlated with naivete about the costs of return chasing. The second is that past returns signal fund quality and commission based advisers help clients by reducing their search costs for quality funds. For funds that report negative excess returns, both alternative explanations predict increased relative redemptions while hypothesis 2 predicts the opposite. In section 1.5, I use this distinction to separate the conflict of interests explanation from the aforementioned alternatives.

1.4 Data

I obtained mutual fund data from the Center for Research in Securities and Prices (CRSP). For ease of benchmarking and calculating excess returns, I restrict my sample to actively managed U.S. equity funds that were classified by Morningstar as large cap, mid cap, or small cap. I also excluded share classes of funds which were not institutional, but were also not available through retail channels, such as restricted shares for 529 education savings accounts and some class R shares restricted to 401(k) plans.

My sample period covers October 1999 to June 2012. The number of observations per period grew significantly over my sample period, from 1,583 in October 1999 to 3,276 in June 2012. Table 1.1 reports summary statistics for the full sample of 424,115 observations.

Following prior works (Sirri & Tufano 1998; Barber, Odean, & Zheng 2005), I measure monthly net flows into each fund share class as a percentage of the total net assets at the beginning of the month. This measure can be thought of as the monthly growth rate each fund share class.

\[
NetFlows_t = \frac{TotalNetAssets_t - TotalNetAssets_{t-1} \cdot (1 + \text{Returns}_t)}{TotalNetAssets_t} \tag{1.1}
\]

Measuring excess returns

To capture performance benchmarks that are easily accessible and salient to retail investors, I use the after fee returns from Vanguard index funds. This approach closely follows recent related papers such as Berk and van Binsbergen (2014). The benchmarks for the three categories of large, mid, and small cap are respectively S&P 500 index fund investor

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10The Morningstar categories included for my sample were: large cap blend, large cap value, large cap growth, mid cap blend, mid cap value, mid cap growth, small cap blend, small cap value, and small cap growth.
Table 1.1: Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Retail shares</th>
<th></th>
<th>Institutional shares</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>mean</td>
<td>sd</td>
</tr>
<tr>
<td>Monthly net flow (%)</td>
<td>0.67</td>
<td>5.94</td>
<td>0.99</td>
<td>7.46</td>
</tr>
<tr>
<td>12 month excess returns (%)</td>
<td>-0.03</td>
<td>11.99</td>
<td>-0.18</td>
<td>9.58</td>
</tr>
<tr>
<td>Annual total fees (%)</td>
<td>1.52</td>
<td>0.53</td>
<td>0.94</td>
<td>0.30</td>
</tr>
<tr>
<td>Annual 12b-1 fee (%)</td>
<td>0.42</td>
<td>0.38</td>
<td>0.02</td>
<td>0.08</td>
</tr>
<tr>
<td>Annual mgmt fee (%)</td>
<td>0.74</td>
<td>0.29</td>
<td>0.70</td>
<td>0.26</td>
</tr>
<tr>
<td>Max. front load (%)</td>
<td>1.93</td>
<td>2.59</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Rear load (%)</td>
<td>0.66</td>
<td>0.91</td>
<td>0.26</td>
<td>0.64</td>
</tr>
<tr>
<td>Fund size ($million)</td>
<td>668.1</td>
<td>3,094</td>
<td>316.6</td>
<td>839.8</td>
</tr>
<tr>
<td>Fund age (months)</td>
<td>130.1</td>
<td>134.5</td>
<td>95.1</td>
<td>72.0</td>
</tr>
<tr>
<td>Min. investment ($1,000s)</td>
<td>1.9</td>
<td>2.7</td>
<td>2,177</td>
<td>13,981</td>
</tr>
<tr>
<td>(Share class)X(month) observations</td>
<td>318,373</td>
<td></td>
<td>105,742</td>
<td></td>
</tr>
<tr>
<td>Number of share classes</td>
<td>3,438</td>
<td></td>
<td>1,584</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: class A/C twin shares

<table>
<thead>
<tr>
<th></th>
<th>ClassA</th>
<th></th>
<th>Class C</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>mean</td>
<td>sd</td>
</tr>
<tr>
<td>Monthly net flow (%)</td>
<td>0.510</td>
<td>5.374</td>
<td>0.495</td>
<td>5.662</td>
</tr>
<tr>
<td>12 month excess returns (%)</td>
<td>-0.271</td>
<td>10.74</td>
<td>-1.019</td>
<td>10.67</td>
</tr>
<tr>
<td>Annual total fees (%)</td>
<td>1.311</td>
<td>0.316</td>
<td>2.055</td>
<td>0.325</td>
</tr>
<tr>
<td>Annual 12b-1 fee (%)</td>
<td>0.245</td>
<td>0.0780</td>
<td>0.966</td>
<td>0.0875</td>
</tr>
<tr>
<td>Annual mgmt fee (%)</td>
<td>0.716</td>
<td>0.238</td>
<td>0.716</td>
<td>0.238</td>
</tr>
<tr>
<td>Max. front load (%)</td>
<td>5.305</td>
<td>1.104</td>
<td>0.0658</td>
<td>0.248</td>
</tr>
<tr>
<td>Rear load (%)</td>
<td>0.344</td>
<td>0.735</td>
<td>1.042</td>
<td>0.515</td>
</tr>
<tr>
<td>Fund size ($million)</td>
<td>1,206</td>
<td>5,068</td>
<td>157.4</td>
<td>521.6</td>
</tr>
<tr>
<td>Fund age (months)</td>
<td>183.8</td>
<td>200.8</td>
<td>91.45</td>
<td>49.39</td>
</tr>
<tr>
<td>Min. investment ($1,000s)</td>
<td>1.624</td>
<td>2.661</td>
<td>1.430</td>
<td>1.082</td>
</tr>
<tr>
<td>(Share class)X(month) observations</td>
<td>57,724</td>
<td>57,598</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of funds</td>
<td>709</td>
<td></td>
<td>709</td>
<td></td>
</tr>
</tbody>
</table>
shares (ticker: VFINX), Vanguard Mid Cap index fund investor shares (ticker: VIMSX), and Vanguard Small Cap index fund investor shares (ticker: NAESX). All three Vanguard index funds are passively managed, open to public investment, available to be sold by any adviser/broker, and have low minimum investment requirements of $2,500. I chose Vanguard index funds because, unlike Fama-French type factor portfolios, the Vanguard index funds represent benchmarks which are salient to retail investors (ie. S&P 500) and easily implementable as investment strategies. This approach provides a more realistic measure of the retail investors’ opportunity costs. My results are robust to replacing this excess returns measure with excess returns from CAPM and Fama-French three factor models (see appendix 1.7).

1.5 Results

Baseline regressions

Table 1.2 reports results from panel regressions using retail share classes. Panel A reports estimates using OLS regressions with time fixed effects and standard errors clustered by time and fund company, panel B reports estimates using Fama-MacBeth regressions with standard errors corrected for 12-month lag autocorrelations using the Newey-West (1987) procedure.

Starting with OLS, the baseline specification examines the impact of commissions on the net flow of share class \(i\), from fund \(j\), at time \(t\) using the following specification:

\[
NetFlows_{i,j,t} = \gamma_0 + \gamma_{er} R_{i,j,t}^e + \delta^C C_{i,j,t} + \delta^M M_{i,j,t} + X_{i,j,t} \eta + \epsilon_{i,j,t} \quad (1.2)
\]

Where \(R_{i,j,t}^e\) is the past excess returns, and \(X_{i,j,t}\) is a matrix of control variables. Controls include fund size, age, past volatility, and fee structure. Estimates show strong return chasing. Funds that beat the market by 10 percentage points during the past 12 months will grow its assets under management by an extra 1 percentage point in the next month. This would be a 11% increase over the average growth rate of 0.88 percentage points per month among retail share classes.

If fund choice were driven only by investors’ preferences, with no intervention from advisers, then we should expect the impacts of 12b-1 and management fees to be the same. Many retail investors only see the total fees and do not know the difference between 12b-1 and management fee components. If investors are sensitive to high fees, then they ought to be equally sensitive to 12b-1 and management fees. To test hypothesis 1, I estimate the sensitivity of fund flows to excess returns as a function of commissions \(C_{i,j,t}\) and management fees \(M_{i,j,t}\):

\[
NetFlows_{i,j,t} = \gamma_0 + (\gamma_{er} + \gamma^C_{er} C_{i,j,t} + \gamma^M_{er} M_{i,j,t}) R_{i,j,t}^e + \delta^C C_{i,j,t} + \delta^M M_{i,j,t} + X_{i,j,t} \eta + \epsilon_{i,j,t} \quad (1.3)
\]
### Table 1.2: Baseline regressions - Retail

<table>
<thead>
<tr>
<th>Dep. Var. - monthly net flow % (mean=0.67)</th>
<th>A: OLS</th>
<th>B: Fama-Macbeth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past excess returns</td>
<td>0.107***</td>
<td>0.117***</td>
</tr>
<tr>
<td></td>
<td>(0.00926)</td>
<td>(0.0131)</td>
</tr>
<tr>
<td>(Past excess returns)X(12b-1 fees)</td>
<td>0.0454***</td>
<td>0.0407***</td>
</tr>
<tr>
<td></td>
<td>(0.0105)</td>
<td>(0.0101)</td>
</tr>
<tr>
<td>(Past excess returns)X(mgmt fees)</td>
<td>-0.0278***</td>
<td>-0.0230***</td>
</tr>
<tr>
<td></td>
<td>(0.0104)</td>
<td>(0.00677)</td>
</tr>
<tr>
<td>12b-1 fees</td>
<td>-0.613***</td>
<td>-0.593***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>mgmt fees</td>
<td>-0.769***</td>
<td>-0.764***</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>other fees</td>
<td>-0.134</td>
<td>-0.158</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Fund size, age, sales load, &amp; volatility controls</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>318,373</td>
<td>318,373</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.115</td>
<td>0.117</td>
</tr>
</tbody>
</table>

**A: OLS standard errors two-way clustered by date and management company.**

**B: Fama-MacBeth standard errors corrected for 12-month autocorrelation using Newey-West (1987) procedure.***

*** p<0.01, ** p<0.05, * p<0.1
CHAPTER 1. INFLUENCE OF FINANCIAL ADVISERS ON RETURN CHASING

The key parameters of interest are $\gamma_C$ and $\gamma_M$ which capture the contribution of 12b-1 and management fees to return chasing. If commissions do not distort advise, then $\gamma_C$ should equal $\gamma_M$. However, if advisers use return chasing to sell high commission shares, then hypothesis 1 should hold and $\gamma_C$ should be greater than $\gamma_M$.

Column 2 reports the OLS results from adding only interaction effect of 12b-1 fees and excess returns, and column 3 reports the full specification using both 12b-1 and management fee interactions. The results are consistent with hypothesis 1. There is a strong positive correlation between 12b-1 fees and return chasing. The estimated effect of management fees is opposite to that of 12b-1 fees. In the absence of 12b-1 commissions, flows into expensive funds are less sensitive to past returns. The opposite effects of 12b-1 and management fees can not be explained by investor preferences because most investors do not know the difference between these two fees.

To put the estimated effect sizes into perspective, consider a comparison between share classes with 100 basis point of 12b-1 fees against share classes with zero 12b-1 fees. These groups roughly correspond to the top and bottom quartiles of 12b-1 fees. The high 12b-1 shares show 35% more return chasing than low 12b-1 shares, as measured in sensitivity of flows to excess returns. In terms of magnitude, a one standard deviation increase in 12 month excess return (10.3 percentage points) would correlate with a 0.4 percentage point increase in monthly growth rate, a roughly 60% increase relative to the average growth rate of 0.67 percentage points. For the average 100 basis point 12b-1 share class, which manages $158$ million in assets, this translates into $662$ thousand in monthly excess inflows. Within my sample, total assets managed by 100 basis point 12b-1 shares averaged $79$ billion.

Panel B of table 2 repeats the estimations from panel B using Fama-MacBeth regressions, the point estimates differ from the OLS regressions, but the qualitative results remain unchanged. Differences in the point estimates between the two methods are mostly different weighting of observations. In traditional applications of Fama-MacBeth regressions, the number of observations per panel is roughly equal over time. However, in my data set, the number of observations per panel more than double from its lowest point in late 1999 (1,500 per month) to its peak in early 2009 (3,100 per month), but the Fama-MacBeth regressions weight all periods equally. Estimations from this point forward are done using OLS with time fixed effects because the fund and management fixed effects that I introduce are incompatible with Newey-West autocorrelation corrections for Fama-MacBeth.

Twin shares and within management company comparisons

The multiple share class structure of mutual funds offer a novel way to isolate the effects of commission fees. The two most common retail share classes, A and C, are usually identical in every way except for the their commission structures. Within my sample period, class A shares mostly carry 12b-1 fees around 25 basis points, while class C shares have 12b-1 fees.

\[11\] I have repeated the estimations using basic Fama-MacBeth without autocorrelation corrections. The results are qualitatively similar to those from OLS, but the standard errors are much smaller.
Figure 1.5: Returns of class A & C fund. Each point represents one pair of class A & C twin shares of the same fund. Sample is 709 funds which simultaneously offered class A and C shares.

of around 100 basis points. Shares classes of the same fund invest in the same underlying portfolios, share the same fund managers, charge the same management fees, and are promoted under the same marketing campaigns. Comparisons of the fund flows between class A and C shares yields a true \textit{ceteris paribus} test for the effect of commissions.

To illustrate the twin nature of class A and C shares, figure 1.5 plots the average net returns of each class C share against its class A twin. All of the points line up just below the 45 degree line, because the twin shares derive their returns from the same underlying portfolios, and the class C shares simply charge higher annual fees.

A potential confound from using class A shares is that they allow maximum front-end sales loads of around 5% to be charged at the time of sale, and the proceeds from the front loads are paid to brokers as commissions. However, front-end sales loads are mostly waived in practice. A 2014 report from the Investment Company Institute found that although front-load equity funds averaged 5.3% in maximum front loads, the actual amount paid by investors was only 1% (See appendix for a more detailed break down). To check the correlation between maximum and actual front loads, I have collected data on the actual front load charged using annual reports and N-SAR fillings to the Security and Exchanges Commission. In my sample of 227 large cap equity class A shares from the years 2006 and
CHAPTER 1. INFLUENCE OF FINANCIAL ADVISERS ON RETURN CHASING

2011, the average actual front load charge was 1.4 %, but there was no correlation between maximum front loads and the likelihood of waiving front loads. In all of my regressions, I control for maximum front loads as well as interaction effect of maximum front loads and past excess returns. The estimates for front load effects are always small, and never statistically significant (see appendix for more detail).

Panel B of table 1 summarizes the class A and C twin shares sample, which consists of 709 pairs of twin shares. Aside from the differences in 12b-1 and front loads, class C shares are also on average smaller and younger than their class A twins.

To estimate the contribution of commissions to return chasing using the twin share classes, I estimate the following equation:

\[
NetFlows_{i,j,t} = \gamma_j + (\gamma_{er,j} + \gamma_{Cer} C_{i,j,t}) R_{i,j,t}^C + \delta C_{i,j,t} + X_{i,j,t} \eta + \epsilon_{i,j,t}
\]  

(1.4)

Where \( \gamma_j \) are portfolio fixed effects for growth rates, \( \gamma_{er,j} \) are portfolio fixed effects for return chasing, and \( C_{i,j,t} \) are commission levels. \( \gamma_{Cer} \) captures the contribution of commissions to return chasing when comparing twin share classes. To see this, consider that if commission levels \( C_{i,j,t} \) were constant over time 12, then the \( \gamma_{Cer} \) estimate from above specification is mathematically equivalent one that would be obtained using the following two step procedure:

1. Estimate the sensitivity of fund flows to excess returns (\( \hat{\gamma}_{er,i,j} \)) separately for each share class \( i \) in each portfolio \( j \):

\[
NetFlows_{i,j,t} = \gamma_j + \hat{\gamma}_{er,i,j} R_{i,j,t}^C + \delta C_{i,j,t} + \delta M_{i,j,t} + X_{i,j,t} \eta + \epsilon_{i,j,t}
\]

(1.5)

2. Regress the \( \hat{\gamma}_{er,i,j} \) estimates on commission levels and portfolio fixed effects:

\[
\hat{\gamma}_{er,i,j} = \gamma_{er,j} + \gamma_{Cer} C_{i,j} + \epsilon_{i,j}
\]

(1.6)

Where \( \gamma_{er,j} \) are fixed effects for each portfolio \( j \), and \( \epsilon_{i,j} \) are i.i.d. errors. The inclusion of the fund fixed effects \( \gamma_{er,j} \) makes it so that the \( \gamma_{Cer} \) parameter is identified using only variation between twin share classes of the same portfolio.

This second step is similar to a regression of \( \hat{\gamma}_{er,j} \) on portfolio fixed effects and a dummy variable for class C commission funds, with the difference that (1.6) utilizes the continuous variation in 12b-1 commissions.

Panel A of table 1.3 reports the estimates from using twin class A and C shares. Column 1 estimates the baseline specification from (1.2) using restricted twin shares sample. Point estimates are qualitatively similar to those from the full sample, but standard errors are larger because of the reduced sample size. Column (2) show estimates from the fund fixed

---

12Commission levels are very close to being constant over time, within fund-share classes. 350 out of 641 the class C funds in the twin share sample had zero variation in 12b-1 fees over time, and 547 had average variances of less than 1 basis point.
effects specification (1.4)\(^{13}\). After controlling for fund fixed effects, the estimated impact of 12b-1 commissions on return chasing is about twice as strong as those from the baseline regression.

A shortcoming of the class A/C twin shares comparison is that, by construction, it cannot identify the effects of management fees. To address this, I perform a similar analysis using management company fixed effects. That is, I re-estimate (1.2) with the addition of management company fixed effects for return chasing and fund growth. This allows me to identify the effects of 12b-1 and management fees using only comparisons between share classes from the same management company. The estimated specification is as follows:

\[
NetFlows_{i,k,t} = \gamma_k + (\gamma_{er,k} + \gamma^C_{er,k} C_{i,k,t} + \gamma^M_{er,k} M_{i,k,t})R_{i,j,t}^e + \delta^C C_{i,j,t} + \delta^M M_{i,j,t} + X_{i,k,t}\eta + \epsilon_{i,k,t} \tag{1.7}
\]

Where \(\gamma_k\) and \(\gamma_{er,k}\) are management company \(k\) fixed effects for monthly growth and responsiveness of growth to past excess returns respectively.

Fund companies often cultivate a specific image and target specific types of investors in their marketing campaigns. For example, Fidelity is a well known discount brokerage that offers many of their own funds for purchase at zero transaction costs to retail clients. Past research by Barber, Odean and Zheng (2005) have shown strong return chasing behavior among discount brokerage investors. The fixed effects in equation (1.7) controls for company branding and marketing effects, so that estimates would not be affected if return chasing investors were more (or less) likely to self-select or be recruited into any company’s funds. The impacts of 12b-1 and management fees are identified solely via comparisons of share classes from the same company.

Results of the management company fixed effects estimations are reported in panel B of table 1.3. Column (3) reports the results from estimating equation (1.2) using the subsample of fund companies that offered at least two share classes, and column (4) shows the results from management fixed effect estimation. The estimated impact of 12b-1 fees on fund flows is 1.6 times stronger compared to the full sample estimates in table 1.2.

\(^{13}\)The direct effects of past excess returns are omitted because they are captured by fund fixed effect and the management fees effects are omitted because the twin shares have identical management fees.
Table 1.3: Twin shares and within management company comparisons - Retail

<table>
<thead>
<tr>
<th></th>
<th>A: Twin shares</th>
<th>B: Same mgmt company</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base FE (1)</td>
<td>Fund FE (2)</td>
</tr>
<tr>
<td>Past excess returns</td>
<td>0.109***</td>
<td>(0.0349)</td>
</tr>
<tr>
<td></td>
<td>(Past excess returns)X(12b-1 fees)</td>
<td>0.0796** 0.0819***</td>
</tr>
<tr>
<td></td>
<td>(Past excess returns)X(mgmt fees)</td>
<td>-0.0526 0.0323</td>
</tr>
<tr>
<td></td>
<td>12b-1 fee</td>
<td>-0.447 -0.507</td>
</tr>
<tr>
<td></td>
<td>mgmt fee</td>
<td>-1.064***</td>
</tr>
<tr>
<td></td>
<td>other fees</td>
<td>-0.173 0.335</td>
</tr>
<tr>
<td>Fund fixed effects -</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>net flow &amp; return</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mgmt. co. fixed</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>effects - net flow &amp;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>return chase</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Fund size, age,</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>front/rear load, and</td>
<td></td>
<td></td>
</tr>
<tr>
<td>volatility controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>115,322</td>
<td>115,322</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.150</td>
<td>0.277</td>
</tr>
</tbody>
</table>

OLS standard errors two-way clustered by date and management company

*** p<0.01, ** p<0.05, * p<0.1
CHAPTER 1. INFLUENCE OF FINANCIAL ADVISERS ON RETURN CHASING

Positive vs negative past returns

So far I have shown that return chasing is stronger among funds sold with high commissions, which is consistent with the conflict of interest hypothesis that advisers exploit return chasing to sell high commission funds. However, these fund flow patterns may also be consistent with alternative explanations such as commission based advisers reducing their clients’ search costs for quality funds, or return chasers self-selecting into high commission accounts. To disentangle the conflict of interest hypothesis from the above alternatives, I examine the effect of 12b-1 commissions separately for positive and negative excess returns, where hypothesis 2 and the predictions from the competing explanations diverge.

If past performance signaled fund quality and commission based advisers help investors to find quality funds, then high commission shares should show increased sensitivity to both positive and negative excess returns. Similarly, if return chasers were self-selecting into accounts managed by high commission advisers, those accounts should exhibit increased sensitivity to both positive and negative excess returns. Both of these explanations predict increased purchases after high excess returns, as well as increased redemptions after low excess returns. In contrast, the advisers’ incentives for maximizing 12b-1 commissions predict only increased purchases, but not redemptions. 12b-1 commissions are paid annually to advisers based on the amount of money their clients have in the fund, and these payments continue indefinitely so long as the clients stay in the fund. Advisers are paid to steer clients into high commission funds, and keep them in. They have no incentives to move clients out of high commission funds, even after poor performance.

Figure 1.1 shows the difference between high and low 12b-1 share classes in terms of return chasing is most pronounced for positive excess returns. When excess returns are negative, the growth of high and low 12b-1 share classes look very similar. I test this directly by splitting the sample into positive and negative excess returns, and repeating my estimate for each sub-sample. The results, are consistent with hypothesis 2. Table 1.4 shows that, compared to low 12b-1 fee shares, high 12b-1 fee shares enjoy substantially higher inflows after positive excess returns, but no increase in outflows after negative excess returns. This result is robust controlling for fund fixed effects using the twin shares sample, as well as fund company fixed effects using the multi-share sample. This pattern is hard to reconcile with the explanations based on advisers reducing search costs for high quality funds, or return chasers self-selecting into high commission advisers. However it is consistent with the adviser incentives for keeping clients in high 12b-1 commissions funds. This is suggests that advisers selectively draw attention to past performance when it is useful for selling high commission funds.
Table 1.4: Decomposing by positive and negative excess returns - Retail

<table>
<thead>
<tr>
<th>12 month period</th>
<th>Full Sample</th>
<th>(+) vs (-) excess returns</th>
<th>Same mgmt company</th>
</tr>
</thead>
<tbody>
<tr>
<td>Past excess returns</td>
<td>(+) excess ret.</td>
<td>(-) excess ret.</td>
<td>(+) excess ret.</td>
</tr>
<tr>
<td>Past excess returns X (12b-1 fees)</td>
<td>0.0573*** (0.0148)</td>
<td>-0.00381 (0.00934)</td>
<td>0.101*** (0.0313)</td>
</tr>
<tr>
<td>Past excess returns X (mgmt fees)</td>
<td>-0.0455*** (0.0138)</td>
<td>-0.0115 (0.0124)</td>
<td>-0.172*** (0.433)</td>
</tr>
<tr>
<td>12b-1 fee</td>
<td>-0.904*** (0.227)</td>
<td>-0.670*** (0.143)</td>
<td>-1.172*** (0.433)</td>
</tr>
<tr>
<td>mgmt fee</td>
<td>-0.319 (0.227)</td>
<td>-0.900*** (0.143)</td>
<td>-0.495 (0.433)</td>
</tr>
<tr>
<td>other fees</td>
<td>-0.255 (0.224)</td>
<td>-0.109 (0.109)</td>
<td>0.905 (0.980)</td>
</tr>
</tbody>
</table>

Fund fixed effects - net flow & return chase | N Y Y N Y N | N Y Y N Y N |
Mgmt. co. fixed effects - net flow & return chase | N N N N Y Y |
Time fixed effects | Y Y Y Y Y Y |
Fund size, age, sales load, & volatility controls | Y Y Y Y Y Y |

Observations: 142,591 175,782 48,818 66,504 130,971 166,508
R-squared: 0.127 0.069 0.353 0.202 0.191 0.112

OLS standard errors two-way clustered by date and management company

*** p<0.01, ** p<0.05, * p<0.1
In terms of magnitude, point estimates from table 1.4 predict that high commission class C fund shares that beat the market by 10% over the past year would receive a 0.75 percentage points of excess inflows per month compared to its twin low commission class A share. This translates into more than $400 million excess monthly inflows into high commission fund share across the US retail mutual fund market\(^\text{14}\).

**Comparison with institutional shares**

In addition to retail shares, many multi-class funds offer institutional shares that target smaller institutions such as small pension funds. This provides a novel opportunity to benchmark the trading behavior of retail advisers against those of institutional money managers. If the increase return chasing in high commission shares is driven by advisers helping their client to find high quality funds, then the same pattern should show up in the institutional shares. Furthermore, unless retail commission based advisers have lower search costs than institutional investors, the adviser sold shares should not exhibit more return chasing than institutional shares.

To form an apples-to-apples comparison, I analyze a sub-sample of 551 funds which simultaneously offered class A retail, class C retail, and institutional share classes. Figure 1.6, plots the return chasing patterns of the three share classes. The institutional shares has a slightly shallower slope than the two retail shares, indicating less return chasing, but the magnitude is still quite large. Consistent with the previous results in this paper, the high 12b-1 fee class C shares exhibits the most return chasing.

Table 1.5 compares the share classes using multi-variate regressions. Column (1) shows results from a panel regression using the sub-sample of 551 funds which offer all three share classes. Column (2) adds fund fixed effects for fund flows and sensitivity to past excess returns, so that the estimated effects for class C and institutional shares are identified using only within fund comparisons. The results mirror that from the graph, showing institutional shares to have weaker return chasing than both retail shares, and class C to have the strongest return chasing.

While it is possible that return chasing may be motivated by rational search for fund quality, it is unreasonable to expect retail advisers to have lower search costs than institutional investors. Thus, the excess return chasing exhibited by high commission retail shares relative to institutional shares is hard to reconcile with a rational search costs explanation.

---

\(^{14}\)Point estimates show 0.1 percentage point increase in monthly inflows for each 1 percentage point increase in 12b-1 fees. Average class C fund charges an extra 75bp of 12b-1 fees relative to class A. Level load class C shares account for $568 billion assets under management as of 2013 (ICI 2014), and ~10% of funds beat the market by 10% each year.
Figure 1.6: Comparison between A, C, and institutional share classes. Sample is 551 funds that simultaneously offered all three share classes. 12 month excess returns are Winsorized at the 1st and 99th percentiles.
### Table 1.5: Retail vs. Institutional

<table>
<thead>
<tr>
<th>Dep. Var. - monthly net flow %</th>
<th>Funds w/Inst. Share class</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 month period</td>
<td>Cross-section</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Past excess returns</td>
<td>0.149***</td>
</tr>
<tr>
<td></td>
<td>(0.0207)</td>
</tr>
<tr>
<td>(Past excess returns)X(Class C)</td>
<td>0.0185*</td>
</tr>
<tr>
<td></td>
<td>(0.00966)</td>
</tr>
<tr>
<td>(Past excess returns)X(Inst. Share class)</td>
<td>-0.0314***</td>
</tr>
<tr>
<td></td>
<td>(0.00998)</td>
</tr>
<tr>
<td>Class C dummy</td>
<td>-0.619***</td>
</tr>
<tr>
<td></td>
<td>(0.0950)</td>
</tr>
<tr>
<td>Inst. share class dummy</td>
<td>0.207</td>
</tr>
<tr>
<td></td>
<td>(0.156)</td>
</tr>
<tr>
<td>Fund fixed effects - net flow &amp; return chase</td>
<td>N</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Y</td>
</tr>
<tr>
<td>Fund size, age, and volatility controls</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>121,877</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.101</td>
</tr>
</tbody>
</table>

OLS standard errors two-way clustered by date and management company.

*** p<0.01, ** p<0.05, * p<0.1

Sample is 551 funds which simultaneously offered class A, class C, and at least one institutional share. 12b-1, mgmt fee, and sales load controls omitted because they are colinear with share class dummies.
1.6 Conclusion

I use mutual fund flow data from 1999-2012 to provide market level evidence of financial advisers exploiting returning chasing to sell high commission funds. I leverage the multiple share class structure of mutual funds to isolate the influence of commissions, and I find that return chasing is increasing in broker commissions. The effect is robust to controlling for company and portfolio fixed effects by comparing share classes of the same fund and also funds offered by the same company. Consistent with the incentive structure of 12b-1 commissions—which pay for holding length, not churn—most of the impact is on the purchase of past winners, with no detectable effect on the redemption of past losers. In addition, I find that investors in institutional shares of mutual funds exhibit almost as much return chasing as retail investors. My findings support the SEC’s recent efforts to restructure mutual fund 12b-1 commissions, as well as impose fiduciary duties on all financial advisers.
1.7 Appendix

Mutual fund ownership through advisers

Figure 1.1: Mutual fund ownership through advisers
CHAPTER 1. INFLUENCE OF FINANCIAL ADVISERS ON RETURN CHASING

Distribution of excess returns

Figure 1.2: Distribution of excess returns
Other measures of excess returns

My main result are robust to using CAPM alpha or Fama-French 3 factor alpha as the measure of excess returns. I calculated CAPM and Fama-French 3 factor return for each 12-month period by regressing the funds’ daily returns on the daily Market, Size, and Book-to-market factors from Kenneth R. French’s online data library. I normalize each of the excess return measures by their sample standard deviations to make them comparable.

Figure 1.3 plots the distributions of the normalized excess returns measures. “Raw returns minus Vanguard index” is the measure used in the paper. After normalization, the three measures are very similar, because most funds have market beta values very close to 1. The average of the CAPM alphas are a little higher than the other two measures because it does not control for the size factor.

Figure 1.3: Comparison of Excess Returns Measures

Figure 1.4 compares the sensitivity of fund flows to the three measures of excess returns. The results are virtually identical.
Table 1.6 replicates the main results from table 1.2 using the alternative measures of excess returns. All three excess returns are normed by their standard deviations to make the magnitudes of the estimates comparable. Column (1) reports results from using raw returns minus Vanguard index (same measure as in the paper), column (2) uses CAPM alphas, column (3) uses Fama-French 3 factor alphas. The results across the three measures are very similar, with return chasing being positively correlated with 12b-1 fees, and negatively correlated with management fees. The magnitudes of the point estimates are not statistically different across the columns.
### Table 1.6: Return chasing using different excess returns

<table>
<thead>
<tr>
<th></th>
<th>Base (1)</th>
<th>CAPM (2)</th>
<th>FF-3 (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Past excess returns</strong></td>
<td>1.419***</td>
<td>1.495***</td>
<td>1.367***</td>
</tr>
<tr>
<td></td>
<td>(0.131)</td>
<td>(0.147)</td>
<td>(0.150)</td>
</tr>
<tr>
<td><strong>(Past excess returns)X(12b-1 fees)</strong></td>
<td>0.190**</td>
<td>0.315***</td>
<td>0.268**</td>
</tr>
<tr>
<td></td>
<td>(0.0961)</td>
<td>(0.107)</td>
<td>(0.115)</td>
</tr>
<tr>
<td><strong>(Past excess returns)X(mgmt fees)</strong></td>
<td>-0.213*</td>
<td>-0.291**</td>
<td>-0.261**</td>
</tr>
<tr>
<td></td>
<td>(0.111)</td>
<td>(0.113)</td>
<td>(0.119)</td>
</tr>
<tr>
<td><strong>12b-1 fees</strong></td>
<td>-0.456***</td>
<td>-0.443***</td>
<td>-0.413***</td>
</tr>
<tr>
<td></td>
<td>(0.142)</td>
<td>(0.135)</td>
<td>(0.145)</td>
</tr>
<tr>
<td><strong>mgmt fees</strong></td>
<td>-0.627***</td>
<td>-0.794***</td>
<td>-0.681***</td>
</tr>
<tr>
<td></td>
<td>(0.166)</td>
<td>(0.158)</td>
<td>(0.163)</td>
</tr>
<tr>
<td><strong>other fees</strong></td>
<td>-0.0162</td>
<td>-0.0763</td>
<td>0.0944</td>
</tr>
<tr>
<td></td>
<td>(0.196)</td>
<td>(0.196)</td>
<td>(0.197)</td>
</tr>
<tr>
<td><strong>Time fixed effects</strong></td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong>Fund size, age, sales load, &amp; volatility controls</strong></td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>289,806</td>
<td>289,806</td>
<td>289,806</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.131</td>
<td>0.141</td>
<td>0.126</td>
</tr>
</tbody>
</table>

OLS standard errors two-way clustered by date and management company.

*** p<0.01, ** p<0.05, * p<0.1
Estimation results from front load fees

All regression from in the paper include controls for maximum front load fees, as well as interactions between front loads and past excess returns. The front load estimates were omitted from the main tables because front loads were mostly waived during my sample period, so the maximum front loads reported to CRSP were not indicative of actual front loads charged. Figure 1.5 from the ICI shows that although maximum front loads averaged around 5% in the 2000s, actual front loads paid were only around 1%. 80% of class A front loads were waived.

![Figure 1.5: Actual front loads paid from class A shares](image)

Table 1.7 reports results from table 1.2 including estimates from front loads. Both the direct and interaction effects of front loads show up as precise zeros in the estimations. This is consistent with my findings that maximum reported front loads from CRSP are not correlated with actual front loads.
### Table 1.7: Regression results including front loads

<table>
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</thead>
<tbody>
<tr>
<td></td>
<td>Base (1)</td>
<td>12b-1 fees (2)</td>
<td>All fees (3)</td>
</tr>
<tr>
<td><strong>Dep. Var. - monthly net flow %</strong> (mean=0.67)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 month period</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Past excess returns</td>
<td>0.107***</td>
<td>0.0917***</td>
<td>0.117***</td>
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<tr>
<td></td>
<td>(0.00926)</td>
<td>(0.0111)</td>
<td>(0.0131)</td>
</tr>
<tr>
<td>(Past excess returns)X(12b-1 fees)</td>
<td>0.0454***</td>
<td>0.0407***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0105)</td>
<td>(0.0101)</td>
<td></td>
</tr>
<tr>
<td>(Past excess returns)X(mgmt fees)</td>
<td></td>
<td>-0.0278***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0104)</td>
<td></td>
</tr>
<tr>
<td>(Past excess returns)X(max .front loads)</td>
<td>-0.000859</td>
<td>-0.00151</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00152)</td>
<td>(0.00143)</td>
<td></td>
</tr>
<tr>
<td>12b-1 fees</td>
<td>-0.613***</td>
<td>-0.596***</td>
<td>-0.593***</td>
</tr>
<tr>
<td></td>
<td>(0.133)</td>
<td>(0.133)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>mgmt fees</td>
<td>-0.769***</td>
<td>-0.770***</td>
<td>-0.764***</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.160)</td>
<td>(0.159)</td>
</tr>
<tr>
<td>other fees</td>
<td>-0.134</td>
<td>-0.141</td>
<td>-0.158</td>
</tr>
<tr>
<td></td>
<td>(0.150)</td>
<td>(0.150)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>max. front loads</td>
<td>0.000775</td>
<td>0.00111</td>
<td>0.00328</td>
</tr>
<tr>
<td></td>
<td>(0.0157)</td>
<td>(0.0156)</td>
<td>(0.0156)</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Fund size, age, sales load, &amp; volatility controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>318,373</td>
<td>318,373</td>
<td>318,373</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.115</td>
<td>0.116</td>
<td>0.117</td>
</tr>
</tbody>
</table>

OLS standard errors two-way clustered by date and management company.

*** p<0.01, ** p<0.05, * p<0.1
Chapter 2

Video Games and Youth Crime

2.1 Introduction

Do violent games lead to violent youths and increased crime? Over the past two decades, video games sales have skyrocketed, driven in a large part by sales of violent games\(^1\). During that same period, youth violent crimes rates in the US fell by more than half, from a peak of 497 per 100,000 in 1995 to 183 per 100,000 in 2012 (OJJDP 2014). This paper attempts to isolate the effects of violent video game sales on crime using a novel data set of state-level game sales from 2006 to 2010.

The debate of whether media violence contributes to social violence is as old as the history of media. The level of violence seen in modern games, while shocking to some, is not out of the ordinary by Hollywood standards. The graphical levels of gore in Oscar-winning blockbusters such as “Saving Private Ryan” equal or exceed anything video games have to offer. However, unlike movies, which are passive experiences, video games are active experiences designed to immerse players. Watching people shoot at each other is a different experience from aiming down the gun sights and personally pulling the trigger. Violent video games may arouse violent thoughts and increase crime, but those games may also serve as cathartic release valves for violent thoughts and decrease crime. A priori, it is impossible to predict which effect will dominate. With regards to movie violence, Dahl and DellaVigna (2009) showed that the later effect dominates and that violent crime rates dropped on release nights of violent block-buster movies. Compared to movies, video games have stronger arousal and cathartic effects. The net impact of video games on crime remains an empirical question.

There is a growing body of empirical studies devoted to the effects of video games on violence, but the findings have been far from conclusive. The research thus-far can be divided into two categories: short-term laboratory experiments and longer-term correlation

\(^{1}\)The top selling game of 2013 was "Grand Theft Auto V", wherein the player take on the role of a former bank robber who engages in shoot-outs, heists, and police chases in a photo-realistic “sand box” simulation of Los Angeles. The second best selling game of 2013 was "Call of Duty: Ghosts", which is a “online first person shooter”, where players compete in simulated death matches, using avatars who wield photo-realistic renderings of real-world military firearms. Bonus points are awarded for “head-shots". 

CHAPTER 2. VIDEO GAMES AND YOUTH CRIME

studies. Among the short-term laboratory experiments on media exposure and aggression, the evidence has been mixed. The results span the range from positive correlation (Ivory and Kaestle 2013; Anderson and Buschman 2001; Anderson et al. 2003), to null (Tear & Nielson 2013), to negative (Valadez & Ferguson 2012). Among longer-term and large-scale correlation studies, the results have also been inconclusive, mostly due to limitations in data. Ferguson (2014) finds a negative correlation between violent game sales and youth violence, but it difficult to show statistical robustness and control for other social factors because the study is limited to 16 years of annual data. Cunningham, Engelstatter and Ward (2011) used weekly sales data and found weak negative correlation between violent video game sales and crime, but they were also unable to show statistical significance because of data limitations.

I contribute to this literature by constructing panel database of state-level game sales, which overcomes the time-series data restrictions faced by previous works. I build this panel database by combining national sales data from NPD group publications and state-level sales weights computed from Google Trends search data. The state-level variation in this panel data could help disentangle the impact of game sales from time trends. To the best of my knowledge, this is the first time that Google Trends data have been to re-construct panel data in this fashion. This methodology could also prove useful in other situations where panel data is difficult or expense to obtain.

2.2 Aggregate Trends

I first analyze the time series correlation between video game sales and youth crime using game sales data NPD group and crime data from the Federal Bureau of Investigation’s Uniform Crime Reporting (UCR) database. From 2006 to 2010, NPD released the national sales totals for the top 10 video games in each month. After 2010, NPD stopped releasing sales data to the public and required switched to a paid subscription model. The UCR database provides monthly data, by county for total offenses as well as cases cleared by crime category. Violent versus non-violent crime can be separated crime categories (i.e. assault would be categorized as violent, theft would not).

To distinguish between crimes committed by youth and adults, I look at the crime clearance data. Ideally, I would like to see the portion total offenses that were committed by adults versus youth, but in reality, the age of the offender can only be known after the crime was solved. Using clearances as the measure of crime introduces issues such as lags between crime reports and their clearance, as well as differential clearance rates for types of crimes, populations, and geographical regions. However, if the impact of these issues on youth and adult crime clearance rates do not vary significantly over time, then the adult crime rates can be used as a “control” baseline for the youth crime rates.

Figure 2.1 shows the trends of youth crime and violent game sales. Consistent with previous findings in the literature, there is a downward trend in youth crime while violent game sales grew. However, it is difficult to disentangle the impact of video game sales from time trends and other social factors using only this time series data.
Figure 2.1: Youth Crime and Violent Video Game Sales. “Youth/Adult Crime Clearance” is calculated as the ratio of crimes clearances with youth offenders to crime clearances with adult offenders. Violent games are those which are labeled have “violent content” by the Entertainment Software Rating Board (ESRB). Both crime and game sales time series are detrended for month fixed effects.
2.3 Using Google Search to Reconstruct State-Level Sales

To address the statistical inference issues of working with pure time series variation, I combine Google search data with national game sales figures to reconstruct at a panel data of video games sales across states and months. To do this, I obtain the Google Search Volume Index (SVI) of each game for each month from the Google Trends website. The SVI can be thought of as the number of Google queries per capita, and they are highly correlated with game playing. I use the relative search intensities across states to reconstruct relative sales across states.

To ensure that, I first check that Google SVI is correlated with actual game sales and playing. Figure 2.2 plots the daily national Google SVI against total player counts for three popular video games on the popular STEAM PC gaming platform. In each case, Google SVI closely tracks player counts. Univariate regressions of SVI on player counts yield r-squared close to 0.8.

The strong correlation between Google SVI and game play activity makes it reasonable to assume that Google searches are proportional to game sales, so that search\textsubscript{ist} = \delta \cdot sales\textsubscript{ist} for some constant \delta. Given that Google SVI is a measure of search intensity, which can be roughly thought of as a scaled version of search per capita, we have the following expression.

\[
SVI_{i,s,t} = \frac{\text{search}_{i,s,t}}{\text{pop}_{s,t}} = \frac{\delta \cdot sales_{i,s,t}}{\text{pop}_{s,t}}
\]

To calculate the share of game is sales that go to each state s during month t, I use the following formula, which is derived by isolating sales\textsubscript{ist} from equation 2.1. Note that all of the constants cancel out in this formula, and one needs only the SVI values and the population in each state.

\[
SalesShare_{i,s,t} \equiv \frac{sale_{i,s,t}}{\sum_s sale_{i,s,t}} = \frac{SVI_{i,s,t} \cdot \text{pop}_{s,t}}{\sum_s (SVI_{i,s,t} \cdot \text{pop}_{s,t})}
\]

To obtain the sales of game i, in each state during month t, I multiply the national sales of game i in time t by the Google-derived sales shares. I sum the sales across games within each state-month to obtain a state by month panel of game sales.
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Figure 2.2: Google search and daily peak player counts on STEAM PC platform.
Figure 2.3 plots the results of the total game sales across the ten largest states over the sample period. There is a lot of variation between the sales levels of the states, but most of this variation are differences in the level of sales.

Figure 2.4 plots the game sales divided by population of each state, to approximate sales per capita. By inspection, it is clear that the sales per capita across states closely track each other. This is confirmed by statistical analysis, a regression the state-by-month total game sales on only time fixed effects produces r-squared of greater than 0.94. Given this extremely high correlation of game sales across states, panel analysis of state-level sales provides no increased identification relative to the original time series analysis of national sales.
2.4 Discussion

In retrospect, the high correlation of sales across states is not terribly surprising. Video games in the modern era are mostly played online on platforms such as Xbox-Live, PlayStation Network, and STEAM. Promotions of games are done through online ad campaign, and much of the distribution of games are also through online download services. In the current age of increasing media concentration and internet consumption, geographic distance may no longer be a reliable way to differentiate consumers.

Google search SVI was successfully used to re-construct state-level video game sales when only national sales figures were available. The resulting panel sales data had little variation across states, but this was a feature of the data, not a failure of the method. The procedure that I described in section 2.3 is novel. To my knowledge, it has not been widely applied in empirical economics studies, and I believe it could be useful in constructing detailed panel datasets when the true underlying data is expensive or difficult to procure. Retail sales for specific products across regions and time would be a good candidate for such a procedure.
Bibliography


