Slow Trading and Stock Return Predictability

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Abstract

The state of market returns positively predicts the size premium (or the difference in the return on small and large firms). A trading strategy that buys (sells) small firms and sells (buys) large firms following positive (negative) market return states yields large, risk-adjusted monthly profits of 1.8%, 3.0% or 4.3% when rebalanced monthly, weekly or daily. Moreover, this predictability is also present in actively traded ETFs and in recent years. We uncover that when rebalancing portfolios, institutional investors execute trades in large-cap stocks swiftly, but are slower in trading small firms, hence contributing to the predictability of size-based stock returns.

Keywords: institutional trading, liquidity, return predictability, size premium

JEL classification: G12, G23

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1. Introduction

Rapid execution of orders in the stock market creates price impact and return reversals (Grossman and Miller (1988)). Several theoretical models demonstrate that it is optimal for investors, especially large traders, to trade gradually over time to minimize trading costs (Vayanos (1999, 2001)).[1] In this paper, we document that the tendency for investors to trade large firms swiftly and trade small firms slowly generates predictable time variation in the size premium - the difference in the returns of small market capitalization firms and the returns on large firms.

Our main finding is that the size premium is positively dependent on the past market return. Following positive market returns, the small firms outperform the large, generating a positive size premium. Similarly, negative market returns are associated with weak future returns of small firms relative to large firms. To illustrate, the monthly size premium is a large 1.1% following a positive market return (positive market state), and this declines to -0.5% when the prior market state is negative. This effect of the market state is economically significant when compared to the unconditional size premium of 0.5% per month.[2]

Figure 1 plots the cumulative return to the unconditional size premium, which is close to zero over our sample period from 1963 to 2014. It also plots the cumulative returns from investing in the size premium following either positive or negative market states. As Figure 1 shows, investments in the size premium are highly profitable when conditioned on positive

[1] Garleanu and Pedersen (2013) and Rostek and Weretka (2015) present dynamic trading models where it is optimal for investors to trade slowly in the presence of price impact and transaction costs. Empirical evidence on significant price impact of institutional trading and a preference for slow trading (or order breakup) in some environment is provided by Chan and Lakonishok (1995) and Keim and Madhavan (1995). See also Almgren and Chriss (2000) and Engle, Ferstenberg and Russell (2012) for models of the trade-off between transaction costs and volatility risk in executing trades.
[2] Asness, Frazzini, Israel, Moskowitz and Pedersen (2015) find a stronger and more robust size premium after controlling for various "quality" factors.

market states, while shorting the size premium is profitable following negative market states. This result holds at daily, weekly, or monthly portfolio rebalancing frequencies.[3]

<FIGURE 1 HERE>

Capturing the predictability shown in Figure 1, we examine a simple trading strategy that buys small firms and sells large firms in positive market states and switches to selling small and buying large firms in negative market states. This "spillover strategy" is highly profitable with monthly (weekly or daily) portfolio rebalancing frequency yielding economically large risk-adjusted profits of 1.8% (3.0% or 4.3%) per month.

We also evaluate the returns to investing similarly in small-cap and large-cap exchange traded funds (ETFs), as these ETFs form liquid and low cost investment vehicles to capitalize on the slow adjustment of the size premium in the direction of past market returns. Interestingly, the spillover strategy applied to actively traded small- and large-cap ETFs also generates an economically significant monthly four-factor alpha of 0.45%, confirming that liquidity differences do not fully explain our findings.

When we examine the behavior of individual stock returns, we find that the idiosyncratic component of small firms' return reverts in subsequent days (consistent with negative autocorrelation of illiquid stocks), but the component associated with market-wide returns exhibit slow adjustment. On the other hand, large firms' returns do not have predictable idiosyncratic component (i.e. they are liquid), but their returns seem to have a small negative relation to the lagged market returns, especially in the recent decades. The

[3] As shown in our Internet Appendix in Figure A1, the findings are qualitatively similar if we account for microstructure concerns by skipping a day between the formation and the holding periods.

latter finding is new to the literature and contributes to the sustained predictability of the size premium conditional on market states.

After carefully documenting the negative (positive) effect of market return on subsequent large (small) firm returns, we turn to examining the source of this predictability. Our aim is to link the predictability of the size premium to investors' size dependent speed of trading: the idea that institutions execute their orders in large firms swiftly when facing portfolio re-balancing needs, while trading the small firms more slowly. First, employing the price delay framework of Hou and Moskowitz (2005) to evaluate delays in trading, we document that small firms display greater delays in their trading activities and that delays in their returns and trading activity are highly correlated. Specifically, we find that the turnover of small stocks is significantly correlated with lagged market-average turnover and this "trading delay" declines monotonically as we move to large firms. Consistent with price impact from rapid trading of large stocks we find that the large stocks delayed return response to market returns is negative. Second, using the arguably exogenous 2003 mutual fund trading scandal as a natural experiment, we are able to confirm that when mutual funds are forced to sell large quantities of their stock holdings, they adjust initially their positions in large stocks, and trade the small firms' stocks more gradually. The same phenomenon, we argue, is behind the predictability of the size premium by market returns. Consistent with this, we find that the returns on the spillover strategy are larger following periods with large aggregate market trading volume or market volatility.

There are several reasons to believe that investors may not trade small and large stocks at the same speed. First, in the case of market-wide information affecting investors' optimal portfolio allocations, the large institutional investors may choose to adjust their holdings of large firms more quickly than those of small firms, as the large firms are likely to account for a bigger fraction of the value of their portfolio and hence, their capital at risk. Similarly, in case of large systematic liquidity shocks, the investors may first focus on trading large and liquid stocks, as they are easier to liquidate, as argued by Vayanos (1999, 2001).

A second factor affecting the slow trading of small stocks could be the limited cognitive processing capacity of investors (e.g. Hirshleifer and Teoh (2003), Hirshleifer, Lim and Teoh (2009), Peng (2005) and Peng and Xiong (2006)). For example, according to Peng and Xiong (2006), investors allocate their attention across multiple risky assets to minimize total portfolio uncertainty, leading to asset category based return correlations. Corwin and Coughenour (2008) in turn show that limited attention drives the market makers to allocate relatively more attention to large firms during busy trading periods, as these stocks have bigger impact on their profits and risks than small stocks. The increased market makers' attention on large stocks may further increase investors' incentive to focus on large stocks at busy trading periods, thus delaying those investors trading of small stocks.

To further investigate the links between investors' fast trading of large stocks, their slow trading of small stocks, and their effect on the predictability of the size premium, we utilize a database on institutional investors' daily trades collected by ANcerno. We focus on the trading activities of institutional investors as these investors dominate trading in the U.S. markets. Using the ANcerno sample during the 2000-2010 period, we find several pieces of evidence in support of differences in the speed of trading large and small firms. First, we find a lead-lag relation in institutional trading volume, where the institutions' trading in large stocks leads that of small stocks. In particular, we find that an institution's trading volume in large stocks predicts the same institution's trading volume in small stocks in the same direction. Second, consistent with Chan and Lakonishok (1995), Keim and Madhavan (1995) and Vayanos (1999, 2001), we find that institutional investors often split their trades over multiple days, and more so when trading large orders in small-cap stocks.

Finally, we look at the effect of commonality in institutional ownership in determining the return spillovers from large to small stocks. If the predictability of small stock returns is indeed driven by institutions' delayed execution of trades in small stocks, the predictability of the returns on any given small firm *i* should originate from the return of those firms that are held by the same institutional investors as firm *i*, more than the return on the market portfolio. We find evidence that this is indeed the case.

To summarize, our paper makes several important contributions. First, we document that the lagged market return is a strong and remarkably resilient predictor of the size premium and we uncover a new source of this return predictability: the reversal of market wide component in large stock returns. Second, we provide evidence that the institutional trading patterns in their buying and selling activities contribute to the predictability of the size premium. Finally, our findings add to the previously documented lead-lag relations in size-based stock returns, first reported in the seminal paper by Lo and Mackinlay (1990). Several subsequent papers have attributed some of the size-based lead-lag relation in short-horizon stock returns to differences in analyst coverage (Brennan, Jegadeesh and Swaminathan (1993)), institutional ownership (Badrinath, Kale and Noe (1995)), trading volume (Chordia and Swaminathan (2000)) and portfolio autocorrelations (Bodoukh, Richardson and Whitelaw (1994)). We add to the literature by offering a new explanation for the lead-lag relation: slow trading in small relative to large firms. Specifically, when rebalancing their portfolios, investors initially trade relatively more of the large firms, which allows them to quickly adjust their overall risk exposure. The slow trading explanation is different from the slow adjustment of small stock prices emanating from less informed investors reacting to common information with a delay (Badrinath, Kale and Noe (1995), Hou (2007) and Chordia, Sarkar and Subrahmanyam (2011)). Hence, we argue that trading frictions and slow moving capital (Duffie (2010)) contribute to the predictability of the size premium.

This paper is organized as follows. Section 2 describes the data. In Section 3, we document predictability of returns on small-cap stocks, large-cap stocks and the size premium. In Section 4 we show that this predictability implies highly attractive trading strategies, which can be implemented utilizing low cost ETFs. In Section 5, we show evidence on delays in the trading of small stocks by institutions while in Section 6, we investigate the relation between commonality in the institutional ownership of stocks and its impact on the observed return predictability. Section 7 concludes the paper.

2. Data

We collect daily data on stock returns and volume (numbers of shares traded and dollar trading volumes) from CRSP for all common stocks listed on the NYSE, the AMEX and the NASDAQ over the period of 1962-2014. We adjust the returns for the delisting bias by including delisting returns from the CRSP daily event file. When the delisting return is missing, and the delisting is performance-related, we follow Shumway (1997) and impose a return of -30%. For the NASDAQ listed firms, we adjust trading volume prior to 2004 following Gao and Ritter (2004).[4].

To minimize concerns about microstructure effects, we discard the most infrequently traded stocks from our sample by only considering stocks that had a positive trading volume

[4] For the period prior to February 1st 2001, the period between February 1st 2001-December 31st 2001, and January 1st 2002 - December 31st 2003, the volume on NASDAQ stocks is divided by 2.0, 1.8, and 1.6, respectively.

on at least 200 days in the previous calendar year and start our analysis in January 1963. To minimize effects of non-synchronous trading in our analysis of daily stock returns, we require that the stock traded on both the portfolio formation day and the prior trading day.

To analyze the size premium, we sort stocks by size into deciles using the NYSE breakpoints (size is measured by the stocks' market capitalization on the last trading day in June of the previous calendar year). For each size decile, we compute daily, weekly, and monthly value-weighted average returns. We define size premium as the return difference between the smallest firm decile (decile 1) and the largest firm decile (decile 10). To ensure that our results are not biased by the smallest firms in CRSP, we also consider a size premium that is measured as the difference in the returns on stocks in deciles 2 and 10.

We next match the stocks and their characteristics to the Abel Noser Solutions (ANcerno) transaction data. This dataset contains trade-level observations for hundreds of different institutions (hedge funds, mutual funds, pension funds, and other money managers). This data includes the trades of many of the largest institutional investors such as CalPERS, the YMCA retirement fund, Putman Investments, and Lazard Asset Management (see Puckett and Yan (2011)). This dataset is widely used in academic research as it provides a highly representative sample of the institutional fund management industry. According to Puckett and Yan, the institutions covered in this dataset account for 8% of the daily trading volume in CRSP.

The analysis with ANcerno data covers the years 2000-2010. When analyzing institutional trading data, we do not only consider the smallest and the largest deciles of stocks, but we classify all stocks either as large-cap (deciles 6 and higher) or as small-cap (deciles 5 and lower). We impose two data filters to ensure that institutional investors in our sample actively trade both small and large stocks. In each calendar year, for an institutional investor to be included in our sample, we require that the institution reports transactions on both small and large stocks and that it trades during at least 200 days of the calendar year.

We also use mutual fund ownership data from the CRSP mutual fund database, the CDA/Spectrum database, and the Mutual Funds linktable created by Russ Wermers (1999).

3. Predictability of the size premium

Figure 1 shows that past market returns predict the size premium. In this Section, we confirm this finding using regression analysis. Using rolling regressions, we document how the lead-lag relations between the market and size-based portfolios returns have evolved over time. Finally, we study the robustness of our main finding that market returns predict the size premium.

3.1 Portfolio returns

We start our analyses by showing that there is strong predictable time-variation in the size premium. To do this, we run the following three regression specifications:

$$R_{St} = \alpha_S + \beta_S R_{VW,t-1} + \varepsilon_{St} \quad (1)$$

$$R_{Lt} = \alpha_L + \beta_L R_{VW,t-1} + \varepsilon_{Lt} \quad (2)$$

$$R_{SMLt} = \alpha_{SML} + \beta_{SML} R_{VW,t-1} + \varepsilon_{SMLt} \quad (3)$$

where R_{St} is the return on small firms measured by the value-weighted return on the decile of the smallest market capitalization firms, R_{Lt} is the return on large firms measured by the value-weighted return on the decile of the largest firms, R_{SMLt} is the size premium ($R_{St} - R_{Lt}$), and $R_{VW,t}$ refers to the value weighted CRSP market return in period *t*. We estimate the regressions in (1) to (3) at daily, weekly and monthly frequencies over the period 1963-2014. To control for seasonalities in stock returns, all regressions include month dummies and the regressions at the daily frequency also includes weekday dummies.

Panel A of Table 1 presents the estimates of Equations (1) to (3). The results confirm the observations in Figure 1 that market returns significantly predict the difference in the returns of small and large stocks. This result is consistent with the lead-lag relations between small- and large-cap returns documented by Lo and MacKinlay (1990) and Chordia and Swaminathan (2000).[5]

However, the predictability of small-cap stocks documented in Lo and MacKinlay (1990) and Chordia and Swaminathan (2000) has steadily declined over time. To examine the extent to which the long-short size portfolio's returns remain predictable in the recent period, we supplement the regressions (1) to (3) with a post January 2000 dummy (*POST-2000*) and its interaction with lagged market returns. As shown in Panel B of Table 1, the predictability of the size premium at daily, weekly and monthly frequencies is present both in the pre and the post 2000 samples.

From the regressions performed at a daily frequency, we observe that the impact of market returns on small stocks' returns has reduced by one half in the recent sub-period. Interestingly, the impact of the lagged market returns on the large-cap stocks is negative in the post 2000 sample. As a result of these two trends, the impact of lagged market returns on the size premium has not markedly changed during our entire sample period. This predictability is also economically significant. For example, a one standard deviation

[5] Table A1 in the Internet Appendix provides more evidence on the autocorrelation and cross-correlations of stock returns across the entire size distribution.

increase in the mean market return on day *t* predicts that small firms will outperform the large firms on day *t+1* by 0.5% (or 11.7% per month).

Figure 2 graphs the time variation in βs from these regressions estimated over rolling windows of five years and the related R^2s. The impact of lagged market returns on expected small-cap returns (β) peaked around 1970 and has declined since, as has the R^2 of this predictive regression. The impact of lagged market returns on large-cap returns has also declined sharply over this period, and, as discussed, has turned negative since around 2000. Consistent with the estimates in Table 1, the predictability of the size premium has stayed fairly constant both in terms of β and R^2.

To sum up, following a positive market return, small-cap stocks tend to outperform the market, while in recent years large-cap stocks revert and underperform the market. These effects are reversed following a negative market state. The continuation of small-cap returns and the reversals of large-cap returns in response to market returns both contribute to the stable predictability of the size premium.[6]

<TABLE 1 HERE>

<FIGURE 2 HERE>

The findings in Table 1 are highly robust. Table A2 and Figures A2 and A3 in the Internet Appendix present several robustness checks on the predictability of the size premium. Specifically, we obtain similar size related predictability in returns if we (i) include multiple

[6] The reversal of market return component of large firms' stock returns is consistent with the intuition that during large market moves institutions focus on large stocks creating temporary price pressure in the large stocks that later reverts.

lags of market returns; (ii) consider the sign of returns rather than the returns as a continuous variable in the regressions (1) to (3); (iii) replace the smallest size decile with the second smallest decile of stocks; and (iv) replace the size portfolios with the small-minus-big (SMB) factor from Kenneth French's data library.

We also consider the robustness of the findings in Table 1 by examining portfolios that are double-sorted on firm size and various other firm characteristics. These portfolios consist of stocks sorted on eleven firm characteristics (including well known risk factors) that finance literature has shown to affect the cross-section of stock returns. Our objective is to perform a comprehensive investigation of whether our main finding on the predictive effect of market return state on size premium is robust to controlling for each of these firm characteristics. [7]

Our analyses is based on the 5x5 double sorted portfolios on size and one of the other eleven characteristic made available in Kenneth French's website. Specifically, we examine if the lagged market return predicts the return on R_{SMLt}, defined as the difference between returns on the quintile of smallest firms and the quintile of largest firms, *within* the top/bottom quintile of stocks formed by sorting on one of the eleven characteristics. To illustrate using the book-to-market ratio as the sorting variable, we examine if the estimates of Equation (3) are similar and significant within stocks belonging to the top and the bottom quintiles based on the book-to-market ratio. We do this for stock returns at both the daily and the monthly frequencies. The results, presented in Table 2, show that the positive

[7] Using the classification from Kenneth French's website we consider subsamples based on firms' (i) book-to-market ratio (Fama and French (1992)); (ii) investment factor (Novy-Marx (2013)); (iii) one-month stock returns (Jegadeesh (1990)); (iv) 12 month stock returns (Jegadeesh and Titman (1993)); (v) 36-months returns (DeBondt and Thaler (1985)); (vi) operating profitability (Aharoni et al. (2013)); (vii) accruals, (Sloan (1996)); (viii) market beta (Frazzini and Pedersen (2014)); (ix) net share issuance (Fama and French (2008)); (x) residual variance (Ang et al. (2006)); and (xi) variance. Table A3 in the Internet Appendix provides detailed explanations on the way each of the eleven variables and the corresponding portfolios are constructed.

predictability of the size premium by lagged market returns is highly significant within all subsets of stocks, at both daily and monthly frequency. For example, the estimate of the monthly regression coefficient in Equation (3) is highly significant in each of the 22 characteristic-sorted quintile portfolios and lies within a narrow range of 0.19 (high market-beta quintile) and 0.36 (high residual variance quintile). The corresponding R^2 from these predictive regressions ranges from 2% to 10%. We reach a similar conclusion with daily return regressions also presented in Table 2.[8]

<TABLE 2 HERE>

3.2 Individual stock returns

Next, we confirm that similar predictability from market returns exists in individual stock returns. Table 3 shows that small stocks' idiosyncratic return shocks revert, consistent with stocks' cross-sectional return reversals (see e.g. Lo and MacKinley (1990), Lehmann (1990) or Jegadeesh (1990)), but they adjust to market returns with a delay. Large stocks show little sign of reversal of their idiosyncratic shocks, but instead they react negatively to past market returns. These results are again consistent with Figures 1 and 2, and Tables 1 and 2.

<TABLE 3 HERE>

We next examine a measure of (return) delay proposed by Hou and Moskowitz (2005) to capture the delayed adjustment in prices of (individual) small firms to lagged market

[8] In Internet Appendix Table A4, we document the predictability of premiums for the 11 firm characteristics within the quintiles of large and small stocks separately. The predictability of these 11 premiums using lagged market returns is small and insignificant compared to the predictability of the size premium documented in Table 2.

returns. Following Hou and Moskowitz (2005), at the end of June of each year, we use daily returns on stock *i* over 12 months to estimate the following two regression models:

$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \sum_{k=1}^{5} \beta_{ik} R_{VW,t-k} + \varepsilon_{i,t} \quad (4)$$

and

$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \varepsilon_{i,t}, \quad (5)$$

The return-delay measure involves comparing the regression R^2 from the unrestricted model in Equation (4), denoted as R^2(Eq.4), with the R^2 from the restricted model in Equation (5), denoted as R^2(Eq.5):

$$return\ delay_i = 1 - \frac{R^2(Eq.5)}{R^2(Eq.4)}. \quad (6)$$

The ratio of the goodness of fit of the restricted and unrestricted regression models indicates how much of the variation in a firm's return variation is captured by lagged market returns. While our earlier measures looked at the effect of the immediate lagged market return, the measure of Hou and Moskowitz (2005) considers five lagged market returns. As Hou and Moskowitz (2005) explain, a higher *return delay*$_i$ implies that more variation in the returns on stock *i* is captured by lagged market returns and, hence, it reflects a slower adjustment to market-wide returns.

Table 4 reports the mean of *return delay* within each of the size deciles. It shows that the delay measure decreases monotonically in firm size, so that the smallest firms show the most delayed response to market movements. Table 4 also shows the average sum of lagged adjustment parameters for returns in Equation (4) ($\sum_{k=1}^{5} \beta_{ik}$). As expected, the slope parameters show that the smallest firms have the strongest dependence on lagged market states, and this dependence decreases almost monotonically in firm size. In the case of large stocks, the sum of the coefficients of past market returns is again negative. These findings confirm that our results are robust to using alternative measures of delayed adjustment in prices.

<TABLE 4 HERE>

4. A Long-Short Spillover Strategy

4.1. Returns to spillover strategy

The results so far show that market states significantly predict the size premium. To assess the economic magnitude of this predictability, we define a ”spillover” strategy that is long in small stocks and short in large stocks during periods following a positive market return, while reversing the positions to being long in large stocks and short in small stocks following a negative market return. The small and the large stock portfolios contain the smallest and the largest decile of stocks in our CRSP sample, where size classification is updated in June of the previous year to the formation period. The return on this strategy is given by the difference in the value-weighted returns on the small and the large stock portfolios during the holding period. We consider rebalancing the portfolio at daily, weekly and monthly frequencies.

In Table 5, we report the average returns on the zero-investment spillover strategy as well as the associated Sharpe-ratios, skewness, kurtosis and alphas from CAPM and Fama-French (1996) - Carhart (1997) 4-factor models. The long-short spillover strategy yields strikingly large returns at daily, weekly and monthly horizons. The average monthly returns on the spillover strategy vary from 3.8% with daily rebalancing to 1.4% with monthly rebalancing. The evidence that the returns to the spillover strategy are positive is robust. The spillover strategy generates large Fama-French four-factor alphas of between 2% to 4% per month with little exposure to the risk factors. For perspective, the unconditional size premium of 0.5% per month reduces to insignificance after adjusting for the Fama-French-Carhart factors. Moreover, our results remain largely intact when we replace the small stock portfolio, based on the smallest decile of stocks, to one based on the second smallest decile (or decile 2). This reaffirms that the spillover strategy returns are not solely due to the smallest stocks.

<TABLE 5 HERE>

4.2 Time-variation in spillover returns

Beyond the magnitude of spillover strategy returns, the profitability of the strategy is also remarkably stable over time. Figure 3 presents the returns to the spillover strategy using different holding periods and compares them to the behavior of the unconditional size premium (a static, annually rebalanced strategy that is long in the smallest decile and short in largest decile of firms). The black bars in Figure 3 show the average returns on the daily spillover strategy for each calendar month (Panel A), each weekday (Panel B), and decades of the 60s, 70s, 80s, etc. The grey bars show the same seasonal patterns and time trends for the unconditional size premium. Payoffs from the spillover strategy have remained remarkably profitable throughout the entire sample, ranging from average monthly returns of 2.3% in the 1960s to 7.1% in the 2000s, indicating that the underlying phenomenon is not diminishing over time. The unconditional size premium, on the other hand, has declined significantly since the 1970s. Moreover, there is a clear Friday and January seasonal effect in the unconditional size spread (documented by Schwert (2003), and others). Instead, we find no significant seasonal variation in the spillover strategy.[9] Hence, the magnitude and the pattern of profits from the spillover strategy is different from the unconditional size premium.

<FIGURE 3 HERE>

If the profits from the spillover returns reflect some impediments in the financial markets that are associated with slow moving capital, we expect the payoffs to be higher during periods of market stress and/or when funding and market liquidity are low (Brunnermeier and Pedersen (2009) and Duffie (2010)). Hence, we investigate if the intertemporal variation in the spillover profits relates to various (lagged) measures of market and funding liquidity suggested in recent research. Table 6 shows the results when the monthly returns on the daily spillover strategy (i.e. the returns on the spillover strategy with daily rebalancing, aggregated into monthly observations) are regressed on the prior month's VIX (Nagel (2012)), TED spread (Frazzini and Pedersen (2014)), innovations in aggregate Pastor-Stambaugh liquidity (Pastor and Stambaugh (2003)), and three-month cumulative value-weighted equity market returns (Hameed, et al (2010)). The results in Table 6 reveal that lower market or funding liquidity increases the spillover returns. In particular, the returns on the spillover strategy are

[9] In Table A6 of the Internet Appendix, we show that the daily rebalanced spillover strategy returns are significantly larger following periods of market volatility, represented by lagged absolute market returns. This is consistent with slower trading in small stocks following periods of more volatile market or more trading activity.

higher following periods of low funding liquidity (high VIX or TED spread) and low market liquidity (negative equity market returns, or low Pastor-Stambaugh liquidity).[10]

<TABLE 6 HERE>

These results support the premise that the return predictability we document relates to investors' delayed trading of small stocks relative to large stocks. During periods of low market or funding liquidity, there appears to be a relatively slower (faster) pace of execution of trades of small (large) stocks, leading to delayed (over) reaction in prices. These effects culminate in predictable returns to the spillover strategy.

4.3 Spillover in ETFs

The returns on the spillover strategies do not account for transaction costs, which may be non-trivial, especially in the case when the portfolio is rebalancing daily.[11] To demonstrate that our findings are not simply driven by the relative illiquidity of the small and large firms, we turn to spillover trading strategy implemented using size-based exchange traded funds (ETFs) which are known to be highly liquid. For example, Subrahmanyam (1991) demonstrates that adverse selection costs are lower for bundled assets, while Madhavan and Sobczyk (2014) find that bid-ask spreads of ETFs are in general lower than the average spread in the underlying securities. We identify three actively traded small-firm ETFs

[10] We thank Lubos Pastor for making the liquidity factor data available on his website at : http://faculty.chicagobooth.edu/lubos.pastor/research/

[11] In a recent paper, Frazzini, Isreal and Moskowtiz (2015) show that the trading costs faced by institutional investors are relatively small, and that they are smaller than those estimated in earlier studies by Keim and Madhavan (1995, 1997), Engle, Ferstenberg, and Russell (2012). Novy-Marx and Velikov (2015) find that the size strategy is among the strategies with the highest capacity to support new capital.

(*iShares Russel 2000, iShares Core S&P SmallCap, and Vanguard SmallCap*) and construct an equal-weighted portfolio of these 3 ETFs, denoting the corresponding portfolio return on month t as $ETF_{Small,t}$. Similarly, we form a portfolio of three large stock ETFs (*SPDR S&P500, SPDR DJIA, iShares Core S&P500*) and denote the monthly returns as $ETF_{Large,t}$.[12] Table 7 presents the regression of the difference in monthly returns on the small and the large cap ETFs, ($ETF_{Small,t}$ minus $ETF_{Large,t}$, or $ETF_{SML,t}$) on prior month's value-weighted market index return. We find that the monthly spread between the returns on the small and the large ETF portfolios is positively related to lagged market returns, consistent with our findings on stock returns: in months following positive (negative) market returns, small-cap ETFs outperform (underperform) large-cap ETFs.

The spillover strategy implemented on ETFs involves going long (short) the small-cap (large-cap) ETFs following months with positive market returns and taking the opposite positions when the past market returns are negative. Returns on this strategy are denoted by $ETF_{Spillover,t}$. Table 7 shows that the ETF spillover strategy yields an economically and statistically significant positive four-factor alpha of 0.45% per month.[13] The spillover strategy appears to be have a negative market beta, unlike the returns on the passive ETF strategy returns, $ETF_{SML,t}$. As shown in Table 7, the four-factor alpha for the passive long-short portfolio in the small- and the large-cap ETFs is not statistically different from zero. Instead, timing the exposure to the small- and the large-cap ETFs according to market states yields positive alpha for investors.

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[12] These are the most traded small-cap and large-cap ETFs in terms of dollar trading volume, over the period 2002-2014 and are highly liquid. For example, the average daily dollar trading volume in 2014 on the SPDR S&P500 is $21.1B and the average bid-ask spread is 0.005%. For the iShares Russel 2000 average daily dollar trading volume in 2014 is $4.2B and the average bid-ask spread 0.01% (source CRSP).

[13] At the daily and weekly frequencies we do not find significant predictable time-variation in the spread between the small- and large-cap ETFs, which is possibly due to short-term pricing discrepancies between the ETFs and their underlying assets (See, e.g. Petajisto (2016) and Ben-David et al. (2016)).

<TABLE 7 HERE>

5. Sequential Trading of Large and Small Firms

5.1. Evidence from trading of individual stocks

We hypothesize that the slow adjustment of individual stock prices to market wide component in returns is due to delayed trading in those stocks. To examine this hypothesis, we introduce a measure of trading delay in stock i, denoted as trading $delay_i$. Just as individual stock returns relate to market returns, trading volume in each stock is related to systematic trading volume in the market. For example, Lo and Wang (2000, 2006) show that valuable information about price dynamics can be extracted from trading volume and its systematic components. We examine the extent to which delays in the trading of stocks are captured by a delayed reaction in the systematic component of a stock's trading volume to lagged market volume. To this end, we propose a measure of trading delay that is similar in spirit to the return delay measure in Hou and Moskowitz (2005). Specifically, we use at the end of June of each year, the past 12 months of data to estimate the following regressions of daily turnover of stock *i* on market turnover:

$$TURN_{i,t} = \delta_i + \gamma_i TURN_{Mkt,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{Mkt,t-k} + \varepsilon_{i,t} \qquad (7)$$

and

$$TURN_{it} = \delta_i + \gamma_i TURN_{Mkt,t} + \varepsilon_{i,t}, \qquad (8)$$

where $TURN_{i,t}$ is defined as the ratio of stock *i*'s daily trading volume to its shares outstanding on day *t*, and $TURN_{Mkt,t}$ is the ratio of daily market trading volume on day *t* total market capitalization on day *t*.[14] The regression R^2 from Equations (7) and (8) are denoted as R^2(Eq. 7) and R^2(Eq. 8) respectively. We define trading delay analogously to return delay for each firm *i* each year as:

$$trading\ delay_i = 1 - \frac{R^2(Eq.8)}{R^2(Eq.7)}. \qquad (9)$$

Similar to *return delay*, the *trading delay* measure indicates how much of the variation in a stock's turnover can be explained by lagged market-wide variation in turnover. Supporting the idea that price delays and turnover delays are related, Table 8 shows that our measure of trading delay is closely related to firm size and to the return delay measure introduced by Hou and Moskowitz (2005). The correlation between trading delay and return delay is highly positive at 0.43. The average trading delay is huge for the firms in the smallest decile at 0.61 and it declines monotonically to 0.18 for the largest firms. The estimated slope coefficients also decline from 0.11 for the smallest firms to a negative -0.05 for the largest firms. Hence, the pattern of delays in the trading of small and large firms mirrors the pattern we observe in their stock returns, supporting our hypothesis that the slow adjustment in prices are related to slow trading.

<TABLE 8 HERE>

[14] Stock-level turnover and market turnover are defined as $TURN_{i,t} = log\left(1 + \frac{volume\ in\ shares_{i,t}}{shares\ outstanding_{i,t}}\right)$ and $TURN_{Mkt,t} = log\left(1 + \frac{market\ trading\ volume\ in\ dollars_t}{total\ market\ capitalization_t}\right)$.

5.2 Evidence from institutional transactions

To provide more direct evidence on investor trading behavior, we turn to an analysis of institutional trading data. For the institutions reporting to ANcerno, we obtain all US equity trades. We aggregate all trades by the same institution in a stock within a day to obtain a three-dimensional panel depicting the daily net trading volume (or turnover) by institution *f* on stock *i* on day *t.*

To test whether institutions trade small stocks with a delay, we analyze *institution-specific* trading volumes in the same spirit as we analyzed trading delays in Section 5.1. Specifically, we estimate the following two panel regression models:

$$TURN_{f,S.t} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,S,t} \qquad (10)$$

$$TURN_{f,L.t} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,L,t} \qquad (11)$$

where $TURN_{f.t}$ is the dollar volume of stocks traded by institution *f* on day *t* as a percentage of the market capitalization of the stocks traded. $TURN_{f,S.t}$ and $TURN_{f,L.t}$ are the same measures computed using transactions in the subset of small and large stocks respectively. In classifying stocks as either small or large, small stocks are defined as those belonging to size deciles 1 to 5, and large stocks are stocks in deciles 6 to 10 (sorted by market capitalization at the end of June of the previous year using NYSE breakpoints). Therefore, $TURN_{f.t}$ is the sum of $TURN_{f,S.t}$ and $TURN_{f,L.t}$. Table 9 reports the regression results.

<TABLE 9 HERE>

Similar to the patterns documented in Section 5.1, we find that an institution's trading activity in small (but not large) stocks responds with a delay to its own total trading activity. More specifically, an institution's trading activity (turnover) in small stocks is predictable by the institution's total trading activity during each of the past five days. This result is consistent with the idea that during a day of high trading, institutions rebalance their large stock positions immediately, but execute part of their trades in small stocks over the next several days. This institutional trading pattern holds for both their buy as well as their sell transactions.

It is important to note that the institution's delayed trading of small firms following their high trading activity is not simply a manifestation of the delayed trading of small firms following shocks to aggregate turnover that we documented in Section 5.1, because we include date fixed effects that control for market-level variations in trading volume. The volume spillovers documented in Table 9 occur *within* institutions. This result differs from Badrinath et al. (1995), who argue that price of small stocks adjust to common information with a delay because small firm investors are often uninformed and learn with a delay about market-wide news. Moreover, our finding of institutions' slow execution of small firm trades relative to large firm trades is consistent with the prolonged duration of the size premium predictability.[15]

[15] As a robustness test, we show in the Internet Appendix in Table A8 that trading volume of small-cap stocks relative to large-cap stocks increases after institutions experience high trading activity. This lead-lag effect in institutional trading activity persist at daily, weekly and monthly horizons.

We find similar delayed trading in small stocks, when we apply the framework of Hou and Moskowitz (2005). At the end of June of each year, we use daily, institution-and stock-level trading volume over the prior 12 months to estimate the following two panel regression models for each stock in our sample:

$$V_{f,i.t} = \mu_f + \delta_t + \gamma_{i0} V_{f,t} + \sum_{k=1}^{5} \gamma_{ik} V_{f,t-k} + \omega_{f,i,t} \quad (12)$$

$$V_{f,i.t} = \mu_f + \delta_t + \gamma_{i0} V_{f,t} + \omega_{f,i,t}, \quad (13)$$

where $V_{f,i.t}$ is the trading activity by institution f in stock *i* on day *t*, and $V_{f,t}$ is the total trading activity by institution *f* on day *t*. Both $V_{f,i.t}$ and $V_{f,t}$ are measured using three proxies for trading activities: dollar volume (*USD*), number of shares traded (*Shares*), and turnover (*TURN*; market value of shares traded as a percentage of total market value of the stock). We define institution-level trading delay for each stock *i* in each year as:

$$institutional\ trading\ delay_i = 1 - \frac{R^2(Eq.10)}{R^2(Eq.9)}. \quad (14)$$

where R^2(Eq.9) and R^2(Eq.10) correspond to the R-squares from the regressions in Equations (9) and (10). Table 10 reports the mean institutional trading delays for the small and large stocks for all three definitions of trading activity (*USD, Shares* and *TURN*). Consistent with the results in Table 9, institution-specific trading delay is significantly higher for the small as compared to the large firms regardless of the definition of trading activity employed. For example, the institutional trading delay based on *TURN* for the small firms is 0.54, whereas it is 0.30 for the large firms. The difference is statistically significant at the 1% level. The findings are comparable for buy and sell transactions.

<TABLE 10 HERE>

5.3 Splitting trades

The evidence in Chan and Lakonishok (1995) shows that institutions routinely split their trades over several days. In this sub-section, we examine if the probability of splitting trades differs across small and large firms. We say that an institution is splitting trades when the institution is a net buyer (seller) of a stock on at least two days within a five day period, without selling (buying) the stock in between. More precisely we measure splitting of trades as follows. For each institution *f* trading stock *i* on day *t*, we define $trade_{f,i,t,t+k}$ as an indicator variable that equals one if institution *f* trades stock *i* on day *t* and in some day $\tau \in \{t+1, t+k\}$. If institution *f* trades stock *i* on day *t*, but not on days $\tau \in \{t+1, t+k\}$ $trade_{f,i,t,t+k}$ equals zero. Additionally, $split_{f,i,t,t+k}$, is set to equal to one if the first trade by institution *f* in stock *i* during days $\tau \in \{t+1, t+k\}$ *is in the same direction as the trade on day t (i.e. buy (or sell) is followed by a buy (or sell)*), and zero otherwise. Panel A in Table 11 shows that the probability of splitting trades during a window of 5 subsequent days $P(split_{f,i,t,t+5}|trade_{f,i,t,t+5})$ is 85% for small firms and 75% for large firms.[16] The results from Table 11 suggest that institutions have a higher probability of splitting both their buy and sell

[16] These conditional probabilities are obtained as the sample mean of the variable $split_{f,i,t,t+k}$, with the sample limited to all institution-stock-date observations for which $trade_{f,,t,t+k}$ =1 (i.e. the probability that a repeated trade is on the same side, conditional on a repeated trade on either side taking place). That is, the first entry in Table 10 is the number of occurences in which an institution trades the same small firm for two consecutive days in the same direction, as a percentage of the number of occurences of an institution trading a small firm for two consecutive days in either direction.

orders in small stocks compared to large stocks. Hence, investors engage in slow trading of small stocks.

<TABLE 11 HERE>

To examine further the role of firm size as a determinant of splitting trades, we consider a regression where we can control for stock liquidity and trade size. We estimate a linear probability model for the conditional probability of splitting trades $P(split_{f,i,t,t+1}|trade_{f,i,t,t+1})$.[17] Firm characteristics that we include in these regressions are: (i) $Illiq_{i,t}$, the log of Amihud (2002)'s illiquidity measure for stock *i* over the previous year; (ii) $R_{i,t,}$ the return on stock *i* on day *t*; (iii) $Order_{f,i,,t}$, the (absolute) dollar value of stock *i* purchased (or sold) by institution *f* on day *t*, as a percentage of stock *i*'s market capitalization on day *t* and (iv) $Size_{i,t}$, the market capitalization of firm *i* at the end of June of the prior year. Our panel regressions include institution and date fixed effects. The reported results refer only to splits on two consecutive days, but the results are similar when we consider splits that occur within 2-5 days.

As Table 11, Panel B shows, we find a strong negative relation between size and the probability of splitting even after controlling for the other firm characteristics. We find also that institutions are more likely to split their trades if the stock is more illiquid, and if the trade size is large. The probability of a continuation in buy (sell) trades is also higher for stocks that have performed well (poorly) during the prior day, consistent with the idea that

[17] More specifically, we regress $split_{f,i,t,t+1}$ on a set of stock-specific variables, while limiting the sample to all institution-stock-date observations for which $trade_{f,I,tt+1}$ =1.

large absolute stock returns reflect price pressure on day *t* that affects the investors' decision to delay trading by splitting trades.

5.4 Institutional trading around a mutual fund scandal: a natural experiment

In an attempt to identify a causal relation from investors' portfolio rebalancing needs to their tendency to prioritize the trading of large stocks, we look at a natural experimental setting: the September 2003 mutual fund scandal. In September 2003, twenty-five mutual fund families were caught violating SEC trading rules and accused of illegal trading activities. This resulted in large withdrawals from these fund families starting in September 2003 and continuing in the months afterward (see Kisin (2011) and Anton and Polk (2014), for more detailed accounts of the scandal). In our setting, we are interested in whether the affected funds prioritize selling large stocks over small stocks in the inevitable selloff given the withdrawals.

We first identify the mutual funds that belong to the 25 fund families involved in the mutual fund scandal and select all funds that satisfy the following two criteria: Funds need to report their holdings at the end of 2003Q2 and at the end of 200Q3, while their holdings at the end of 2003Q2 (prior to the event) need to include both small and large stocks. Our sample of 164 funds is matched to a control group of funds from non-affected families. Affected funds and the funds in the control group are matched by the dollar value of their total stock holdings prior to the event (end of 2003Q2). We then run a difference-in-difference analysis in which we compare the small and the large firm holdings of the affected and the non-affected funds prior to the scandal (end of 2003Q2) and directly after the scandal became public (end of 2003Q3). Next, we repeat the analysis by comparing holdings prior to the scandal (end of 2003Q2) with the holdings one year after the scandal (end of 2004Q2). The results from this analysis are in Table 12.

<TABLE 12 HERE>

Consistent with our hypothesis, we find that in the first quarter of the scandal (the third quarter of 2003), the affected funds significantly reduced their holdings of large firm shares but there is no significant decline in their holdings of small firm shares. When we consider the changes in holdings over a full year, we find a significant decline in the holdings of both large and small firms. This means that the affected funds prioritized selling large firms in their portfolios when confronted with outflows in September 2003, while they sold the small firms gradually in the course of several months.[18]

6. Commonality in ownership and return predictability

The results in Section 5 provide evidence that institutions prioritize their trading of large firms relative to small firms. If the predictability of small stock returns is indeed driven by institutions' delayed execution of trades, the predictability of the returns on any given small firm *i* should originate from the return of those firms that are commonly held by the same institutional investors as firm *i*, more so than the return on the market portfolio.

[18] When we look at dollar holdings rather than holdings in shares, we find that the results that are qualitatively similar, but less significant. The dollar holdings are however noisier due to changes in the valuations of the holdings that are unrelated to the mutual fund scandal.

To test this hypothesis, we construct at each quarter-end, for each pair of distinct stocks *i* and *j* in our sample, the mutual fund ownership commonality measure $FCAP_{ij,t}$, as defined by Anton and Polk (2014). When *F* mutual funds hold shares of both firms *i* and *j* the measure equals the total value of the shares in firm *i* and *j* held by these *F* common owners as a percentage of total market capitalization of the two firms. Letting $S_{f,i,t}$ denote the number of shares in firm *i* held by mutual fund *f* at time *t*, $S_{i,t}$ the number of shares outstanding in firm *i* at time *t* and $P_{i,t}$ the time *t* share price of firm *i*, we have:

$$FCAP_{ij,t} = \frac{\sum_{f=1}^{F}(S_{f,i,t}\, P_{i,t} + S_{f,j,t}P_{j,t})}{S_{i,t}P_{i,t} + S_{j,t}P_{j,t}} \qquad (15)$$

Polk and Anton (2014) find that return correlation is increasing in ownership commonality. Instead of contemporaneous correlations, we are interested in the lead-lag relations of large and small stocks with high ownership commonality. We first define for each stock *i* the daily returns on a basket of stocks weighted by their ownership-commonality with stock *i*:

$$R_{FCAP,i,t} = \frac{\sum_j FCAP_{ij,t} * R_{j,t}}{\sum_j FCAP_{ij,t}} \qquad (16)$$

We then run panel regressions, regressing daily returns on individual small stocks (stocks in the smallest decile) on the prior day's return on the ownership-commonality weighted portfolio. The results are reported in Table 13. Consistent with our hypothesis, the coefficient on $R_{FCAP,i,t-1}$ is positive and significant, implying that small stock returns are predictable by a basket of stocks held by the same mutual funds. In the second and third column, we add lagged stock returns to control for idiosyncratic return reversals, and lagged value weighted market returns. Interestingly, the impact of lagged market returns then becomes insignificant and is, therefore, subsumed by the impact of stocks with high ownership commonality. This also provides evidence that the return predictability that we find from market returns to small stocks' relative returns originates from slow trading as opposed to uninformed investors' delayed reaction to arrival of common information.

<TABLE 13 HERE>

7. Conclusion

In this paper, we document that the state of the market returns positively predicts the size premium. Specifically, following positive (negative) market return states, small stocks outperform (underperform) the large stocks. This predictability remains strong in recent decades even if the predictability of small firm returns has steadily decayed over time. Using data on aggregate market trading activity and institutional trades, we show that investors trade large firms' stocks quickly when rebalancing their portfolios, but they trade small stocks more gradually over time. As a result, large firms' stock prices tend to overreact to market-wide returns (consistent with high demand for immediacy and hence larger price impact), and partially revert the next day. Stock prices of small firms, on the other hand, adjust to market-wide returns slowly over several days, consistent with the predictions of slow trading in Vayanos (1999, 2001) and others. The predictability of the size premium is also higher when the asset and funding liquidity of the market are low, suggesting that the slow adjustment in prices is related to the liquidity environment.

The predictability of the size premium that we document is new and is highly robust. We also find statistically and economically significant predictability when we apply the strategy to small-cap and large-cap ETFs, which are generally liquid instruments. Our findings also contribute to a better understanding of the lead-lag relation in size-based stock returns, documented in the seminal paper by Lo and MacKinlay (1990).

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Figure 1: Size premium conditional on market states

The thin black line in Figure 1.A shows the cumulative returns on a passive strategy that is long in small stocks and short in large stocks (Size premium). The upward sloping thick black line shows the cumulative return on a strategy that invests in the size premium only following days with a positive market state (defined as a day with positive value weighted market return). The downward sloping thick grey line shows the cumulative return on a strategy that invests in the size premium only following days with a negative market state. In Figures 1.B and 1.C, market states are defined as the previous week's or month's value weighted market returns. Logarithmic scale.

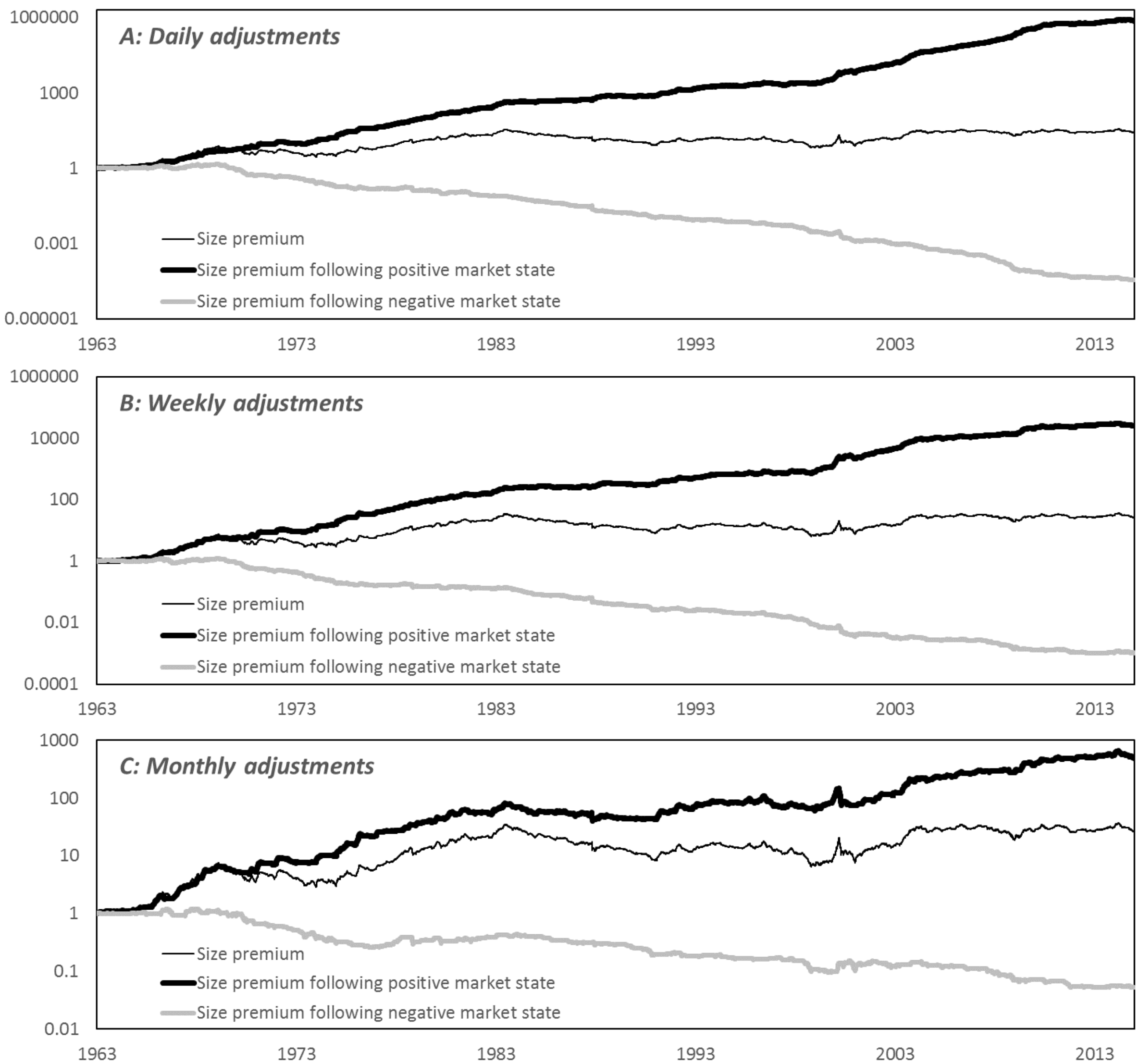

Figure 2: Returns following market states

The solid line in Panel A shows rolling window estimates of the coefficient β from the regression

$$R_{St} = \alpha_S + \beta_S R_{VW,t-1} + \varepsilon_{St}$$

estimated with daily data over 5-year rolling windows. R_{St} refers to daily returns on the decile of smallest firms. Size deciles are sorted annually at the beginning of the year based on the stocks' market capitalizations prevailing at the end of June of the previous year. $R_{VW,t}$ is the value weighted CRSP market return on day t. The shaded grey areas denote the 95% confidence interval for β based on Newey-West standard errors. The dashed line shows the regression's R^2. Panel B and C show the same information for the rolling window regressions

$$R_{Lt} = \alpha_L + \beta_L R_{VW,t-1} + \varepsilon_{Lt}$$
$$R_{SMLt} = \alpha_{SML} + \beta_{SML} R_{VW,t-1} + \varepsilon_{SMLt}$$

where R_{Lt} refers to returns on the decile of the largest firms and the size premium R_{SMLt} is defined as $R_{St} - R_{Lt}$. The regressions include weekday and month dummies, as well as a dummy for Black Monday October 19, 1987

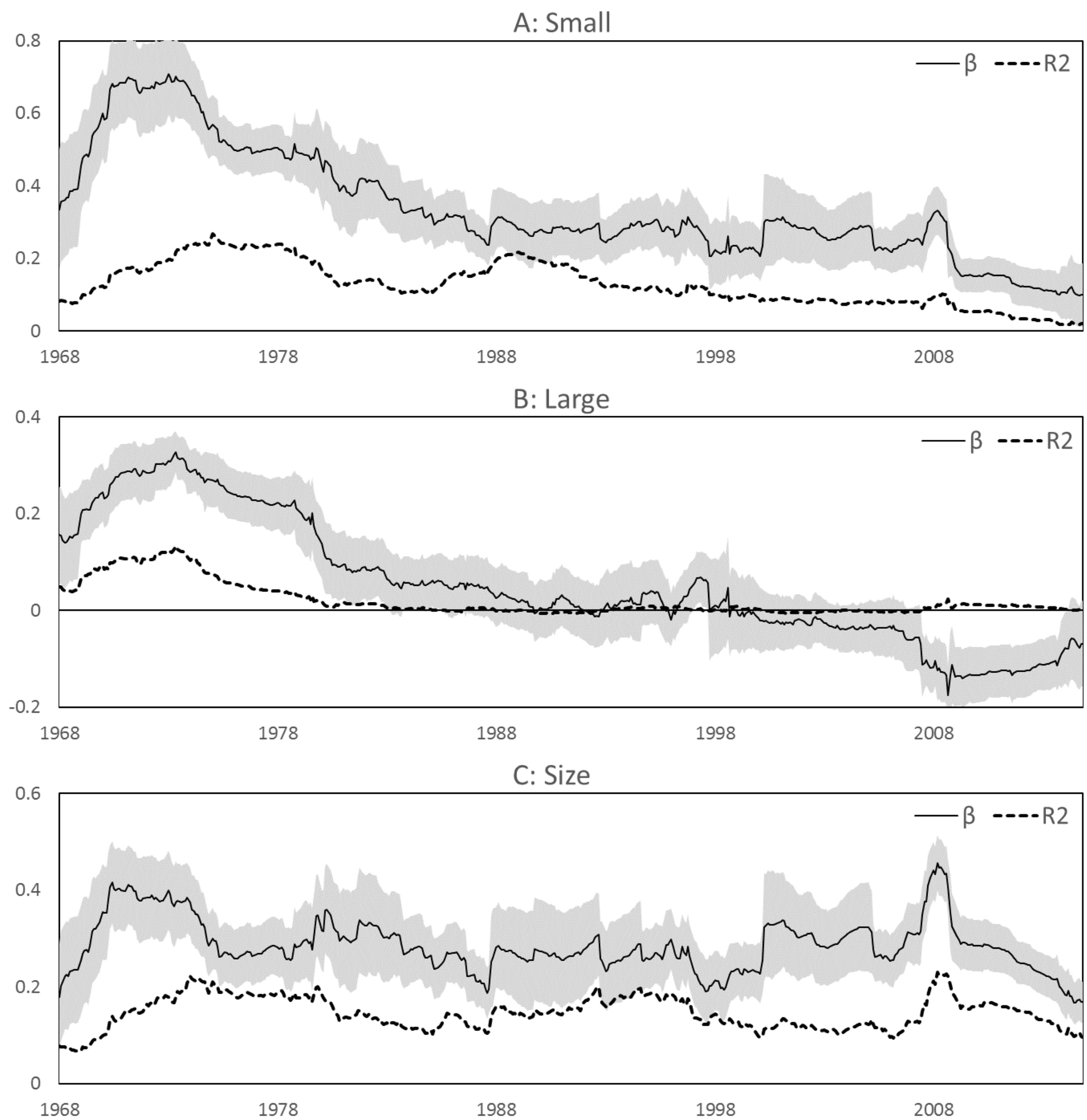

Figure 3: Trends and seasonalities in the spillover strategy

Black bars indicate the average monthly return by calendar month (Panel A), the average daily return by weekday (Panel B) and the average monthly return by decades (Panel C) for a ”spillover” strategy that is long in small firms and short in large firms during days following a positive market return, and reversing to being long in large firms and short in small firms following a negative market return. Grey bars indicate the average returns for a passive annually adjusted strategy that is long in the smallest decile and short the largest decile of stocks sorted by size (Size premium).

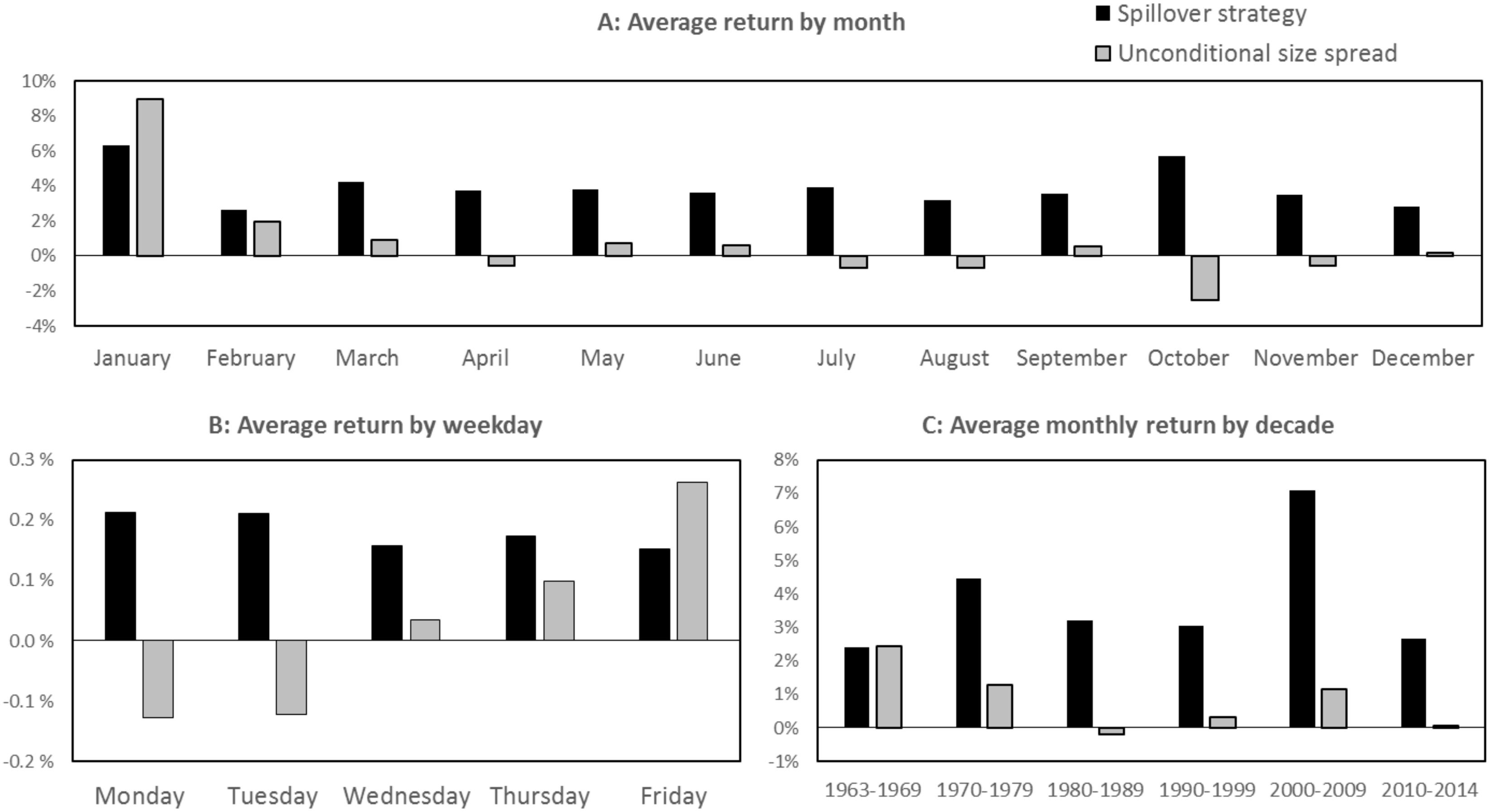

Table 1: Predictability of the size premium

This table reports the results from regressing the returns on the portfolio of the large firms (R_{Lt}), the small firms (R_{St}) and the size premium (R_{SMLt}, defined as $R_{St} - R_{Lt}$) in period t on the CRSP value-weighted market return in period t-1 ($R_{VW,t-1}$). We report results based on daily, weekly and monthly return frequencies. The large and the small firms are defined as those belonging to the top and the bottom deciles of stocks sorted by the stocks' market capitalizations prevailing at the end of June of the previous year. Panel B shows the results of similar regressions as in Panel A, but includes a dummy $Post\text{-}2000_t$ to indicate observations after January 1st 2000. *t-statistics* are reported below the coefficients in italics and are based on Newey-West standard errors. All regressions in Panels A and B include weekday and month dummies. The sample period is from 1963 to 2014.

A	Daily			Weekly			Monthly		
	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$
Intercept	0.002 ***	0.002 ***	0.000	0.020 ***	0.023 ***	0.003 *	0.087 ***	0.097 ***	0.010
	4.61	3.98	-0.25	9.41	8.98	1.68	7.95	7.29	1.49
$R_{VW,t-1}$	0.29 ***	0.29 ***	0.01	0.36 ***	0.30 ***	-0.06 **	0.33 ***	0.36 ***	0.03
	14.61	11.95	0.32	12.62	7.53	-2.44	5.52	4.95	0.69
adj. R^2	0.13	0.10	0.00	0.18	0.08	0.00	0.20	0.13	0.00

B	Daily			Weekly			Monthly		
	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$	$R_{SML,t}$	$R_{S,t}$	$R_{L,t}$
Intercept	0.002 ***	0.002 ***	0.000	0.019 ***	0.023 ***	0.003 *	0.086 ***	0.098 ***	0.013 *
	4.49	3.81	-0.37	9.08	8.74	1.91	7.58	7.08	1.77
$R_{VW,t-1}$	0.30 ***	0.39 ***	0.09 ***	0.42 ***	0.36 ***	-0.05	0.35 ***	0.36 ***	0.00
	9.51	15.62	4.57	13.41	7.56	-1.59	4.83	4.35	0.08
$Post\text{-}2000_t$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01 *
	0.37	-0.38	-1.14	0.75	-0.36	-1.41	0.58	-0.60	-1.66
$Post\text{-}2000_t * R_{VW,t-1}$	-0.03	-0.20 ***	-0.18 ***	-0.13 **	-0.16 **	-0.03	-0.07	0.01	0.08
	-0.77	-5.66	-6.59	-2.34	-2.10	-0.54	-0.54	0.03	0.78
adj. R^2	0.13	0.11	0.01	0.18	0.09	0.00	0.20	0.13	0.01
Weekday dummies	yes	yes	yes	no	no	no	no	no	no
Month dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table 2: Predictability of the size premium within characteristics sorted portfolios

This table reports the results from a regression of the size premium in period t (R_{SMLt}) on the lagged CRSP value-weighted market return in period *t-1* ($R_{VW,t-1}$), similar to Table 1, but within characteristics sorted quintiles. We obtain daily and monthly portfolio returns on stocks sorted into 5x5 groups based on size and 11 other firm characteristics available on the Kenneth French's data library. These 11 firm characteristics are book to market, investment, long-term reversal, momentum, short-term reversal, operating profitability, accruals, market beta, net share issuance, residual variance, and variance portfolios (see Internet Appendix Table A3 for details). R_{SMLt} is the difference in returns between the portfolios of stocks in the smallest and the largest size quintiles. The first two rows report the slope coefficients from regressing R_{SMLt} on $R_{VW,t-1}$ within the lowest and the highest quintiles of book to market firms at monthly and daily frequencies. We repeat the same regressions also within the lowest and the highest quintiles of stocks sorted on the other remaining firm characteristics provided by Kenneth French. *t-statistics* based on Newey West standard errors are reported in italics. (Source: Kenneth French's data library daily. Sample: 1963-2014).

Size spread for different groups			Monthly				Daily			
X		Size	$R_{vw,t-1}$			adj. R2	$R_{vw,t-1}$			adj. R2
Book-to-Market	Low	Small-Large	0.27	***	5.15	0.04	0.19	***	9.15	0.04
	High	Small-Large	0.23	***	4.97	0.05	0.13	***	5.92	0.02
Investment	Low	Small-Large	0.27	***	5.38	0.05	0.15	***	7.26	0.03
	High	Small-Large	0.26	***	5.88	0.06	0.15	***	8.29	0.03
Long-term Reversal	Low	Small-Large	0.32	***	6.08	0.07	0.15	***	8.80	0.02
	High	Small-Large	0.20	***	4.48	0.04	0.14	***	7.98	0.03
Momentum	Low	Small-Large	0.32	***	6.56	0.07	0.15	***	5.89	0.02
	High	Small-Large	0.24	***	5.74	0.06	0.15	***	8.43	0.03
Operating Profitability	Low	Small-Large	0.29	***	5.69	0.06	0.10	***	4.94	0.01
	High	Small-Large	0.24	***	5.69	0.05	0.17	***	9.04	0.04
Short-term Reversal	Low	Small-Large	0.25	***	4.56	0.05	0.19	***	6.17	0.01
	High	Small-Large	0.28	***	6.38	0.08	0.10	***	7.76	0.01
Accruals	Low	Small-Large	0.28	***	5.87	0.06				
	High	Small-Large	0.27	***	5.85	0.06				
Market Beta	Low	Small-Large	0.20	***	5.07	0.05				
	High	Small-Large	0.19	***	3.49	0.02				
Net Share Issues	Low	Small-Large	0.24	***	4.59	0.04				
	High	Small-Large	0.27	***	5.00	0.04				
Residual Variance	Low	Small-Large	0.23	***	6.36	0.09				
	High	Small-Large	0.36	***	6.35	0.08				
Variance	Low	Small-Large	0.24	***	7.09	0.10				
	High	Small-Large	0.34	***	5.78	0.07				

Table 3: Predictability of the size premium based on individual stock returns

This table shows the result from regressing the daily return on stock *i*, $R_{i,t}$, on the prior day's stock return and the prior day's value-weighted market return, $R_{VW,t-1}$. Results are reported for the full sample 1963-2014 and for pre- and post-2000 subsamples. The first three columns show the results for a panel of stocks containing only small firms, that is only those firms that belong to the lowest decile of stocks sorted by their market capitalizations prevailing at the end of June of the previous year. The last three columns contain the results for the large firms (highest decile). *t-statistics* are reported below the coefficients in italics and are based on two-way clustered standard errors at the date and firm level. (Source: CRSP)

	Small firms			Large firms		
	$R_{i,t}$	$R_{i,t}$	$R_{i,t}$	$R_{i,t}$	$R_{i,t}$	$R_{i,t}$
Intercept	0.0031 ***	0.0033 ***	0.0024 ***	0.0004 ***	0.0004 ***	0.0004 *
	26.70	23.69	12.82	4.93	4.65	1.69
$R_{i,t-1}$	-0.15 ***	-0.17 ***	-0.11 ***	0.02 ***	0.02 ***	0.02
	-26.47	-23.32	-16.18	3.75	5.75	1.29
$R_{VW,t-1}$	0.40 ***	0.54 ***	0.22 ***	0.05 ***	0.12 ***	-0.07 **
	18.81	19.69	9.67	2.60	5.29	-2.17
adj. R^2	0.025	0.031	0.014	0.001	0.005	0.001
Period	1963-2014	1963-1999	2000-2014	1963-2014	1963-1999	2000-2014

Table 4: Return delay and firm size

At the end of June of each year, we regress the daily returns on stock *i*, R_{it}, where *t* stands for time, on the value-weighted market return, $R_{VW,t}$ over the prior one year using the following two regression models:

$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \sum_{k=1}^{5} \beta_{ik} R_{VW,t-k} + \varepsilon_{i,t} \qquad \text{(a)}$$
$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \varepsilon_{i,t}. \qquad \text{(b)}$$

The return-delay measure for stock *i* involves comparing the regression R^2 from the unrestricted model in equation (a), denoted as R^2(Eq.a), to the R^2 from the restricted model in equation (b), denoted as R^2(Eq.b):

$$Return\ delay_i = 1 - \frac{R^2(Eq.\text{b})}{R^2(Eq.\text{a})}.$$

The first row in the table gives the mean *Return delay* for the firms in each size decile (sorted by market capitalization at the end of June, NYSE breakpoints). The second row shows the sum of lagged market betas from regression (a). The final column shows the difference in mean between the smallest and largest deciles. Here * indicates significance at the 1% level, derived from a cluster-robust (clustered at year and firm) t-test on the difference in means.

Size decile	Small	2	3	4	5	6	7	8	9	Large	Small-Large
Return delay	0.63	0.48	0.33	0.29	0.26	0.24	0.22	0.19	0.15	0.11	0.52 *
$\sum_{k=1:5} \beta_k$	0.50	0.41	0.27	0.24	0.22	0.20	0.19	0.13	0.07	-0.04	0.55 *

Table 5: Spillover strategy

This table reports monthly returns, Sharpe-ratios, skewness, kurtosis, and alphas from a CAPM regression (α_{CAPM}) and from a Fama-French-Carhart 4-factor regression ($\alpha_{4-Factor}$) for a ”spillover” strategy that is long in small firms and short in large firms during periods following a positive market return, and reversing to being long in large firms and short in small firms following a negative market return. Size deciles are sorted annually at the beginning of the year based on the stocks’ market capitalizations prevailing at the end of June of the previous year. The first 3 columns show the results based on a strategy that trades the 1st (smallest) and 10th (largest) size deciles, with daily, weekly, or monthly portfolio adjustments. Columns 4 to 6 show the same results based on trading the 2nd decile of smallest stocks. The final column shows a passive annually adjusted strategy that is short the 10th decile and long the 1st decile of stocks sorted by size (Size premium). Adjustments/year refers to the average number of portfolio adjustments the strategy requires annually. *t-statistics* are reported below the coefficients in italics and are based on Newey-West standard errors. Sample period is 1963-2014.

	Spillover strategy			"2-10" Spillover strategy			Size
	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Premium
Monthly Return	3.8 %	2.8 %	1.4 %	3.0 %	2.2 %	1.0 %	0.5 %
Sharpe Ratio	0.74	0.59	0.25	0.67	0.54	0.21	0.11
Skewness	1.17	0.32	-0.30	1.18	0.43	-0.58	-0.96
Kurtosis	19.93	9.39	8.45	23.70	9.33	9.39	19.66
α_{CAPM}	4.1 % ***	2.9 % ***	1.6 % ***	3.3 % ***	2.2 % ***	1.2 % ***	0.5 % *
	13.75	12.42	6.92	12.92	11.87	4.94	1.78
$\alpha_{4\text{-Factor}}$	4.3 % ***	3.0 % ***	1.8 % ***	3.3 % ***	2.3 % ***	1.3 % ***	0.2 %
	12.25	10.84	6.62	9.63	9.62	5.66	1.04
Adjustments/year	113.6	25.9	6.5	113.6	25.9	6.5	1

Table 6: Spillover returns and Liquidity

This table reports the results from regressing returns from the daily spillover strategy (See Table 5 for details) on various measures of liquidity. The dependent variable is the return on the daily spillover strategy, aggregated into monthly observations. These monthly returns are regressed on the prior month's VIX (end of the month - divided by 100 for scaling purposes), the TED spread (end of the month), the Pastor-Stambaugh (2003) Innovations in Aggregate Liquidity Measure (PS-liquidity) and Cumulative value-weighted market returns over the prior 3 months. *t-statistics* are reported below the coefficients in italics and are based on Newey-West standard errors.

	Spillover strategy	Spillover strategy	Spillover strategy	Spillover strategy	Spillover strategy
intercept	-0.001	0.026 ***	0.042 ***	0.041 ***	-0.012
	-0.054	2.684	13.224	11.167	-0.937
VIX $_{t-1}$	0.224 ***				0.002 ***
	3.317				3.358
TED spread $_{t-1}$		0.027 *			0.032 **
		1.660			2.386
PS-liquidity $_{t-1}$			-0.169 ***		-0.068
			-3.071		-1.034
3-month cumulative returns $_{t-1}$				-0.072 *	0.076
				-1.686	1.396
Period	1990-2014	1986-2014	1968-2014	1963-2014	1990-2014
adj. R^2	0.10	0.05	0.03	0.01	0.14

Table 7: ETF strategies

This table reports the results from regressing monthly returns on size-based ETF portfolios on the Fama-French-Carhart factors and on the prior months' value weighted market return. $ETF_{SML,t}$ is the monthly return spread between an equal-weighted portfolio consisting of three small cap ETFs *(iShares Russel 2000, iShares Core S&P SmallCap, Vanguard SmallCap*) and an equal-weighted portfolio consisting of three large-cap ETFs (*SPDR S&P500, SPDR DJIA, iShares Core S&P500*). $ETF_{Spillover,t}$ is the monthly return on a strategy that is long in small-cap ETFs and short in large-cap ETFs during months following a positive market return, and reversing to being long in large-cap ETFs and short in small-cap ETFs following a negative market return. *t-statistics* based on Newey West standard errors are in italics. Sample period is 2000-2014.

	$ETF_{Spillover,t}$	$ETF_{SML,t}$	$ETF_{SML,t}$
intercept	0.45% **	-0.04%	0.0035 *
	2.32	-0.63	1.66
$R_{VW,t-1}$			0.09 **
			2.04
$R_{VW,t}-R_{f,t}$	-0.18 ***	0.06 *	
	-3.18	1.66	
SMB_t	0.14	0.87 ***	
	1.25	26.87	
HML_t	0.06	0.21 ***	
	0.74	6.56	
UMD_t	-0.05	0.04	
	-0.95	1.13	
adj. R^2	0.04	0.84	0.02

Table 8: Trading delay and firm size

At the end of June of each year, we regress the turnover on stock *i* on day *t*, $TURN_{i,t}$, on the value-weighted market turnover, $TURN_{Mkt,t}$, over the prior one year using the following two regression models:

$$TURN_{i,t} = \delta_i + \gamma_i TURN_{Mkt,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{Mkt,t-k} + \omega_{i,t} \quad \text{(a)}$$
$$TURN_{i,t} = \delta_i + \gamma_i TURN_{Mkt,t} + \omega_{i,t} \quad \text{(b)}$$

The trading-delay measure for stock *i* involves comparing the regression R^2 from the unrestricted model in equation (a), denoted as R^2(Eq.a), to the R^2 from the restricted model in equation (b), denoted as R^2(Eq.b):

$$Trading\ delay_i = 1 - \frac{R^2(Eq.\text{b})}{R^2(Eq.\text{a})}$$

The first row in the table gives the mean *Trading delay* for the firms in each size decile (sorted by market capitalization at the end of June, NYSE breakpoints). The second row shows the sum of lagged slope parameters in regression (a). The final column shows the difference in mean between the smallest and the largest decile. Here * indicates significance at the 1% level, derived from a cluster-robust (clustered at year and firm) t-test on the difference in means. The bottom panel shows the time-series average of annual rank correlations between market capitalization (*Size*), *Return delay* (see Table 4) and *Trading delay*.

Size decile	Small	2	3	4	5	6	7	8	9	Large	Small-Large
Trading delay	0.61	0.52	0.42	0.38	0.36	0.33	0.31	0.28	0.24	0.18	0.43 *
$\sum_{k=1:5} \gamma_k$	0.11	0.06	0.03	0.03	0.04	0.03	0.02	0.01	-0.01	-0.05	0.15 *

Annual rank correlation

	Return delay	Trading delay
Return delay		0.43
Size	-0.52	-0.36

Table 9: Delay in Institutional trading activities

This table shows the results from the following two panel regression models:

$$TURN_{f,S.t} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,S,t} \qquad (a)$$

$$TURN_{f,L.t} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,\mathrm{L},t} \qquad (b)$$

where $TURN_{f.t}$ is the dollar volume by institution f on day t as a percentage of market capitalization of the traded stocks. $TURN_{f,S.t}$ and $TURN_{f,L.t}$ are the same measures for small and large firms denoted with subscripts S and L respectively. Small firms are defined as stocks in deciles 1-5, and large firms as stocks in deciles 6-10 (sorted by market capitalization at the end of June, NYSE breakpoints). μ_f and δ_t are institution and date fixed effects. In columns 1-2, turnover includes all transactions, while in columns 3-4 (5-6) only buy (sell) transactions are included.

	All transactions		Buy transactions		Sell transactions	
	Small	Large	Small	Large	Small	Large
$TURN_{f,t}$	0.43 ***	0.73 ***	0.45 ***	0.67 ***	0.46 ***	0.63 ***
	15.18	22.37	15.95	22.02	17.59	19.80
$TURN_{f,t-1}$	0.04 ***	0.00	0.04 ***	0.00	0.03 ***	0.00
	4.87	0.51	6.42	-0.02	5.17	0.92
$TURN_{f,t-2}$	0.03 ***	-0.01	0.02 ***	0.00	0.02 ***	0.00
	4.46	-1.32	3.28	-0.57	3.44	-0.20
$TURN_{f,t-3}$	0.02 **	-0.01	0.02 ***	0.00	0.01 *	0.00
	2.19	-1.38	2.82	-0.81	1.73	0.80
$TURN_{f,t-4}$	0.02 **	0.00	0.02 ***	0.00	0.02 ***	-0.01
	2.04	0.33	2.83	-0.25	2.73	-1.47
$TURN_{f,t-5}$	0.03 ***	0.00	0.02 ***	0.00	0.01 *	0.00
	4.88	-0.08	3.42	-0.86	1.83	0.39
Observations	303792	303792	303792	303792	303792	303792
Adj. R^2	0.41	0.70	0.38	0.65	0.36	0.62
Institution fixed effects	yes	yes	yes	yes	yes	yes
Date fixed effects	yes	yes	yes	yes	yes	yes

Table 10: Institutional trading delay

At the end of June of each year, we use daily institution-level trading volumes over the prior one year to estimate the following two panel regression models for each stock:

$$V_{f,i.t} = \mu_f + \delta_t + \gamma_{i0} V_{f,t} + \sum_{k=1}^{5} \gamma_{ik} V_{f,t-k} + \omega_{f,i,t} \quad \text{(a)}$$

$$V_{f,i.t} = \mu_f + \delta_t + \gamma_{i0} V_{f,t} + \omega_{f,i,t}, \quad \text{(b)}$$

where $V_{f,i.t}$ is volume by institution *f* in stock *i* on day *t*, and $V_{f,t}$ is total volume by institution *f* on day *t*. Volumes are measures as dollar volume (*USD*), number of shares traded (*Shares*) or turnover (*TURN*; market value of shares traded as a percentage of market valuations of the underlying assets). μ_f and δ_t are institution and date fixed effects. We define institution-level volume delay for each stock in each year as:

$$institutional\ trading\ delay_i = 1 - \frac{R^2(Eq.\text{b})}{R^2(Eq.\text{a})},$$

where the regression R^2 from the unrestricted model in equation (a) is denoted by R^2(Eq.a), and the R^2 from the restricted model in equation (b) is denoted by R^2(Eq.b). The table gives the mean i*nstitutional trading delay* for small and large firms separately, for all three definitions of trading volume. Small firms are defined as stocks in deciles 1-5, and large stocks as stocks in deciles 6-10 (sorted by market capitalization at the end of June, NYSE breakpoints). The bottom row shows the difference in means between small and large firms. Here * indicates significance at the 1% level, derived from a cluster-robust (clustered at year and firm) t-test on the difference in means. In columns 1-3, $V_{f,i.t}$ and $V_{f,t}$ include all transactions, while in columns 4-6 (7-9) only the buy (sell) transactions are included.

	All transactions			Buy transactions			Sell transactions		
Volume:	USD	Shares	TURN	USD	Shares	TURN	USD	Shares	TURN
Small stocks	0.75	0.77	0.54	0.80	0.81	0.66	0.80	0.81	0.65
Large stocks	0.54	0.55	0.30	0.66	0.67	0.40	0.71	0.70	0.42
SML	0.21 *	0.22 *	0.24 *	0.14 *	0.15 *	0.26 *	0.09 *	0.10 *	0.23 *

Table 11: Splitting trades

Panel A reports the probability that an institution continues to trade the same stock on the same side (i.e., splits its trade) during a five day window around each trade. We define $trade_{f,i,t,t+k}$ as an indicator variable that equals one if the institution f trades stock i on day t and its consecutive trade is on day $\tau \in \{t+1, t+k\}$, and it equals zero otherwise. Additionally, we define $split_{f,i,t,t+k}$, to equal one if the institution f trades stock i on day τ *in the same direction as in day t (i.e. buy (or sell) is followed by a buy (or sell))*, and zero otherwise. Buys and sells are evaluated using daily net trades of the institution. The table reports the mean value of $split_{f,i,t,t+k}$ across all institutions, dates and stocks, for small and large stocks separately, for the subsample of observations where $trade_{f,i,t,t+k}$ is equal to 1. That is, the reported percentages give the probabilities that institutions split their trades, conditional on trading the stock again $P(split|trade)$.

Panel B reports the results from a linear probability model regressing $split_{f,i,t,t+1}$ on firm-level characteristics. The sample is restricted to all occurrences where $trade_{f,i,t,t+1}$ is equal to 1. *Size* refers to the log of stock *i*'s market capitalization at the end of June of the prior calendar year. *Illiq* refers to the log of the Amihud illiquidity measure over the previous calendar year. *Stock Return* is the return on stock *i* during day *t*, Order size is the net volume of stock *i* bought (sold) by institution *f* on day *t*, as a percentage of the stock's market capitalization on day *t*. Columns 2-3 show the same regressions for the subsamples of buy and sell orders on day *t* separately. Regressions include date and institution fixed effects. T-statistics are reported below the coefficients in italics and are based on two-way clustered standard errors at date and institution level. The sample period is 2000-2010.

A: Probability of splitting trades

k	1	2	3	4	5
Small stocks	90 %	88 %	87 %	86 %	85 %
Large stocks	78 %	77 %	76 %	75 %	75 %
Small-Large	12 % *	11 % *	11 % *	11 % *	10 % *

B: Determinants of splitting trades

	All transactions	Buy transactions	Sell transactions
	$split_{f,i,t+1}$	$split_{f,i,t+1}$	$split_{f,i,t+1}$
$Size_{i,t}$	-0.024 ***	-0.025 ***	-0.023 ***
	-10.86	-12.45	-7.34
$Illiq_{i,t}$	0.014 ***	0.010 ***	0.019 ***
	5.42	5.14	4.15
$Stock\ Return_{i,t}$	0.004	0.104 ***	-0.093 ***
	0.40	3.77	-5.06
$Order\ size_{f,i,t+1}$	0.011 *	0.016 ***	0.010
	1.93	3.04	1.62
Observations	6961453	3634504	3326949
Adj. R^2	0.13	0.17	0.16
Institution fixed effects	yes	yes	yes
Date fixed effects	yes	yes	yes

Table 12: Mutual Fund Scandal and Changes in Mutual Fund Holdings

We identify the mutual funds that belong to the 25 fund families involved in the mutual fund scandal of September 2003, and select a control group of funds from non-affected families, matched by the market valuation of the funds US equity holdings prior to the event (end of quarter 2 (Q2) of year 2003, denoted 2003Q2). We first run a difference-in-difference analysis in which we compare the small firm and large firm holdings by the affected and the non-affected funds prior to the scandal (end of 2003Q2) and the quarter immediately after the scandal became public (end of 2003Q3). Next, we repeat the analysis by comparing holdings prior to the scandal (end of 2003Q2) and one year after the scandal (end of 2004Q2). *t-statistics* are reported below the coefficients in italics and are based on standard errors clustered at the fund level.

A: One quarter Diff-in-Diff	Holdings at end of 2003Q2 and end of 2003Q3					
	Holdings in #shares (log)			Holdings in dollars (log)		
	Total	Large stocks	Small stocks	Total	Large stocks	Small stocks
after (2003Q3)	0.05 ***	0.02 *	0.10 ***	0.09 ***	0.06 ***	0.20 ***
	3.86	1.70	4.28	6.99	3.93	9.18
Scandal*after	-0.07 **	-0.08 **	0.03	-0.07 **	-0.06 *	0.04
	-2.41	-2.29	0.45	-2.22	-1.76	0.60
Observations	328	328	328	328	328	328
Fund fixed effects	yes	yes	yes	yes	yes	yes

B: Four quarter Diff-in-Diff	Holdings at end of 2003Q2 and end of 2004Q2					
	Holdings in #shares (log)			Holdings in dollars (log)		
	Total	Large stocks	Small stocks	Total	Large stocks	Small stocks
after (2004Q2)	0.28 ***	0.22 ***	0.36 ***	0.46 ***	0.38 ***	0.69 ***
	10.19	7.30	8.28	16.72	12.71	17.42
Scandal*after	-0.23 ***	-0.25 ***	-0.15 **	-0.25 ***	-0.26 ***	-0.11
	-4.17	-3.64	-2.20	-3.82	-3.41	-1.23
Observations	312	312	312	312	312	312
Fund fixed effects	yes	yes	yes	yes	yes	yes

Table 13: Ownership commonality and small-cap return predictability

This table shows the result from regressing the return on stock *i* on day t ($R_{i,t}$) on $R_{i,t-1}$, the value-weighted market return, $R_{VW,t-1}$, and the *ownership-commonality weighted returns*, $R_{FCAP,i,t-1}$. Ownership-commonality weighted returns are the daily returns on a basket of stocks weighted by their ownership commonality with stock *i*. Commonality is measured by $FCAP_{i,j,t}$ which measures the total value of stocks *i* and *j* held by *F* common mutual funds, scaled by total market capitalization (See Anton and Polk, 2014). The sample includes all stocks in the decile of smallest stocks (sorted by market capitalization at the end of June of the prior calendar year, NYSE breakpoints), and the sample period is 2000-2014. *t-statistics* are reported below the coefficients in italics and are based on two-way clustered standard errors at the date and firm level.

	$R_{i,t}$	$R_{i,t}$	$R_{i,t}$
Intercept	0.001 ***	0.001 ***	0.001 ***
	7.66	8.01	7.99
$R_{FCAP,i,t-1}$	0.23 ***	0.29 ***	0.31 ***
	12.57	15.67	8.55
$R_{i,t-1}$		-0.11 ***	-0.11 ***
		-28.83	-28.82
$R_{VW,t-1}$			-0.02
			-0.53
adj. R^2	0.002	0.015	0.015
Period	2000-2014	2000-2014	2000-2014