Fund Managers' Use of Discretion in Time-Constrained Capital Reallocation Decisions

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ABSTRACT: I examine firm linkages within and across institutional holdings to test investors' trading behavior. This paper finds evidence of short-term return predictability stemming from fund managers' time-constrained capital reallocation decisions. In the presence of institutional frictions which make adjusting cash balances prohibitively costly, the results suggest that managers adjust portfolio holdings immediately following liquidity shocks. Using ownership links to identify firm-pairs, I show that fund managers use discretion when choosing which portfolio holdings to adjust in response to unexpected capital needs. Specifically, fund managers discriminately choose to adjust holdings based on industry exposure, portfolio risk, idiosyncratic risk, and geographic location.

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I. Introduction

Investment fund managers are often tasked with creating, and maintaining, portfolios comprised of an optimal mix of securities to achieve predetermined financial objectives. Price changes to any one security held in a manager's portfolio may prompt trading activity in other securities to rebalance the portfolio. Likewise, exogenous shocks to a manager's portfolio (i.e., unexpected fund inflows, extreme price movements, etc.) may subsequently impact prices of some, or all, individual securities held in the manager's portfolio. These shocks often accelerate the need for immediate action via a time-constrained capital reallocation process.[1] Thus, two otherwise unrelated securities may exhibit correlated price movements resulting from common portfolio shocks. Consistent with the capital reallocation process affecting security returns, prior research has documented that stock prices may (temporarily) deviate from fundamental values when multiple investors holding the same security face correlated liquidity shocks (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012; Greenwood and Thesmar, 2011). Negative liquidity shocks (i.e., unexpected capital demands from open-ended mutual fund investors) introduce an increased supply of existing portfolio securities in the marketplace, thereby depressing stock prices and offering liquidity providers significant abnormal returns. Likewise, positive liquidity shocks (i.e., unexpected inflows) infuse funds with excess capital that may be used to increase existing portfolio positions. Investor responses to monthly liquidity shocks, as documented in the prior literature, highlight a fundamental trading decision process. Whether this process extends to more

[1] Capital reallocation is distinct from the classical notion of portfolio rebalancing. Under normal rebalancing activity, fund managers react to ordinary stock price movements to revert the portfolio back to its original state. Conversely, capital reallocation may shift funds away from the portfolio's original state in response to economic shocks. Capital reallocation needs may arise from changes in long-term forecasts or investment objectives, or unexpected shocks leading to time-constrained, short-term adjustments. In this paper, I focus on time-constrained capital reallocation needs.

frequent trading intervals and endogenous trading activity, such as daily capital reallocation following short-term liquidity shocks, is an open empirical question.

In this paper, I examine the stock price implications of fund managers' responses to daily liquidity shocks. In particular, I show that following extreme negative (positive) firm return days, stocks with the highest cross-ownership with the event firm experience positive (negative) three-day abnormal returns, on average. This result is consistent with negative news prompting investors to sell and to reinvest sale proceeds within their existing portfolio holdings. Likewise, the results are also consistent with investors buying on good news, and obtaining needed capital by reducing their existing holdings. Further evidence shows that the choice of which paired securities to adjust is not random or uniform across all existing holdings; but rather, is the result of a discriminatory decision-making process based on firm fundamentals, risk factors, and operating environment.

Three conditions must be met for cross-ownership links to affect stock returns: (i) a shock to one firm has to result in unexpected trading activity by the current owners of the firm, (ii) holding cash must be costly to market participants, and (iii) portfolio managers must exhibit a preference for existing portfolio securities. The first condition is likely to be met for large public securities traded on major stock exchanges. Except in rare cases, a variety of market participants provide the necessary liquidity to complete trades at or near current prices for highly visible stocks. The second condition can reasonably be assumed since numerous investment mandates restrict managers from amassing large cash balances, and holding unmarked cash makes it difficult for managers to outperform market-based benchmarks (Coval and Stafford 2007; Khan et al. 2012). Furthermore, to the extent fund managers' compensation is tied to assets under management, holding cash suppresses managers' earnings potential.

If holding cash is indeed costly, fund managers will be inclined to reinvest proceeds from unexpected sales back into the market. Coval and Stafford (2007), Khan et al. (2012), and Ali et al. (2011) show that when faced with unexpected fund inflows, mutual fund managers initially adjust their existing portfolio positions, rather than creating new positions or holding excess cash. This seemingly mechanical behavior supports the third condition. Although prior studies have studied the reallocation decision using monthly fund flows, the extant literature is largely silent regarding unexpected shocks generated from endogenous daily trade activity. Relying on a similar capital reallocation process, I expect, and find evidence consistent with, fund managers adjusting current portfolio holdings in response to unexpected trade activity.

When faced with capital reallocation decisions, fund managers likely consider the vehicle necessitating the reallocation need, and respond accordingly. For example, if a fund manager hastily reduces her portfolio holdings in a particular stock following bad news (i.e. pending restatement), the decision regarding where and how to reinvest those sale proceeds will likely consider the restatement firm's characteristics (i.e., industry, risk profile, geographic location, etc.). By discriminately choosing to reallocate capital to a subset of portfolio holdings, fund managers are better equipped to manage risk while meeting financial objectives. I examine fund managers' use of discretion in the capital reallocation process and find evidence consistent with fund managers reallocating capital toward (away from) firms in the same industry and with similar idiosyncratic risk as the event firm following extreme one-day losses (gains). Fund managers also appear to shift capital toward (away from) high beta stocks and away from (toward) firms headquartered in the same state as the event firm following extreme one-day losses (gains).[2]

[2] The shift toward high beta stocks is consistent with fund managers responding to benchmarking pressures, as discussed in Christoffersen and Simutin (2014). The geographic location result is consistent with fund managers considering contagion within local economic conditions when making capital reallocation decisions.

To construct the sample, I first created a master list of all firms listed in the CRSP-Compustat merged database from 2006-2010. I restricted the sample to include only the common shares (CRSP share codes 10 and 11) from those firms traded on NYSE, AMEX, or NASDAQ. After matching on applicable firm identifiers, the base sample includes 6,730 firms. I downloaded the ownership composition of all sample firms from the first quarter of 2006 through the fourth quarter of 2010 from Thomson Reuters. An Ownership Score (OSCORE) was calculated for every possible firm pair for each quarter in the sample. The OSCORE was then used to rank all firm pairs each quarter. For this study, I kept the highest OSCORE pairings for each firm-quarter. The central prediction is that OSCORE may be used to identify paired firms exhibiting predictable short-term abnormal returns following extreme one-day price changes.

To illustrate this scoring approach, consider the case of Brown Shoe Co., Inc. (BWS). On August 25, 2010, BWS experienced a 14.06% one-day negative return, or approximately a $79 million decline in market capitalization. Assuming a significant portion of sale proceeds was captured by the 'former' owners of BWS and stockpiling cash was prohibitively costly, a substantial amount of capital could reasonably be expected to be reallocated from BWS to other securities. If fund managers exhibit a preference for current portfolio holdings, as documented in Coval and Stafford (2007), we could trace the firm's ownership links to identify and forecast paired firms' future returns.

According to ownership holdings disclosures as of September 30, 2010, the owners of BWS also owned 88.4% of the outstanding shares of Freeport McMoran Copper & Gold (FCX); 85.5% of CPFL Energia SA (CPL); 84.8% of Tanger Factory Outlet Centers (SKT); and 82.5% of Polycom Inc. (PLCM). Brown Shoe Co.'s 2010 10-K does not mention any of these four firms by name, and all five companies operate in separate industries. Yet, when BWS suffered a 14.06%

drop in stock price on August 25, all four of these otherwise unrelated firms experienced significant positive abnormal returns the following day. In fact, the average three-day abnormal return for BWS' top ten firm-pairs was 1.60%. *That is 160 bps over three days!* Subsequently, the market partially corrected for this upward price pressure, as the mean buy-and-hold abnormal return for the same ten firms over the 14 trading days subsequent to the event date was only 0.07% (see Appendix A). The above illustration is representative of price patterns across the sample. Consistent with the behavior documented in Coval and Stafford (2007), fund managers appear to adjust existing holdings in response to short-term liquidity shocks.

In this paper, I overcome two important limitations in prior research examining the capital reallocation decision. By focusing on periodic (i.e., quarterly; monthly) aggregate fund flows, prior research has been unable to identify: (1) the precise timing or (2) the underlying root cause prompting the need for capital reallocation. Periodic flow data inhibits researchers' ability to detect short-term return predictability. Furthermore, since prior research treats all unexpected fund flows equally, an implicit assumption is that fund managers indiscriminately allocate capital across all portfolio holdings. Without observing underlying root causes, prior research has been unable to identify subsets of portfolio holdings most likely to be affected by temporary price pressure.

I overcome these limitations by focusing the analysis on paired firms' short-term returns immediately following extreme one-day price changes. By identifying the timing and root cause of unexpected capital needs, I am able to test for discretion in the capital reallocation process. Specifically, I examine whether investors incorporate information about the source of capital needs when choosing which positions to adjust, or simply reallocate funds indiscriminately across their existing portfolio holdings. To my knowledge, this paper is the first to document short-term return predictability following stock return-based liquidity shocks via the capital reallocation process.

The main contribution of this paper is to explicitly document for the first time fund managers' use of discretion in the capital reallocation process. By shifting the analysis from unexpected periodic fund flows (as found in prior literature)[3] to clearly identifiable exogenous events (extreme one-day returns) spurring unexpected trade activity, I am able to develop sharper predictions regarding which securities will most likely be affected by capital reallocation. Complementing the main findings, I show that portfolio holdings disclosures contain value relevant information when constructing measures of cross-ownership, and that disclosure frequency impacts mispricing.

This paper is organized as follows. Section 2 discusses institutional background and prior literature. Section 3 describes the data and summary statistics. Section 4 presents the empirical results and robustness checks. Section 5 concludes.

2. Institutional Background and Literature Review

Fund managers experiencing unexpected capital reallocation needs may pursue several options in reallocating capital, including buying shares of their benchmark index, initiating new positions, and adjusting current holdings.[4] Coval and Stafford (2007) examine mutual funds experiencing large capital inflows and find that stocks held in common by these funds exhibit temporary upward price pressure following flows into the funds. This result is consistent with fund managers systematically reinvesting unexpected proceeds into their existing holdings. Supporting

[3] For examples, see Coval and Stafford (2007), Frazzini and Lamont (2008), Gao et. al (2015), Khan et. al (2012), Lou (2012)

[4] A fourth option, adjusting cash reserve balances, is another possible avenue available to fund managers when faced with unexpected capital reallocation needs. However, Coval and Stafford (2007) suggest that mutual funds immediately reinvest unexpected cash inflows because holding large cash reserves makes it increasingly difficult to outperform benchmarks. Additionally, many investment managers may be precluded from stockpiling cash by their investment mandate. A fifth option, short-selling, is not explicitly considered in this paper due to the prevalence of short-selling restrictions across many fund managers. Additional investment vehicles, such as options, futures, and other financial products are not explicitly examined herein primarily due to data limitations.

this finding, Khan et al. (2012) suggest that "[t]his excess liquidity is channeled into a narrow set of stocks since mutual funds follow specialized investment strategies, and since they likely face diminishing marginal investment prospects." By systematically reallocating funds across a pre-defined narrow set of stocks, fund managers often engage in trade activity that may not necessarily correspond to firm-specific fundamentals, and when aggregated, may (temporarily) drive prices away from fundamental values.

Firm managers appear to react opportunistically to flow-driven mispricing. The probability of a mispriced firm issuing an SEO or completing a stock-based transaction increases during the mispricing period (Khan et al. 2012). Furthermore, corporate insiders exploit flow-driven mispricing via insider trading and by shifting the timing of option grants for personal benefits (Ali et al. 2011). Superior equity analysts are also able to detect and respond to flow-driven mispricing by issuing recommendation changes and smaller forecast revisions than other analysts (Sulaeman and Wei 2014). Managerial and analyst responses to flow-driven mispricing do speed up the price correction process, thus slowly improving the informational efficiency of prices. Taken together, prior research offers compelling evidence suggesting that firm managers opportunistically exploit flow-driven mispricing in their own firms; however, relatively little is known about whether firm managers can detect, and subsequently react to, short-term mispricing driven by common ownership links. While not directly explored in this paper, the results presented herein open the door to future research examining corporate reaction to short-lived mispricing opportunities.

While firm managers and analysts have been successful at detecting flow-driven mispricing, the market as a whole has, at times, been slow to correct misvalued securities. Perhaps this lengthy correction process is not surprising as prior research has documented investor inattention related to lagged exchange rate movements, intra-industry returns and earnings surprises, and customer-supplier relationships, all of which exhibit return predictability (Bartov and Bodner, 1994; Ramnath, 2002; Hou, 2006; Cohen and Frazzini, 2008). Investor inattention in the current setting is perhaps even more likely than in the above-mentioned studies given that ownership links are not salient information that investors should reasonably be expected to collect. Although I do not test a limited attention hypothesis in this paper, the autocorrelation in ownership links is significantly high, suggesting that investors do not necessarily have to continuously update ownership metrics to exploit cross-ownership-related mispricing. I examine the effect of timing and the use of stale ownership data in subsequent robustness tests.

3. Data and summary statistics

Data are obtained from several sources. Quarterly stock ownership data for all public US firms from 2006-2010 come from Thomson One Banker. Stock returns, firm characteristics, and other market and accounting data are pulled from CRSP and Compustat, via Wharton Research Data Services (WRDS).

3.1 Sample selection and OSCORE calculation

Sample selection started with all firms listed in the CRSP-Compustat merged database from 2006-2010. The sample was restricted to only those firms traded on NYSE, AMEX, or NASDAQ, yielding a base sample of 6,730 firms (after matching applicable firm identifiers to the sample). Similar to prior studies, I measure common ownership as the percentage of Firm j's total market value owned by Firm i's owners (Anton and Polk, 2014; Matvos and Ostrovsky, 2008). An Ownership Score (OSCORE) is calculated for every firm-pair using a two-step process. First, I collect ownership composition data from Thomson Reuters for every firm in the sample for twenty (20) quarters from 2006-2010. Then, I sum each investors' market share of Firm j conditional on the investor also owning shares of Firm i. Holdings data is converted into a market share for all investor-firm pairs using firms' most recently reported Total Shares Outstanding as follows:

$$MktShare_{k,i} = \text{Shares held by investor k in Firm i / Total Shares Outstanding for Firm i}$$

OSCORE is then calculated for all possible i, j firm-pairs in each quarter, *t*. Firm pairs are then ranked each quarter by OSCORE. Only the top 0.2% of OSCORE pairings for each firm-quarter were used in the main analyses. See Appendix A for more details.

As expected, OSCORE exhibits a high degree of autocorrelation. Pearson correlation coefficients typically exceed 90% four quarters after the original pairing (Table II). This empirical regularity may be interpreted as justification for relying on stale OSCORE measures when developing a trading strategy based on OSCORE. I test whether relying on stale disclosures impacts hedge portfolio returns in the next section, and as expected, I find that abnormal returns are greatest when the measurement date is in close proximity to the portfolio reporting date. This result supports the hypothesis that OSCORE, when measured accurately, may be used to identify paired firms exhibiting predictable short-term abnormal returns following extreme one-day price changes in event firms.

3.2 Summary statistics

Summary statistics are provided in Table I. OSCORE is computed for every firm-pair each quarter. For each quarter, I compute an OSCORE for over 40 million firm-pairs. Only the top 0.2% of the entire universe of OSCORE pairs are included in the sample. For every firm j, I keep approximately ten paired firms with the highest OSCORE each quarter.[5] Using daily raw

[5] Firm-pairs are rank ordered by OSCORE using 500 groupings each quarter. The mean number of pairs for each firm using this methodology is 9.91. I also restrict paired firms from appearing more than once within a 28-day period.

returns, I decile-rank all sample firms by market value lost each day. Event firms in the lowest (highest) decile are the biggest market losers (gainers) on that day. To the extent that large one-day stock price declines (increases) result in unexpected cash inflows (outflows) for current shareholders, I predict that OSCORE may be used to identify and forecast paired-firms future returns. Consistent with prior literature, I expect investors will redistribute unexpected cash flows by adjusting current portfolio holdings. I present summary statistics for OSCORE and paired-firms in Table I.

Panel A presents distribution metrics for OSCORE for the final sample. Summary statistics are presented by decile rankings of event firms' change in market value (*r_SumMV*).[6] The mean (median) OSCORE for the entire sample is 23.4% (17.3%), with an interquartile range of 11.8% to 25.5%. These averages increase significantly in the extreme deciles. Decile 0, comprised of firms paired with event firms suffering extreme one-day losses, has a mean (median) OSCORE of 41.0% (25.8%), whereas Decile 9, comprised of firms paired with event firms experiencing extreme one-day gains, has a mean (median) OSCORE of 49.4% (31.6%).

Panel B compares firm characteristics of paired firms in Decile 0 to those in Decile 9. Decile 0 firms appear to underperform their counterparts during the year, as EBITDA and cash flow from operations are lower for these firms. Total assets and long-term debt are not significantly different; however, Decile 9 firms have a larger market capitalization than firms included in Decile 0. Contrary to the relative annual underperformance of firms in Decile 0, the capital reallocation process outlined above predicts Decile 0 firms will outperform Decile 9 firms in the three-day return window subsequent to event firms' extreme one-day returns.

[6] Note that the number of observations in Deciles 0 and 9 are lower due to additional data requirements in subsequent tests.

4. Empirical analysis and results

4.1 Main results

Table III shows the relationship between event-firm returns and subsequent three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE). The coefficients on *r_SumMV* and summary statistics from four regressions are displayed. I regress $CAR_{i,(+1,+3)}$ ($BHAR_{i,(+1,+3)}$) on the decile-rank of the event firms' daily change in market value; three Fama-French factors; and Carhart's momentum factor. $CAR_{i,(+1,+3)}$ is the three-day cumulative abnormal return for each paired-firm. $BHAR_{i,(+1,+3)}$ is the three-day buy-and-hold abnormal return for each paired-firm. I use Carhart's four-factor model with a [-300, -46] estimation window relative to the event date as the benchmark for expected returns. The key independent variable, *r_SumMV*, is a decile rank-ordering of daily returns (change in market value) calculated for all firms traded on NYSE, AMEX, or NASDAQ and with price information in the CRSP database. Paired firms may only appear once every 28 days. I compute clustered standard errors by event date and report t-statistics in parentheses.

The coefficient on *r_SumMV* is negative and statistically significant in all four regression models, suggesting that investors predictably reallocate unexpected daily cash flows (i.e., day zero event-firm returns forecast subsequent three-day returns in paired firms). The results suggest that paired-firms in decile 9 are expected to outperform their decile 0 counterparts by 18 bps over the three-day window subsequent to the event date. Figure 1 provides illustrative support for this result, as weekly cumulative abnormal returns (CARs) are plotted for paired firms in Deciles 0 and 9. As expected, paired firms in Decile 0 outperform their Decile 9 counterparts by a significant margin during the three-day window subsequent to the event date. This outperformance is short-lived; however, as temporary mispricing driven by the capital reallocation process appears to be corrected 8-13 weeks after the event date.

Table IV further examines the effect of common ownership on return predictability by documenting paired-firms' abnormal returns conditioned on the magnitude of event firms' daily change in market value (*r_SumMV*). Panel A (Panel B) reports regression results from a market (four-factor) model. As documented in Panel B column 2 (Decile 0), when an event firm experiences a large one-day drop in market value, paired firms exhibit positive subsequent three-day abnormal returns. Likewise, following a large one-day increase in market value, paired firms exhibit significantly negative subsequent three-day abnormal returns (see column 11). These results are consistent with investors following a predictable capital reallocation process by redistributing funds across existing holdings in response to short-term liquidity shocks to their portfolios.

4.2 Discretion in the reinvestment process

I next turn to fund managers' use of discretion in the capital reallocation process. In this section, I examine four distinct avenues whereby fund managers may discriminately select a subset of portfolio holdings from which to reallocate capital following unexpected exogenous shocks to their portfolio. To my knowledge, this is the first paper to examine fund managers' use of discretion in the time-constrained capital reallocation process.

4.2.1 Industry

Asset allocation across industries is an important consideration in effective portfolio management. Firms operating within the same industry often exhibit higher return covariance than firms operating across different industries due to exposure to common economic characteristics

(Markowitz, 1952). Prior research has examined, and found evidence consistent with, industry contagion effects following both good and bad economic events (Gleason et. al, 2008; Hertzel and Officer, 2012; Lang and Stulz, 1992). Consistent with findings in prior literature, I expect, and find, that fund managers consider industry exposure during the capital reallocation process.

To test whether fund managers use discretion in the capital reallocation process, I employ a difference-in-differences research design, regressing paired-firms' three-day cumulative abnormal returns on decile and industry dummy variables, an interaction term, and known risk factors. The regression results, displayed in Table V Panel A, suggest that fund managers reallocate proceeds from unexpected sales to existing portfolio holdings in the same industry; and accumulate funds for unexpected purchases by selling off parts of existing holdings, also in the same industry. Despite the stringent time constraints restricting fund managers during the reallocation process, these results provide evidence consistent with managers favoring industry exposure when making decisions regarding capital reallocation.

4.2.2 Risk profile

As noted in Christoffersen and Simutin (2014), fund managers often turn to high-beta stocks in response to benchmarking pressures. If fund managers do employ discretion during the reallocation process, this flight to high-beta strategy is likely to emerge following poor return performance. Conversely, fund managers may be inclined to reverse their positions in high beta stocks when performance recovers. To empirically examine whether fund managers consider a firm's beta in the reinvestment process, I regress paired-firms' three-day cumulative abnormal returns on decile and high beta[7] dummy variables, an interaction term, and known risk factors, using the same difference-in-differences research design as above.

The regression results reported in Table V Panel B show results consistent with fund managers using discretion in the reallocation process to shift capital toward (away from) high-beta stocks following low (high) event firm returns. The statistically significant positive coefficient on *HiBeta* indicates that fund managers reinvest proceeds from unexpected sales of poorly performing securities into high-beta stocks. Moreover, the statistically significant negative coefficient on *Decile*HiBeta* indicates that fund managers willingly reduce their positions in high-beta stocks to capitalize on good news affecting other stocks in their portfolio.

4.2.3 Returns volatility

Complementing their hypothesized high-beta strategy, Christoffersen and Simutin (2014) posit that as fund managers adopt this asset selection strategy, they also manage to maintain (or even lower) their portfolio's idiosyncratic risk. By selectively choosing to replace portfolio assets with higher-beta, but similarly-volatile, assets, fund managers can reduce tracking error. To empirically examine whether fund managers consider a firm's return volatility in the reallocation process, I again employ the same research design as above, and regress paired-firms' three-day cumulative abnormal returns on decile and return volatility[8] dummy variables, an interaction term, and known risk factors.

[7] I assign stocks with a beta of 1.7 or above a H*ighBeta* of 1; for all others, *HighBeta* equals zero. In untabulated tests, I re-ran the analysis with *HighBeta* cutoffs of 1.2 and 1.5. The results were qualitatively similar to those reported.

[8] I assign paired firms with return volatility within 10% of the event firm's return volatility a *CloseVol* of 1; for all others, *CloseVol* equals zero. In untabulated tests, I re-ran the analysis with *CloseVol* cutoffs of 8%, 15%, and 20%. The results were qualitatively similar to those reported.

The regression results reported in Table V Panel C show results consistent with fund managers using discretion in the reallocation process to shift capital toward (away from) paired stocks with similar return volatility following low (high) event firm returns. The statistically significant positive coefficient on *CloseVol* indicates that fund managers reinvest proceeds from unexpected sales of poorly performing securities to paired stocks sharing similar idiosyncratic risk to the event firm. Moreover, the statistically significant negative coefficient on *Decile*CloseVol* indicates that when fund managers need capital to respond to good news elsewhere in their portfolio, they choose to reduce positions in carefully selected securities so as to maintain a consistent portfolio return volatility.

4.2.4 Location

Prior research suggests that geography plays a central role in investors' stock selection decisions. French and Poterba (1991) find that investors overwhelmingly select domestic securities when constructing portfolios. Coval and Moskowitz (1999, 2001) and Huberman (2001) extend the home bias literature by examining stock selection decisions within investors' home countries, and find evidence that investors' bias for choosing local securities goes beyond national boundaries. A growing literature on local bias contends that investors choose geographically close securities for various information-based or intrinsic value reasons (Cooper and Kaplanis (1994), Kang and Stulz (1997), Hau (2001), Hong et. al (2008), Seasholes and Zhu (2010), Sinclair (2011)). Teo (2009) finds that hedge funds with a physical presence in their investment space significantly outperform their counterparts. Aside from direct performance measures, geography also affects venture capital stage financing, the likelihood of being acquired, and access to political power (Tian (2008), Rossi and Volpin (2004), Kim et. al (2012)). Analysts are also affected by geography. Malloy (2005) documents an information advantage for local analysts, relative to all other analysts. Together, these results provide compelling evidence suggesting that investors at least consider firms' physical location when making investment decisions.

To test whether fund managers consider geography during the capital reallocation process, I repeat the above difference-in-differences analysis, replacing industry with location. The regression results, displayed in Table V Panel D, support the conjecture that fund managers pay close attention to local economic conditions when reallocating funds across existing securities. In particular, returns for paired securities located in the same state as an event firm are positively correlated with the event firms' returns. These results are consistent with fund managers' rational assumption that extreme returns are, at least partially, attributed to local economic conditions or more generally, to investors' local bias.[9] All together, the results presented in this section provide strong evidence that fund managers do not simply sprinkle unexpected proceeds across all portfolio holdings or reduce holdings across their entire portfolio to raise needed capital, but rather exercise discretion in their time-constrained capital reallocation decisions.

4.3 Robustness tests

In this section, I conduct a battery of robustness tests pertaining to measurement issues related to disclosure timing and event identification.

4.3.1 Proximity to quarter-end date

Any event study relying on quarterly holdings data to proxy for current shareholders on a given day inherently has measurement error. To the extent that fund managers' holdings change intra-quarter, OSCORE may not precisely reflect daily cross-ownership levels. I address this

[9] Pirinsky and Wang (2006) support this conjecture by providing evidence of local stock co-movement for a large sample of firms.

concern in two ways. First, I re-ran the main analysis separately by splitting the sample into three buckets, based on the event date's proximity to the closest quarter-end date. OSCORE is expected to more accurately capture cross-ownership levels when measured in close proximity to the quarter-end, and to lose its measurement effectiveness as the event date moves further away from quarter-end. Consistent with this conjecture, Table VI Panel A documents that OSCORE is most effective at predicting returns when measured in close proximity to the quarter-end. The coefficient on *r_SumMV* is negative and significant when the event date is less the nine days away from the nearest quarter-end date. As expected, OSCORE becomes less predictive of future returns as its measurement precision declines.

As noted earlier, OSCORE exhibits high autocorrelation. As a second test of measurement efficiency, I re-ran the main analysis again, this time measuring OSCORE at alternate filing dates relative to the event date: the previous quarter, two quarters prior, and the current quarter. Given the high correlation of $OSCORE_t$ and $OSCORE_{t-1}$, it may be reasonable to expect the results to still hold when relying on stale measurement dates. Alternatively, if return predictability is sensitive to measurement error, then the results are likely to be strongest when using the closest quarter-end to measure OSCORE. Consistent with the alternative, Table VI Panel B suggests that reducing measurement error is essential to reliably predicting returns using OSCORE. The coefficient on *r_SumMV* is negative across all alternate filing quarters, but is only statistically significant at conventional levels when using the closest reporting date.

4.3.2 Changes to S&P 500 composition

As an alternative event identification strategy, I re-ran the analysis using additions to and deletions from the S&P 500 index to identify event firms. Prior research has documented significant price and trading volume reactions to firms' inclusion and exclusion in large stock indices (i.e., Pruitt and Wei (1989; Chen et. al (2004); Chan et. al (2013)). Many investment funds have established policies specifically addressing holdings in stocks included in major stock indices; effectively mandating fund managers to restructure portfolios upon these relatively low-frequency events. Despite restrictions governing index-based holdings, fund managers are often free to choose among large samples of stocks to meet their investment objectives. S&P 500 composition changes offers a unique setting of exogenous events to test fund managers' use of discretion in the capital reallocation process.[10]

Using a base sample of 93 additions to and 32 deletions from the S&P 500 index from 2006-2010 and OSCORE measurements from the closest quarter-end date to identify firm-pairs, I analyze three-day abnormal returns for paired firms around the event date. For the index addition (deletion) subsample, I regressed the three-day CAR before (after) the event date on industry and state indicator variables and four risk factors. The regression results, reported in Table VII, further support the hypothesis that fund managers use discretion in the capital reallocation process. Consistent with additions to the S&P 500 index signaling good news for an industry, the coefficient on *SameInd* is positive and significant, indicating that fund managers dedicate additional resources toward portfolio holdings in the same industry as the event firm up to three days before the index addition. These resources appear to be reallocated away from firms in the same state as the event firm, possibly to prevent overweighting in local economies.

[10] Chan et. al (2013) argues that changes to the S&P 500 contain value-relevant information about firms' industries. If this argument holds true, fund managers may rationally adjust industry holdings around addition and deletion announcement dates. Although not at odds with each other, to distinguish the capital reallocation hypothesis advanced in this paper from the more general information-based proposition, I re-ran the analysis in Table VII using low and medium OSCORE pairs. In untabulated tests, the coefficients of interest were all insignificant, and in most cases, the sign was flipped.

The results from the deletion sample also support discretion entering the capital reallocation process. The coefficient on *SameInd* is negative and significant, indicating that fund managers reduce holdings in portfolio stocks operating in the same industry as deleted firms, but only in firms not located in the same geographic location. Sale proceeds appear to be reallocated toward firms operating in the same state as the event firm. Overall, the results from Table VII further validate fund managers' use of discretion in the capital reallocation decision process.

4.3.3 Alternative liquidity shock measurements

Throughout the paper, I define extreme one day returns using the sum of firms' daily change in market value, and assume the firms' 'current' shareholders recover a significant portion of downward price movement via selling activity. This proxy for fund managers' capital reallocation needs is measured with error. In light of this measurement difficulty, I do consider two alternative measures. Rather than using a sum measure, I alternatively identify extreme return days by using average daily return percentages and the average market value lost by firms' owners. In un-tabulated results, I re-ran the main analysis using these alternative measures, and the results are qualitatively similar.

5. Conclusion

I provide comprehensive evidence on short-term return predictability stemming from fund managers' time-constrained capital reallocation decisions. In the presence of institutional frictions which make holding cash balances prohibitively costly, the evidence suggests that fund managers adjust their portfolio holdings immediately following unexpected trade activity. The well-documented preference for current holdings is also present in this paper; however, contrary to assumptions underlying prior work in this area, the evidence presented herein suggests that fund managers use additional discretion when choosing *which* portfolio holdings to adjust in response to unexpected capital needs. Specifically, following unexpected trade activity, the evidence suggests that fund managers consider industry exposure, portfolio risk, idiosyncratic risk, and geographic location when selecting which portfolio holdings to adjust.

This paper contributes to the growing literature on unexpected fund flows and the capital reallocation process. Instead of using periodic fund flow data, I identify a setting where fund managers are likely to engage in unexpected trade activity; extreme one-day price changes in currently held securities. Unlike normal price appreciation, which leads to periodic portfolio rebalancing requirements, extreme price changes often result from significant shocks to investors' expectations. Fund managers can respond to these shocks in a number of ways, including doing nothing at all. The evidence presented in this paper suggests that fund managers respond to unexpected shocks by following a predictable capital reallocation strategy.

The results presented in this paper present several opportunities for future research. Identifying the nature of the good or bad news responsible for the extreme one-day returns may provide additional insights into fund managers' reallocation decision process. For example, do fund managers focus more on earnings quality following an accounting restatement? Furthermore, by identifying firm-pairs with high OSCOREs, future research could examine pockets of stock return co-movement following local economic or liquidity shocks. Building on the underlying relationships spurred by ownership links can be useful for future research that is becoming increasingly interested in behavioral explanations for asset pricing anomalies.

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Appendix A: Variable List

R_SUMMV: rank variable numbered 0 to 9 based on the event firms' daily change in market value (if multiple event firms share a common paired-firm on a particular event date, the ranking is based on the sum of the event firms' daily change in market value)

DECILE: indicator variable equaling 1 for observations in the top decile of r_SUMMV, and 0 for observations in the lowest decile of r_SUMMV

SAMEIND: indicator variable equaling 1 for observations where the event firm and paired firm share the same one-digit SIC code, and 0 otherwise

HIBETA: indicator variable equaling 1 for observations where the paired firm's beta (calculated over 255 days ending 46 days prior to the event date) is greater than 1.7, and 0 for observations where the paired firm's beta is less than 0.7

CLOSEVOL: indicator variable equaling 1 for observations where the paired firm's return volatility is within 10% of the event firm's return volatility; and 0 otherwise

SAMESTATE: indicator variable equaling 1 for observations where the paired firm is headquartered in the same state as the event firm; and 0 otherwise.

MKTRF: the excess return on the market, calculated as difference between the value-weighted return on all NYSE, AMEX, and NASDAQ stocks and the one-month Treasury bill rate.

SMB: the difference between a portfolio of "small" stocks and "big" stocks

HML: the difference between a portfolio of "high" book-to-market stocks and "low" book-to-market stocks

UMD: the difference between a portfolio of high past one-year returns and low past one-year returns

Appendix B: Case Study: Brown Shoe Co.

On August 25, 2010, Brown Shoe Co. Inc. (BWS) revised their revenue guidance for Fiscal Year 2010. On that day, BWS stock price dropped 14.06%.

Immediately following the significant drop in BWS stock price, several stocks that exhibited high OSCOREs with Brown Shoe Co. Inc. experienced a price increase:

Firm	Ticker	August 25	August 30 (3-day raw ret)	(+1,+3) BHAR	(+1,+14) BHAR
FREEPORT MCMORAN COPPER & GOLD	FCX	66.66	70.36 (5.55%)	(6.39%)	(11.62%)
POLYCOM INC	PLCM	27.45	28.74 (4.70%)	(4.53%)	(-4.98%)
TANGER FACTORY OUTLET CENTERS I	SKT	44.83	45.73 (2.01%)	(2.58%)	(-2.87%)
HUB GROUP INC	HUBG	26.04	26.60 (2.15%)	(2.28%)	(7.67%)
WHITING PETROLEUM CORP	WLL	84.41	85.14 (0.86%)	(1.31%)	(-6.36%)
C P F L ENERGIA S A	CPL	71.39	72.14 (1.05%)	(1.04%)	(-7.56%)
EATON CORP	ETN	69.97	70.07 (0.14%)	(0.40%)	(2.45%)
SMITH A O CORP	AOS	51.29	51.37 (0.16%)	(0.14%)	(0.89%)
H D F C BANK LTD	HDB	161.75	159.28 (-1.53%)	(-1.29%)	(-0.33%)
BALL CORP	BLL	56.34	55.49 (-1.51%)	(-1.33%)	(0.15%)
EQUAL-WEIGHTED BHAR				**(1.60%)**	**(0.07%)**
S&P 500		1055.33	1048.92 (-0.61%)		
RUSSELL 3000		62.23	61.91 (-0.51%)		

Appendix C: OSCORE Calculation

$$\text{OSCORE}_{j,i,t} = \sum\nolimits_{k=1}^{n} \text{MktShare}_{k,j,t} | \text{MktShare}_{k,i,t} > 0$$

An Ownership Score (OSCORE) is calculated using a two-step process. First, I collect quarterly holdings data from Thomson Financial for every firm in the sample from 2006-2010. Then, I sum each investors' market share of Firm j conditional on the investor also owning shares of Firm i. The holdings data is converted into a market share for all investor-firm pairs using the firms' most recently reported Total Shares Outstanding ($\text{MktShare}_{k,i}$ = Shares held by Investor k in Firm i/Total Shares Outstanding for Firm i). An Ownership Score is calculated for all possible i,j firm-pairs. The following example illustrates the process:

Step 1: Collect portfolio holdings (download from Thomson Financial)

Investors A-C Portfolios at Time t

	A	**B**	**C**
Shares held of firm x *(total shares outstanding = 295)*	100	0	70
Shares held of firm y *(total shares outstanding = 150)*	50	80	0
Shares held of firm z *(total shares outstanding = 345)*	0	120	20

Step 2: Calculate OSCORE*

Sum of Market Share

	x	y	z
Conditional on owning x	-	33.33%	5.80%
Conditional on owning y	33.90%	-	34.78%
Conditional on owning z	23.73%	53.33%	-

* $\text{OSCORE}_{j,i,t}$ Calculations

	Calculation	OSCORE
Oscorex,y,t	(100 + 0) / 295	**33.90%**
Oscorex,z,t	(0 + 70) / 295	**23.73%**
Oscorey,x,t	(50 + 0) / 150	**33.33%**
Oscorey,z,t	(80 + 0) / 150	**53.33%**
Oscorez,x,t	(0 + 20) / 345	**5.80%**
Oscorez,y,t	(0 + 120) / 345	**34.78%**

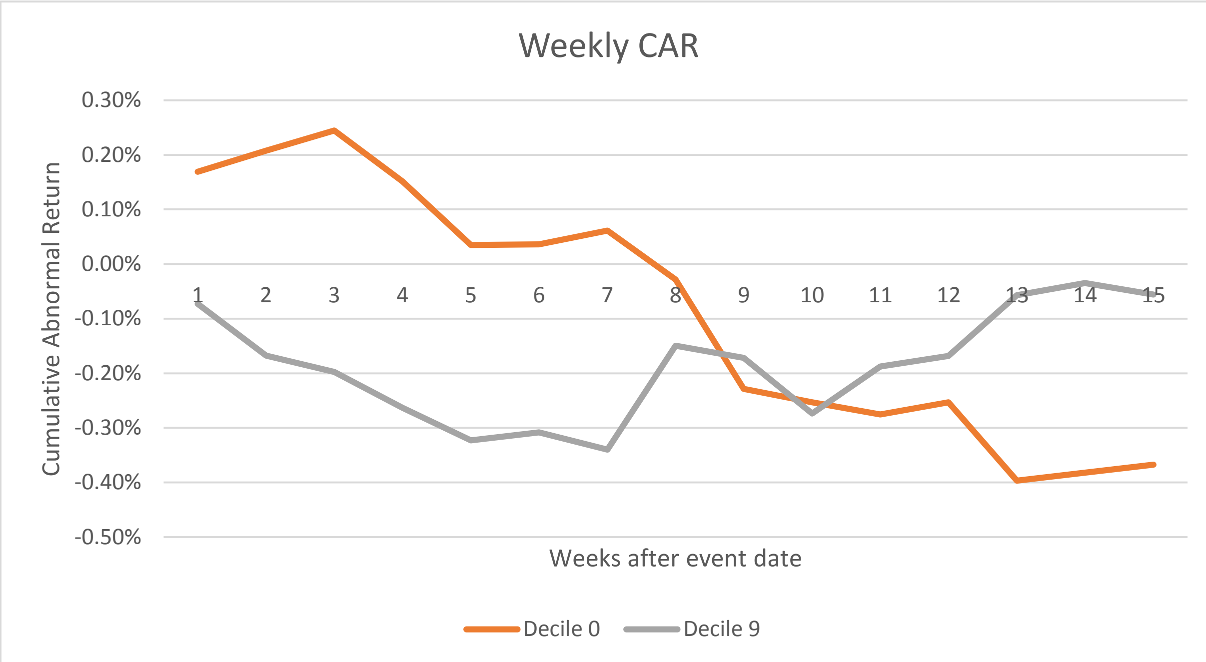

Figure 1. Cumulative abnormal return following event date. Plotted above are the cumulative weekly abnormal returns for paired firms in Deciles 0 and 9. The horizontal axis counts weeks following the event date, with 1 representing one entire trading week following the extreme return day. The vertical axis is the cumulative abnormal return.

Table I

Summary Statistics

Panel A provides summary distribution statistics for the final sample for OSCORE by *r_SumMV* decile. *r_SumMV* is a rank variable numbered 0 to 9 based on the event firms' daily change in market value (if multiple event firms share a common paired-firm on a particular event date, the ranking is based on the sum of the event firms' daily change in market value). The number of observations for the two extreme deciles is lower due to data requirements in subsequent analyses. Firm-pairs are rank ordered by OSCORE using 500 groupings each quarter. The mean number of pairs for each event firm using this methodology is 9.91. Paired firms may only appear once within a 28-day period. This table presents statistics for the top-ranked OSCORE pairs.

Panel A: OSCORE by decile								
	N	Mean	Min	25%	Med	75%	Max	STD
Total	76,643	0.234	0.000	0.118	0.173	0.255	1.200	0.213
0 (Lowest Event Firm Returns)	6,740	0.410	0.022	0.165	0.258	0.510	1.200	0.351
1	7,770	0.213	0.009	0.126	0.183	0.256	1.192	0.131
2	7,862	0.184	0.000	0.113	0.160	0.225	1.019	0.101
3	7,827	0.166	0.000	0.105	0.147	0.207	1.020	0.087
4	7,958	0.162	0.000	0.104	0.142	0.198	1.003	0.084
5	7,992	0.167	0.000	0.106	0.146	0.206	1.020	0.088
6	7,897	0.176	0.000	0.110	0.155	0.216	0.944	0.094
7	7,840	0.195	0.002	0.120	0.171	0.238	1.177	0.107
8	7,662	0.225	0.015	0.136	0.194	0.272	1.188	0.137
9 (Highest Event Firm Returns)	7,095	0.494	0.017	0.184	0.316	0.855	1.200	0.391

Table I (continued)

Summary Statistics

Panel B displays mean values, as of the end of the fiscal year, for several paired-firm characteristics. Column 2 (3) presents mean values for paired-firms with high cross-ownership with event firms experiencing large one-day market value losses (gains). Column 4 presents the t-statistics from a pooled test of differences across means.

Panel B: Firm characteristics			
	Decile 0	Decile 9	Diff
Total assets	11,684	10,739	0.72
Total LT debt	1,976	1,965	0.04
Employees	12.05	13.71	-2.45**
Dividends	124.7	138.9	-1.43
Capital expenditures	382.4	452.9	-1.82*
EBITDA	872.6	1,005.0	-2.38**
Cash flow from operations	653.0	804.6	-3.01***
Market capitalization	3,080.6	4,223.5	-6.94***

Table II

Correlation Table

This table presents Pearson pairwise correlation coefficients for OSCORE across the sample period.

	'06 Q1	'06 Q2	'06 Q3	'06 Q4	'07 Q1	'07 Q2	'07 Q3	'07 Q4	'08 Q1	'08 Q2	'08 Q3	'08 Q4	'09 Q1	'09 Q2	'09 Q3	'09 Q4	'10 Q1	'10 Q2	'10 Q3
'06Q2	0.96																		
'06Q3	0.93	0.97																	
'06Q4	0.92	0.95	0.97																
'07Q1	0.90	0.92	0.95	0.97															
'07Q2	0.87	0.90	0.92	0.94	0.96														
'07Q3	0.86	0.88	0.90	0.92	0.93	0.97													
'07Q4	0.85	0.87	0.88	0.90	0.91	0.94	0.96												
'08Q1	0.84	0.86	0.87	0.88	0.90	0.93	0.94	0.97											
'08Q2	0.83	0.84	0.86	0.87	0.88	0.91	0.92	0.94	0.96										
'08Q3	0.82	0.83	0.85	0.86	0.87	0.89	0.90	0.92	0.94	0.97									
'08Q4	0.82	0.83	0.84	0.85	0.87	0.88	0.89	0.91	0.93	0.95	0.97								
'09Q1	0.81	0.82	0.84	0.85	0.86	0.87	0.88	0.90	0.91	0.94	0.95	0.97							
'09Q2	0.80	0.82	0.83	0.84	0.85	0.87	0.87	0.89	0.90	0.92	0.93	0.95	0.97						
'09Q3	0.80	0.81	0.82	0.83	0.84	0.86	0.86	0.88	0.89	0.91	0.92	0.94	0.95	0.98					
'09Q4	0.79	0.81	0.82	0.83	0.83	0.85	0.86	0.87	0.88	0.90	0.91	0.92	0.94	0.96	0.98				
'10Q1	0.79	0.81	0.81	0.82	0.83	0.85	0.85	0.86	0.87	0.89	0.90	0.92	0.93	0.95	0.96	0.98			
'10Q2	0.79	0.80	0.81	0.82	0.82	0.84	0.85	0.85	0.87	0.88	0.89	0.90	0.91	0.93	0.94	0.95	0.97		
'10Q3	0.78	0.79	0.80	0.81	0.82	0.83	0.84	0.85	0.86	0.88	0.88	0.90	0.90	0.92	0.93	0.94	0.95	0.98	
'10Q4	0.77	0.79	0.80	0.81	0.81	0.83	0.83	0.84	0.85	0.87	0.88	0.89	0.89	0.91	0.92	0.93	0.94	0.96	0.98

Table III

Predicting Returns Using Ownership Score

This table shows the relationship between event-firm returns and subsequent three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE). The coefficients on *r_SumMV* and summary statistics from four regressions are displayed below: two different dependent variables ($CAR_{i,(+1,+3)}$ and $BHAR_{i,(+1,+3)}$) regressed on the rank of the sum of the event firms' daily change in market value and three Fama-French factors and Carhart's momentum factor. $BHAR_{i,(+1,+3)}$ is the three-day buy-and-hold abnormal return for each paired-firm. $CAR_{i,(+1,+3)}$ is the three-day cumulative abnormal return for each paired-firm. I use the four-factor model (from Carhart (1997)) with a [-300, -46] estimation window relative to the event date as the benchmark for expected returns. The key independent variable, *r_SumMV*, is a decile rank-ordering of daily returns (change in market value) calculated for all firms traded on NYSE, AMEX, or NASDAQ and with price information in the CRSP database. Standard errors are clustered by event date. The *t-statistics* are in parentheses.

	$CAR_{i,(+1,+3)}$		$BHAR_{i,(+1,+3)}$	
Intercept	0.0005	0.0004	0.0004	0.0003
	(0.95)	(0.84)	(0.76)	(0.65)
r_SumMV	**-0.0002**	**-0.0002**	**-0.0002**	**-0.0002**
	(-2.32)	**(-2.23)**	**(-2.30)**	**(-2.21)**
MKT_RF		0.0430		0.0428
		(0.87)		(0.81)
SMB		-0.0177		-0.0263
		(-0.21)		(-0.31)
HML		-0.1134		-0.1143
		(-1.09)		(-1.14)
UMD		**-0.2056**		**-0.1964**
		(-4.79)		**(-4.67)**
Observations	76,641	76,641	76,641	76,641
Clusters (days)	840	840	840	840
R^2	0.01%	0.23%	0.01%	0.21%

Table IV
Time Series Regressions of 3-Day Cumulative Abnormal Returns on Fama-French Factors

This table shows the relationship between event-firm returns and subsequent three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE) by decile ranking. The dependent variable, $CAR_{i,(+1,+3)}$, is the three-day cumulative abnormal return for each paired-firm. Panel A presents results from a market model, with a [-300, -46] estimation window relative to the event date as the benchmark for expected returns. Alpha coefficients are represented by the intercept. Standard errors are clustered by event date. The *t-statistics* are in parentheses.

	Lowest Event Firm Returns									Highest Event Firm Returns
Decile	0	1	2	3	4	5	6	7	8	9
MODEL 1										
intercept	0.0011	-0.0006	-0.0002	-0.0000	-0.0001	-0.0003	-0.0003	-0.0015	-0.0011	-0.0010
	(1.64)	(-0.92)	(-0.36)	(-0.03)	(-0.18)	(-0.33)	(-0.32)	(-1.88)	(-1.53)	(-1.45)
mktrf	0.1340	0.0789	0.1223	0.1127	0.0637	0.1432	0.0752	0.1461	0.0149	0.0294
	(0.89)	(1.70)	(2.20)	(1.63)	(1.61)	(1.72)	(2.01)	(1.91)	(0.26)	(0.41)
R2	0.18%	0.06%	0.13%	0.11%	0.09%	0.14%	0.18%	0.19%	0.00%	0.01%

Table IV (continued)

Time Series Regressions of 3-Day Cumulative Abnormal Returns on Fama-French Factors

This table shows the relationship between event-firm returns and subsequent three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE) by decile ranking. The dependent variable, $CAR_{i,(+1,+3)}$, is the three-day cumulative abnormal return for each paired-firm. Panel B presents results from a four-factor model (from Carhart (1997)) with a [-300, -46] estimation window relative to the event date as the benchmark for expected returns. Alpha coefficients are represented by the intercept. Standard errors are clustered by event date. The *t-statistics* are in parentheses.

	Lowest Event Firm Returns									Highest Event Firm Returns
Decile	0	1	2	3	4	5	6	7	8	9
MODEL 2										
intercept	0.0011	-0.0006	-0.0001	0.0008	0.0001	-0.0002	-0.0001	-0.0014	-0.0011	-0.0013
	(1.59)	(-0.84)	(-0.21)	(0.08)	(0.08)	(-0.30)	(-0.09)	(-1.89)	(-1.47)	(-1.79)
mktrf	0.1514	-0.0072	0.0492	0.0646	-0.0107	0.0676	0.0487	0.0439	-0.0431	0.0411
	(0.89)	(-0.13)	(0.80)	(0.94)	(-0.19)	(0.92)	(0.56)	(0.59)	(-0.62)	(0.55)
smb	-0.0399	-0.0371	-0.0562	-0.0175	-0.1374	0.1706	0.1191	0.0048	-0.0781	-0.1269
	(-0.19)	(-0.34)	(-0.44)	(-0.12)	(-1.06)	(1.22)	(0.74)	(0.03)	(-0.55)	(-0.86)
hml	-0.0938	-0.1648	-0.1777	0.0709	0.0348	-0.3713	0.1694	0.0171	-0.0954	-0.5659
	(-0.43)	(-1.07)	(-1.37)	(0.49)	(0.20)	(-1.64)	(0.88)	(0.13)	(-0.53)	(-2.81)
umd	-0.0106	-0.2557	-0.2690	-0.0817	-0.2282	-0.4071	-0.1740	-0.2199	-0.1623	-0.2571
	(-0.13)	(-3.13)	(-3.32)	(-0.88)	(-2.54)	(-2.51)	(-2.08)	(-2.44)	(-1.91)	(-2.90)
R2	0.21%	0.28%	0.34%	0.16%	0.32%	0.49%	0.39%	0.39%	0.10%	0.41%
N	6,740	7,770	7,862	7,827	7,958	7,992	7,897	7,838	7,662	7,095

Table V

Investor Discretion Following Liquidity Shocks

This table reports the results from cross-sectional, difference-in-differences regressions of three-day cumulative abnormal returns (CARs) on extreme decile rankings and four measures of discretion. The dependent variable, $CAR_{i,(+1,+3)}$, is the three-day cumulative abnormal return for each paired-firm. *Decile* is an indicator variable equaling 1 for observations in the top decile of r_SumMV; and 0 for observations in the lowest decile of r_SumMV. *Industry* is an indicator variable equaling 1 for observations where the event firm and the paired firm operate in the same one-digit, or two-digit, SIC industry code; and 0 otherwise. *HiBeta* is an indicator variable equaling 1 for observations where the paired firm has a beta above 1.7; and 0 otherwise. *CloseVol* is an indicator variable equaling 1 for observations where the paired firm's return volatility is within 10% of the event firm's return volatility; and 0 otherwise. *SameState* is an indicator variable equaling 1 for observations where the paired firm is headquartered in the same state as the event firm; and 0 otherwise (observations in NY, CA, and outside the US were excluded from the analysis in Panel D).

Panel A: Industry

	intercept	Decile	SameInd	Decile * SameInd	Mktrf	Smb	Hml	Umd	R^2	N
One Digit SIC	0.0003	-0.0009	**0.0049**	**-0.0085**	0.0988	-0.0804	**-0.3028**	**-0.1112**	0.0035	13,835
	(0.44)	(-0.82)	**(2.28)**	**(-2.78)**	(0.89)	(-0.55)	**(-1.88)**	**(-1.97)**		
Two Digit SIC	0.0005	-0.0007	0.0022	**-0.0057**	0.0973	-0.0818	**-0.3087**	**-0.1124**	0.0032	13,835
	(0.61)	(-0.66)	(1.40)	**(-2.48)**	(0.88)	(-0.56)	**(-1.91)**	**(-1.99)**		

Panel B: Beta

	Intercept	Decile	HiBeta	Decile * HiBeta	Mktrf	Smb	Hml	Umd	R^2	N
Beta > 1.7	0.0007	-0.0015	**0.0061**	**-0.0125**	0.1024	-0.0767	**-0.3144**	**-0.1114**	0.0033	13,835
	(1.02)	(-1.60)	**(1.86)**	**(-2.74)**	(0.92)	(-0.53)	**(-1.93)**	**(-1.97)**		

Table V (continued)

Investor Discretion Following Liquidity Shocks

This table reports the results from cross-sectional, difference-in-differences regressions of three-day cumulative abnormal returns (CARs) on extreme decile rankings and four measures of discretion. The dependent variable, $CAR_{i,(+1,+3)}$, is the three-day cumulative abnormal return for each paired-firm. *Decile* is an indicator variable equaling 1 for observations in the top decile of r_SumMV; and 0 for observations in the lowest decile of r_SumMV. *Industry* is an indicator variable equaling 1 for observations where the event firm and the paired firm operate in the same one-digit, or two-digit, SIC industry code; and 0 otherwise. *HiBeta* is an indicator variable equaling 1 for observations where the paired firm has a beta above 1.7; and 0 otherwise. *CloseVol* is an indicator variable equaling 1 for observations where the paired firm's return volatility is within 10% of the event firm's return volatility; and 0 otherwise. *SameState* is an indicator variable equaling 1 for observations where the paired firm is headquartered in the same state as the event firm; and 0 otherwise (observations in NY, CA, and outside the US were excluded from the analysis in Panel D).

Panel C: Return Volatility										
	Intercept	Decile	CloseVol	Decile * CloseVol	Mktrf	Smb	Hml	Umd	R^2	N
Within 10%	0.0004	-0.0012	**0.0043**	**-0.0065**	0.1022	-0.0780	**-0.3093**	**-0.1116**	0.0031	13,835
	(0.55)	(-1.19)	**(2.35)**	**(-2.70)**	(0.92)	(-0.54)	**(-1.91)**	**(-1.98)**		

Panel D: Location										
	intercept	Decile	SameState	Decile * SameState	Mktrf	Smb	Hml	Umd	R^2	N
(excluding CA, NY, Int'l)	0.0010	**-0.0027**	-0.0061	**0.0116**	0.1408	-0.0275	-0.2666	-0.0530	0.0031	9,014
	(1.10)	**(-2.25)**	(-1.56)	**(2.22)**	(1.39)	(-0.19)	(-1.57)	(-0.74)		

Table VI

Predicting Returns Using Ownership Score – Alternate Filing Quarters

This table shows the relationship between event-firm returns and subsequent three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE). The coefficients for *r_SumMV* are displayed below (FF factors and Carhart's momentum factor have been suppressed for expositional purposes). The dependent variable, $CAR_{i,(+1,+3)}$, is regressed on the rank of the sum of the event firms' daily change in market value and three Fama-French factors and Carhart's momentum factor. $CAR_{i,(+1,+3)}$ is the three-day cumulative abnormal return for each paired-firm. I use Carhart's four-factor model with a [-300, -46] estimation window relative to the event date as the benchmark for expected returns. The key independent variable, *r_SumMV*, is a decile rank-ordering of daily returns (change in market value) calculated for all firms traded on NYSE, AMEX, or NASDAQ and with price information in the CRSP database. Standard errors are clustered by event date. The *t-statistics* are in parentheses.

Panel A: Proximity to Closest Quarter-End Date			
	Less than 9 days	9 to 30 days	Greater than 30 days
Intercept	0.0037	0.0005	-0.0009
	(3.23)	(0.70)	(-0.93)
r_SumMV	**-0.0005**	-0.0001	-0.0001
	(-2.61)	(-0.84)	(-0.69)
Observations	11,787	36,249	29,554
Clusters (days)	168	410	278
R^2	0.55%	0.15%	0.49%

Panel B: Alternate Filing Quarters				
	Closest Quarter	Prior Quarter	Two Quarters Prior	Current Quarter
Intercept	0.0004	0.0009	0.0004	0.0004
	(0.84)	(1.36)	(0.69)	(0.85)
r_SumMV	**-0.0002**	-0.0001	-0.0001	-0.0000
	(-2.23)	(-1.40)	(-0.64)	(-0.65)
Observations	76,641	74,999	70,535	76,483
Clusters (days)	840	684	657	1,075
R^2	0.23%	0.24%	0.23%	0.21%

Table VII

Predicting Returns Using Ownership Score – S&P 500 Additions and Deletions

This table shows the relationship between S&P 500 composition changes and three-day abnormal returns for paired-firms with the highest cross-ownership scores (OSCORE). The dependent variable, $CAR_{i,(t,t+2)}$, is the three-day cumulative abnormal return for each paired-firm. *SameInd* is an indicator variable equaling 1 for observations where the event firm and the paired firm operate in the same one-digit SIC industry code; and 0 otherwise. *SameState* is an indicator variable equaling 1 for observations where the paired firm is headquartered in the same state as the event firm; and 0 otherwise (observations in CA and outside the US are excluded).

	Additions to S&P 500			Deletions from S&P 500		
	$CAR_{i,(-3,-1)}$	$CAR_{i,(-3,-1)}$	$CAR_{i,(-3,-1)}$	$CAR_{i,(+1,+3)}$	$CAR_{i,(+1,+3)}$	$CAR_{i,(+1,+3)}$
Intercept	0.0003	0.0014	0.0007	-0.0035	-0.0080	-0.0047
	(0.22)	(0.95)	(0.45)	(-0.79)	(-1.60)	(-0.99)
SameInd	**0.1600**		**0.0185**	**-0.0415**		**-0.0512**
	(1.70)*		**(1.82)***	**(-2.03)***		**(-2.71)****
SameState		**-0.0089**	**-0.0082**		**0.0211**	**0.0146**
		(-1.79)*	**(-1.99)***		**(2.49)****	**(1.73)***
Ind*State			-0.0154			**0.0931**
			(-0.57)			**(4.00)*****
mktrf	0.0246	0.0328	0.0157	-0.5294	-0.4768	-0.5096
	(0.16)	(0.21)	(0.10)	(-2.22)**	(-1.93)*	(-2.23)**
Smb	-0.0212	-0.0166	-0.0231	-0.1356	-0.2864	-0.0237
	(-0.07)	(-0.06)	(-0.08)	(-0.20)	(-0.44)	(-0.04)
Hml	-0.3816	-0.4038	-0.3661	0.0370	0.0864	0.0313
	(-1.23)	(-1.22)	(-1.19)	(0.08)	(0.20)	(0.07)
Umd	-0.2197	-0.2262	-0.2268	-0.3983	-0.3451	-0.3249
	(-1.20)	(-1.23)	(-1.24)	(-1.45)	(-1.18)	(-1.27)
Observations	929	929	929	320	320	320
Clusters (days)	83	83	83	30	30	30
R^2	1.05%	0.70%	1.29%	5.17%	3.59%	7.11%