The Growth and Limits of Arbitrage: Evidence from Short Interest*

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Abstract

We develop a novel methodology to infer the amount of capital allocated to quantitative equity arbitrage strategies from stock-level short interest data. Using this technique, which exploits time-series variation in the cross-section of short interest, we document that the amount of capital devoted to quantitative equity strategies such as value and momentum has increased significantly since the early 1990s. We find evidence suggesting that arbitrageurs have reacted to heightened competition by altering their strategies. Specifically, arbitrageurs increasingly favor stocks where the risk of over-crowding is lower such as small stocks and stocks with weaker mispricing signals. We then use these strategy-level capital measures to test theories about the limits of arbitrage. We find that strategy-level capital flows are influenced by past strategy returns, strategy return volatility, and past returns to other strategies in the directions predicted by these theories. Finally, we find that arbitrageurs have invested more capital in strategies prior to periods when those strategies perform poorly.

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I. Introduction

The professional arbitrage industry devoted to exploiting so-called equity market "anomalies" such as the value and momentum effects has grown explosively in recent years. Assets managed by long-short equity hedge funds, which pursue strategies that seek to profit from these anomalies, grew from $103 billion in 2000 to $364 billion at the end of 2009 according to Lipper – an average annual growth rate exceeding 15%. This growth has been accompanied by increased interest from market participants and academics alike.

Of primary concern to both groups is the interaction between arbitrage capital and strategy returns. Such interactions may occur at two frequencies. First, long-run returns to anomaly strategies may eventually be competed away by the long-term growth of arbitrage capital (Stein (2009)). Second, there may be higher-frequency feedback between returns and capital, such as performance chasing and deleveraging spirals, which may limit the extent to which anomaly returns are arbitraged away.

Both types of feedback have been studied extensively in the theoretical literature. However, empirical work has been hindered by the lack of appropriate data. In particular, while arbitrage *strategies* are often the relevant unit of economic analysis for assessing these theories, the amount of capital allocated to various strategies is unknown because existing data are aggregated to (at least) the fund level. As a result, researchers have often been forced to test these theories at either the individual stock level or the fund level.[1]

In this paper, we propose a novel technique for measuring the amount of capital allocated to an equity arbitrage strategy at a given time. We focus on quantitative equity strategies, which attempt to exploit the return anomalies uncovered by academic finance over the past 25 years.

[1] See e.g., Aragon and Strahan (2010), Ben-David Franzoni, and Moussawi (2010), Savor and Gamboa-Cavazos (2011).

These strategies typically use short sales to construct low- or zero-beta portfolios that generate abnormal risk-adjusted returns or "alpha."

Our key insight is that the cross-section of short interest reveals how intensely arbitrageurs are using a particular quantitative equity strategy at a given time. For instance, when the cross section of short interest is particularly weighted towards growth stocks, we should infer that a lot of capital is playing a value strategy. We can then interpret time-series variation in the cross-section of short interest as variation in the amount of capital playing various strategies. We formalize this intuition in a regression setting. Specifically, we run cross-sectional regressions explaining stock-level short interest and interpret the coefficients from these regressions as proxies for strategy-level capital.

Short interest is a good laboratory for studying strategy-level arbitrage capital flows for several reasons. First, short sellers are typically sophisticated investors.[2] Second, the costs of short selling make it more likely that short positions are put on by managers who are actively seeking alpha. Finally, short interest data may be more informative than long-side data because, in the aggregate, long-side institutional investors hold the market portfolio and show little tendency to bet on characteristics known to predict returns (Lewellen 2010). In other words, any long-side analysis must screen out the large number of institutions that passively index; otherwise, it will have little power to detect time variation in arbitrage capital.

Focusing on the value and price momentum strategies, we first use our capital measures to explore low-frequency trends in arbitrage capital. We show that capital in both strategies has increased dramatically, particularly since the early 2000s. We consider several possible explanations for these trends. First, we ask whether the trends could be driven by an expansion of

[2] By some estimates, hedge funds account for 85% of short positions in the U.S. equity market (see e.g., Goldman Sachs Hedge Fund Trend Monitor, February 20, 2008).

share lending supply. We attempt to disentangle demand and supply shifts by using institutional ownership as a proxy for lendable share supply. Interestingly, we find similar upward trends when we focus only on stocks with high institutional ownership, which are less likely to experience a significant easing of supply constraints. Thus, we argue that shifts in shorting demand have played an important role in driving the trends we find.

We next consider the possibility that the increases in arbitrage capital we observe could be the result of slow diffusion of information about strategy profitability, leading to increased shorting demand. If this is the case, the degree of competition among arbitrageurs may have increased as the pool of arbitrage capital has grown. We find some evidence consistent with this interpretation. For instance, as more capital uses a reliable signal of mispricing, arbitrageurs may become concerned about the capacity or profitability of the signal. As a result, they may begin using a signal that is less crowded but has historically been a weaker indicator of expected returns. Similarly, if crowding or diminished strategy profitability is a greater concern in large, liquid stocks, then smaller stocks might become more appealing. Consistent with these predictions, we find that arbitrageurs have shifted to weaker signals and smaller stocks in recent years.

The low frequency growth of arbitrage capital we document suggests that the returns to the value and momentum strategies may be competed away over time. However, a large theoretical literature suggests that agency problems and funding constraints may create limits of arbitrage that allow abnormal returns to persist even in the face of substantial arbitrage capital.[3] Thus, we explore the higher-frequency feedback between capital and strategy returns and ask whether the observed patterns are consistent with theories of limited arbitrage.

[3] A partial list includes Shleifer and Vishny (1997), Barberis and Shleifer (2003), Brunnermeier and Pedersen (2009), Stein (2009), and Gromb and Vayanos (2010).

We first explore the relationship between capital flows and past performance. We find evidence of a positive performance-flow relationship for momentum. After low returns, capital tends to flow out of momentum strategies. We also explore how arbitrage capital responds to changes in the volatility of strategy returns. For both value and momentum, we find that capital tends to exit strategies following increases in volatility. We also find evidence of cross-strategy spillovers and that funding constraints may impede arbitrage activity. Specifically, we find that capital exits momentum when other arbitrage strategies do poorly and when the Treasury Eurodollar spread widens. This suggests that hedge funds may choose to liquidate momentum positions in order to meet margin requirements or capital redemptions.

Finally, we examine the relationship between arbitrage capital and subsequent strategy returns. We find that capital flows into both value and momentum negatively forecast future returns. This finding, combined with the fact that strategy returns mean revert in our sample, means that arbitrage capital demonstrates negative market timing ability. Taken together, these results suggest that quantitative equity arbitrage does suffer from the limits suggested by the theoretical literature.

The remainder of this paper is organized as follows. Section II describes the data. Section III describes our methodology and examines trends in arbitrage capital since 1992. Section IV describes our results concerning the feedback between arbitrage capital and strategy returns. Section V concludes.

II. Data

We use monthly data on short interest from January 1992 through December 2010. From 1992-2007, short interest data for NYSE and AMEX stocks is downloaded from Bloomberg and data for NASDAQ stocks is obtained directly from the exchange. From 2008-2010, we obtain short interest data for all stocks from Compustat.[4] Short interest for stock *i* in month *t*, $SHORT_{i,t}$, is the total number of uncovered shares sold short for transactions settling on or before the 15th of the month. We normalize short interest by total shares outstanding as of the reporting date to form short interest ratios: $SR_{i,t} = SHORT_{i,t} / SHROUT_{i,t}$. Short interest ratios are winsorized at the 99.5%-tile in each cross-section.

Several trends in the short interest data are worth highlighting. Figure 1 shows that short interest rose significantly during our 1992-2010 sample on both an equal- and value-weighted basis. Short interest ratios trended upwards during the mid-1990s, declined somewhat during the technology bubble as noted by Lamont and Stein (2004), and rose dramatically from 2001 to 2007. The financial crisis period from 2007 to 2009 saw large swings in short interest. Short interest peaked in July 2007 and registered a marked drop over the following three months, presumably due to the fire-sale induced de-leveraging associated with the “quant meltdown” of August 2007 (see e.g., Khandani and Lo (2007, 2008) and Pedersen (2009)). Short interest rose rapidly again in the first half of 2008, peaking in July 2008 before declining sharply after September 2008 when the SEC imposed a partial ban on short sales for financial stocks.[5] Aggregate short interest levels stabilized in 2009 and 2010.

Moreover, short interest among small stocks has surged since 2000. In fact, the entire

[4] Compustat’s short interest data is provided by FT Interactive and is available in the Security Monthly file beginning in 2003. From 2003-2008, short interest ratios constructed using Compustat data are virtually indistinguishable from ratios constructed using our Bloomberg and NASDAQ data. The few discrepancies appear to stem from disagreements about the exact timing of stock splits.

[5] On September 19, 2008, the Securities and Exchange Commission adopted an emergency order that temporarily banned most short sales in over 900 financial stocks. However, Figure A3 in the Internet Appendix shows that short interest ratios declined for both nonfinancial and financial firms following the imposition of the ban. Boehmer, Jones, and Zhang (2009) provide a detailed examination of the market impact of the short sales ban.

cross-sectional relationship between size and short interest has shifted dramatically. In Figure 2 we plot average short interest ratios by NYSE size decile at six different years in our sample. Short interest ratios for firms in size deciles 2 through 5 have risen sharply since 1999, all hovering near 10% as of year-end 2007 (short interest for small stocks declined somewhat from 2007 to 2009).[6] Average short interest for size decile 1 has also grown, but still lags other small stocks. By contrast, short interest for size decile 10 has been remarkably stable. Although we will see that quantitative equity signals are associated with significant differences in short interest, the growth of quantitative equity arbitrage does not appear to completely explain the broad surge in short interest among small stocks.[7]

To this short interest data, we add stock characteristics from CRSP and Compustat, including size (*ME*) deciles, book-to-market (*B/M*) deciles, and past 12-month return deciles (i.e., "momentum" deciles). All deciles are based on NYSE breakpoints. We also compute the fraction of shares held by 13-F institutions as of the most recent quarter-end, the three month moving average of share turnover (volume over shares outstanding), trailing 12-month return volatility, exchange dummies (i.e., a NASDAQ dummy and an NYSE dummy), and a dummy indicating whether a firm has convertible securities outstanding. All continuous variables are winsorized in each cross-section at the 0.5% and 99.5%-tiles. Appendix A provides further detail on the data and relevant variable definitions.

III. The Evolution of Arbitrage Capital: 1992-2010

[6] These trends are not driven by outliers: the entire distribution of *SR* shifted to the right for small stocks.

[7] Possible explanations include the rapid growth of non-quantitative hedge funds, the expansion of institutional share-lending programs, and technological changes (e.g., the evolution of the prime-brokerage and information technology may have lowered search and other transaction costs associated with short sales).

A. *Short Interest for Extreme Growth and Loser Stocks*

The basic premise of our methodology for measuring arbitrage capital is that short interest should be high for stocks that an arbitrage strategy recommends shorting. We test this key assumption before further fleshing out our approach. To do so, we trace out the "event-time" path of short interest ratios for stocks falling into the lowest *B/M* decile by estimating the following quarterly panel regression:

$$\begin{aligned} SR_{it} = {} & \delta^{-8} 1_{it}^{-8}\{B/M\} + \cdots + \delta^{0} 1_{it}^{0}\{B/M\} + \cdots + \delta^{+8} 1_{it}^{+8}\{B/M\} \\ & + \boldsymbol{\delta}^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}'\mathbf{x}_{it} + Stock_i + Time_t + \varepsilon_{it}. \end{aligned} \tag{1}$$

Here the $1_{it}^{-k}\{B/M\}$ dummy indicates that stock *i* will enter the lowest *B/M* decile in *k* quarters (i.e., at *t*+*k*). By contrast, the $1_{it}^{+k}\{B/M\}$ dummy indicate that stock *i* exited the lowest *B/M* decile *k* quarters ago.[8] While the $1_{it}^{-k}\{B/M\}$ indicators are forward-looking, our goal is not to forecast short interest. Rather it is simply to understand the dynamics of short interest for the group of stocks that eventually fall into the extreme growth decile.

The regression includes a full set of size ($\mathbf{1}_{it}^{SIZE}$) and momentum ($\mathbf{1}_{it}^{MOM}$) decile dummies as well as a vector ($\mathbf{x}_{it}$) of additional controls that have previously been shown to be important determinants of short interest, namely, institutional ownership, 3-month turnover, trailing 12-month return volatility, dummies for the exchange on which a stock trades, and a convertible dummy. Since equation (1) includes a full set of stock fixed effects, identification is based exclusively on within-stock variation consistent with our "event-time" interpretation of the results. Equation (1) also includes a full set of time effects. To trace out the event-time path of

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[8] If a firm has a "spell" of consecutive quarters in the lowest *B/M* decile, the dummies are coded relative to the first quarter in the spell. Similarly, the dummies are coded relative to the last quarter in the spell. Thus, the event-time path is identified using true transitions into and out of the extreme decile. We also include dummies for the number of consecutive quarters that a stock has spent in the lowest *B/M* decile. While not shown here, we find that *SR* increases with each quarter that a firm spends in the extreme growth decile.

short interest for momentum losers, we estimate an analogous regression. Since momentum deciles are updated each month, this regression is run with monthly data.

Figure 3 plots the coefficients on the event-time dummies from regression (1). We draw 95% confidence bands around the estimates using standard errors that cluster by both stock and time as in Thompson (2011). Over our 1992-2010 sample, entering the lowest *B/M* decile raised *SR* by 59 bps, while entering the lowest momentum decile raised *SR* by 75 bps. The average short interest ratio over our sample is 240 bps, so these magnitudes are economically significant. Thus, Figure 3 confirms the basic premise underlying our methodology.[9]

B. Measuring Capital Intensities Using Short Interest

Figure 3 confirms that short interest is high for stocks that familiar quantitative strategies recommend shorting. This means that each cross-section of short interest is potentially informative about the distribution of capital across arbitrage strategies. To see this, imagine a situation where there are only two stocks *A* and *B*, and the only short sellers are quantitative investors. If *A* is the only stock momentum traders short and *B* is the only stock value traders short, then by observing the cross-section of short interest, we are actually observing the amounts of short-side capital playing momentum and value, respectively.

Two caveats follow from this simple thought experiment. First, if the value and momentum strategies perfectly overlap and both recommend going long *B* and short *A*, then the cross-section of short interest contains no information about the allocation of capital across strategies. Empirically, momentum and value are not highly collinear, but do have some overlap. For this reason, we favor an approach based on cross-sectional regressions over univariate

[9] Figure 3 shows that the increase in short interest for growth stocks is concentrated in the quarter when they enter the lowest *B/M* decile, whereas the increase in *SR* for 12-month momentum losers is more gradual. Presumably, this reflects the fact that some arbitrageurs play shorter horizon (e.g., 6-month) momentum strategies.

alternatives (e.g., averaging *SR* by momentum decile) to handle overlapping recommendations across strategies and to control for other determinants of *SR*. If we did not use a cross-sectional regression framework, we would be mixing these confounds together in varying proportions, making it difficult to compare the resulting measures over time.

Second, our methodology assumes that we know which stocks particular strategies would short. Clearly, quantitative investors use more sophisticated expected return models than those implicit in the simple cross-sectional sorts we use below. While our sorts will not perfectly capture the value or momentum portfolios generated by state-of-the-art quantitative investing techniques, our approach is a reasonable first approximation. Furthermore, Figure 3 confirms that arbitrageurs do respond to the information contained in these cross-sectional sorts.

We adopt a relatively non-parametric specification for our cross-sectional regressions. For each cross-section t, we regress stock i's short interest ratio on a full set of size, book-to-market, and momentum decile dummies (the omitted dummy is always decile 5). We also include the same set of additional controls $\mathbf{x}_{it}$ that were used in equation (1) above. Thus, our baseline specification for each cross section is:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}. \tag{2}$$

The coefficient on the dummy for the lowest momentum decile, $\delta_t^{MOM(1)}$, reflects the increase in short interest at time t associated with being an extreme loser relative to the omitted decile 5. Thus, $\delta_t^{MOM(1)}$ forms our main proxy for the quantity of short-side capital devoted to momentum strategies at time t.[10]

[10] The coefficients for the other deciles are also potentially informative. For instance, if arbitrage capital is flowing into momentum, we might also expect to see reductions in short interest for extreme. As discussed in the Internet Appendix, we have experimented with other measures of strategy intensities such as the spread in *SR* between extreme losers and winners. These other measures lead to similar conclusions.

One practical issue is whether and how to smooth the raw time series of monthly coefficients. Smoothing reduces the measurement error associated with monthly cross-sectional estimates. Since we explore low and medium frequency variation in strategy capital, we smooth coefficients by estimating annual and quarterly panel regressions. That is, we stack all firm-month observations for a given year (or quarter) in a panel and estimate a single pooled regression that includes month fixed effects.[11] However, all our results are qualitatively unchanged if we do not smooth, albeit with slightly reduced significance in a few cases.

We have examined a number of other equity anomaly strategies in addition to value and price-momentum, including earnings-momentum (i.e., post-earnings-announcement-drift or "PEADs"), net stock issuance, accruals, distress (as proxied by Shumway's (2001) bankruptcy hazard rate), idiosyncratic volatility, and asset growth. Many of the patterns we describe below for value and price-momentum also hold for these other anomalies. We provide a brief overview of these results in the Internet Appendix.

C. Trends in Value and Momentum Capital from 1992-2010

We now turn to the time series of our estimated capital intensities, which are estimated from annual cross-sectional regressions. In the Internet Appendix, we plot and discuss the cross-sectional R^2, number of observations, and the coefficients on the additional control variables.

Figure 4 plots the coefficients for the lowest *B/M* and momentum deciles along with the associated 95% confidence intervals. Figure 4 shows that the coefficient for *B/M* decile 1 is significant in each year of our 1992-2010 sample, while the coefficient for momentum decile 1 is significant in all but one year. Consistent with anecdotal evidence, the figure suggests that large

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[11] Consistent with our cross-sectional interpretation, virtually all of the identification in these short panels is from between- as opposed to within-firm variation. Thus, the resulting annual coefficients are indistinguishable from 12-month averages of the coefficients from monthly cross-sectional regressions (e.g., the correlations exceed 0.99).

quantities of arbitrage capital have flowed into value and momentum strategies, particularly since 2001. Specifically, Figure 4 shows that there has been a steady increase in short interest for extreme growth stocks and momentum losers. Regressing $\hat{\delta}_t^{B/M(1)}$ on a time trend reveals a trend of +8.0 bps per annum (t = 7.3). While the trend for $\hat{\delta}_t^{MOM(1)}$ is slightly smaller at +3.6 bps per annum (t = 3.9), both $\hat{\delta}_t^{B/M(1)}$ and $\hat{\delta}_t^{MOM(1)}$ have tripled over the past 19 years.

The relative magnitudes of our capital proxies are also interesting. We find that $\hat{\delta}_t^{B/M(1)}$ is greater than $\hat{\delta}_t^{MOM(1)}$ in each year of our sample. This suggests that more short-side capital has been allocated to value strategies than to momentum strategies. Value strategies have a longer history among both practitioners and academics than momentum strategies (e.g., dating back to Graham and Dodd (1934)) and are use by a variety of sophisticated investors other than quantitative hedge funds. Thus, it is not surprising to find more short-side capital dedicated to value strategies.

Figure 4 also reports estimates based on 3-month rolling windows as discussed above which allow us to examine higher frequency movements in arbitrage capital. For instance, there is a clear decline in the shorting of growth stocks during the tech bust from 2000 to 2001. Short interest for momentum losers is also noticeably more volatile than that for extreme growth stocks. Specifically, Figure 4 shows that short interest for extreme momentum losers spiked during the beginning of the tech bust in 2000 and again in 2004. Short interest for extreme loser stocks reached all at time peak in June 2007, just before the quant meltdown of August 2007. Short interest for extreme losers plummeted following the imposition of the short interest ban in

September 2008, before spiking again in early 2010.[12] The divergence of our value and momentum capital measures during the 2007-2009 financial crisis is also interesting. Specifically, short-side capital devoted to value strategies continued to grow in late 2008 even as short-side momentum capital was retreating.[13]

D. Why has Short-side Value and Momentum Capital Grown?

We consider several possible explanations for the long-run trends we observe in our short-side capital proxies. First, the shifts we observe could be driven by an expansion of share lending supply. Second, shorting demand may have risen due to a rise in the expected returns to the value and momentum strategies. Third, shorting demand may have grown due to a slow diffusion of information about the profitability of these strategies. Such a diffusion of information would have lead additional arbitrageurs to enter these strategies, potentially resulting in heightened competition or strategy crowding over time.

D.1. Disentangling Supply and Demand Shifts

We first consider explanations that hinge on an expansion of share lending supply over time. Specifically, it could be that the demand to short a particular set of stocks has always been high, but has only gradually been revealed in equilibrium short interest quantities as supply constraints have relaxed over time. However, we argue that shifts in shorting demand have played an important, though perhaps not exclusive, role in shaping the trends described above.

Since we do not have data on the relevant prices (i.e., share lending fees), we cannot separate supply and demand shifts using the approach of Cohen, Diether, and Malloy (2008).

[12] As discussed in the Internet Appendix, short interest for extreme losers falls for both nonfinancial and financial stocks post September 2008. However, the decline for financials is far more pronounced than that for nonfinancials.

[13] This might either be because investors recognized that momentum strategies are often not very profitable in volatile bear markets (Daniel (2011)) or because momentum strategies were employed by a set of institutions who were more heavily exposed to funding disruptions during the crisis (e.g., highly levered hedge funds).

Instead, we use institutional ownership, IO_{it}, as a proxy for the shortable supply of stock *i* at time *t*. Consider the stylized view of the equity lending market is depicted in Figure 5. D'Avolio (2002) suggests that shorting supply curves are kinked; being highly elastic for $SR_{it} < c_{it} \cdot IO_{it}$ and inelastic beyond that kink. Here $c_{it} \in [0,1]$ represents the fraction of institutional owners with active share lending programs. If $SR_{it} < c_{it} \cdot IO_{it}$ so shorting supply is highly elastic, the stock is considered "general collateral" and the lending fee will typically be quite small. If $SR_{it} > c_{it} \cdot IO_{it}$ and short sales constraints bind, the stock is said to be on "special" and short-sellers wishing to borrow shares will have to pay a larger fee. The figure suggests that short interest in stocks with high institutional ownership is unlikely to be affected by loosening supply constraints. For such stocks, it is likely that $SR_{it} < c_{it} \cdot IO_{it}$, so outward shifts in the kink or changes in the cost of shorting constrained stocks will not affect equilibrium short interest quantities.[14]

This analysis leads us to an important prediction of the supply-driven explanation. If shorting demand has been relatively constant, we should not see significant time trends once we condition on institutional ownership. Instead, we should simply find that the time series for unconstrained stocks lies above that for constrained stocks. Under a pure supply shift hypothesis, our aggregate trend simply reflects a changing mix of these two flat lines. By contrast, if there have been important shifts in shorting demand, we would expect to see trends for both the unconstrained and constrained stocks. A time trend for the unconstrained (i.e., high *IO*) stocks would be especially suggestive of an outward shift in shorting demand.

Since shifts in lending supply are likely to be most important for small stocks, we look

[14] However, the fee for shorting unconstrained stocks may have dropped (i.e., the horizontal segment of the supply curve may have shifted). Shifts in the general collateral lending fee will affect equilibrium short interest for unconstrained stocks and are thus harder to disentangle from demand shifts. Anecdotally, general collateral lending fees have been relatively constant over time. Furthermore, such shifts will only have large effects on equilibrium *SR* if shorting demand curves are extremely price elastic which seems unlikely.

for evidence supporting these predictions. We group stocks into small (NYSE size deciles 1-2), medium (deciles 3-5), and big (deciles 6-10) stocks ($me \in \{S,M,B\}$). To explore the importance of the supply shifts, we use a fixed ownership cut-off of 30%, so stocks with IO_{it} < 30% are considered to have "low" institutional ownership. This 30% cut-off is close to the median institutional ownership across all observations in our sample of 35.3%.[15] Thus, we have a set of 6= 3×2 size by *IO* bins in each cross-section. For each cross-section, we run our baseline specification, allowing each of the 6 size by *IO* bins to have its own intercept ($\alpha_{t(me,io)}$) and its own coefficients on the *B/M* and momentum quintile dummies ($\boldsymbol{\delta}^{B/M}_{t(me,io)}$ and $\boldsymbol{\delta}^{MOM}_{t(me,io)}$).

Figure 6 plots the time series of coefficients for the lowest *B/M* and momentum quintiles for small stocks, broken out by high and low institutional ownership. These coefficients show the boost in *SR* relative to stocks of similar size and similar institutional ownership. Shorting of small growth stocks with low *IO* has increased, consistent with the idea that short-sales constraints have eased for this group. Furthermore, there is essentially no increase in short interest for small loser stocks with low institutional ownership. One possible explanation for this contrast with value is that the high turnover rates of momentum strategies makes them less profitable in small stocks with low *IO*. The key to our argument are the results for small-caps with high institutional ownership. Here we find large increases in short interest for both growth and loser stocks. Since these high-*IO* stocks have likely always been unconstrained, Figure 10 suggests that there have large increases in shorting demand for small growth and loser stocks.

D.2. Changing Expected Returns

What explains these shifts in shorting demand? One possibility is that the expected returns to value and momentum strategies have increased. Arbitrageurs would naturally respond

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[15] We obtain similar results if the *IO* cut-off for each period is based on the cross-sectional median.

to such increases in expected returns by allocating more capital to the strategies. Empirically, however, there is little evidence of a secular increase in the expected returns associated with value and momentum strategies. If anything, there is weak evidence of a secular decline in expected returns and a secular rise in the volatility of these strategies.

D.3. Information Diffusion and Increased Competition

Another explanation for the low-frequency trends we observe in value and momentum capital is that information on the profitability of these strategies has diffused slowly over time. An emerging literature in finance, including Duffie and Manso (2007), Stein (2008), and Duffie, Malamud, and Manso (2009), studies the diffusion of value-relevant information among competitive agents. These papers show that under certain conditions competitors have incentives to truthfully share information, so that the number of informed agents increases over time.[16] In our setting, this suggests that the degree of competition among arbitrageurs may be increasing over time, as the pool of informed capital has grown. And, interestingly, we find some evidence consistent with concerns about heightened strategy-level competition or crowding.

D.3.1. Shifting Out of Large and into Small Stocks

If diminished strategy profitability or strategy crowding are a greater concern in large, liquid stocks, then smaller stocks might have become more appealing over time. As a result, arbitrageurs may shift out of large stocks and into smaller stocks as competition increases. For both value and momentum, we find that arbitrageurs have moved away from large stocks and into small stocks. This is consistent with the idea that increases in competition have been

[16] In Stein's (2008) model an investor might choose to share information on a new trading strategy with a competitor because he hopes that the competitor will be able to further refine the strategy. Furthermore, Stein argues that there may be a tendency for broad or underdeveloped ideas to diffuse more widely than specific and well developed ideas. For instance, researchers affiliated with quantitative equity funds often publish articles outlining the general contours of trading strategies (e.g., "beta arbitrage is profitable," "momentum and value are everywhere," "don't fight the fed," "there is an interaction between value and momentum," etc.), but rarely publish on the specific implementation of these ideas (e.g., exactly how they construct a given signal.).

particularly significant among large, informationally efficient stocks.

To understand these size interactions, we break each of the *B/M* decile into size groups: small stocks (NYSE size deciles 1-2), medium stocks (deciles 3-5), and big stocks (deciles 6-10). In Figure 7, we plot the size interactions associated with extreme growth stocks (*B/M* decile 1). These coefficients represent the boost in *SR* associated with being an extreme growth stock relative to a value-neutral (decile 5) stock in the same size category.

As expected, Figure 7 reveals a steady increase in short interest for small-and medium cap growth stocks. A regression of $\hat{\delta}_t^{B/M(1),SMALL}$ on time yields a trend of +10.5 bps per annum (t = 7.2). The trend for medium stocks is similar at +9.9 bps per annum (t = 4.2). The patterns for large growth stocks are perhaps most interesting. Specifically, we see that large growth stocks were actively shorted in the early 1990s. This activity began to decline in 1995 and during the fallout from the tech bubble there was actually less short interest for large-cap growth stocks than large-caps in *B/M* decile 5. Shorting activity among large-cap growth stocks has staged a modest rebound in recent years and is again comparable to levels in the early 1990s.

We find similar patterns for extreme momentum losers. Specifically, we see increased shorting of small losers since the mid-1990s. The trend for $\hat{\delta}_t^{MOM(1),SMALL}$ is +6.0 bps per annum (t = 6.3). Large-cap loser stocks were actively shorted in mid-1990s, but this has not been the case since 2000. Specifically, $\hat{\delta}_t^{MOM(1),BIG}$ rises from zero during 1992 to a level of approximately 1% from 1995-1998 before falling off in the late 1990s. Evidently, arbitrageurs were fairly reluctant to short large-cap losers during 2001-2003 and 2007-2009.

D.3.2. Trading on Lower Quality Signals

Similarly, as more capital uses a reliable signal of mispricing, arbitrageurs may become concerned about either the capacity or profitability of the signal. As a result, they may begin using a signal that is less “crowded” but has historically been a weaker indicator of mispricing. Consistent with this intuition, we find that arbitrageurs have begun trading on “lower quality” signals. Specifically, short interest for firms in *B/M* or momentum decile 2 has increased substantially in recent years. This is consistent with the idea that arbitrageurs facing increased competition are concerned about the capacity or profitability of previously “high quality” signals such as being in *B/M* or momentum decile 1. Such concerns then lead them to use historically less profitable signals such as being in *B/M* or momentum decile 2.

In Figure 8 we plot the coefficients for *B/M* decile 2, $\hat{\delta}_t^{B/M(2)}$. While $\hat{\delta}_t^{B/M(2)}$ is significant in all but 4 years in our sample, we see a steady trend toward more aggressive shorting of decile 2 growth stocks over our sample. A simple regression of $\hat{\delta}_t^{B/M(2)}$ on a time trend reveals a trend of +4.1 bps per annum (t = 6.0). Turning to momentum decile 2, we again see statistically and economically significant shorting of these stocks during most years in our sample. However, the overall time trend is less apparent. While a simple regression of $\hat{\delta}_t^{MOM(2)}$ yields a trends of +1.1 bps (t = 2.4), Figure 8 shows that short interest for decile 2 losers has been more uneven.[17]

Another way to examine these issues is to plot the full set of decile dummies for momentum and *B/M*. These plots reveal time variation in the full mapping from characteristics to short-interest. Examining short interest for stocks that a strategy recommends going long is useful since the stocks that investors choose not to short are also potentially informative about allocation of arbitrage capital across strategies. For example, if the amount of short-side arbitrage capital playing momentum increases relative to other strategies, we would expect to see less shorting of momentum winners (i.e., deciles 9 and 10).

[17] Furthermore, the *ratio* of to has risen over time. However, there is little trend in .

We turn first to momentum. In Figure 9 we plot the full set of momentum decile dummies, $\{\hat{\delta}_t^{MOM(d)}\}_{d=1}^{10}$ for the odd years in our sample. As noted above, there has been a significant increase in short interest for extreme losers (i.e., momentum decile 1) during our sample. However, the most striking feature of Figure 9 is the large reduction in short interest among winners in recent years. A possible interpretation of this reduction is that short-sellers have become increasingly concerned about price pressure from long-side momentum investors. Interestingly, however, the reluctance to short past winners appears to have reversed in 2009.

In Figure 10 we plot the full cross-sectional relationship between *B/M* and short interest for the odd years in our sample. In examining this relationship, it is informative to examine whether value investors use a raw *B/M* signal or an industry-adjusted *B/M* signal. Specifically, we augment our baseline specification which already includes a full set of raw *B/M* decile dummies by adding a set of industry-adjusted *B/M* decile dummies (each firm's *B/M* is demeaned using the 8-quarter trailing average *B/M* of its Fama-French-48 industry).

The increase in short interest among stocks in unadjusted *B/M* deciles 1 through 3 is readily apparent in Figure 10. For the first dozen years of our sample, industry-adjusted *B/M* had no impact on short interest after controlling for unadjusted *B/M*. However, since 2003 we see an increased tendency to short stocks that have low industry-adjusted *B/M*, suggesting the industry-adjusted signal has become significantly more popular.

What caused this shift toward industry-adjusted value strategies? Industry-adjusted *B/M* strategies typically have higher Sharpe ratios than unadjusted *B/M* strategies because industry-adjusted strategies function as within-sector allocation rules, while unadjusted strategies may also place large cross-sector bets. The strong performance of the intra-industry *B/M* strategy was first noted by Asness and Stevens (1995) and Cohen and Polk (1996) and may have taken several years to diffuse throughout the quantitative investment community. Furthermore, industry-adjusted strategies outperformed unadjusted strategies during the growth of the tech bubble from 1998-1999, but then underperformed unadjusted strategies during the subsequent bust. Thus, quantitative investors may have shifted into industry-adjusted value strategies in response to their lower volatility and outperformance during the tech bubble.

IV. Arbitrage Capital and Asset Prices

The low frequency growth of arbitrage capital suggests that the returns to the value and momentum strategies may be competed away over time. However, a large theoretical literature suggests that there may be limits of arbitrage that allow abnormal returns to persist. To explore this possibility, we now turn our attention to the high-frequency feedback between our measures of arbitrage capital and returns. We first examine the effects of past returns and volatilities on changes in arbitrage capital. We then turn to the relationship between arbitrage capital and future returns.

We use δ_t^k to denote the coefficient on the decile 1 dummy for strategy k from the cross-sectional short interest regression at time t. We work with quarterly data, so the δ_t^k are estimated by running regression (2) where all monthly observations in a given quarter are pooled together in a single panel. Using coefficients from monthly cross-sectional regressions introduces greater noise into the δ_t^k measures, but yields similar results. We use quarterly changes in these coefficients, $\Delta\delta_t^k = \delta_t^k - \delta_{t-1}^k$, to proxy for strategy-level capital flows. Our δ_t^k and $\Delta\delta_t^k$ measures have units of basis points of short interest.

We use the *HML* and *UMD* factors returns available from Ken French's web-site to proxy for the returns to value and momentum strategies, respectively. We cumulate the monthly returns to form quarterly and annual factor returns. We also compute 1-quarter rolling factors volatilities, σ_t^k, as the standard deviation of daily factor returns during quarter *t*. The quarterly and annual returns are in percentages and our factor volatility measures are in annualized percentages. To proxy for the returns to hedge funds more generally we use the return indices for "Equity Hedge" and "Event Driven" hedge funds available from Hedge Fund Research (HFR).

We present the results both for our entire sample period and the period 1992-2007, which excludes the recent financial crisis. While the crisis was a period when arbitrage constraints may have bound tightly, the short sales bans and withdrawal of share supply due to concerns about the re-investment portfolios of securities lenders led to wild fluctuations in short interest. Thus, we also present results for the pre-crisis period to understand how these outlying observations may affect the results.

A. Determinants of Capital Flows

We set the stage with some simple plots that show that there is a strong relationship between our capital measures and strategy returns and volatility. Figure 11 plots the 4-quarter moving average of our capital measures (the δ_t^k coefficients) versus annual strategy returns and realized volatilities over the same 4-quarter period. A few noticeable relationships stand out. First, there is a strong negative correlation between the level of *B/M* capital and past *HML* returns (ρ = –0.27). Second, there is a strong positive correlation between the level of momentum capital and past *UMD* returns before 2001 (ρ = 0.62). However, the correlation is more modest in the latter half of the sample (ρ = 0.26). Third, there is also a strong negative relationship between the level of *B/M* capital and past *HML* return volatility (ρ = –0.47) prior to 2008. The relationship between capital and realized volatility for momentum is less apparent over this period. However, from 2008-2010 there was a strong inverse relationship between momentum capital and realized *UMD* volatility.

A.1. Effects of Past Strategy Returns on Capital Flows

A critical assumption of much of the literature on limits of arbitrage, beginning with Shleifer and Vishny (1997), is the existence of a performance-flow relationship.[18] If arbitrageurs suffer outflows after their trades move against them, then they may exacerbate the very mispricing they set out to arbitrage. In equilibrium, this may discourage arbitrageurs from attempting to arbitrage the mispricing ex ante.

Existing empirical work has focused on individual mutual funds and hedge funds and found such performance-flow relationships at the individual fund level.[19] A handful of papers have also found evidence of a positive performance flow relationship at the level of the aggregate mutual fund or hedge fund industry.[20] Why might we expect a performance-flow relationship to exist at the strategy level? First, fund managers may themselves chase performance across strategies. Second, a fund-level performance-flow may naturally lead to a strategy-level performance-flow relationship if end investors chase performance across funds that mix strategies in different proportions.

In Table 1, we regress capital flows in quarter t on strategy returns in quarter t–1:

$$\Delta\delta_t^k = \alpha^k + \beta^k \cdot r_{t-1}^k + \varepsilon_t^k. \tag{3}$$

The t-statistics are computed using heteroskedasticty robust standard errors. There is little

[18] While Shleifer and Vishny (1997) take the performance-flow relationship as given, Barberis and Shleifer (2003) and Berk and Green (2004) micro-found it using as the result of performance chasing and rational updating about fund manager ability, respectively.

[19] Chevalier and Ellison (1997) and Sirri and Tufano (1998) find a convex performance-flow relationship for mutual funds. Ding, Liang, Gemansky, and Wermers (2009) find that the flow-performance relationship for hedge funds is also convex in the absence of share restrictions, but that the relation becomes concave in the presence of restrictions.

[20] Goetzmann and Massa (2003) find evidence of daily performance flow relationship using U.S. index funds. Specifically, outflows increase following down-market days. Wang and Zheng (2008) find a positive relation between quarterly aggregate hedge fund flows and past aggregate hedge fund returns using Lipper TASS data.

evidence of a quarterly performance-flow relationship for value strategies. In fact, the point estimate for β^k is slightly negative. By contrast, we find a reliably positive performance-flow relationship for momentum at a quarterly frequency in the pre-2008 period. The magnitudes here seem reasonable. The estimates indicate that a 10% quarterly momentum return generates capital flows of 8.8 bps; the mean and standard deviation of quarterly momentum flows are 0.3 and 31 bps respectively.

A.2. Effects of Strategy Volatility and Funding Constraints on Capital Flows

Even in the absence of a performance-flow relationship, arbitrage may be limited if the leverage supplied to arbitrageurs is a function of past return volatility. For instance, in Brunnermeier and Pedersen (2009) a rise in volatility leads risk-averse lenders to raise margins on both long and short positions. As a result, leveraged arbitrageurs with limited capital are forced to scale back both long and short positions in order to meet margin requirements, potentially further raising volatility and margins in a "margin spiral."[21]

Arbitrageur positions are also decreasing in margins in Garleanu and Pedersen (2011). Furthermore, they argue that the difference between uncollateralized and collateralized short-term interest rates is a good proxy for the tightness of arbitrageurs' margins constraints.[22] Thus, we investigate whether short-side capital declines following a tightening of funding constraints, proxied using changes in the Treasury Eurodollar (TED) spread as in Frazzini and Pedersen (2010). Of course, without detailed micro-data on hedge fund leverage and margins, we cannot

[21] Since strategy-level volatility is persistent, standard mean-variance considerations would predict a similar relationship between volatility and capital. For instance, the quarterly auto-correlations of *HML* and *UMD* volatility realizations are 0.77 and 0.79, respectively, in our 1992-2010 sample. Thus, a rational arbitrageur would forecast high future volatility for strategy *k* if past volatility has been high and, if he has a short performance horizon, this would lead him to reduce his allocation to strategy *k*.

[22] This is because uncollateralized borrowing effectively relaxes an arbitrageur's margins constraint which collateralized borrowing does not. Thus, the difference between the uncollateralized rate and the collateralized rate equal the multiplier on the arbitrageur's margins constraint.

distinguish between these various mechanisms, but we can verify their common prediction.

Table 2 considers the effect of changes in strategy return volatility on strategy capital:

$$\Delta\delta_t^k = \alpha^k + \psi^k \cdot \Delta\sigma_{t-1}^k + \varepsilon_t^k. \tag{4}$$

There is evidence of the predicted negative relationship between capital and volatility for value. Regressing our capital flow measure on lagged changes in 1-quarter *HML* volatility yields a negative and significant coefficient. Again, the magnitudes seem reasonable. A 10% spike in annual *HML* volatility is associated with a 27 bps decline in our capital measure. For reference, the mean and standard deviation of the value flow measure are 1.8 bps and 24 bps respectively.

For momentum, there is no evidence of the hypothesized negative relationship. This may be due to the fact that realized 1-quarter volatility fluctuates more for momentum than for value. Changes in 1-quarter momentum volatility have a standard deviation that is 65% higher than that for changes in 1-quarter value volatility. However, there does appear to be a negative relationship between momentum capital and overall market volatility, which is driven by the financial crisis period.

When we examine the relationship between strategy capital and funding constraints, proxied by the Treasury Eurodollar (TED) spread, we find a strong negative relationship for momentum, but no relationship for value.

A.3. Contagion and Spillovers Across Strategies

We next investigate the effects of the returns on other strategies on the capital in a given strategy. This allows us to quantify the extent of wealth contagion or deleveraging spillovers across strategies. For instance, suppose there are two strategies, *A* and *B*, and that there is an initial adverse shock to the returns of strategy *A*. In the regression,

$$\Delta\delta_t^B = \alpha + \gamma \cdot r_{t-1}^A + \beta \cdot r_{t-1}^B + \varepsilon_t^B, \tag{5}$$

the coefficient γ captures the effects of strategy-*A* returns on strategy-*B* capital flows. Limits-to-arbitrage or deleveraging stories would suggest that γ will be large and positive when many arbitrageurs play both strategies *A* and *B*. By contrast, if strategies *A* and *B* are used by entirely distinct sets of arbitrageurs, γ would be close to zero.

In Table 3 we regress $\Delta\delta_t^{MOM}$ on lagged of its own factor return (i.e., *UMD*), the market return, and HFR Indices tracking the performance of Event Driven and Equity Hedge (long/short) hedge funds. Hedge fund returns, rather than individual returns to other strategies, are likely to be the most powerful indicators of contagion because they "correctly" weight returns to other strategies. The table shows strong evidence that momentum capital flows, $\Delta\delta_t^{MOM}$, respond to several other factor returns in addition to UMD_{t-1}.[23] Column 3 shows that, holding $MKTRF_{t-1}$ and UMD_{t-1} fixed, the effect of a one percentage point increase in the lagged return on HFR's Equity Hedge index ($EHEDGE_{t-1}$) is associated with a 4 bps increase in short interest for extreme losers. Thus, a one standard deviation increase in $EHEDGE_{t-1}$ is associated with a 19.5 bps increase in δ_t^{MOM} (the standard deviation of $\Delta\delta_t^{MOM}$ is 29 bps). In untabulated results, we find that the effect of $EHEDGE_{t-1}$ is nearly three times larger for negative returns than for positive returns. Column 4 finds a similar effect for the returns to HFR's Event Driven Index ($EVENT_{t-1}$). Both of these hedge fund returns are included in column 5, and the magnitudes of the effects fall but remain significant.

These results are suggestive of cross-strategy spillovers. When other equity strategies do

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[23] We find little evidence that these other return factors help explain . One possibility is that there is a large group of arbitrageurs that only play value which may contrast with momentum. These value investors may have longer horizons and use relatively low leverage, so they are both willing and able to withstand wealth or contagion effects. To our knowledge, there are no pure momentum arbitrageurs. Momentum is a highly volatile strategy and so it is typically paired with other strategies to diversify away some of its idiosyncratic risk.

poorly, it seems that arbitrageurs liquidate momentum positions, presumably to meet margin requirements or capital redemptions. The sensitivity to event-driven returns is particularly suggestive since it is likely that only large multi-strategy hedge funds combine momentum and event-driven arbitrage.

It is interesting to note that when we control for hedge fund returns the coefficient on the market return becomes negative and significant. Holding fixed how hedge funds are doing, capital flows into momentum when the market does poorly. One possibility is that end investors find the purported low-β of hedge funds more appealing when the overall market is doing poorly. This fits with anecdotal evidence that large quantities of capital flowed into hedge funds during the tech bust as institutions sought low-β alternatives to equities. Alternatively, hedge funds may be trying to inflate their returns by attempting to time the market. When the market does poorly, they stop closet indexing and put their capital back into β-neutral long-short strategies.

B. Arbitrageur Capital and Future Strategy Returns

A third, less direct way to assess theories of limited arbitrage is to examine the relationship between arbitrage capital and future returns to anomaly strategies. If arbitrageurs are unconstrained, then they should increase their strategy capital allocations when they anticipate high returns going forward. If, on the other hand, they are constrained by binding capital or leverage constraints when expected returns are high, the relationship between capital allocations and future returns will be negative.

In Table 4 we forecast strategy returns over the following 4-quarters using capital flows:

$$r^k_{t\to t+4} = \mu^k + \varphi^k \cdot (\delta^k_t - \delta^k_{t-4}) + \varepsilon^k_{t\to t+4}, \tag{6}$$

Due to the overlapping returns, the t-statistics here are computed using Newey-West (1987) standard errors allowing for 6 lags. There is reliable evidence that recent capital flows negatively forecast future value returns. This result continues to hold even after controlling for the value spread, VS_t, and for past returns, $r_{t-4\rightarrow t}^{B/M}$, to capture the mean reversion in *HML* identified in Teo and Woo (2004). The effects in the table are economically large. The returns here are in percentage points and the coefficients are in basis points. Thus, the coefficient for $\delta_t^{B/M} - \delta_{t-4}^{B/M}$ implies that a 1 bp increase in our capital measure forecasts that future annual *HML* returns will decline by 0.13%.

This is unlikely to be purely a price pressure effect. An alternate interpretation is that returns to value are mean reverting and capital slowly chases value returns. This means that arbitrage capital wound up mistiming the value returns quite substantially. We examine this possibility in more detail. Regressing $\delta_{t+4}^{B/M} - \delta_t^{B/M}$ on $r_{t-4\rightarrow t}^{B/M}$ yields an estimated coefficient of 0.99 (t = 4.67) which suggests a strong low-frequency performance flow relationship. This result is driven by events surrounding the tech bubble and bust. Brunnermeier and Nagel (2004) study this period, finding that most hedge funds rode the tech bubble, while short sellers timed it well.

Our measures reveal a more complicated story. Short sellers began shorting growth stocks during 1999, sustaining massive losses in the last two quarters of that year. While their short positions peaked at the height of the bubble in the first quarter of 2000, they closed out these positions too quickly during 2000. Perhaps capital withdrawals or tightening funding and margin constraints limited the ability of arbitrageurs to maintain these short positions. Whatever the reason, short sellers missed the rebound in value and collapse of growth stocks during late 2000 and 2001. They began aggressively shorting growth stocks again in late 2001 and 2002, after the rally in value and collapse of growth had already taken place.

Table 4 also examines the low-frequency relationship between returns and capital for momentum. As with value, regressing future *UMD* returns on past capital flows, $\delta_t^{MOM} - \delta_{t-4}^{MOM}$

reveals evidence that arbitrageurs have negative ability to time momentum at longer horizons in the pre-2008 period. However, this result disappears during the financial crisis period, as arbitrageurs appear to have successfully exited momentum before it incurred low returns.

V. Conclusion

We propose a novel methodology for measuring strategy-level capital using time-series variation in the cross section of short interest. We find evidence suggesting that arbitrageurs have reacted to heightened competition by altering their strategies. In particular, they increasingly short moderate growth and moderate loser stocks, which we interpret as a shift towards using historically weaker signals of mispricing due to concerns that stronger signals have become over-crowded. Furthermore, quantitative investors have shifted away from shorting large stocks and into small stocks. We interpret this as a shift away from more informationally efficient, liquid stocks that is also driven by concerns about crowding.

Next we explore the determinants of capital flows into arbitrage strategies. We assess the evidence in favor of phenomena posited by the theoretical literature on the limits-to and destabilizing consequences of arbitrage, including responses to past returns (performance-flow), past volatility, and past returns in other strategies (cross-strategy spillovers). We find strong evidence of a performance-flow relationship for momentum, while capital flows for both value and momentum respond to volatility. For momentum, we also find evidence of spillovers using hedge fund return indices as a proxy for the performance of other arbitrage strategies. We also examine the forecasting power of capital flows for strategy returns and volatilities. For both value and momentum, lagged capital flows have strong negative forecasting power for returns, indicating that arbitrage capital has mistimed returns over our sample.

Our methodology for measuring strategy-level capital may be of independent interest to policymakers interested in detecting "crowded trades" because of the systemic risks they might pose. Existing approaches to detecting time-variation in crowding such as Adrian (2007), Pericoli and Sbracia (2010), and Pojarliev and Levich (2011) analyze changes in correlation structure of *ex post* returns. However, our approach may be better suited to detecting crowding *ex ante* because in relies on changing patterns in arbitrageurs positions.

Appendix: Data Construction

Our timing conventions ensure all firm characteristics are publicly available as of the date on which short interest is measured. Below we provide detailed definitions for each of the anomaly sort variables used in the paper.

Value (*B/M*): *B/M* deciles are refreshed quarterly, allowing for at least 3 months between the fiscal quarter-end when book equity is measured and the sort date. For instance, short interest observations for July, August, and September are associated with a *B/M* sorts performed at the end of June. These book-to-market ratios are based on market equity as of the end of the prior quarter (March) and on book-equity from fiscal quarters ending in the prior calendar quarter (January, February, or March). This is the quarterly analog of the familiar timing conventions established by Fama and French (1992). Book equity is defined as stockholder's equity, plus balance sheet deferred taxes and investment tax credits (when available), minus the book value of preferred stock.

We also sort firms on the basis of industry-adjusted *B/M* using the 48 Fama-French (1997) industries. Specifically, we subtract the 8-quarter moving average of aggregate industry *B/M* (industry book over industry market value) from each individual firm's book-to-market ratio.

Price/return momentum: 12-month return momentum deciles are based on cumulative returns from months *t*–12 to *t*–1. That is, we skip a month when computing past returns to avoid contaminating over measures with the short-term reversal phenomenon documented by Jegadeesh (1990). Momentum deciles are refreshed each month. For instance, short interest observations for July are associated with momentum sorts performed at the end of June. These sorts are based on the 11 month cumulative returns from July (of the previous year) through May.

Earnings momentum: For earnings momentum or post-earnings-announcement-drict (i.e. "PEADs") we follow Chan, Jegadeesh, and Titman (1996) and use a standardized unexpected earnings measure based on the seasonal random-walk earnings model. This "earnings surprise" is normalized by share price, $SUE_{it} = (EPS_{it} - EPS_{it-4}) / P_{it}$.

Share issuance: Following Fama and French (2008), we compute the year-over-year change in split-adjusted shares from quarterly Compustat data: $NS_{it} = \log[SHR_{it}^{Adj} / SHR_{it-4}^{Adj}]$

where SHR_{it}^{Adj} is the product of common shares outstanding (*CSHOQ*) and Compustat's adjustment factor (*AJEXQ*).

Accruals: Balance sheet accruals in quarter *t* are defined as in Sloan (1996):

$$ACC_{it} = (\Delta CurrAssets_{it} - \Delta Cash_{it}) - (\Delta CurrLiab_{it} - \Delta STDebt_{it} - \Delta TaxesPayable_{it}) - Deprec_{it}.$$

Our measure of accruals is just then sum of balance sheet accruals over the past 4 quarters divided by average quarterly assets. The accruals measure and associated decile is refreshed each quarter following the timing conventions discussed above. Following Bergstresser and Philippon (2006), we also compute a cashflow-based measure of quarterly accruals as $EBXI_{it} - CFO_{it}$ where *EBXI* is reported earnings before extraordinary items and *CFO* is cash flows from continuing operations (operating cash-flows minus cash-flows from extraordinary items and discontinued operations).

CAPM Residual Volatility: $\sigma_{it}(\varepsilon)$ is the residual volatility from a trailing 24-month CAPM regression. In order to compute $\sigma_{it}(\varepsilon)$ we require that a firm has valid returns for at least 12 of the past 24 months.

Distress: We use the bankruptcy hazard rate estimated by Shumway (2001). The hazard model estimated by Shumway is $H_{it} = \exp[SHUM_{it}]/(1+\exp[SHUM_{it}])$ where

$$SHUM_{it} = -13.303 - 1.982 \cdot (NI/A)_{it} + 3.593 \cdot (L/A)_{it} - 0.467 \cdot RELSIZE_{it} - 1.809 \cdot (R_{it} - R_{Mt}) + 5.791 \cdot \sigma_{it}$$

NI/A is 4-quarter trailing net income over period-end total assets, *L/A* is total liabilities over total assets, *RELSIZE* is the log of a firm's market equity divided by the total capitalization of all NYSE and AMEX stocks, $R_{it} - R_{Mt}$ is firm's cumulative return over the prior 12-months minus the cumulative return on the value-weighted CRSP NYSE/AMEX index, and σ_{it} is volatility of residuals from trailing 12-month market-model regression (treating the CRSP NYSE/AMEX index as the market return). This distress measured is refreshed each quarter.

Asset Growth: Following Fama and French (2008), we also compute measures of gross and net asset. Gross asset growth is simply the percentage change in assets over previous 4 quarters. Net asset growth is asset growth per split-adjusted share. Daniel and Titman (2006) and Fama and French (2008) argue that the forecasting ability of gross asset growth measures is driven largely by the net share issuance component as opposed to net growth component. These growth measures are refreshed each quarter.

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Figure 1: Average short interest ratios, 1992-2010. This figure plots the monthly equal- and value- (i.e., market equity) weighted average short interest ratio for all stocks in our sample. The short interest ratio for stock *i* in month *t* is defined as $SR_{i,t} = SHORT_{i,t} / SHROUT_{i,t}$ where $SHORT_{i,t}$ is short interest as of the mid-month reporting date and $SHROUT_{i,t}$ is shares outstanding as of the reporting date.

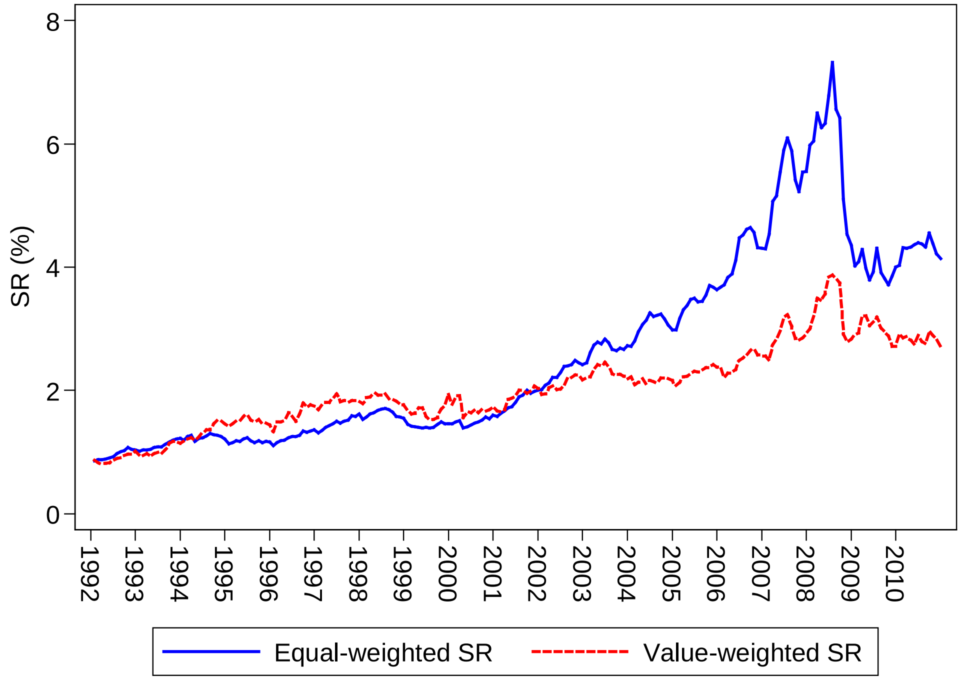


Figure 2: Average short interest ratios by size decile. This figure shows the average short interest ratio by NYSE size decile as of year-end 1995, 1999, 2003, 2005, 2007, and 2009.

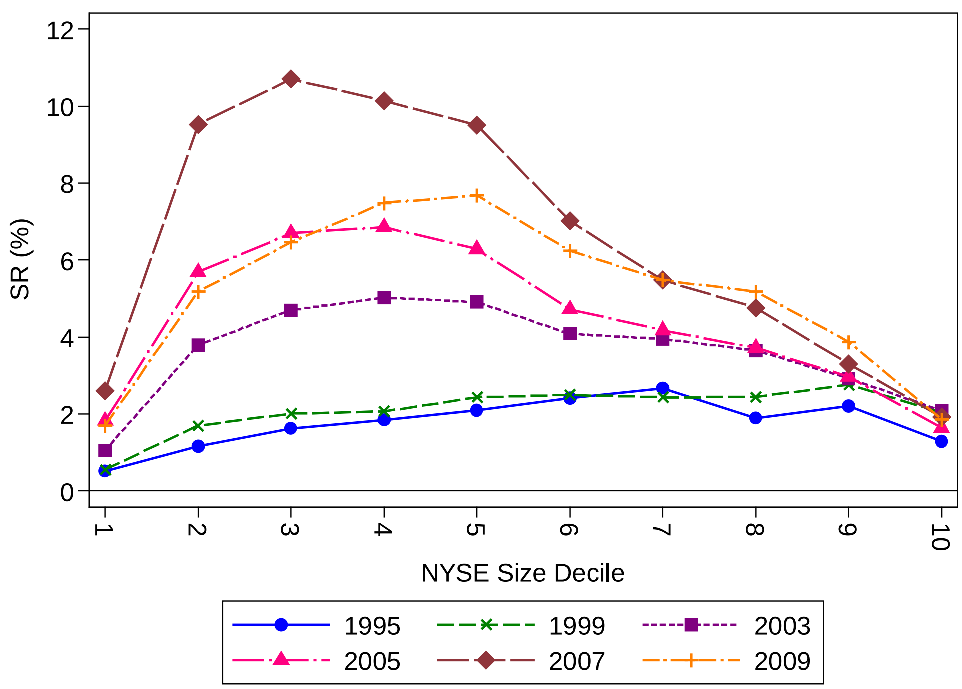
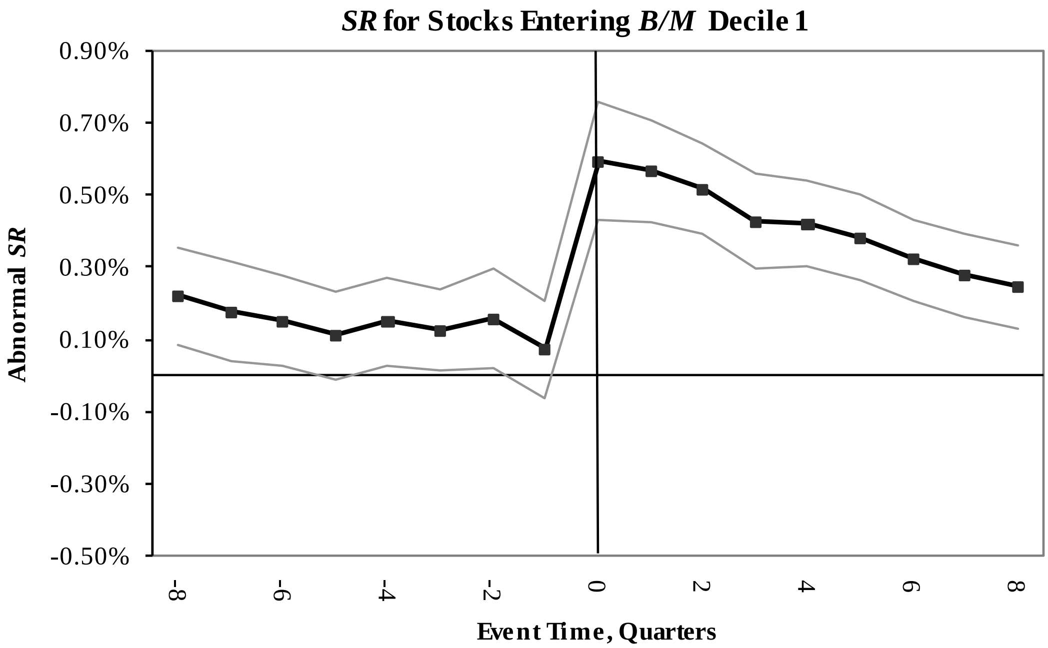


Figure 3: Short interest for stocks entering the extreme *B/M* (growth) or momentum (loser) deciles. The figure plots the "event time" coefficients which show the path of short interest for the typical stock entering the extreme growth or momentum deciles. Specifically, Panel A plots the δ^k for k = -8, …,-1,0,+1,..,+8 obtained from estimating:

$$SR_{it} = \delta^{-8} 1_{it}^{-8}\{B/M\} + \cdots + \delta^{0} 1_{it}^{0}\{B/M\} + \cdots + \delta^{+8} 1_{it}^{+8}\{B/M\}$$
$$+ \boldsymbol{\delta}^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\delta}^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\beta}'\mathbf{x}_{it} + Stock_i + Time_t + \varepsilon_{it}.$$

Panel B repeats this for the analogous specification for stocks entering the extreme momentum (i.e., past "loser") decile.

Panel A: *SR* for stocks entering *B/M* decile 1 (i.e., extreme growth stocks)



Panel B: *SR* for stocks entering momentum decile 1 (i.e., past return "losers")

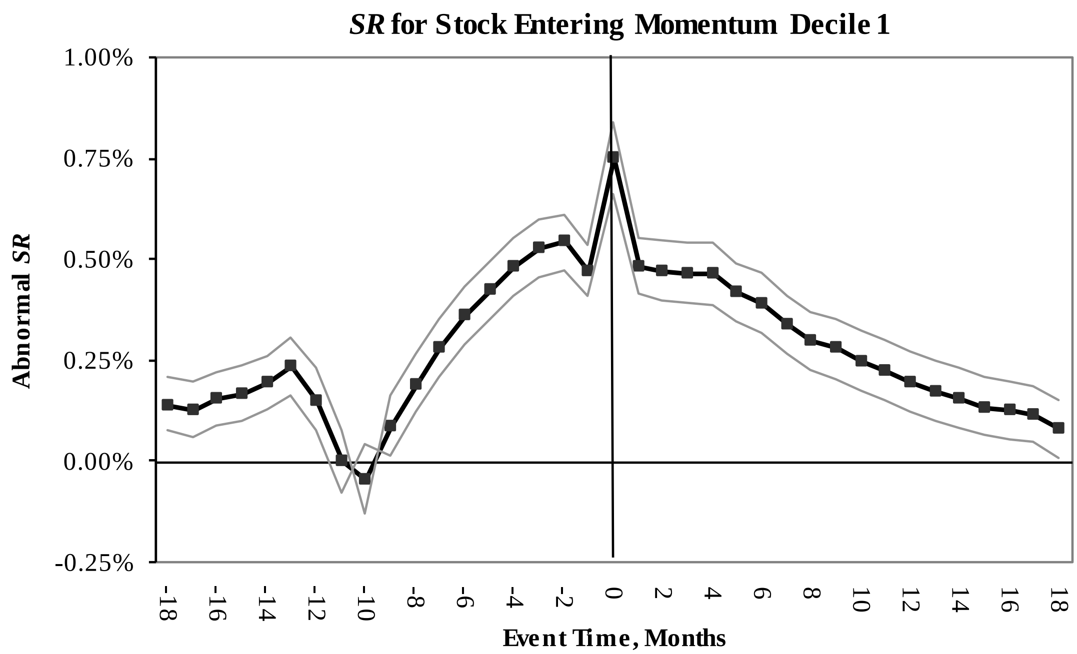


Figure 4: Estimated capital intensities for value and momentum strategies. The figure plots the time series of estimated coefficients on the extreme growth decile ( ) and extreme momentum loser decile (from the following specification:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}.$$

In Panel A, these regressions are estimated annually, pooling all observations in a given year. In Panel B, these regressions are estimating on a rolling quarterly basis, pooling all observations in a given 3 month period. Thus, both specifications also include a full set of month fixed effects. We compute confidence intervals for the estimated coefficients using standard errors that cluster by firm and, thus, are robust to serial correlation at the firm level.

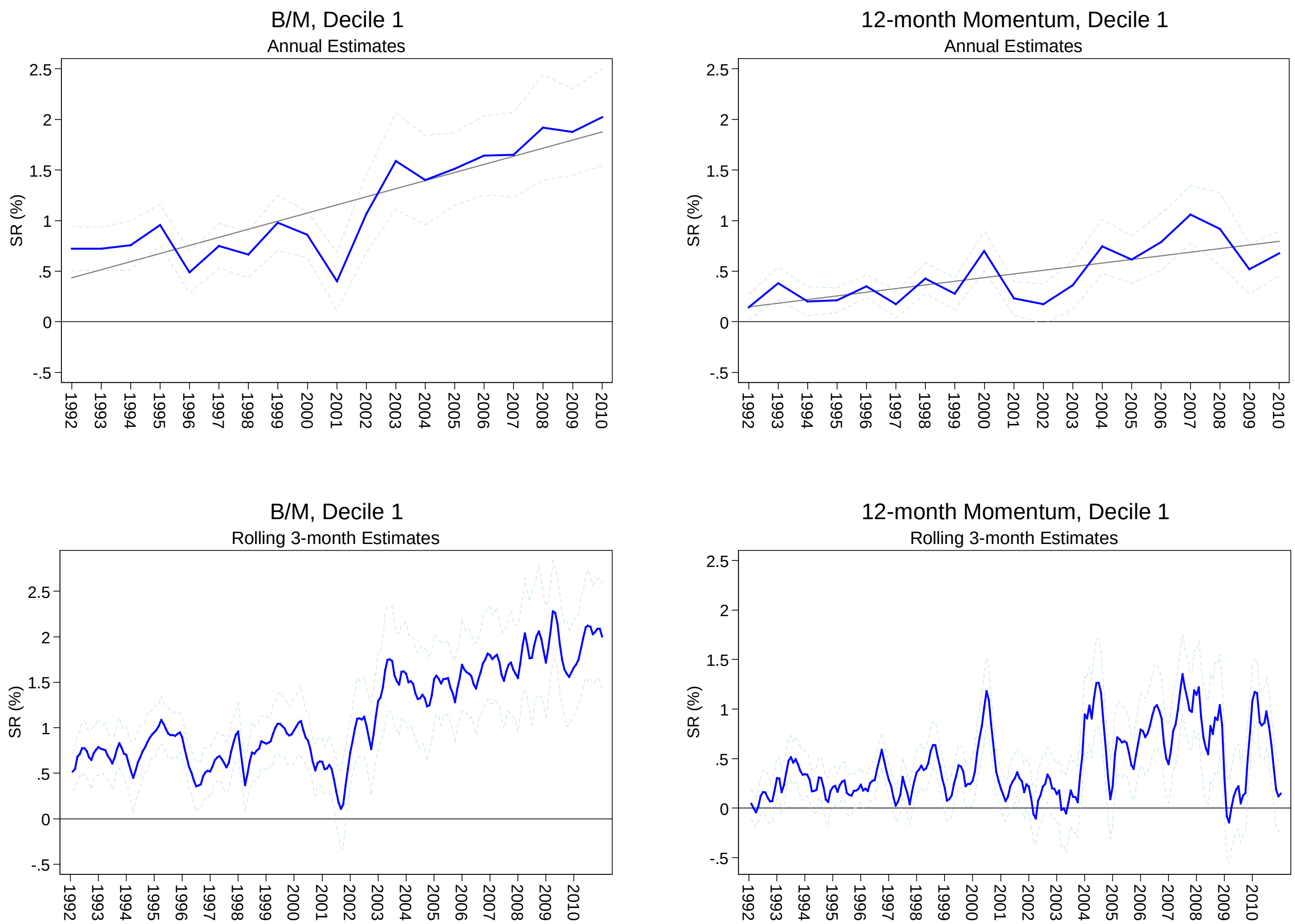


Figure 5: Stylized depiction of the equity lending market. The figure shows shorting demand and share lending supply in (*SR*,*Lending Fee*) space. Following D'Avolio (2002), we assume that shorting supply curves are kinked; being highly elastic for and inelastic beyond that kink. Here represents the fraction of institutional owners with active share lending programs. If so shorting supply is highly elastic, the stock is considered "general collateral" and the lending fee will typically be quite small. If and short sales constraints bind, the stock is said to be on "special" and short-sellers wishing to borrow shares will have to pay a larger fee. The figure shows the effect of an outward shift in both demand and supply for a stock that initially has a high level of institutional ownership. The figure suggests that short interest in stocks with high institutional ownership is unlikely to be affected by loosening supply constraints. For such stocks, it is likely that , so outward shifts in the kink or changes in the cost of shorting constrained stocks will not affect equilibrium short interest quantities.

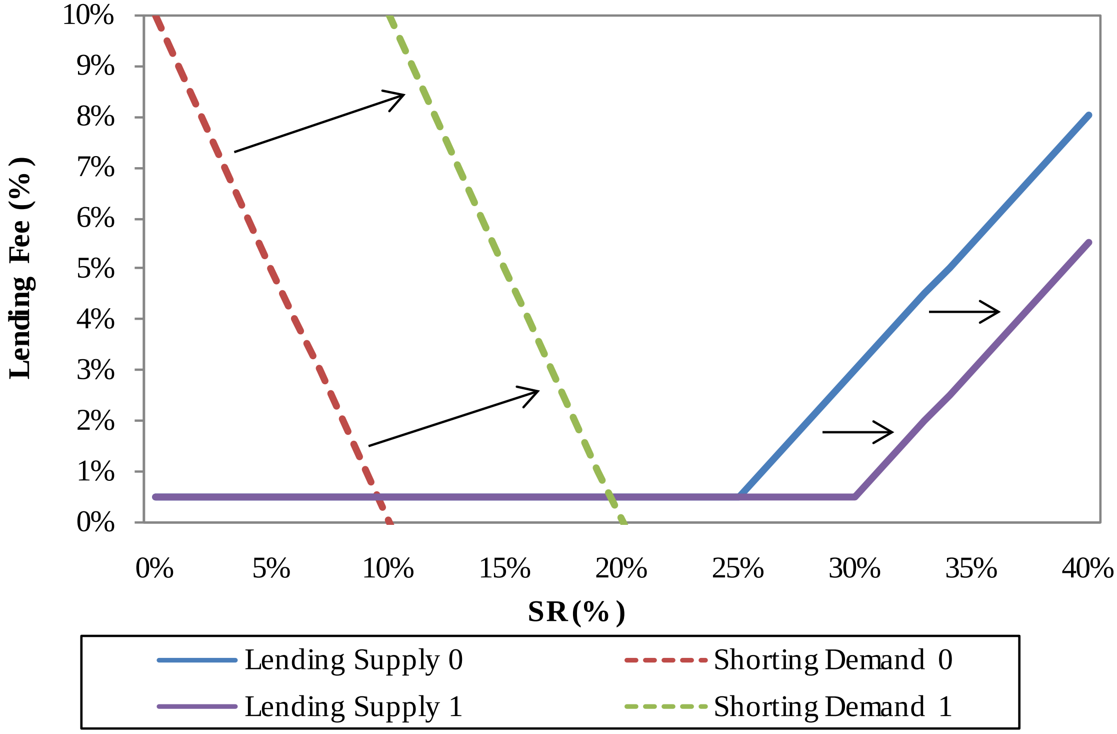
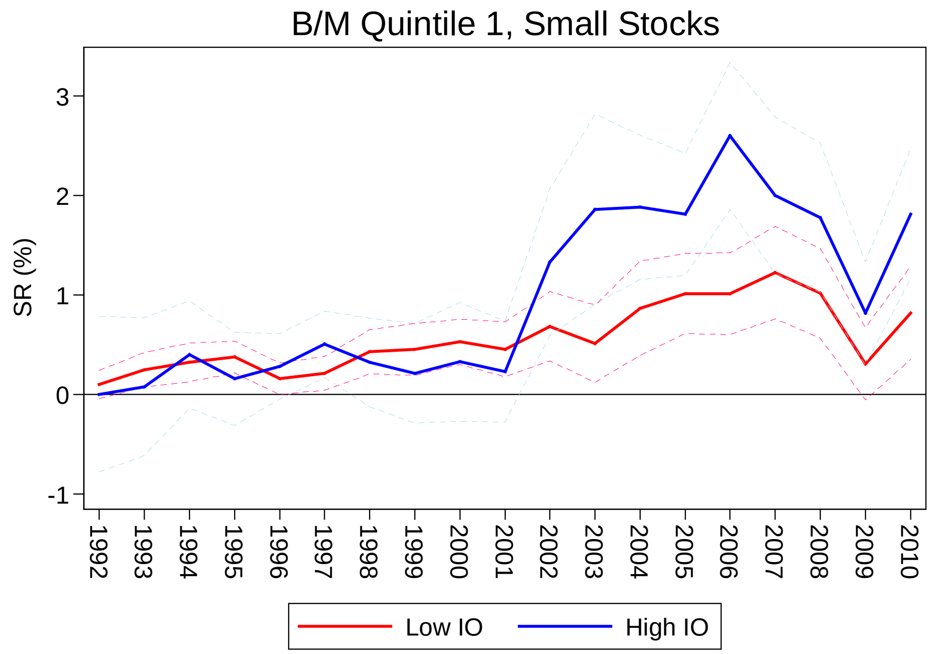


Figure 6: Capital intensities for small stocks by institutional ownership. The figure plots the time series of estimated coefficients on the extreme growth quintile and momentum quintile, allowing for separate effects by size and institutional ownership group:

$$SR_{it} = \sum_{io\in\{L,H\}} \sum_{me\in\{S,M,B\}} (\alpha_{tt(me,io)} + \boldsymbol{\delta}^{B/M}_{t(me,io)} \cdot \mathbf{1}^{B/M}_{it} + \boldsymbol{\delta}^{MOM}_{t(me,io)} \cdot \mathbf{1}^{B/M}_{it}) \times 1\{ME_{it} \in me\} \times 1\{IO_{it} \in io\} + \boldsymbol{\beta}'_t \mathbf{x}_{it} + \varepsilon_{it}.$$



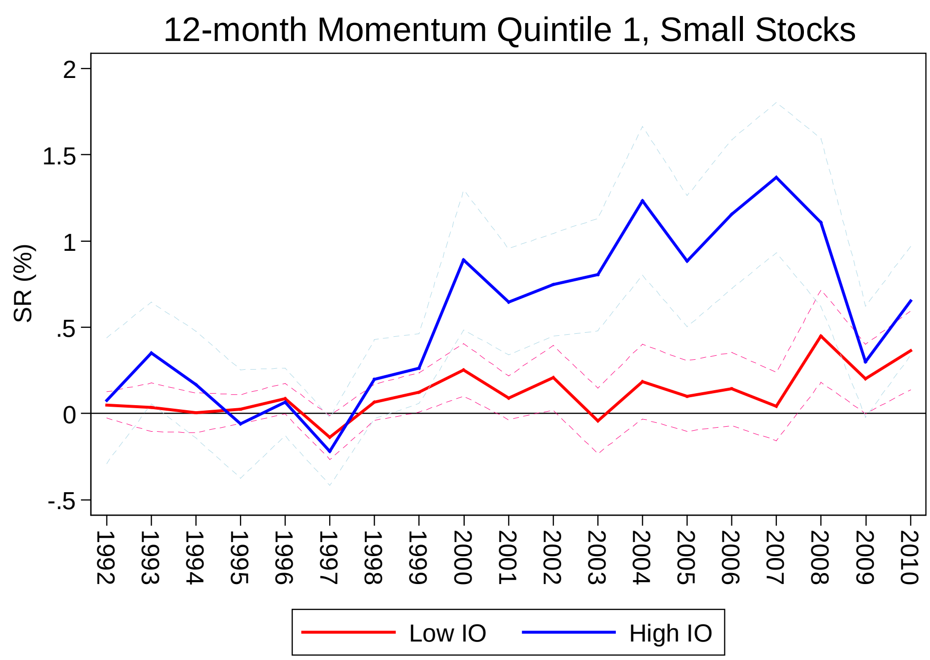
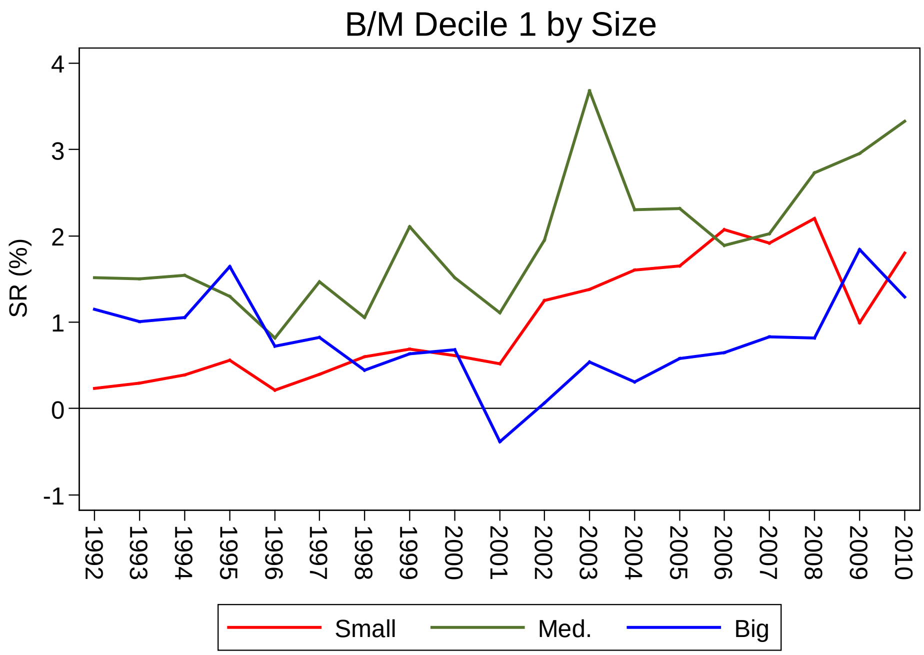


Figure 7: Size interactions. The figure plots the time series of estimated coefficients on the extreme growth decile and momentum decile, allowing for separate effects by size group:

$$
\begin{aligned}
SR_{it} = \alpha_t &+ \boldsymbol{\delta}_t^{B/M,SMALL} \cdot (\mathbf{1}_{it}^{B/M} \times 1_{it}^{SMALL}) + \boldsymbol{\delta}_t^{B/M,MED} \cdot (\mathbf{1}_{it}^{B/M} \times 1_{it}^{MED}) + \boldsymbol{\delta}_t^{B/M,BIG} \cdot (\mathbf{1}_{it}^{B/M} \times 1_{it}^{BIG}) \\
&+ \boldsymbol{\delta}_t^{MOM,SMALL} \cdot (\mathbf{1}_{it}^{MOM} \times 1_{it}^{SMALL}) + \boldsymbol{\delta}_t^{MOM,MED} \cdot (\mathbf{1}_{it}^{MOM} \times 1_{it}^{MED}) + \boldsymbol{\delta}_t^{MOM,BIG} \cdot (\mathbf{1}_{it}^{MOM} \times 1_{it}^{BIG}) \\
&+ \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}.
\end{aligned}
$$

These regressions are estimated annually.



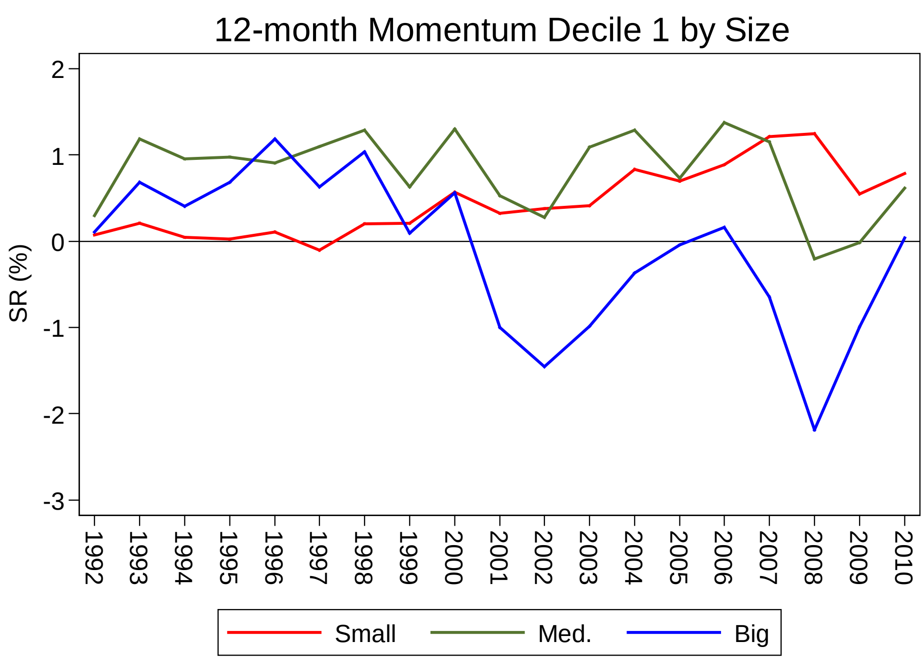


Figure 8: Trading on lower quality signals. The figure plots the time series of estimated coefficients on the growth decile 2 ( ) and momentum decile 2 (from the following specification:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t'\mathbf{x}_{it} + \varepsilon_{it}.$$

These regressions are estimated annually, pooling all observations in a given year, and include a full set of month fixed effects. We compute confidence intervals for the estimated coefficients using standard errors that cluster by firm and, thus, are robust to serial correlation at the firm level.

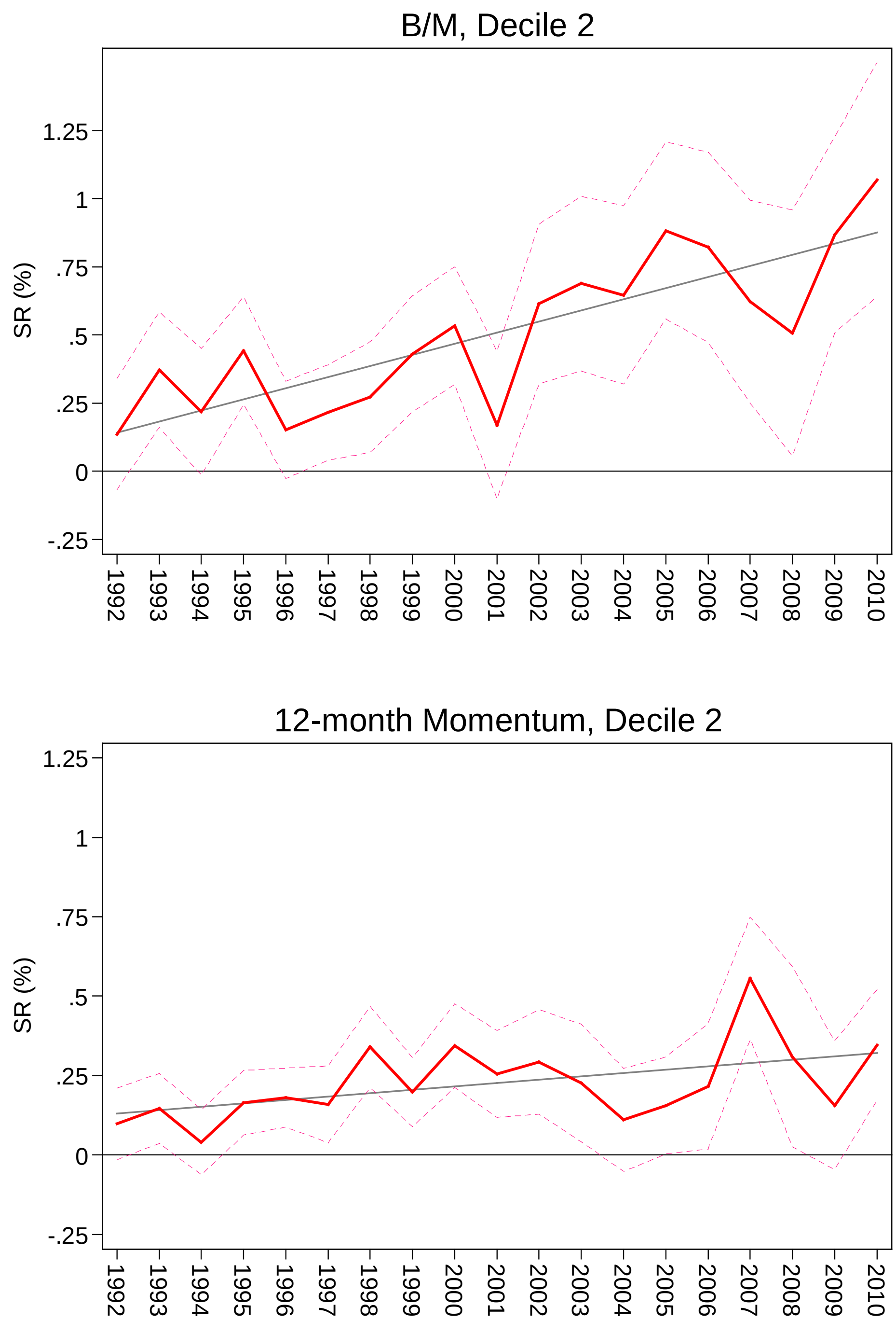


Figure 9: Full cross-sectional relationships for momentum. The figure plots the full set of estimated coefficients on the 10 momentum deciles dummies from the following specification:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}.$$

These regressions are estimated annually, pooling all observations in a given year, and include a full set of month fixed effects. We compute confidence intervals for the estimated coefficients using standard errors that cluster by firm and, thus, are robust to serial correlation at the firm level.

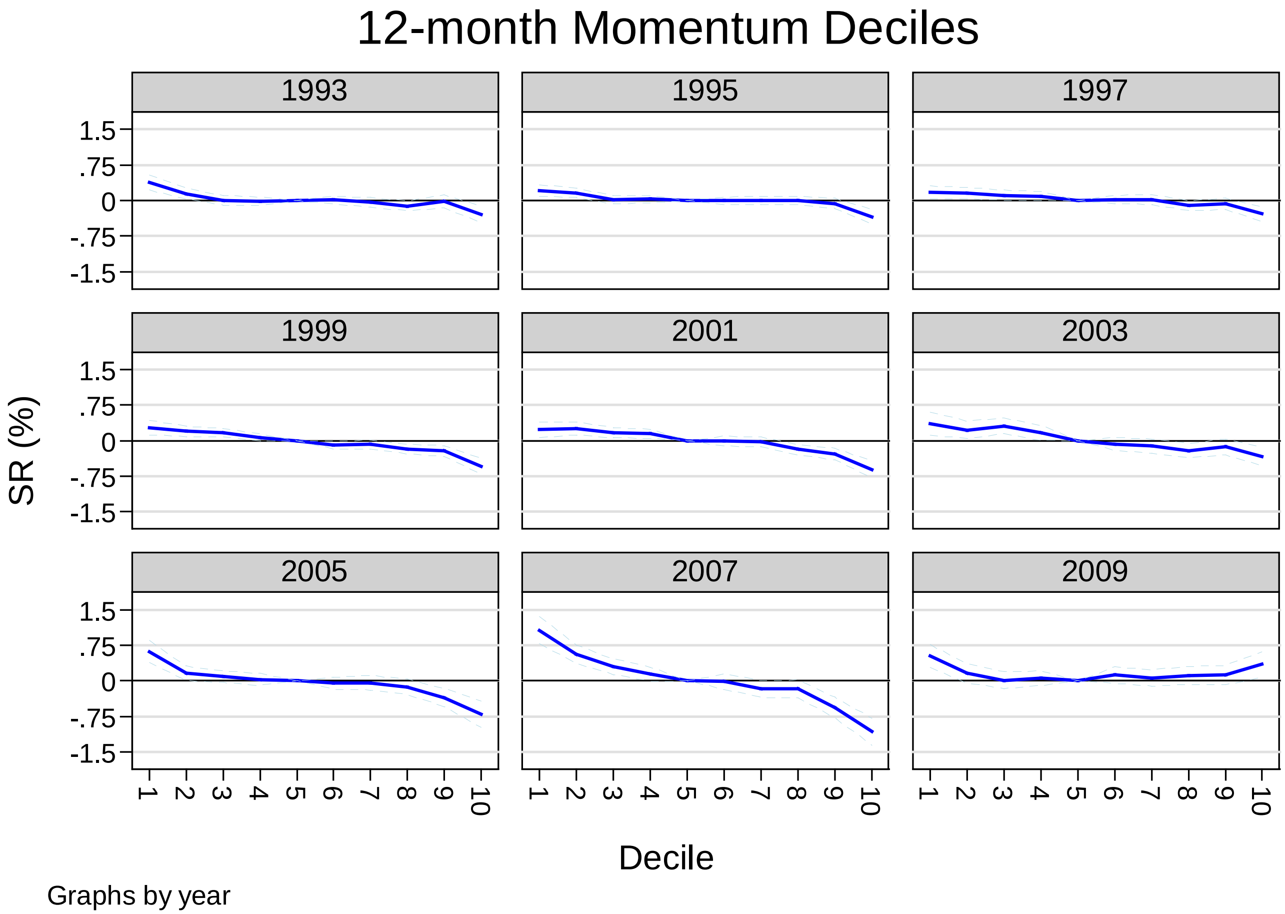


Figure 10: Standard versus industry-adjusted value. The figure plots the full set of estimated coefficients on the standard *B/M* decile dummies and industry-adjusted *B/M* decile dummies from the following specification:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{B/M\,(adj)} \cdot \mathbf{1}_{it}^{B/M\,(adj)} + \boldsymbol{\delta}_t^{MOM\,(12)} \cdot \mathbf{1}_{it}^{MOM\,(12)} + \boldsymbol{\delta}_t^{MOM\,(6)} \cdot \mathbf{1}_{it}^{MOM\,(6)} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}.$$

These regressions are estimated annually, pooling all observations in a given year, and include a full set of month fixed effects. We compute confidence intervals for the estimated coefficients using standard errors that cluster by firm and, thus, are robust to serial correlation at the firm level.

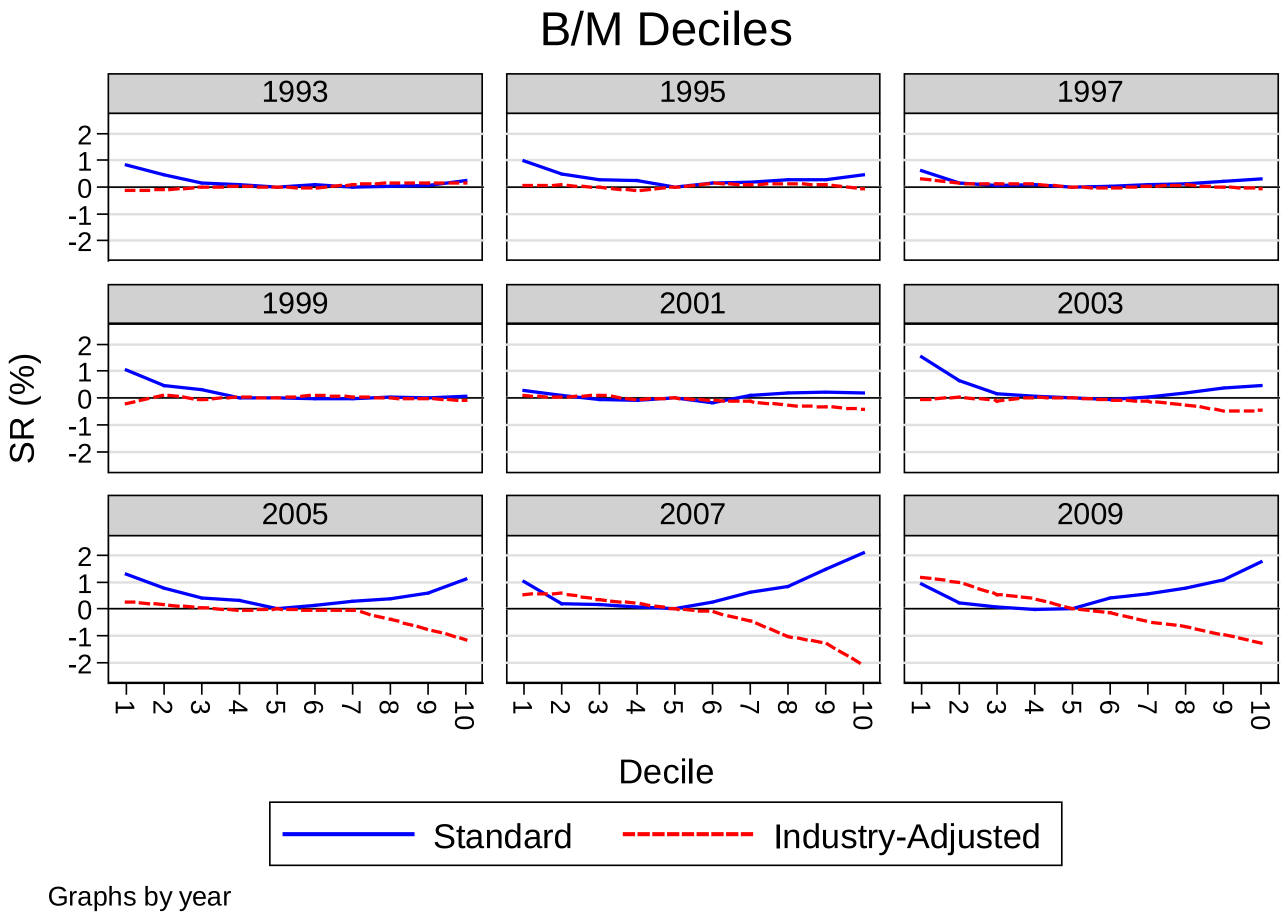


Figure 11: Strategy capital, returns, and volatility. The figure plots the 4-quarter moving average of the estimated quarterly coefficients on the extreme growth decile ( ) and extreme momentum loser decile (versus annual strategy returns and realized volatilities over the same 4-quarter period.

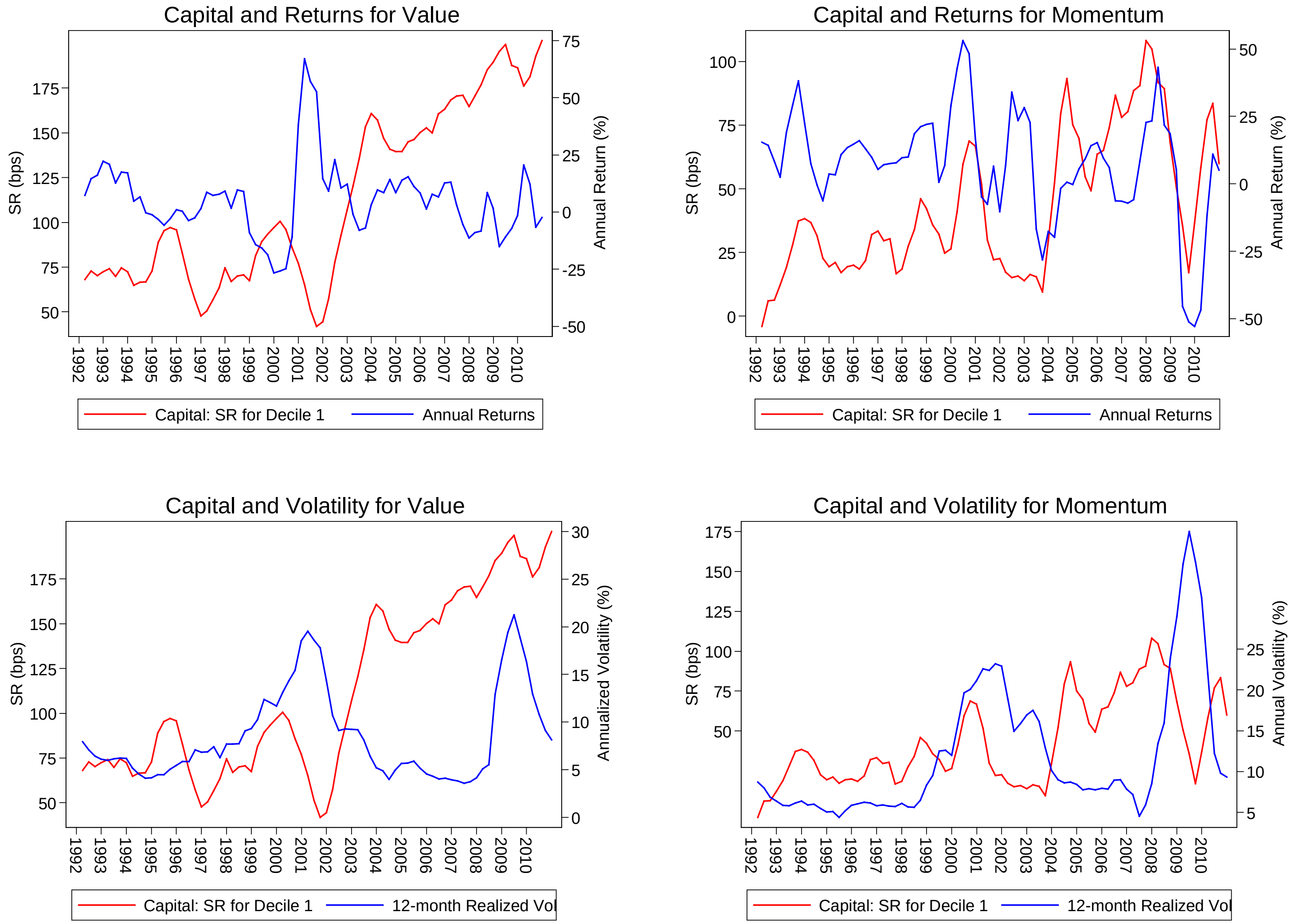


Table 1: The effect of strategy returns on strategy-level capital flows. This table shows regressions of the form:

$$\Delta\delta_t^k = \alpha^k + \beta^k \cdot r_{t-1}^k + \varepsilon_t^k.$$

for value and momentum. *t*-statistics are computed using heteroskedasticity robust standard errors.

	Value				**Momentum**			
	Full Sample		**Pre-2008**		**Full Sample**		**Pre-2008**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	-0.460	-0.567	-0.377	-0.623	0.239	0.563	0.881	1.093
	[-1.17]	[-1.27]	[-1.07]	[-1.58]	[0.60]	[1.54]	[2.53]	[3.13]
		-0.338		-0.406		1.057		0.777
		[-0.77]		[-0.75]		[2.55]		[1.83]
Constant	2.358	3.002	1.968	3.152	-0.134	-2.236	-0.158	-2.172
	[0.84]	[0.93]	[0.72]	[0.91]	[-0.03]	[-0.59]	[-0.04]	[-0.53]
T	75	75	63	63	75	75	63	63
R^2	0.018	0.032	0.013	0.027	0.005	0.082	0.057	0.097

Table 2: The effect of strategy volatility on strategy-level capital flows. This table shows regressions of the form:

$$\Delta\delta_t^k = \alpha^k + \psi^k \cdot \Delta\sigma_{t-1}^k + \varepsilon_t^k .$$

for value and momentum. is the standard deviation of daily factor returns during quarter *t*. The quarterly and annual returns are in percentages and factor volatility measures are in annualized percentages. We measure the TED spread using the difference between the rate on 3-month Eurodollar deposits (i.e., 3-month LIBOR) and the yield on 3-month Treasury bill. Both rates are taken from the Federal Reserve H.15 release. *t*-statistics are computed using heteroskedasticity robust standard errors.

	Value						Momentum					
	Full Sample			Pre-2008			Full Sample			Pre-2008		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	-2.655	-3.742	-3.325	-3.209	-3.484	-3.478	-0.811	-0.413	-0.940	0.651	0.891	1.140
	[-4.10]	[-5.16]	[-3.98]	[-3.10]	[-2.29]	[-2.30]	[-0.83]	[-0.43]	[-1.08]	[0.81]	[1.06]	[1.50]
		1.044	0.417		0.256	0.267		-0.793	0.548		-0.398	-0.231
		[3.20]	[0.69]		[0.27]	[0.28]		[-2.84]	[0.87]		[0.62]	[-0.35]
			17.606			-2.619			-39.142			-58.588
			[1.81]			[-0.21]			[-2.88]			[-2.86]
Constant	1.598	1.444	1.499	1.089	1.034	1.072	-0.042	0.068	-0.044	1.577	1.637	2.475
	[0.61]	[0.58]	[0.61]	[0.41]	[0.40]	[0.40]	[-0.01]	[0.02]	[-0.01]	[0.42]	[0.44]	[0.71]
T	74	74	74	62	62	62	74	74	74	62	62	62
R^2	0.150	0.229	0.264	0.157	0.159	0.159	0.023	0.053	0.155	0.010	0.013	0.122

Table 3: Investigating contagion: The effect of other strategy returns on momentum capital flows. This table shows regressions of the form:

$$\Delta\delta_t^{MOM} = \alpha + \gamma \cdot r_{t-1}^{A} + \beta \cdot UMD_{t-1} + \varepsilon_t^{MOM},$$

where is the lagged quarterly return on some other strategy *A*. *t*-statistics are computed using heteroskedasticity robust standard errors.

	Full Sample					Pre-2008				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	0.239	0.563	0.041	0.660	0.287	0.881	1.093	0.415	1.288	0.809
	[0.60]	[1.54]	[0.11]	[1.94]	[0.84]	[2.53]	[3.13]	[1.04]	[4.11]	[1.90]
		1.057	-1.324	-0.673	-1.520		0.777	-1.454	-0.662	-1.526
		[2.55]	[-1.83]	[-1.31]	[-2.14]		[1.83]	[-1.90]	[-1.41]	[-2.07]
			4.057		2.600			3.937		2.395
			[4.07]		[2.32]			[3.29]		[1.75]
				4.348	2.640				4.232	2.783
				[4.58]	[2.72]				[4.04]	[2.54]
Constant	-0.134	-2.236	-10.611	-13.028	-14.155	-0.158	-2.172	-11.085	-14.718	-15.848
	[-0.03]	[-0.59]	[-2.59]	[-3.20]	[-3.53]	[0.04]	[0.53]	[-2.50]	[-3.32]	[-3.60]
T	75	75	75	75	75	63	63	63	63	63
R^2	0.005	0.082	0.209	0.205	0.238	0.057	0.097	0.215	0.222	0.251

Table 4: The relationship between arbitrage capital and future returns. This table shows regressions of the form:

$$r^k_{t\to t+4} = \mu^k + \varphi^k \cdot (\delta^k_t - \delta^k_{t-4}) + \varepsilon^k_{t\to t+4},$$

where is the 4-quarter annual return from quarter *t* to quarter *t*+4. is the value spread.

	Value								**Momentum**			
	Full Sample				**Pre-2008**				**Full Sample**		**Pre-2008**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	-0.125	-0.123	-0.147	-0.144	-0.135	-0.132	-0.161	-0.170	0.032	0.050	-0.109	-0.085
	[-1.99]	[-2.75]	[-1.61]	[-1.98]	[-2.14]	[-3.59]	[-1.68]	[-2.98]	[0.29]	[0.46]	[-1.97]	[-1.86]
		0.129		0.129		0.224		0.253				
		[1.93]		[1.74]		[2.71]		[2.96]				
			-0.173	-0.171			-0.202	-0.297		-0.274		-0.300
			[-0.86]	[-0.85]			[-0.92]	[-1.42]		[-1.83]		[-2.09]
Constant	4.851	-11.312	5.803	-10.320	5.552	-20.827	6.923	-22.204	6.053	8.310	10.726	13.581
	[1.42]	[-1.55]	[1.31]	[-1.36]	[1.50]	[2.22]	[1.37]	[-2.40]	[1.47]	[1.79]	[3.24]	[3.71]
T	68	68	68	68	60	60	60	60	68	68	60	60
R^2	0.063	0.172	0.091	0.194	0.072	0.255	0.111	0.215	0.004	0.074	0.073	0.159

Internet Appendix: Additional Results

A. Cross-Sectional Regression Summary Statistics

In this Appendix, we provide further details on our annual cross-sectional regressions which take the form given in equation (2). In Figure A1 we plot the cross-sectional R^2 and average number of stocks each month in our annual regressions. The R^2 hovers between 0.25 and 0.30 during the first 10 years of the sample before rising markedly in recent years. The increase in R^2 since 2000 is largely driven by the growing importance of size (*ME*) and institutional ownership (*IO*) in determining the cross-section short interest.

Figure A2 plots the coefficients for our six additional controls: institutional ownership, past turnover, trailing volatility, exchange dummies for NYSE and NASDAQ (AMEX is the omitted category), and a dummy indicating if the firm has convertible securities outstanding. First, we see that the impact of institutional ownership has increased over time and particularly since 2000. By 2007, a one percentage point increase in *IO* was associated with a 0.07% increase in *SR*. The growing impact of *IO* (i.e. the difference in *SR* between supply-constrained and unconstrained stocks) is consistent with a parallel shift in shorting demand for most stocks. When shorting demand is low, the supply constraint doesn't bind for either high or low *IO* stocks. However, when demand shifts out the constraint will bind for firms with low *IO*, but not for those with high *IO*. Thus, a broad increase in shorting demand (not captured by our other controls) would cause the difference in *SR* between high and low-*IO* firms to rise. Interestingly, the coefficient on *IO* fell significantly in 2009 and 2010, and the rolling monthly results show that the coefficient dropped sharply after September 2008. Anecdotally, this likely reflects the withdrawal of several large institutional investors from share lending programs in the late 2008 due to concerns about the re-investment portfolios of securities lenders.

Second, we see that *SR* is reliably increasing in past turnover. Throughout much of our sample a one percentage point increase in average turnover over the previous quarter is associated with a 0.20% to 0.25% increase in *SR*. The effect of past turnover on short interest declined somewhat in the late 1990s, recovered during the early 200s, and declined again following 2008. Third, we see that short-sellers were somewhat less willing to short highly volatile stocks during the 1990s. However, this effect has not been significant in recent years. Fourth, all else equal, we find that short interest is slightly lower for NYSE stocks when compared with AMEX stocks (the omitted group). Fifth, beginning in 2003, we find that *SR* has been noticeably larger for NASDAQ stocks than AMEX stocks. Finally, we find that the impact of having convertible securities outstanding grew steadily from 1991 to 2000. This effect declined following 2000 and from 2006-2008 there was little effect associated with having outstanding convertibles. However, the impact of convertibles on *SR* reemerged in 2009-2010.

B. The Impact of Financial Stocks

In this section, we explore how the short interest patterns for the 2007-2009 financial crisis differ between financial and non-financial stocks. In Figure A3, we plot equal- and value-weighted short interest ratios separately for nonfinancial and financial stocks. On an equal-weighted basis, average short interest for *both* nonfinancial and financial stocks soared prior to the crisis, peaked in July 2008, and dropped sharply following the imposition of the short sales limitations for financial stocks in September 2008. While Figure A3 shows that short interest followed essentially parallel trends for nonfinancials and financials on an equal-weighted basis, the run-up in *SR* was far more pronounced for financial firms on a valued-weighted basis.

We next estimate our baseline cross-sectional specification in equation (2) separately for nonfinancial and financial stocks. In Figure A4, we plot the coefficients associated with the extreme growth and loser deciles. These figures replicate Figure 4 for all stocks separately for nonfinancial stocks in Panel A and financial stocks in Panel B. The figures for nonfinancials in Panel A are similar to those reported in the main text which makes sense given that the vast majority of all stocks are nonfinancial. The results for financials in Panel B show that there is little tendency to short financial stocks with low *B/M* (relative to other financial stocks). However, there was significant shorting of financial losers during the financial crisis and the monthly results suggest that the sharp contradiction in loser short interest in October 2008 may have been driven by the short interest ban for financials.

C. Time-series Plots for Other Quantitative Strategies

C.1. Annual Short-Only Measures for Other Anomaly Strategies

The plots below show the coefficients on our decile 1 dummies for other quantitative arbitrage strategies. First consider the *SUE* measure of earnings momentum. To obtain capital measures for earnings momentum, we add a full set of *SUE* decile dummies to our baseline model, estimating:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{SUE} \cdot \mathbf{1}_{it}^{SUE} + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}. \tag{A1}$$

Our estimates for other strategies are obtained by estimating analogous regressions. When computing deciles for these other strategies, we always code the deciles so that decile 1 is associated with abnormally low returns and decile 10 is associated with abnormally high returns.

In Figure A5, we plot our baseline short-side capital measure, $\delta_t^{k(1)}$, the boost to *SR* associated with being a decile 1 stock for quant signal *k* relative to the omitted decile 5. Given our coding conventions, we should expect to find $\delta_t^{k(1)} > 0$. Turning to the results, we see little effect from having poor earnings momentum (*SUE*). Large net stock issuance is associated with being highly shorted, particularly since 2000. This is consistent with the idea that arbitrageurs have added this signal to their models over this period. There is little effect from having high balance sheet accruals, though high cash-flow based accruals have been associated with high short interest in the years prior to the crisis. The Shumway (1997) distress measure has little effect on short interest, except for 2001 during the tech and telecom bust and 2008-2009 during the financial crisis. High CAPM residual volatility has been important in recent years, suggesting it too has gained popularity as a signal. Both gross and net asset growth have a consistent effect on short interest that has grown somewhat in recent years.

C.2. Annual Long-Short Capital Measures for Value and Momentum

In Figures A6 below we plot the alternate measures of strategy capital described in the text. The lighter lines are the difference between our decile 1 dummies and our decile 10 dummies from regression (2) in the main text – i.e., $\delta_t^{k(1)} - \delta_t^{k(10)}$. As discussed above, the reluctance to short stocks that an arbitrage strategy recommends buying contains information about the amount capital playing that strategy. Given our coding of the deciles we expect to find $\delta_t^{k(1)} - \delta_t^{k(10)} > 0$. The darker lines are the results of running cross-sectional regressions of the form in equation (2) on raw characteristic deciles, rather than a full set of characteristic dummies. These regressions deliver a single coefficient for each characteristic summarizing its impact of *SR*. As seen below, while this "raw decile" approach imposes linearity on the mapping from characteristics to short interest, it appears to capture similar information from the long and short sides as that contained in the more flexible specification (2).

In Figure A6 we see that for *B/M* and momentum, the results using these short-long measures $\delta_t^{k(1)} - \delta_t^{k(10)}$ are quite similar to those presented in the main text, which only use decile

1 dummies $\delta_t^{k(1)}$. The one difference is that in recent years the level of momentum capital has generally been higher than the level of value capital. As discussed above, the reason is that in recent years investors have been extremely reluctant to short winners but not value stocks.

C.3. Annual Long-Short Capital Measures for Other Anomaly Strategies

Turning to the other arbitrage strategies in Figure A7, we find an increase in the amount of capital playing *SUE* in recent years. This differs from the conclusion reached above using only the short side, which suggests that while arbitrageurs are reluctant to short stocks with positive earnings momentum, but they are not particularly eager to short stocks with negative earnings momentum. By contrast, the effects for net stock issuance (*NS*) are smaller than those seen above. This is because, somewhat surprisingly, we find that *SR* is also fairly high for large net repurchasers (i.e. $\delta_t^{NS(10)} > 0$). Turning to our accrual measures, we find that they have little effect, except for the period 2001-2004 which was marked by significant accounting scandals and 2006-2008. Next, we see that while the Shumway distress metric has a meaningful impact on *SR*, the effect is relatively constant over time with the exception of 2008. Residual CAPM volatility has little effect throughout most of the sample, but has gained popularity in 2009 and 2010. The effect of asset growth is similar to what we saw using only the short side.

Figure A1: Regression summary statistics: This figure plots the cross-sectional R^2 and average number of stocks each month in our annual regressions (see equation (2)).

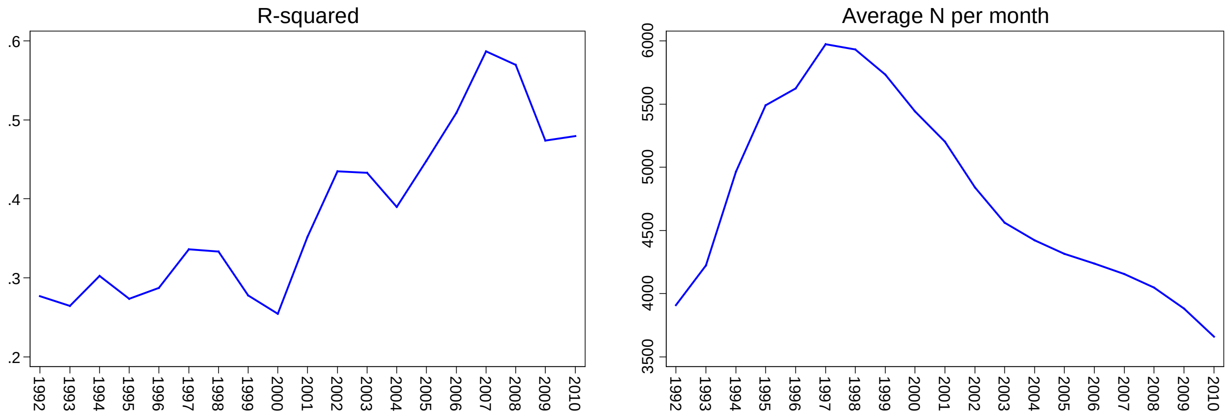


Figure A2: Coefficients for additional controls: This figure plots the time series of coefficients for the additional controls used in our annual cross-sectional regressions (see equation (2)).

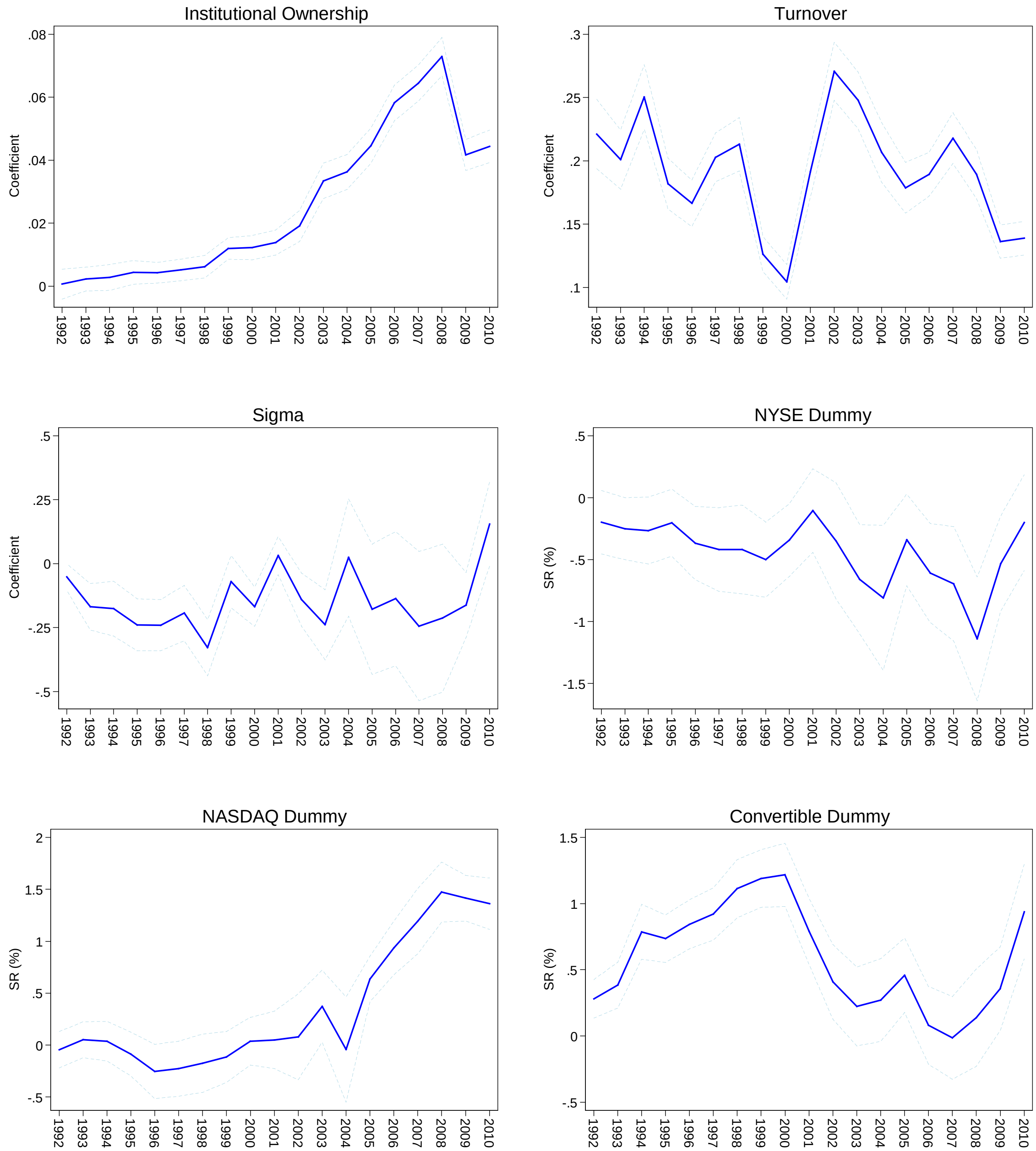


Figure A3. Average short interest ratios for nonfinancial and financial stocks. Panel A plots the monthly equal- and value- (i.e., market equity) weighted average short interest ratio for all nonfinancial stocks in our sample. Panel B plots short interest ratios for financial stocks. Financial stocks are stocks with Fama-French (1997) industry codes 44 (banking), 45 (insurance), 46 (real estate), or 47 (trading) based on their 48 industry classification scheme.

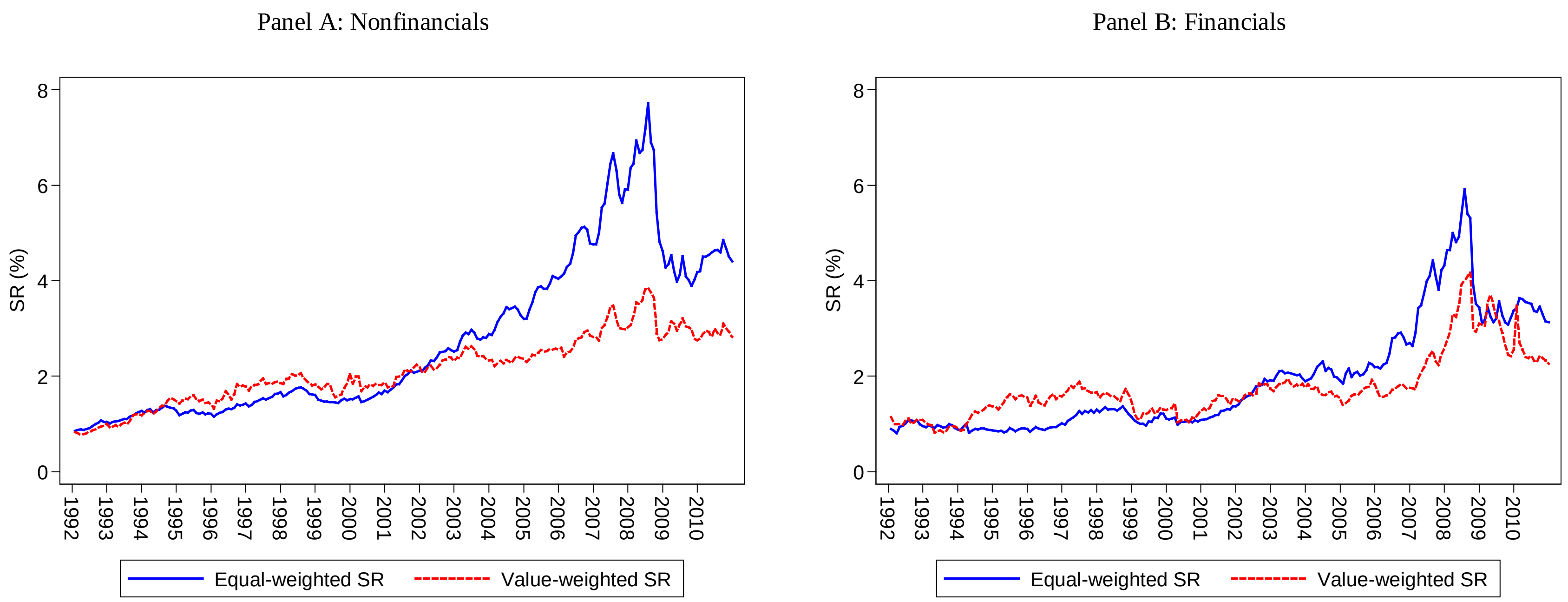


Figure A4: Estimated capital intensities for value and momentum strategies for nonfinancial stocks and financial stocks. The figure plots the time series of estimated coefficients on the extreme growth decile (   ) and extreme momentum loser decile (from the following specification:

$$SR_{it} = \alpha_t + \boldsymbol{\delta}_t^{B/M} \cdot \mathbf{1}_{it}^{B/M} + \boldsymbol{\delta}_t^{MOM} \cdot \mathbf{1}_{it}^{MOM} + \boldsymbol{\delta}_t^{SIZE} \cdot \mathbf{1}_{it}^{SIZE} + \boldsymbol{\beta}_t' \mathbf{x}_{it} + \varepsilon_{it}.$$

These regressions are estimated annually, pooling all observations in a given year or on a rolling quarterly basis, pooling all observations in a given 3 month period. Both specifications also include a full set of month fixed effects. We compute confidence intervals using standard errors that cluster by firm and, thus, are robust to serial correlation at the firm level. In Panel A, we include only nonfinancial stocks. In Panel B, we include only financial stocks.

Panel A: Nonfinancial stocks only

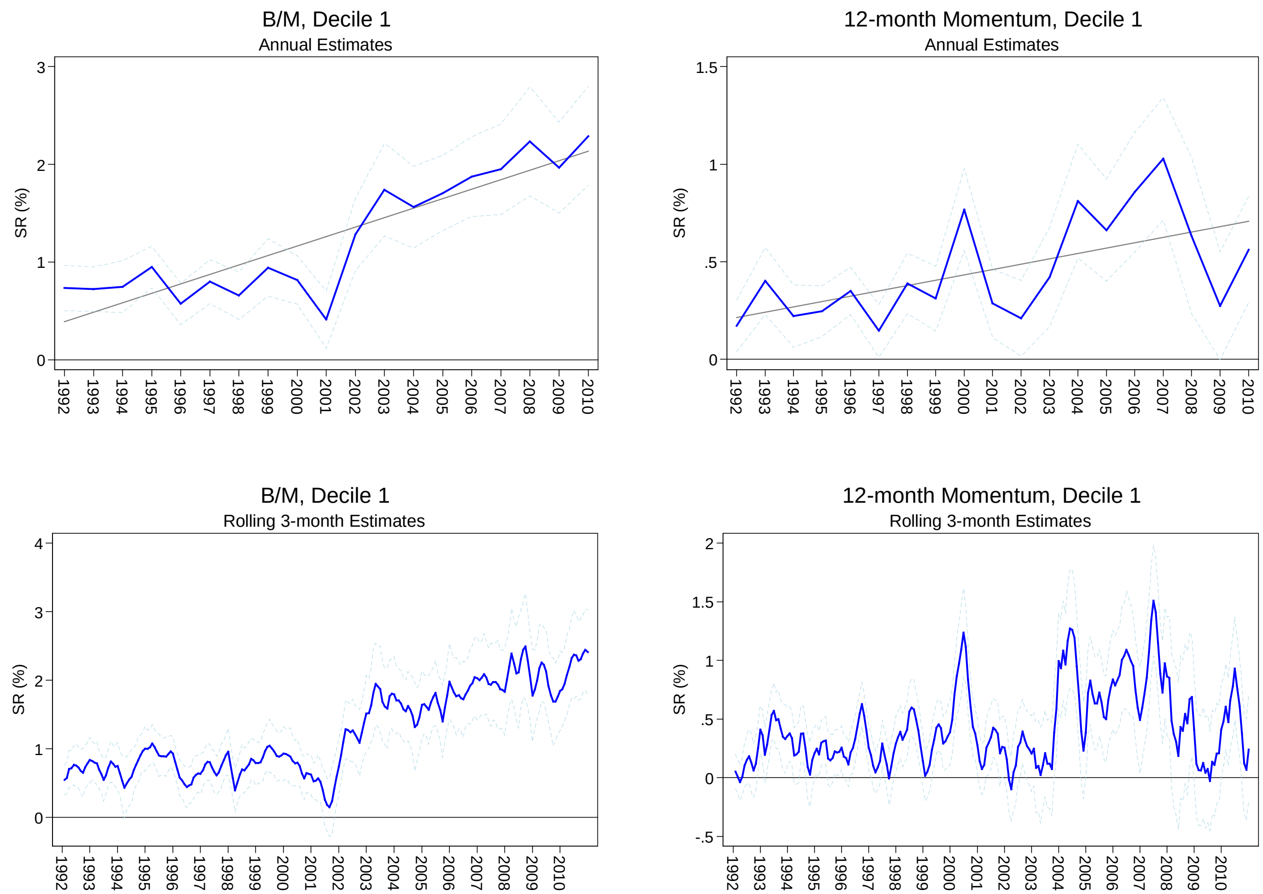


Figure A4: Estimated capital intensities for value and momentum strategies for financial stocks and nonfinancial stocks (continued)

Panel B: Financial stocks only

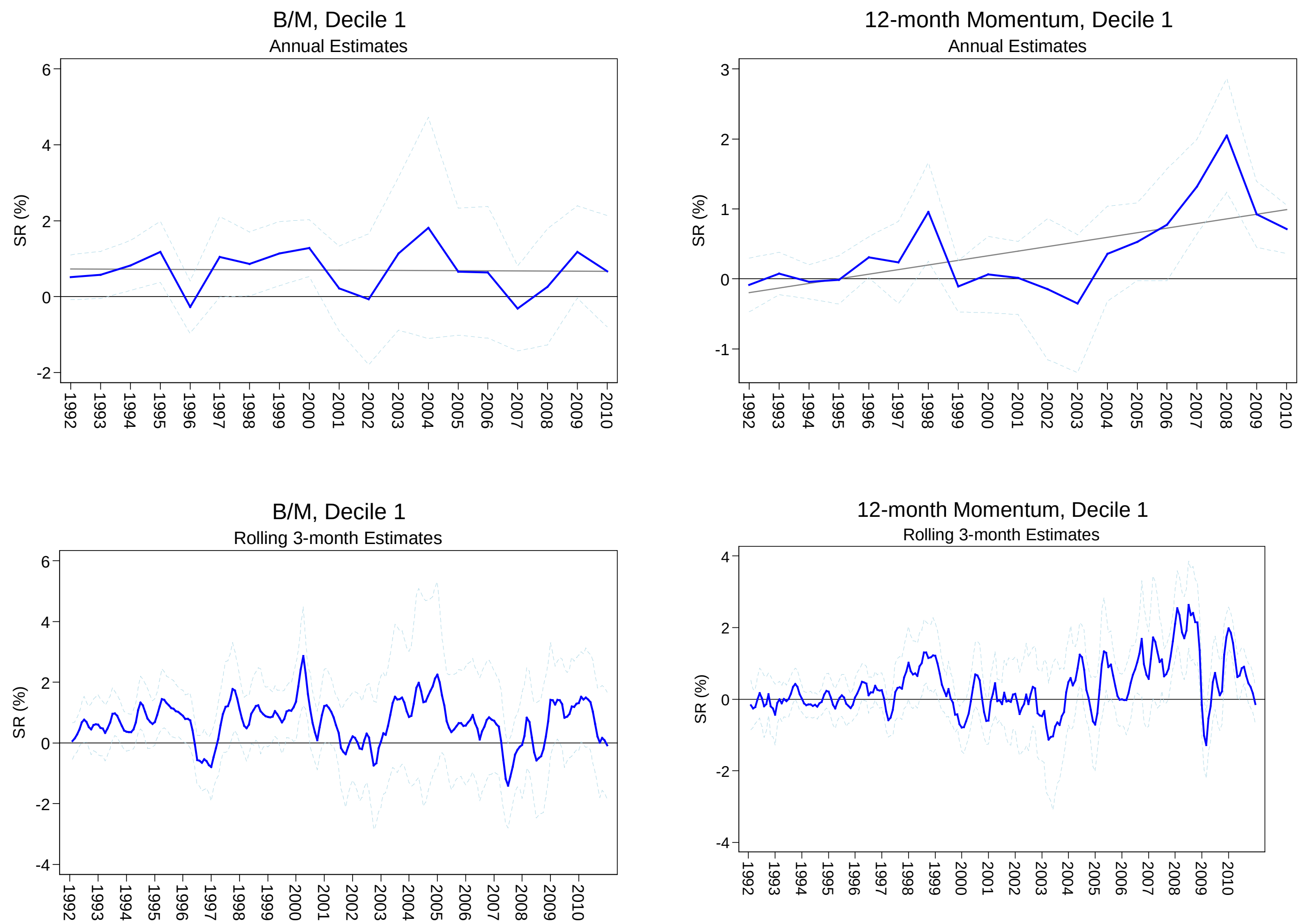


Figure A5: Short-side capital measures for other anomaly strategies: This figure plots the time series of for other anomaly strategies based on annual cross-sectional regressions (see equation (A1)).

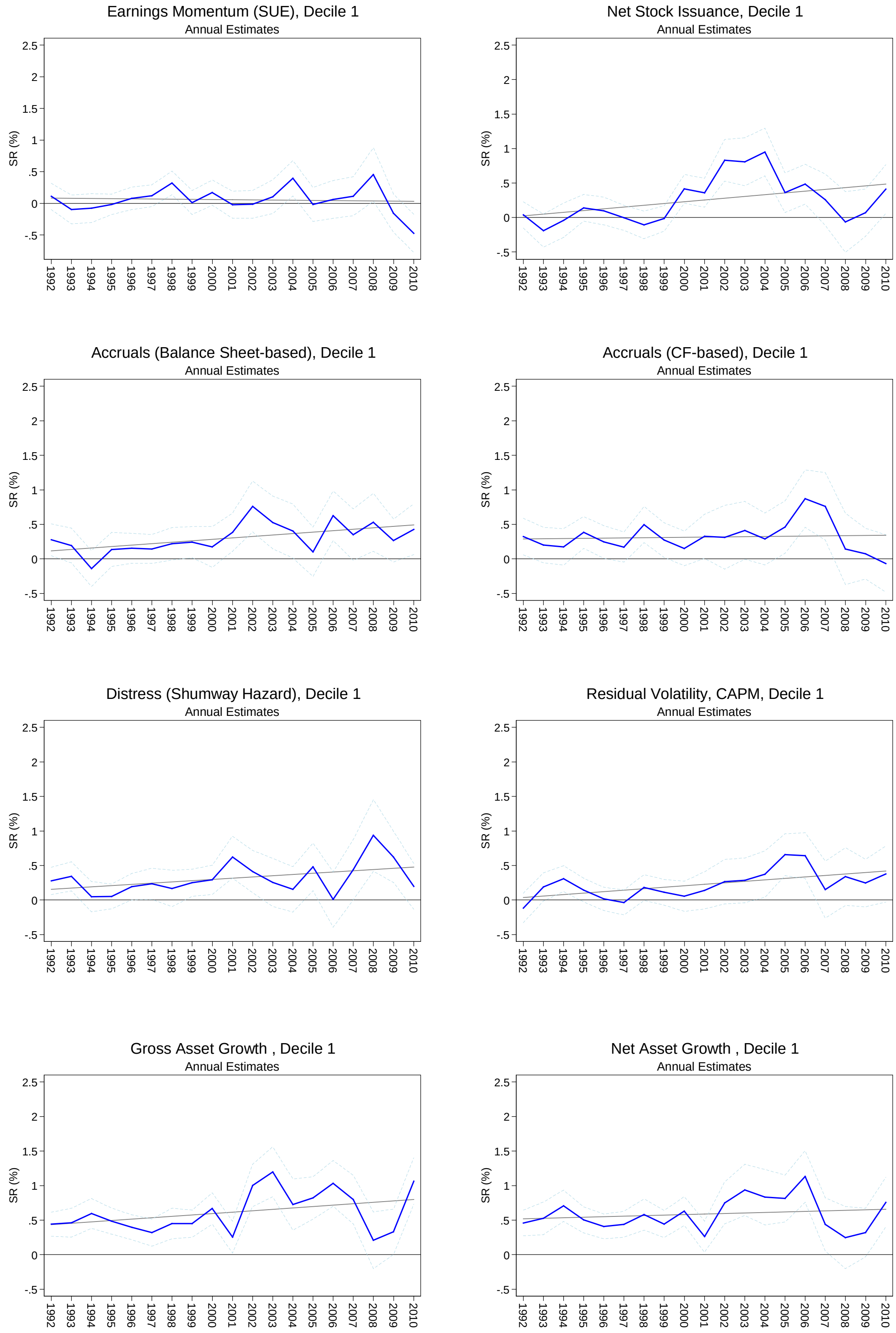


Figure A6: Short-long capital measures for value and momentum: This figure plots difference in coefficients between decile 1 and decile 10 from equation (2), i.e. , alongside the coefficient from a regression of *SR* on raw characteristic deciles.

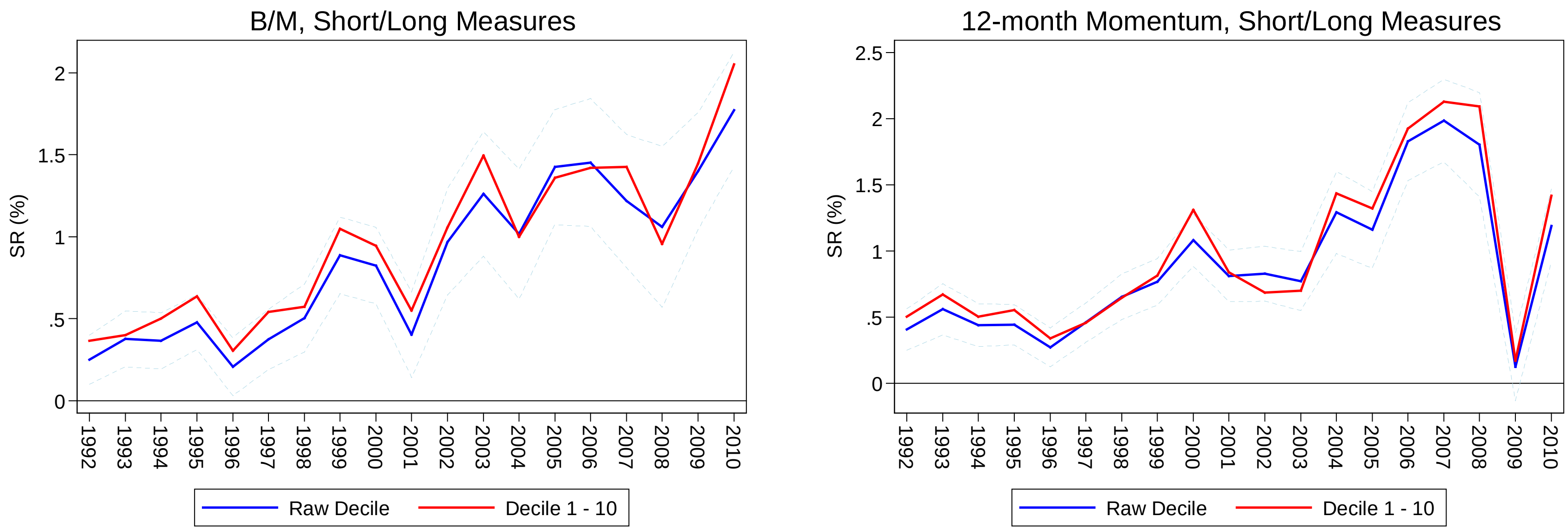


Figure A7: Long-short capital measures for other anomaly strategies: This figure plots difference in coefficients between deciles 1 and 10 from (A1) and the coefficient from a regression of *SR* on raw characteristic deciles.