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) as small stocks adjust to market returns with a delay and large firms revert following market returns. This predictability of the size premium is strongest when aggregate asset and funding liquidity is low and is linked to institutional and informational frictions that manifest as slow institutional trading in small stocks but swift trading in large stocks. For example, slow trading by mutual funds leads to predictable small stock returns in the direction of fund flows.

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

JEL classification: G12, G23

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1. Introduction

There is a long history of papers examining the differential predictability of size-based stock returns. In the seminal paper, Lo and MacKinlay (1990) document a strong lead-lag relation in stock returns: lagged weekly returns on large capitalization stocks predict returns on small stocks but the converse is not true. Several subsequent papers attribute the slow diffusion of market-wide information in small stocks to low analyst coverage (Brennan, Jegadeesh and Swaminathan (1993)), non-synchronous trading (Boudoukh, Richardson and Whitelaw (1994)), uninformed investors (Badrinath, Kale and Noe (1995)), low trading volume (Chordia and Swaminathan (2000)), and low investor recognition (Hou and Moskowitz (2005)). In this paper, we show that the differential predictability of the returns on small and large firms is linked to frictions in institutional trading.

We start by showing that the difference in the returns on small and large market capitalization firms (or the size premium) is positively related to past market returns. As shown in Figure 1, Panel A, the daily size premium is relatively flat during the 1963-2014 sample period. However, conditioning the daily size premium on the lagged market return state (positive or negative market returns on the previous day) dramatically affects the size premium. Small firms consistently outperform large firms following positive market returns. On the other hand, small firms underperform the large firms when the market return is negative the previous day. We also obtain large predictable variations in the size premium at monthly (weekly) holding periods when conditioned on positive and negative monthly (weekly) market return states (See Panels B and C of Figure 1). For example, the monthly size premium is 2.1% following a positive market return state and the premium is -1.4% after a market decline. Interestingly, the predictability of the size premium in Figure 1 remains remarkably strong and has not dissipated in recent years.[1]

<FIGURE 1 HERE>

To document the economic magnitude of the predictability, we develop a simple trading strategy that capitalizes on the predictive effect of the market return state on the size premium, which we term the "spillover strategy". This zero investment strategy involves buying (selling) a portfolio of small (large) firms following positive market returns and switching to selling (buying) small (large) firms after market declines. We implement the strategy at daily, weekly and monthly horizons, where the same horizon is used to measure the past market returns and the subsequent holding period returns on the size-based portfolios. Using the largest and smallest size decile portfolios (using NYSE size-breakpoints), the spillover strategy yields economically and statistically significant risk-adjusted profits of 2.1%, 3.3% or 4.2% when the portfolio is rebalanced monthly, weekly or daily. The spillover profits continue to persist when we replace the smallest size decile portfolio with the 2nd or the 5th smallest size deciles or when the strategy is implemented using large and small cap exchange traded funds (ETFs). For instance, the monthly spillover strategy using the largest decile (large firms) and the middle decile 5 (small firms) generates a significant risk-adjusted return of 0.8% per month. The conditional size effect we document is different from the unconditional size premium: there is no January seasonality in the spillover returns and these returns are not diminishing over time. In fact, the highest spillover returns are in the post-2000 period, where institutional investing is more prevalent. In the post-2000 period, both the large and the

[1] Our findings are robust to skipping a day in computing the holding period return and is economically significant when compared to the unconditional size premium of 0.5% per month. We also reach a similar conclusion after controlling for other firm characteristics such as book-to-market, investment, accruals, profitability, momentum, reversals, and return volatility.

small stocks contributed to the spillover strategy returns, as the small stocks adjust with a delay while the large stocks experience reversals conditional on past market returns.

Next, we link the slow diffusion of market-wide information and the predictability of the size premium to the tendency for institutions to trade large stocks swiftly while trading small stocks gradually over time. Vayanos (1999, 2001), for example, demonstrates that investors, especially large traders, strategically choose to trade slowly to minimize the price impact of their trades. Empirical evidence on liquidity concerns and a preference for order breakup by institutions is provided by Chan and Lakonishok (1995) and Keim and Madhavan (1995). We expect the liquidity concerns to be more prevalent when institutions trade small stocks. On the other hand, when market-wide shocks affect the institutions' optimal portfolio allocation, these investors are likely to adjust their holdings of large firms more quickly as large stocks typically account for a greater fraction of their portfolio value and hence capital at risk.[2] Consequently, the rapid execution of trades following large market moves may lead to immediate price pressure and subsequent return reversals for the large firms (Grossman and Miller (1988), Campbell, Grossman and Wang (1993), and Jegadeesh and Titman (1995)).[3]

We take an encompassing approach to illustrate the role of institutional trading and aggregate illiquidity in explaining the predictive effect of lagged market returns on the differential returns on small and large firms. First, we document that the returns to the spillover strategy are time-varying, with higher returns recorded during periods of high aggregate demand for liquidity (proxied by correlated trading), and low supply of liquidity (proxied by high VIX, high TED spread, and aggregate market declines). We

[2] Corwin and Coughenour (2008) show that limited attention drives the market makers to allocate relatively more attention to large firms during busy trading periods, as these stocks have greater 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 during busy trading periods, thus delaying their trading of small stocks to minimize trading costs.

[3] Garleanu and Pedersen (2013) and Rostek and Weretka (2015) also present dynamic trading models where it is optimal for investors to trade slowly in the presence of price impact and transaction costs. 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.

find that the spillover returns come from both the slow adjustments of small firm returns to market returns and, to a lesser extent, movements in large firm returns in the opposite direction of the past market returns. Larger market-wide return shocks and higher aggregate market trading volume also amplify the returns on the spillover strategy. These findings are consistent with institutional and informational frictions being higher when aggregate capital constraints are tighter.

Second, we present evidence on slow trading by institutions using daily institutional trading data. We find that institution specific buy and sell trades persist over several days in small stocks but not in large stocks. Moreover, institutions are more likely to split their purchase (sale) of small stocks following positive (negative) market returns, more so than their trades in large firms. Utilizing the 2003 mutual fund scandal as an exogenous shock, we provide evidence that when facing unexpected, urgent, and large rebalancing needs, the funds affected by the scandal prioritize selling large stocks and sell small stocks only gradually over time, relative to other comparable funds which are not implicated by the scandal.

Third, we examine the impact of fund flows on future stock returns. Lou (2012) provides evidence of flow induced trading by mutual funds leading to predictable stock returns. Vayanos and Woolley (2013), in turn, develop a model which demostrates that when fund flows are gradual, uncertain and impact prices, there is a predictable effect of institutional trading on asset prices. Consistent with Lou (2012), Vayanos and Woolley (2013), and slow trading in small stocks, we find that the price pressure from the mutual funds’ flow induced trading leads to predictable return effects for the small stocks in the direction of flows. In the final test, we use the return on the portfolio of stocks connected by common institutional ownership (as in Anton and Polk (2014)) to capture the lead-lag effect in small and large stocks due to trading by common institutional investors. We find strong evidence that the return on connected stocks positively (negatively) predicts the return on small (large) stocks, supporting the hypothesis that institutions gradually trade small stock and demand immediacy in large stocks, which in turn contributes to the size-based return predictability.

Our paper contributes to the literature on the size premium and its time variation in three important ways. First, we document that the lagged market return is a strong and remarkably resilient predictor of the intertemporal variation in the size premium. This predictability adds to the idea of delayed price adjustments in Hou and Moskowitz (2005) in that we show that the returns of both small and large firms are predictable depending on the sign of the market return. Second, we provide evidence that institutional trading patterns contribute to the predictability of the size premium. The slow trading channel that we document adds to the evidence that the slow adjustment of small stock prices emanates from less informed investors reacting to common information with a delay (Badrinath, Kale and Noe (1995), Hou (2007), and Chordia, Sarkar and Subrahmanyam (2011)). On the other hand, "fast" trading in large stocks generates price pressure and subsequent price movements (albeit small) in the opposite direction of the market. Third, the recent model by Greenwood, Hanson and Liao (2017) shows that when asset markets are segmented due to institutional and informational frictions, capital moves quickly within an asset class, but capital is slow moving (like in Duffie (2010)) across asset classes, generating a disconnection in the price of risk across asset classes in the short-run. Our research complements Greenwood, Hanson and Liao (2017) in that our results are consistent with capital moving slowly across investment categories (large and small firms) due to frictions in the equity market. Overall, the evidence points to institutional and information frictions as an important source of the variation in the size premium.

The rest of the 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 consider a simple trading strategy to document the economic magnitude and the time variation in the predictability. Section 5 provides evidence on slow trading by institutions and we investigate the effects of mutual fund flows on return predictability. Section 6 concludes the paper.

2. Data

We collect daily data on stock returns and trading volume from CRSP database for all NYSE, AMEX and NASDAQ listed common stocks from 1962 to 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). To allay concerns about microstructure effects, we discard the most infrequently traded stocks from our sample by only considering stocks that had a positive trading volume on at least 200 days in the previous calendar year. In addition, we require that stocks have positive trading volume during the portfolio formation period.

To analyze the size premium, we sort stocks by firm size into deciles using the NYSE breakpoints (firm size is the stocks' market capitalization on the last trading day in June of the previous year). For each size decile, we compute daily, weekly, and monthly value-weighted average returns. We define the 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 solely attributable to the smallest microcap firms in CRSP, we also consider the return difference between deciles 2 and 10, and the return difference between deciles 5 and 10.

In our investigation of the relation between size-based return predictability and institutional trading, we explore several databases. First, we obtain institutional ownership data from the Thompson Reuters 13F database and mutual fund ownership data from the CDA/Spectrum database. Mutual fund flows are obtained from the CRSP mutual fund database, which is matched to the CDA/Spectrum data using the Mutual Funds linktable created by Russ Wermers (1999). Second, we consider the ANcerno dataset that contains trade-level observations for more than six hundred different institutions including hedge funds, mutual funds, pension funds, and other money managers. Our ANcerno data cover the period 2000-2010. According to Puckett and Yan (2011), this dataset includes the trades of many of the largest institutional investors such as CalPERS, the YMCA retirement fund, Putman Investments, and Lazard Asset Management that in total account for 8% of the daily volume in CRSP. This dataset is widely used in academic research on daily trades by institutions, see e.g., Puckett and Yan (2011), Anand, Irvine, Puckett and Venkateraman (2013) and Hu, McLean, Pontiff and Wang (2013). When analyzing size effects using the institutional trading and holdings data, we classify all stocks as large-cap (deciles 6 and higher) or small-cap (deciles 5 and lower), which is equivalent to using the NYSE median size as the size cutoff. Transactions in these small stocks account for approximately 25% of the total number of transactions in the ANcerno database.

3. Predictability of the size premium and past market returns

Figure 1 shows that there is substantial variation in the size premium predicted by past market returns. In this section, we present several additional results on the predictability of size-sorted stock returns. First, we document the cross-sectional variation in the adjustment of individual stock returns to market returns. Next, we report how the predictability of size-based portfolio returns using past market returns has varied over the past 50 years. Finally, we study the robustness of our findings in sub-samples based on other firm characteristics that explain the cross-section of stock returns.

3.1. Predictability of individual stock returns

We first examine the delayed adjustment of individual stock returns to market returns. In each year, we regress individual stock returns on contemporaneous and lagged market returns using the following specification:

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

where R_{it} denotes the return of stock *i* and $R_{VW,t}$ denotes the value-weighted return on the market index. Stock returns are measured at daily, weekly and monthly horizons. The number of lags *l* in equation (1) is set to 5, 4 and 1 for the daily, weekly and monthly horizons, respectively. We also report that our results are robust to the choice of *l*.[4]

Table 1 reports the average value of β_{i0} and the sum of the lagged betas, $\sum_{k=1}^{l} \beta_{ik}$, grouped by size deciles. The size decile in each year is determined by the market capitalization of firms on the last trading day of June of the previous year, using NYSE cutoffs. The parameter estimates reported in the table are the average yearly values, across all years from 1964 to 2014. As shown in Panel A of Table 1, after controlling for the contemporaneous market betas, the daily returns on the smallest size decile have the highest average lagged betas of 0.52. As we move up the size deciles, the lagged betas decline monotonically. Interestingly, the average lagged betas become significantly negative for the largest firms at -0.04. The difference in lagged betas between deciles 1 and 10 is a significant 0.56. The difference in betas between the middle size decile (decile 5) and decile 10 is also significant at 0.27. The magnitude of the differences in lagged betas between small and large firms remains significant when we consider weekly and monthly returns (See the last two columns of Panels B and C of Table 1). These findings

[4] For example, we obtain qualitatively similar results when *l* is set equal to 1 for all three horizons (see Internet Appendix Table IA1).

reinforce the results presented in Figure 1: small stocks exhibit delays in reacting to market returns, while large stocks seem to overshoot in the contemporaneous period and subsequently revert, although the magnitude of the predictive effect is much smaller in large firms. Therefore, observing high (low) market returns predicts high (low) small stock returns and relatively low (high) large-stock returns in the immediate future.

<TABLE 1 HERE>

Regression (1) parallels Hou and Moskowitz (2005), who study the percentage of the regression R^2 that is explained by lagged market returns. Hou and Moskowitz (2005) show that the size premium is explained by a premium for low investor recognition that is related to return delays. We add to their findings by showing that there are substantial intertemporal variation in the size premium, which in turn is related to investor trading frictions.[5]

3.2. Predictability of size-based portfolio returns

After documenting predictable patterns in the individual stock returns, we now turn to the predictability of size-based portfolio returns. We start by showing that there is strong predictable time-variation in the size premium. To do this, we estimate the following three regression specifications with rolling 5-year windows of daily returns:

[5] Similar to Table 1, we also find evidence of delays in trading in small stocks in response to market-wide trading activity. We run the regression specification in equation (1) with measures of stock level and market level trading activities, proxied by turnover and order imbalance. As reported in Internet Table IA2, shocks to aggregate market order imbalances (or aggregate turnover) predicts order imbalances (turnover) in the same direction for small stocks at daily, weekly and monthly horizons. The lagged betas with respect to aggregate trading activity decline monotonically as we move to larger size deciles. This initial evidence is consistent with predictable delays in trading activities in small stocks relative to large stocks.

$$R_{St} = \alpha_S + \beta_S R_{VW,t-1} + \varepsilon_{St} \quad (2)$$

$$R_{Lt} = \alpha_L + \beta_L R_{VW,t-1} + \varepsilon_{Lt} \quad (3)$$

$$R_{SMLt} = \alpha_{SML} + \beta_{SML} R_{VW,t-1} + \varepsilon_{SMLt}, \quad (4)$$

where R_{St} is the (value-weighted) return on the portfolio of firms in the smallest size decile on day t, R_{Lt} is the (value-weighted) return of the largest size decile, R_{SMLt} is the size premium ($R_{St} - R_{Lt}$), and $R_{VW,t}$ is the (value-weighted) return on the CRSP market index. In Figure 2, we plot the time variation in the slope coefficients (β) from these regressions, estimated over rolling windows of five years, and the related regression R^2s. The impact of lagged market returns on small-cap returns (β_S) peaks around 1970 and gradually declines thereafter, but remains significant. Similarly, the regression R^2 of this predictive regression becomes weaker over time (Figure 2, Panel A).

The impact of lagged market returns on large-cap returns (β_L) has also declined sharply over this period, and has, interestingly, turned negative since around 2000 (Figure 2, Panel B). The negative response of the return on the portfolio of large firms to lagged market returns mirrors the findings we report for large-cap individual stock returns in Table 1. The common downward trend in the predictive coefficients for both the small and large stocks helps to maintain a robust gap in the differential response of these stocks to the market returns. Consequently, the predictability of the size premium has remained remarkably stable over time, with equation (4) producing β_{SML} estimates around 0.3 and a predictive R^2 around 15%, as graphed in Figure 2, Panel C.

<FIGURE 2 HERE>

The finding that market returns predict the size premium in equations (2) to (4) is highly robust.

Specifically, we obtain similar size related predictability in returns if we (i) include multiple lags of market returns in the regressions; (ii) consider indicator variables to depict the signs of returns rather than using returns as continuous variables; (iii) replace the returns of the smallest size decile with the returns of the second or the fifth smallest decile of stocks; and (iv) replace the size portfolios with the small-minus-big (SMB) factor available from the Kenneth French Data Library. All these findings show up in daily, weekly and monthly returns as shown in Table IA3 in the Internet Appendix.

3.3. Predictability of size-based portfolio returns and other firm characteristics

We also consider the robustness of the predictability of the size premium 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 that 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 the market return state on the size premium is robust to controlling for each of these firm characteristics.[6]

Our analysis is based on eleven 5x5 double-sorted portfolios that are sorted on size and each of the eleven other characteristics made available in the Kenneth French Data Library. Specifically, we examine if the lagged market return predicts the return on R_{SMLt} within the top/bottom quintiles of stocks formed by sorting on each of the eleven characteristics. To illustrate using the book-to-market ratio as the sorting variable, we examine if the estimates of Equation (4) are significant among stocks belonging to the top and bottom quintiles of 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 effect of lagged market

[6] Using the classification from Kenneth French's website, we consider subsamples based on the following firm characteristics: (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-month 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 IA4 in the Internet Appendix provides detailed explanations on the way each of the eleven variables and the corresponding portfolios are constructed.

returns on the size premium is highly significant within all subsets of stocks, at both daily and monthly frequencies. For example, the estimate of the monthly regression coefficient in Equation (4) 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 adjusted R^2 from these predictive regressions ranges from 2% (high beta stocks) to 10% (low variance stocks). We reach a similar conclusion with the daily return regressions also presented in Table 2.[7]

<TABLE 2 HERE>

4. The spillover strategy

4.1 Returns on small and large stock portfolios

The results so far show that market states significantly predict the size premium. In this section, we devise a simple zero-investment trading strategy to assess the economic magnitude and time-variation in the differential adjustment of small and large stocks to the large market returns, which we call the spillover strategy. Specifically, the spillover strategy goes long on the small stocks and shorts the large stocks following a positive market return; following negative market returns, the strategy switches to long positions on large stocks and shorts the small stocks. The small and the large stock portfolios contain the smallest (decile 1) and the largest decile (decile 10) of stocks in our CRSP sample, where the size classification is updated at the end of June in the previous year using NYSE cutoffs. We also consider two alternative small size portfolios, deciles 2 and 5. The returns on the portfolios are value-weighted. We consider rebalancing the portfolio at daily, weekly and monthly frequencies.

[7] We also examine the effect of lagged market returns on premiums associated with each of these eleven firm characteristics within the top and bottom of stocks sorted by firm size. Unlike the results for the size premium, the predictive effect of lagged market returns are weak. As we report in the Internet Appendix Table IA5, the equivalent R^2 from the monthly regressions using equation (4) do not exceed 3%.

In Table 3, we report the average returns on the spillover strategy as well as the associated Sharpe-ratios, skewness, kurtosis and alphas from CAPM and Fama-French-Carhart 4-factor models. The spillover strategy yields strikingly large returns at daily, weekly, and monthly horizons. The average monthly returns on the strategy varies from 3.7% with daily rebalancing to 1.7% with monthly rebalancing. The evidence that the returns to the spillover strategy are positive is robust. The spillover strategies generate large Fama-French-Carhart 4-factor alphas of between 2.1% to 4.2% per month with little exposure to the risk factors. In fact, the risk-adjusted returns are higher than the raw returns indicating a negative exposure to some risk factor(s). For perspective, the unconditional monthly size premium of 0.6% reduces to insignificance after adjusting for the market premium in the CAPM model (as shown in the last column of Table 3). Moreover, the monthly spillover returns have lower skewness and kurtosis and the Sharpe ratio is higher than that for the unconditional size premium. We also report the number of times the portfolios are rebalanced each year, which averages 114 (6.5) times per year for the daily (monthly) spillover strategy.

<TABLE 3 HERE>

The results remain qualitatively similar when we replace the small stock portfolio, with a portfolio based on the second smallest decile (decile 2), or decile 5. As expected, the spillover returns decrease as we move to bigger size deciles to represent small stocks, but, remain economically significant. For instance, monthly rebalancing the spillover strategy using size deciles 5 and 10 produces a significant 4-factor alpha of 0.8% per month. This reaffirms that the spillover strategy returns are not solely due to the smallest stocks or micro caps. In addition, the returns on the strategy originate from both the long and the short legs of the strategy, with the long leg contributing higher returns than the short side, across all horizons, irrespective of using size deciles 1, 2 or 5 to represent the small firms (details are provided in the Internet Appendix Table IA6).

4.2. Spillover strategy in ETFs

While the spillover strategy using various size deciles indicates strong predictability in small and large stock returns, the returns from these strategies do not account for transaction costs. In this setting, transaction costs increases with the frequency of portfolio rebalancing, which depends on the frequency of changes in the sign of the market returns. Instead of directly introducing transaction costs into the trading strategy, we investigate the magnitude of predictability within size-based exchange traded funds (ETFs). Subrahmanyam (1991), for example, demonstrates that bundled assets are liquid because they lower the adverse selection costs. Madhavan and Sobczyk (2014) find that bid-ask spreads of ETFs are lower than the average spread in the underlying securities.[8]

We identify three actively traded small-firm ETFs (*iShares Russell 2000, iShares Core S&P SmallCap, and Vanguard SmallCap*) and construct an equal-weighted portfolio of these three ETFs, denoting the corresponding portfolio return in month t as $ETF_{Small,t}$. Similarly, $ETF_{Large,t}$. represents the (equal-weighted) portfolio of three large stock ETFs (*SPDR S&P500, SPDR DJIA, iShares Core S&P500*). These are highly liquid and most traded small-cap and large-cap ETFs in terms of dollar trading volume over the sample period of 2002-2014.[9] Table 4 presents the results from regressing the difference in the monthly returns of the small- and the large-cap ETFs ($ETF_{Small,t}$ - $ETF_{Large,t}$, or $ETF_{SML,t}$) on the prior

[8] Frazzini, Israel and Moskowitz (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). In addition, Novy-Marx and Velikov (2015) find that the size strategy is among the strategies with the highest capacity to support new capital.

[9] 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 Russell 2000, the average daily dollar trading volume in 2014 is $4.2B and the average bid-ask spread is 0.01% (Source CRSP).

month's value-weighted market index return. In line with the results of the previous section, we find that $ETF_{SML,t}$ is positively related to lagged market returns. In other words, in the months following positive (negative) market returns, small-cap ETFs outperform (underperform) large-cap ETFs. As expected, column 2 of Table 4 shows that the monthly returns on $ETF_{SML,t}$ load with a coefficient of one on the Fama-French small-minus-big (SMB) size factor. It is not surprising that *ETF*s closely mimic the portfolio of the underlying securities as any price deviation is eliminated via ETF arbitrage activities.

Next, the spillover strategy implemented with ETFs involves going long the small- and short the large-cap ETFs following months with positive market returns, and taking the opposite positions when the past market returns are negative. The return on the monthly rebalanced spillover strategy is denoted by $ETF_{Spillover,t}$. As documented in column 1 of Table 4, the ETF spillover strategy yields an economically and statistically significant positive Fama-French-Carhart 4-factor alpha of 0.49% per month.[10]

<TABLE 4 HERE>

4.3 Seasonality and variation in spillover strategy returns across market states

The returns to the spillover strategy in Table 3 are vastly different in magnitude from the unconditional size premium, stressing the importance of the time-varying nature of the size premium. In this sub-section, we further explore the time series variation in the daily spillover returns and hence the conditional size premium.

In Figure 3, we compare the returns to the daily rebalanced spillover strategy with the annually rebalanced size premium that longs the smallest size decile and shorts the largest size decile. Specifically,

[10] At the daily and weekly frequencies, we do not find significant predictable time-variation in the spread between the small- and large-cap ETFs. This could be due to short-term pricing discrepancies between the ETFs and their underlying assets (See e.g., Petajisto (2017) and Ben-David, Franzoni and Moussawi. (2016)).

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 each decade starting from the 1960s (Panel C). The gray bars show the equivalent returns for the unconditional size premium.

Panels A and B of Figure 3 affirm the well-documented January effect and the Friday seasonality for the size premium (e.g., Schwert (2003) and Keim and Stambaugh (1986)). The conditional size premium captured by the spillover strategy, on the other hand, does not exhibit similar seasonal variations: spillover returns are consistently present across all days and months. More importantly, Panel C of Figure 3 shows that the unconditional size premium has declined considerably since the 1970s. In contrast, the payoffs from the spillover strategy have remained remarkably stable throughout the 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.

<FIGURE 3 HERE>

We also examine the relation between past market returns and the size premium using the market returns as a continuous variable rather than just an indicator variable for positive and negative returns. In particular, we are interested to see if the effect of market states increases with the magnitude of market returns. In Figure 4, we plot the average returns of the daily-rebalanced spillover strategy in the formation period on day t (gray bars) and in the holding period on day $t+1$ (black bars) in different market states. In Panel A, we sort all days within each year into quintiles based on day t market returns. The gray bars show that the spillover strategy's returns are (weakly) decreasing in the contemporaneous market return. More striking is the U-shape in the spillover returns during day $t+1$ depicted by the black bars: the spillover strategy returns are significantly higher following days of large positive or negative market movements than following days of moderate market returns.

<FIGURE 4 HERE>

4.4 Spillover strategy returns and aggregate liquidity

If the profits from the spillover strategy reflect market frictions associated with large market-wide movement in prices, we should expect the payoffs to the spillover strategy to be high during periods of high liquidity demand and/or low liquidity supply. For example, the large investors in Vayanos (1999, 2001) are more likely to delay trading of (small) stocks when there are large liquidity shocks in the market. At the same time, the price impact of fast trading large stocks when facing large market moves is likely to be higher when market supply (demand) liquidity is also low (high). We also expect institutional and informational frictions in models such as Vayanos and Woolley (2013) and Greenwood, Hanson and Liao (2017) to be higher during periods of high aggregate illiquidity. In Brunnermeier and Pedersen (2009), shocks to demand for liquidity generate a spiral effect by lowering asset prices, which in turn decreases liquidity supply (funding liquidity) via the collateral channel. In this sub-section, we investigate whether aggregate illiquidity predicts spillover returns.

We start by asking whether the spillover returns vary with market-wide trading activity. Similar to the analysis in Panel A of Figure 4, we measure daily market turnover as the (value-weighted) daily stock turnover and sort the days into quintiles within each year. As shown in Panel B of Figure 4, the average returns of the daily spillover strategy on day $t+1$ is increasing in aggregate market turnover in day t (or day $t+1$). The plot shows that periods of relatively high aggregate trading volume are associated with larger returns on the spillover strategy. This observation supports, but does not prove, the notion that heavy market-wide trading activity creates high demand pressure for large stocks and a slow-down in trading on small stocks.

To examine in greater depth the effect of aggregate liquidity states on spillover returns, we adopt several proxies for demand and supply of aggregate liquidity suggested in recent research. Nagel (2012) suggests that a high level of the *VIX* index is associated with periods of stress in the funding market and low liquidity provision in the equity market. A high Treasury-Eurodollar spread, TED (90-day LIBOR minus the 90-day Treasury Bill yield), indicates large interbank counterparty credit risk and hence low funding liquidity (Frazzini and Pedersen (2014)). A large decline in aggregate market valuations ($R_{m,t-1-t-3}$, negative cumulative value-weighted equity market returns over the previous three-months) has been shown to capture periods of low supply of liquidity as well (Hameed, Kang and Viswanathan (2010)). Our next measure is the common variation in the trading activity in individual stocks (commonality in turnover or *Turnover-*R^2) advocated in Karolyi, Lee and van Dijk (2012), who show that a high *Turnover-*R^2 proxies for high correlated trading in the market and hence a high demand for liquidity.[11] Finally, innovations in Pastor-Stambaugh liquidity measure are used to capture the state of aggregate liquidity (Pastor and Stambaugh (2003)).[12]

Table 5 presents the results when the monthly returns on the daily spillover strategy are regressed on the above measures of aggregate market and funding liquidity. The spillover returns are significantly higher when funding liquidity is tight ((high *VIX* or *TED*, or negative $R_{m,t-1-t-3}$,), aggregate liquidity is low (low Pastor-Stambaugh liquidity) or when investor demand for liquidity is high (high *Turnover-*R^2). The economic effect of the lagged value of aggregate liquidity on spillover returns is also large. For example,

[11] The commonality in turnover is computed by taking the value-weighted average R^2 of the following monthly stock-level time series regressions: $TURN_{it} = \alpha_i + \beta_i TURN_{VW,t} + \varepsilon_{it}$, where $TURN_{i,t}$ is the share turnover on stock *i* on day *t*, while $TURN_{vw,t}$ is the value-weighted average market turnover on day *t*. The value weighted average R^2 measures the commonality in trading activity across stocks.

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

a one standard deviation increase in VIX leads to an increase in spillover returns of 2.2% per month. While each of these liquidity variables is significant in univariate regressions, in multivariate regressions, *VIX*, *TED* and *Turnover-R^2* are significant predictors of future spillover returns.[13]

<TABLE 5 HERE>

The above results indicate that the differential predictability of small and large firms conditioned on the lagged market return state is related to variations in aggregate liquidity conditions. Taken together with the earlier results, the return predictability we document relates to investors' delayed trading of small stocks relative to large stocks due to market frictions. During periods of low market or funding liquidity, there is a delay before the market information is fully reflected in small stocks prices as the trading of small stocks gets delayed. Similarly, in illiquid markets, the price pressure from investors' demanding immediacy in large stocks causes returns on large stocks to move in the opposite direction to the lagged market return state. These effects culminate in high returns to the spillover strategy in an illiquid market. This conclusion is based on the premise that investors trade small firms with a delay relative to large firms. We lay out a detailed investigation of this proposition in the next section.

5. Evidence from Institutional Trading

We hypothesized in the introduction that the slow adjustment of small stock prices to the market-wide component in returns is due to delayed trading in those stocks. In addition, we argued that the reversal of

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[13] We find qualitatively similar results when the spillover strategies are rebalanced at weekly or monthly frequencies (see Internet Appendix, Table IA7).

the large stocks' returns following market returns is due to price pressure that arises from rapid execution of large stock trades in the market. To provide direct evidence on the hypotheses about investor behavior, we turn to the analysis of institutional transactions data as well as institutional holdings data. After documenting direct evidence of slow trading by institutional investors, we relate the findings to return predictability. In analyzing the effect of mutual fund flows, we find that fund flows have a delayed price impact on small stocks held by these funds. Additionally, we find that small stocks do not only adjust with a delay to the general market returns, but also adjust more slowly to returns of stocks that share common institutional ownership.

5.1. Sequential Trading of Large and Small Firms

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 by institution *f* in stock *i* on day *t.* To define institutional trading in small and large stocks, we classify all stocks in our sample as either small (size deciles 1-5) or large (size deciles 6-10), using the median NYSE firm size as the breakpoint.

To test whether institutions trade small stocks with a delay, we analyze total *institution-specific* trading volume in small and large stocks. Specifically, we estimate the following panel regression models:

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

$$TURN_{f,t}^{L} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,L,t} \qquad (6)$$

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; $TURN_{f,t}^{S}$ and $TURN_{f,t}^{L}$ are the corresponding measures computed using only the transactions in the subset of small and large stocks; μ_f and δ_t represent fund and date fixed effects. Table 6 reports the regression results.

<TABLE 6 HERE>

Consistent with our slow trading hypothesis, we find that an institution's trading activity in small stocks responds positively with a delay to its own total trading activity. Specifically, an institution's trading activity (turnover) in small stocks is positively predictable by the institution's total trading activity during each of the past five days. The predictable effect on large-cap volumes is smaller and of negative sign. Observing high trading activity by an institution on a given day therefore predicts that the institution will be more active in trading small stocks over the next five days, while trading activity in large stocks is expected to be relatively low. This result reaffirms the premise that during a day of intensive trading, institutions rebalance their large stock positions immediately, while partly postponing the execution of their trades in small stocks over the next several days. This institutional trading pattern holds for both buy and sell transactions and is side-specific, i.e., excessive buy (sell) activity predicts high buy (sell) activity in small stocks over the next few days.

5.2. Continuation in small stock trades

After documenting patterns in the institutions' trading of small and large stocks, we turn to their trading patterns in individual stocks and relate this to variation in market states. Chan and Lakonishok (1995) show that institutional investors routinely split their trades over several days. In a similar spirit, we estimate the probability of institutions splitting trades within small and large stocks. We say that an institution is splitting trades when it 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 1 if institution *f* trades stock *i* on day *t* and on day τ, where $\tau \in \{t+1, t+k\}$. If institution *f* trades stock *i* on day *t*, but does not trade on days $\tau \in \{t+1, t+k\}$, $trade_{f,i,t,t+k}$ equals zero. Next, we define $split_{f,i,t,t+k}$, to equal 1 if and only 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)). Panel A in Table 7 shows that the probability of splitting trades during a window of five subsequent days $P(split_{f,i,t,t+5}|trade_{f,i,t,t+5})$ is 73% for small firms and 68% for large firms.[14] More generally, Table 7, Panel A, reveals that institutions have a higher probability of splitting their orders in small stocks compared to large stocks and that the difference between the two is higher when *k* is small. Hence, investors engage in slow trading of small stocks.[15]

<TABLE 7 HERE>

We describe in Panel B of Table 7 the time-series variation in the propensity to split trades. We consider the daily percentage of splits of buy and sell orders for small and large stocks separately, and regress this percentage on the prior day's market return and on its own lag (to accommodate its persistence). For small stocks, we find that buy splits occur more frequently following positive market return, while sell splits occur more frequently following negative market returns. For large stocks, the

[14] 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 7 Panel A 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.

[15] Panel regressions reported in Internet Appendix Table IA8, show that the probability of funds splitting their trades is also related to order size and returns. Buy (sell) splits are more likely following days when the stock price goes up (down) and when the initial order is large.

estimated parameters are of the same sign, but of smaller magnitude and significance. In other words, the fraction of split trades in large stocks does not vary much across market states, which is in accordance with our hypothesis. During a day of positive (negative) market returns and market buy (sell) pressure, investors tend to complete their buy (sell) transactions in large stocks, but continue their buy (sell) transactions in small stocks into the next day. This contributes to the delayed adjustment of small stock prices to the market state.

5.3. Institutional trading around a mutual fund scandal: a natural experiment

In an attempt to identify the effect of investors' portfolio rebalancing needs on 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 following months (See Kisin (2011) and Anton and Polk (2014) for more detailed accounts of the event and its aftermath). 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. We then select all funds that satisfy the following two criteria: Funds need to report their holdings at the end of both 2003Q2 and 2003Q3, and 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 with 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 are shown in Table 8.

<TABLE 8 HERE>

Consistent with our slow trading hypothesis, we find that in the first quarter of the event (the third quarter of 2003), the affected funds significantly reduced their holdings of large firm shares while showing no significant decline in their holdings of small firm shares. Specifically, the interaction coefficient in Panel A of Table 8 is negative for large stocks but not for small stocks, indicating that scandal affected funds immediately reduced their holdings of large stocks relative to other comparable funds. When we consider the changes in holdings over a full year in Table 8, Panel B, we find a significant decline in the holdings of both large and small firms. This means that the affected funds prioritized selling the large firms in their portfolios when confronted with immediate liquidity needs caused by outflows in September 2003. On the other hand, they sold the small firms gradually over the course of several months.[16]

5.4. Flow induced price pressure

There is substantial evidence that mutual fund flows create price pressure at individual stock level (examples include Coval and Stafford (2007), Frazzini and Lamont (2008) and Lou (2012)). In the model by Vayanos and Woolley (2013), institutional flows generate price impact in the direction of the flows,

[16] 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.

particularly when the flows are gradual, and uncertain.[17] Fund managers' decision to trade specific stocks in response to flow may be influenced by the liquidity costs. Lou (2012) finds that mutual fund managers are more likely to liquidate stocks with low liquidity costs in order to meet redemptions. These papers suggest that the effect of fund flows on future stock prices might be higher for small firms, a prediction that is in line with the slow trading hypothesis.

To test this hypothesis, we match quarterly snapshots of mutual fund holdings from the CDA/Spectrum database with monthly mutual fund flows from the CRSP mutual fund database, to create monthly measures of flow pressure. Stock specific flow pressure is calculated as follows: we assume all funds invest in all stocks proportional to their last reported holdings. The stock-fund specific flow pressures are then aggregated across funds and normalized by the stocks' market capitalizations to create stock specific measures of flow pressure. Specifically, the flow pressure on stock *i* in month *t* is defined as:

$$FlowPressure_{i,t} = \frac{\sum_{f=1}^{F} S_{f,i,t-1} \times Flow_{f,t}}{S_{i,t-1}}, \qquad (7)$$

where $S_{f,i,t-1}$ is the number of shares of stock *i* held by fund *f* at the last quarter end before month *t*, $Flow_{f,t}$ is the flow into fund *f* during month *t*, and $S_{i,t-1}$ is the number of shares of stock *i* outstanding at the last quarter end before month *t*. Each month, we sort stocks into terciles based on the flow pressure and create monthly-adjusted value-weighted portfolios of *inflow* stocks (i.e., tercile 3 contains stocks owned predominantly by funds experiencing inflows) and *outflow* stocks (i.e., tercile 1 contains stocks

[17] Vayanos and Woolley (2013) argue that a "bird-in-the-hand" effect may lead risk averse fund managers to buy at current prices despite the expected price impact, which is equivalent to managers hedging against uncertainty about the flows and its expected impact of prices.

owned predominantly by funds experiencing outflows). We perform the computations separately for small stocks (below NYSE median size) and large stocks. Additionally, we create a long-short portfolio that is long in inflow stocks and short in outflow stocks within each size group.

In Table 9, we report average monthly returns of these portfolios as well as alphas from CAPM and Fama-French-Carhart 4-factor models. In Panel A of Table 9, we produce the contemporaneous returns on the inflow and outflow portfolios during the month in which the flows are measured. We find that both large and small stocks yield significantly positive (negative) returns *during* months when their mutual fund owners experience inflows (outflows). The magnitude of the price impact of the trades in response to contemporaneous flows is similar for both small and large stocks. The more interesting results are in Panel B, where we present the future stock returns in the month following the flows. The results clearly indicate that small stock returns can be predicted by lagged fund flows. The portfolio of small stocks experiencing inflows yields a monthly 4-factor alpha of +0.2%, while the portfolio of small stocks experiencing outflows yields a significantly lower 4-factor alpha of -0.2%. For large stocks, however, the risk-adjusted returns in the month following either inflows or outflows are not different from zero. The predictability of small stock portfolios is consistent with fund managers delaying their buying (selling) activity following inflows (outflows), resulting in delayed buying (selling) and associated positive (negative) returns. On the other hand, the predicted flows in small firms are more gradual and uncertain leading to predictable returns (Vayanos and Woolley (2013)). In either case, these findings support the slow trading hypothesis.

<TABLE 9 HERE>

5.5. Return on stocks connected by common ownership

If the predictability of small and large stock returns by lagged market returns is partly driven by frictions associated with institutional investing (such as institutions' delayed execution of trades and price impact of institutional trading), we expect that the return predictability ought to be related to returns on stocks that share common institutional ownership. Our analysis is inspired by the finding in Anton and Polk (2014) that return comovement is increasing in the common ownership by active mutual funds. In this subsection, we investigate the relation between returns on stocks connected by common ownership and the differential predictability of small and large stocks.

We begin by defining the degree of common ownership for each pair of stocks as proposed in Anton and Polk (2014): the total value of the stocks held by all active mutual funds that hold both stocks, expressed as a percentage of the total market capitalization of the two stocks. Specifically, at the end of each quarter *t*, the ownership by *F* common funds for each pair of stocks *i* and *j*, $FCAP_{ij,t}$ is defined as:

$$FCAP_{ij,t} = \frac{\sum_{f=1}^{F}(S_{f,i,t}\,P_{i,t} + S_{f,j,t}P_{j,t})}{S_{i,t}P_{i,t} + S_{j,t}P_{j,t}}, \qquad (8)$$

where $S_{f,i,t}$ denote the number of shares in firm *i* held by institution *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*. As in Anton and Polk (2014), stock *i*'s connected-portfolio return $R_{FCAP,i,t}$ refers to the return on the portfolio of stocks that are connected to stock *i* through common fund ownership at time *t* (weighted by the degree of common ownership):

$$R_{FCAP,i,t} = \frac{\sum_j FCAP_{ij,t} \times R^*_{j,t}}{\sum_j FCAP_{ij,t}}, \qquad (9)$$

where $R^*_{j,t}$ refers to the risk-adjusted return on stock *j* in time *t*.[18] This connected-portfolio return measures price impact of trading by funds in connected stocks and hence provides an alternative to the flow based measure of price pressure (e.g., Lou (2012)). We construct the connected portfolio return for stock *i* ($R_{FCAP,i,t}$) at daily, weekly and monthly frequency, where the common ownership weights are computed from the holdings available at the end of the prior quarter in the Thompson Reuters 13F database.[19] Each year, we regress the returns on stock *i* at time *t*, R_{it}, on contemporaneous (and lagged) returns on the connected portfolio, $R_{FCAP,i,t}$, and the CRSP value-weighted market index, $R_{VW,t}$. We estimate the following regressions using daily, weekly or monthly returns:

$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \vartheta_{i0} R_{FCAP*,i,t} + \beta_{i1} R_{VW,t-1} + \vartheta_{i1} R_{FCAP*,i,t-1} + \varepsilon_{i,t}. \quad (10)$$

Table 10 reports the mean of the coefficients in Equation (10), grouped by small stocks (size deciles 1-5) and large stocks (size deciles 6-10) as well as the difference in the coefficients for small and large firms. The sample period is 1980-2014.

<TABLE 10 HERE>

Similar to Anton and Polk (2014), we find that the return on the connected portfolio generates significant contemporaneous comovement in returns, beyond the correlation with market returns.

[18] Stock returns are risk adjusted using a market model as follows: $R_{j,t} = \alpha_j + \beta_j R_{VW,t} + \varepsilon_{j,t}$, where the parameters α_j and β_j are estimated over a three-year estimation window ending at the end of June before time *t*.

[19] We obtain qualitatively similar results if we base this analysis on the mutual fund holdings reported in the CDA Spectrum database.

Additionally, the increase in return comovement is higher for small stocks relative to large stocks. For example, while the contemporaneous market beta, β_0, is significantly higher for large firms, the connected portfolio return has a greater impact on small firms, as reflected in a higher ϑ_0. More importantly, we find strong evidence of delayed adjustment of small stock returns to shocks to the connected portfolios, beyond the slow adjustment to lagged market returns. The delayed adjustment of small stocks to connected portfolio returns ϑ_1 is economically and statistically significant at daily, weekly and monthly frequencies. For instance, a one standard deviation increase in $R_{FCAP,i,t}$ predicts an increase in the small stock return $R_{i,t}$ of 0.21% during the next month. On the other hand, large stock returns react in the opposite direction to a shock in the return on the connected portfolio, consistent with price impact and subsequent reversals. A high return in the connected portfolio predicts a lower return in the large stock returns and the effect is significant at all the frequencies we examine. A one standard deviation in increase in $R_{FCAP,i,t}$ predicts a decrease in the large stock return $R_{i,t}$ of 0.12% during the next month. As expected, the difference in ϑ_1 between small and large stocks is larger in both magnitude and statistical significance than the difference in delayed adjustment to common market returns (β_1). These results provide further evidence that the differential predictability of small and large stocks using lagged aggregate returns originates at least partly from differences in the speed of trading of these stocks by institutional investors.[20]

[20]As a robustness test, Internet Appendix Table IA9 reports returns and alphas on portfolios of stocks sorted monthly by the returns on their ownership-commonality weighted portfolio $R_{FCAP,i,t}$. Consistent with the slow trading hypothesis, we find that small firm returns are positively predictable by lagged returns on their commonality weighted portfolio, indicating that prices of small stocks adjust with a delay to the returns on the commonly held stocks. For large stocks, performance of the ownership-commonality weighted basket of stocks does not strongly predict returns in the next month.

6. Conclusion

In this paper, we document that the state of market returns positively predicts the difference in the return on small and large firms, or 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. The predictability of the size premium that we document is also highly robust to a battery of tests. Using data on institutional trading, 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 greater 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. In addition to informational frictions, we provide several pieces of evidence in support of the notion that institutional frictions also contribute to the predictability of the size premium. First, the predictability in size-based stock returns we document is significantly higher during periods when asset and funding liquidity is low. Second, we find that institutional investors are more likely to split their trading in the direction of market returns for small stocks relative to large stocks. Third, price pressure from mutual fund flow induced trading predicts returns on small stocks, consistent with delayed institutional trading in these stocks. Finally, we find that the return on the portfolio of stocks connected by common fund ownership partly explains the lead-lag relation in large and small stock returns. Overall, the cumulative evidence shows that frictions in institutional investing contribute to the predictability of the size premium.

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Figure 1: Size premium conditional on market states

The thin black line in Panel A shows the cumulative returns of 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 returns of a strategy that invests in the size premium only following days with a positive market state (defined as a day with a positive value-weighted market return). The downward sloping thick gray line shows the cumulative returns of a strategy that invests in the size premium only following days with a negative market state. In Panel B (C), market states are defined by the previous week's (month's) value-weighted market returns and weekly (monthly) returns are cumulated . The scale is in logarithms.

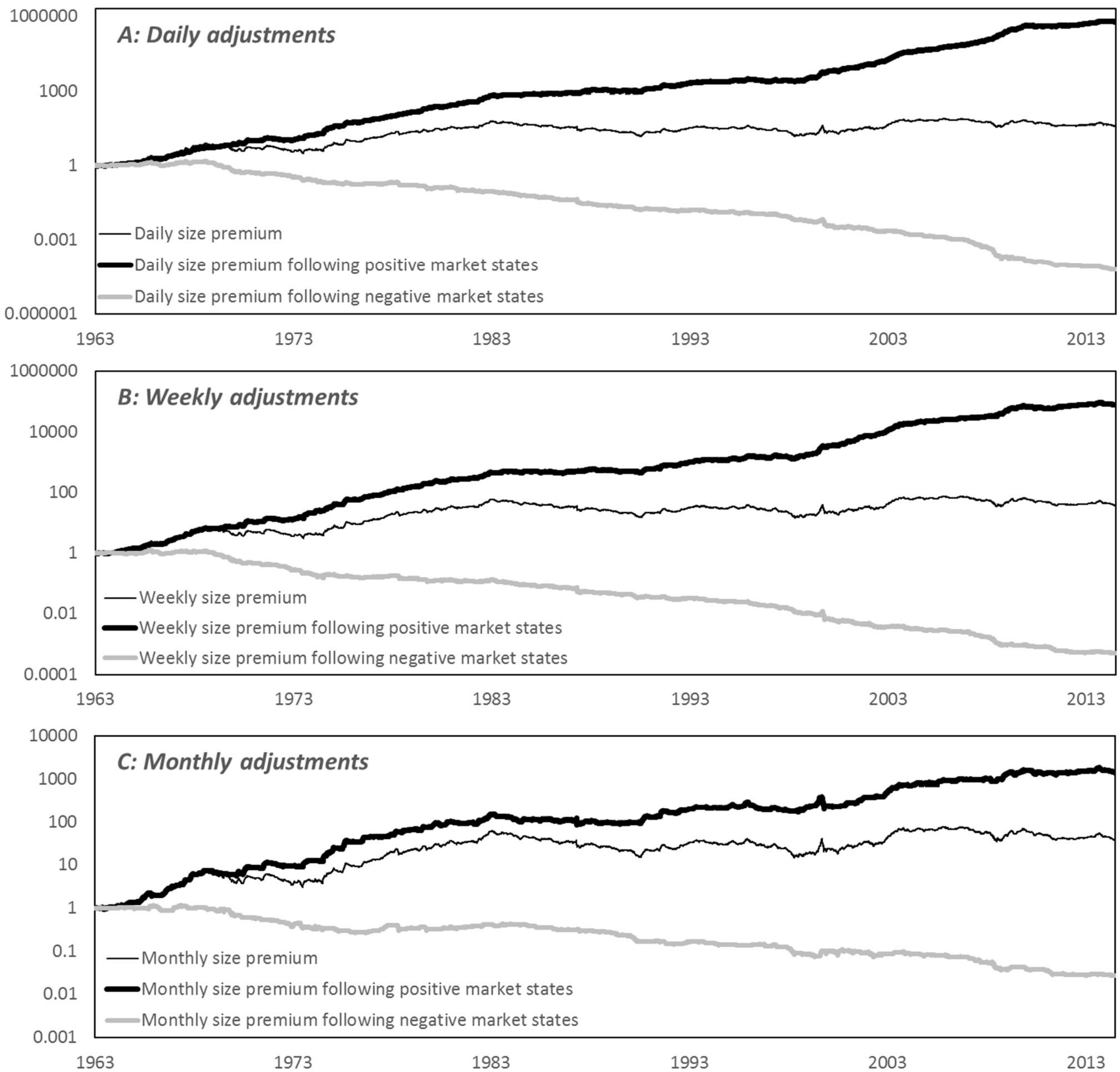


Figure 2: Predictability of portfolio returns

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 of the portfolio of firms in the smallest size decile. Size deciles are sorted annually at the end of June based on stocks' market capitalizations. $R_{VW,t}$ is the value-weighted CRSP market return on day t. The shaded gray areas denote the 90% confidence interval for β based on Newey-West standard errors. The dashed line shows the regression's R^2. Panels 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 the 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.

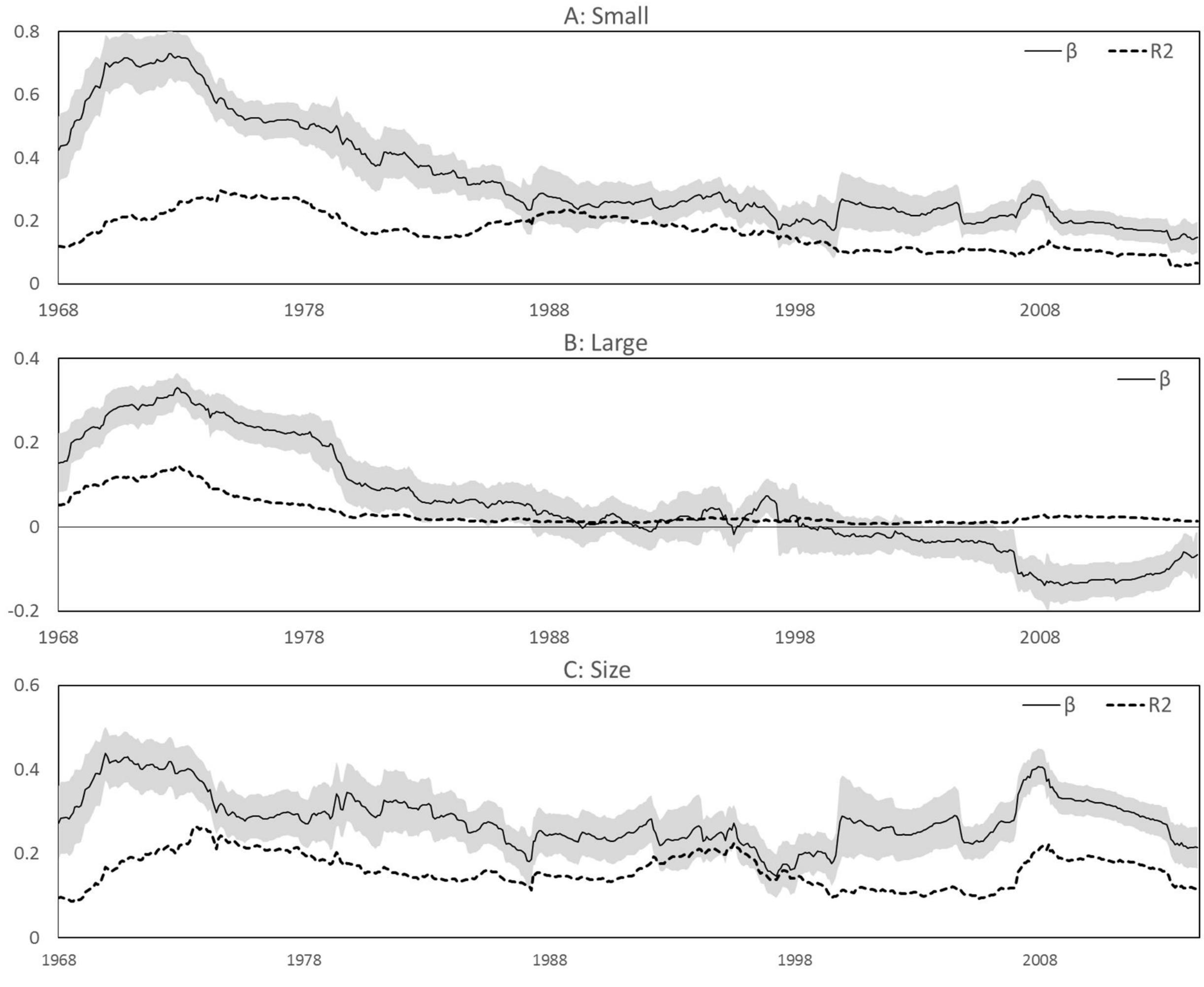


Figure 3: Trends and seasonalities in the spillover strategy

The black bars indicate the average returns on the daily rebalanced spillover strategy that is long in small firms and short in large firms during days following a positive market return, and reversing to long in large firms and short in small firms following a negative market return (See Table 3 for details). Panel A reports average monthly returns by calendar month. Panel B reports average daily returns by weekday. Panel C reports average monthly returns by decade. The gray bars indicate the average returns corresponding to a passive, annually rebalanced strategy that is long in the smallest decile and short in the largest decile of stocks sorted by size (or Unconditional size premium)..

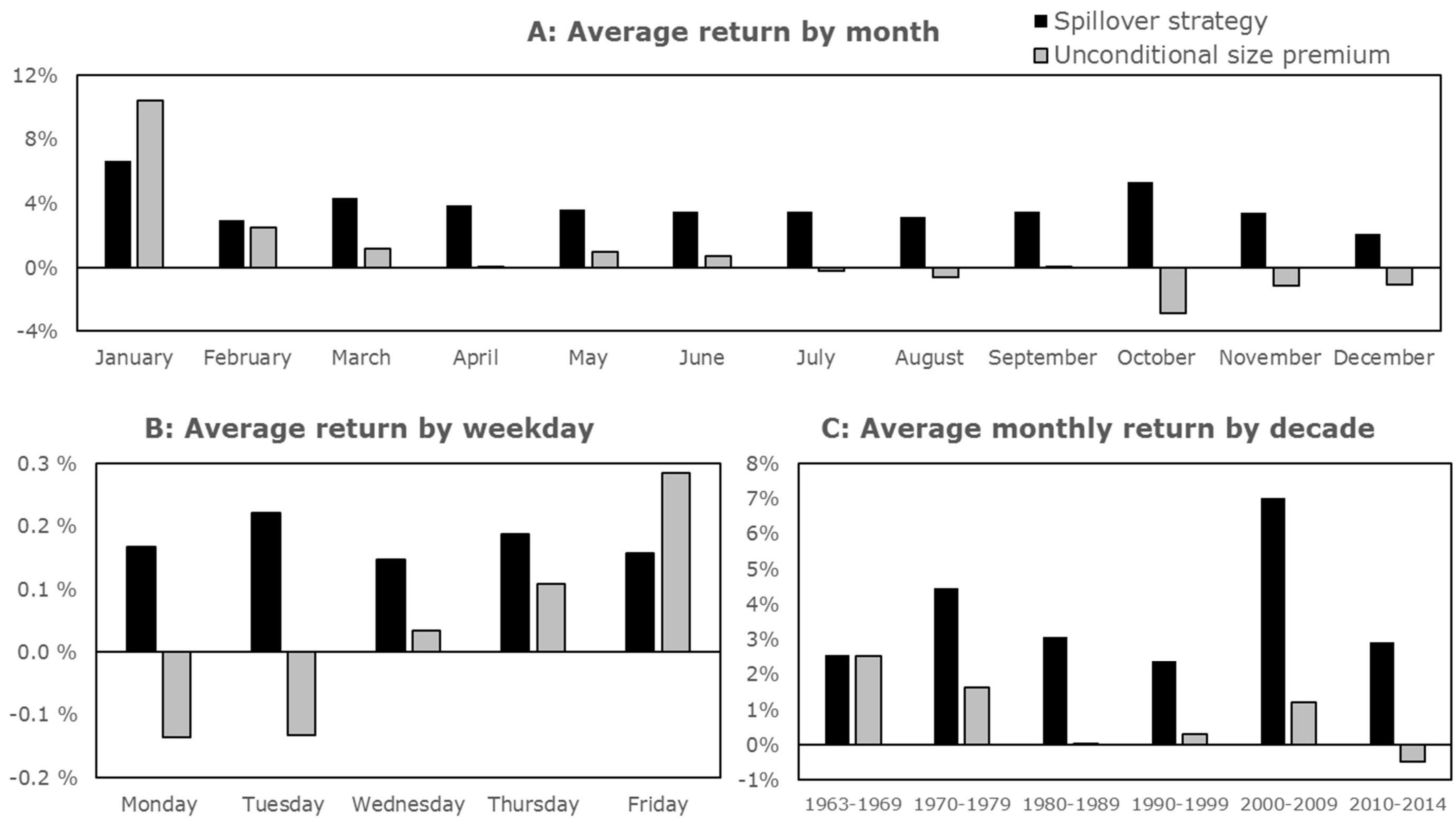
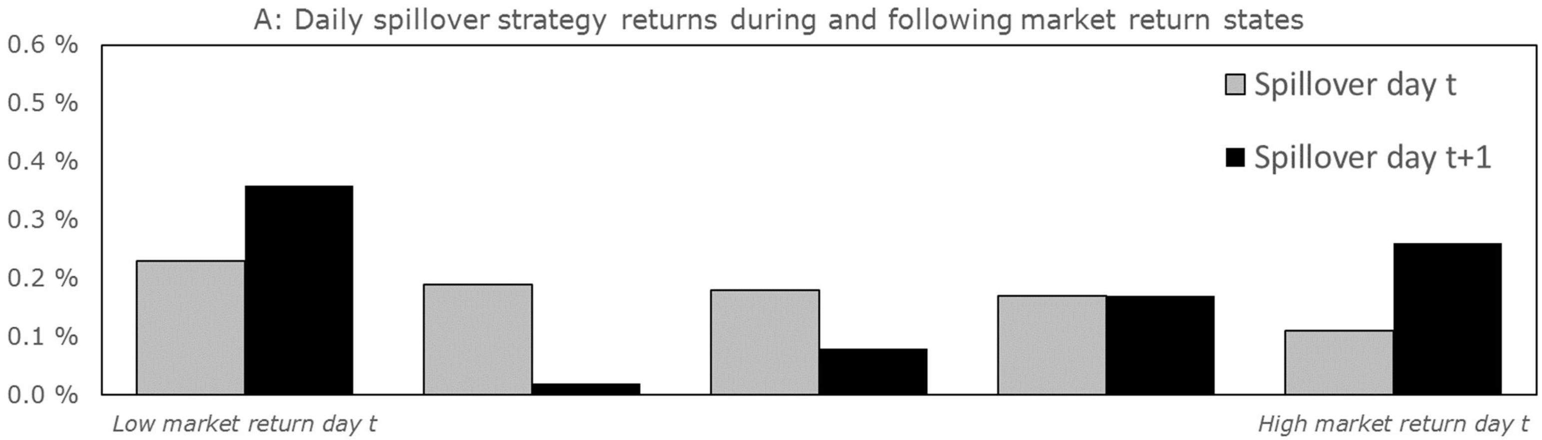


Figure 4: Spillover strategy's returns following market states

Panel A: The gray bars report average daily returns on the daily rebalanced spillover strategy on the formation day *t* (See Table 3 for details), while the black bars report the next day's average return on the spillover strategy, for quintiles sorted on daily CRSP value-weighted market returns within each year. In Panel B, the quintiles are formed based on daily market turnover within each year.



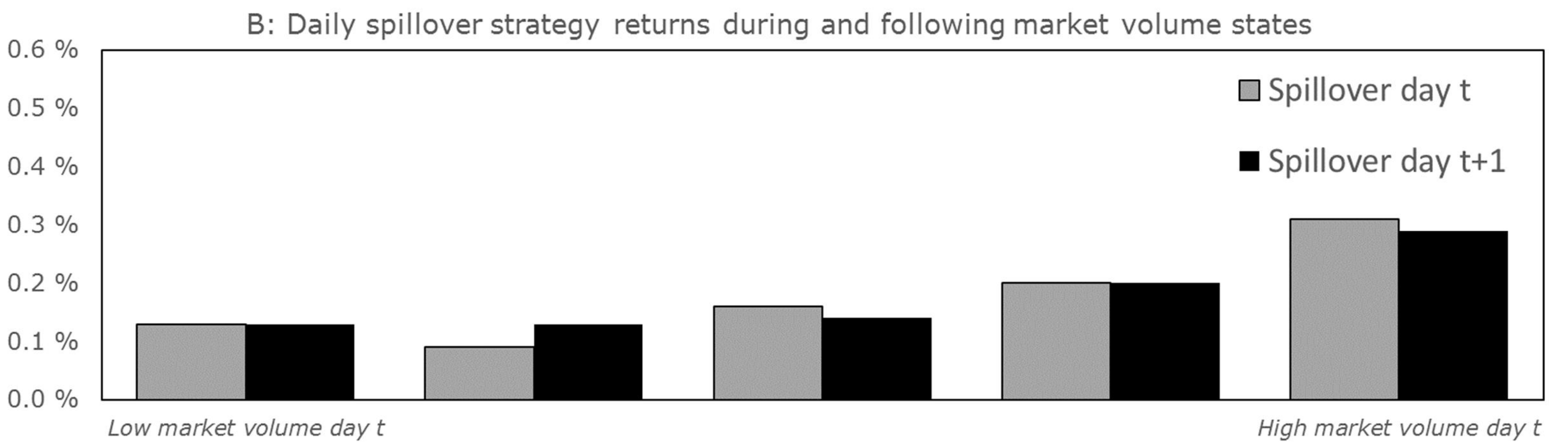


Table 1: Delayed price adjustment to market returns

At the end of June of each year, we regress the daily, weekly, and monthly returns of stock i, R_{it}, on contemporaneous and lagged value-weighted market returns, $R_{VW,t}$, over a sample period of one year:

$$R_{it} = \alpha_i + \beta_{i0} R_{VW,t} + \sum_{k=1}^{l} \beta_{ik} R_{VW,t-k} + \varepsilon_{i,t}.$$

The number of lags l is 5, 4, and 1 for daily, weekly, and monthly data, respectively. The table reports the sample average of β_{i0} and $\sum_{k=1}^{l} \beta_{ik}$ by size decile (sorted by market capitalization prior to the estimation sample, using NYSE breakpoints). The final two columns report the difference in mean between the smallest and largest deciles, and between the 5th and the largest decile. t-statistics are reported in parentheses and are based on two-way clustered standard errors at year and firm level. The sample period is 1963-2014.

A: Daily	Small									Large		
	1	2	3	4	5	6	7	8	9	10	1-10	5-10
β_0	0.57	0.70	0.94	1.00	1.01	1.00	0.96	0.99	0.99	1.03	-0.46	-0.03
	(23.66)	(20.36)	(17.87)	(20.38)	(24.23)	(28.97)	(40.37)	(49.89)	(55.18)	(53.89)	(-13.21)	(-0.57)
$\sum_{k=1:5} \beta_k$	0.52	0.43	0.29	0.24	0.23	0.21	0.19	0.14	0.07	-0.04	0.56	0.27
	(15.26)	(14.68)	(8.92)	(8.06)	(9.13)	(9.93)	(13.09)	(11.88)	(6.11)	(-4.12)	(15.85)	(9.5)
B: Weekly	1	2	3	4	5	6	7	8	9	10	1-10	5-10
β_0	0.77	0.89	1.06	1.12	1.13	1.12	1.09	1.09	1.05	1.02	-0.25	0.11
	(24.52)	(26.58)	(23.46)	(29.37)	(35.83)	(39.9)	(50.5)	(56.61)	(59.31)	(54.1)	(-6.3)	(2.8)
$\sum_{k=1:4} \beta_k$	0.72	0.54	0.38	0.27	0.23	0.18	0.13	0.08	0.03	-0.05	0.77	0.28
	(12.05)	(14.53)	(9.42)	(7.42)	(7.25)	(6.9)	(6.83)	(4.61)	(2.34)	(-5.91)	(12.45)	(8.39)
C: Monthly	1	2	3	4	5	6	7	8	9	10	1-10	5-10
β_0	1.22	1.21	1.31	1.29	1.28	1.25	1.18	1.16	1.09	0.99	0.23	0.29
	(14.35)	(21.19)	(23.27)	(25.48)	(30.81)	(32.8)	(39.12)	(48.88)	(45.19)	(43.44)	(2.41)	(5.96)
β_1	0.59	0.40	0.29	0.19	0.17	0.13	0.10	0.07	0.02	-0.04	0.62	0.21
	(7.32)	(8.18)	(5.8)	(5.7)	(5.5)	(4.98)	(4.6)	(3.86)	(1.29)	(-3.6)	(7.32)	(5.79)

Table 2: Predictability of the size premium within characteristic-sorted portfolios

This table reports the results from regressing the size premium in period t (R_{SMLt}) on the lagged CRSP value-weighted market return in period t-1 ($R_{VW,t-1}$), within characteristic-sorted quintiles. We obtain the daily and monthly portfolio returns of stocks sorted into 5x5 groups based on size and 11 other firm characteristics from Kenneth French's Data Library. The 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 (see Internet Appendix Table IA4 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 also repeat the same regressions within the lowest and highest quintiles of stocks sorted on each firm characteristic provided by Kenneth French. t-statistics based on Newey-West standard errors are reported in parentheses. The sample period is 1963-2014..

			Monthly			Daily		
Characteristic		*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 ***	(8.81)	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 ***	(5.01)	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: 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 long in large firms and short in small firms following a negative market return. Size deciles are sorted annually at the end of June on the previous year based on stocks' market capitalizations. The first three columns show the results based on a strategy that trades the 1st (smallest) and 10th (largest) size deciles, with daily, weekly or monthly portfolio rebalancing. Columns 4 to 6 (7 to 9) show the same results when the returns on the small firm is based on the 2nd (5th) size decile. 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 (unconditional size premium). Adjustments/year refers to the average number of portfolio adjustments the strategy requires annually. t-statistics are reported below the coefficients in parentheses and are based on Newey-West standard errors. The sample period is 1963-2014..

	Spillover strategy			"2-10" Spillover strategy			"5-10" Spillover strategy			Size
	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Daily	Weekly	Monthly	Premium
Monthly Return	3.7 %	3.1 %	1.7 %	3.1 %	2.5 %	1.2 %	1.9 %	1.3 %	0.6 %	0.6 %
Sharpe Ratio	0.69	0.62	0.28	0.66	0.61	0.24	0.53	0.42	0.18	0.12
Skewness	1.06	0.43	-0.42	1.16	0.40	-0.78	1.00	0.35	-0.45	-0.86
Kurtosis	17.79	8.78	9.85	21.45	9.07	10.15	28.54	6.43	7.04	17.71
α_{CAPM}	4.0 % ***	3.3 % ***	1.9 % ***	3.3 % ***	2.6 % ***	1.4 % ***	2.1 % ***	1.3 % ***	0.7 % ***	0.6 %
	(12.44)	(12.66)	(6.88)	(10.83)	(12.79)	(6.56)	(8.42)	(7.11)	(4.81)	(1.1)
$\alpha_{4\text{-}Factor}$	4.2 % ***	3.3 % ***	2.1 % ***	3.5 % ***	2.7 % ***	1.5 % ***	2.1 % ***	1.4 % ***	0.8 % ***	0.3 %
	(10.84)	(11.72)	(7.36)	(10.1)	(11.12)	(6.47)	(8.2)	(7.21)	(4.54)	(0.78)
Adjustments/year	113.6	25.9	6.5	113.6	25.9	6.5	113.6	25.9	6.5	1

Table 4: ETF spillover strategy

This table reports the results from regressing the monthly returns of size-based ETF portfolios on the Fama-French-Carhart factors and the prior month's value-weighted market return. $ETF_{SML,t}$ is the monthly return spread between an equal-weighted portfolio consisting of three small-cap ETFs *(iShares Russell 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 of a strategy that is long in small-cap ETFs and short in large-cap ETFs following a positive market return, and 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 parentheses. The sample period is 2002-2014.

	$ETF_{Spillover,t}$	$ETF_{SML,t}$	$ETF_{SML,t}$
α	0.49 % **	-0.02 %	0.0019
	(2.54)	(-0.34)	(1.13)
$R_{VW,t-1}$			0.13 **
			(2.51)
$R_{VW,t} - R_{f,t}$	-0.18 ***	0.03	
	(-3.13)	(1.25)	
SMB_t	0.32 **	0.99 ***	
	(2.27)	(30.3)	
HML_t	0.02	0.14 ***	
	(0.16)	(3.35)	
UMD_t	-0.01	0.02	
	(-0.18)	(0.58)	
Adj. R^2	0.08	0.91	0.04

Table 5: Time-variation in spillover returns

This table reports the results from regressing returns of the daily spillover strategy (See Table 3 for details) on various measures of aggregate 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), cumulative value-weighted market returns over the prior three months, and the commonality in turnover measure *Turnover-*R^2. t-statistics are reported below the coefficients in parentheses and are based on Newey-West standard errors..

	Spillover strategy	Spillover strategy	Spillover strategy	Spillover strategy	Spillover strategy	Spillover strategy
Intercept	-0.015 *	0.023 ***	0.038 ***	0.040 ***	0.015 ***	-0.033 ***
	(-1.76)	(4.68)	(17.35)	(17.06)	(3.05)	(-2.98)
VIX_{t-1}	0.287 ***					0.218 ***
	(7.01)					(4.37)
$TED\ spread_{t-1}$		0.026 ***				0.031 ***
		(4.03)				(3.35)
$PS\text{-}liquidity_{t-1}$			-0.135 ***			0.000
			(-3.46)			(-0.01)
$R_{t-1:t-3}$ (3 months)				-0.061 **		0.070
				(-2.23)		(1.63)
$Turnover\text{-}R^2_{t-1}$					0.121 ***	0.062 *
					(5.22)	(1.95)
Adj. R^2	0.139	0.042	0.017	0.006	0.041	0.176
Period	1990-2014	1986-2014	1968-2014	1963-2014	1963-2014	1990-2014

Table 6: Delays in institutional trading activity

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

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

$$TURN^{L}_{f,t} = \mu_f + \delta_t + \gamma_{i0} TURN_{f,t} + \sum_{k=1}^{5} \gamma_{ik} TURN_{f,t-k} + \omega_{f,i,t} \quad \text{(b)}$$

where $TURN_{f.t}$ is the dollar trading volume by institution *f* on day *t* as a percentage of market capitalization of the traded stocks. $TURN^{S}_{f,t}$ and $TURN^{L}_{f,t}$ are the same measures for small and large firms denoted with superscripts *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 of the previous year, 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 (or sell) transactions are included. *t*-statistics are reported in parentheses and are based on two-way clustered standard errors at date and institution level. The sample period is 2000-2010.

	All transactions		Buy transactions		Sell transactions	
	Small	Large	Small	Large	Small	Large
$TURN_{f,t}$	0.42 ***	0.74 ***	0.44 ***	0.69 ***	0.45 ***	0.66 ***
	(16.81)	(27.87)	(18.21)	(26.9)	(18.97)	(23.53)
$TURN_{f,t-1}$	0.03 ***	-0.001	0.03 ***	-0.003	0.02 ***	-0.001
	(4.14)	(-0.36)	(5.65)	(-0.65)	(4.15)	(-0.1)
$TURN_{f,t-2}$	0.03 ***	-0.01 **	0.02 ***	-0.002	0.02 ***	-0.002
	(4.94)	(-2.06)	(4.0)	(-0.84)	(3.88)	(-0.8)
$TURN_{f,t-3}$	0.02 ***	-0.01 **	0.02 ***	-0.01	0.01 **	-0.002
	(3.25)	(-2.17)	(3.32)	(-1.52)	(2.08)	(-0.15)
$TURN_{f,t-4}$	0.03 ***	0.00	0.02 ***	-0.003	0.02 ***	-0.01 ***
	(3.7)	(-1.23)	(3.47)	(-0.94)	(3.64)	(-3.29)
$TURN_{f,t-5}$	0.03 ***	-0.001	0.02 ***	-0.004 *	0.02 ***	-0.002
	(4.1)	(-0.16)	(4.23)	(-1.7)	(2.82)	(-0.53)
Observations	362635	362635	362635	362635	362635	362635
Adj. R^2	0.41	0.74	0.38	0.69	0.36	0.66
Institution fixed effects	yes	yes	yes	yes	yes	yes
Date fixed effects	yes	yes	yes	yes	yes	yes

Table 7: 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 following each trade. 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 its next trade in the same stock is on day *t+k*, and zero otherwise. Additionally, we define $split_{f,i,t,t+k}$, which is equal to 1 if institution *f* trades stock *i* on day *t+k* in the same direction as on 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. The reported percentages give the probabilities that institutions split their trades, conditional on trading the stock again *P(split|trade)*. Panel B reports the result from regressing the daily cross-sectional average of $split_{f,i,t,t+1}$ across all stocks and institutions, on its own daily lag and on the prior day's market return, for small and large stocks and for buy and sell trades separately. t-statistics based on Newey-West standard errors are reported in parentheses. The sample period is 2000-2010..

A: Probability of splitting trades					
k	1	2	3	4	5
Small stocks	88 %	79 %	75 %	74 %	73 %
Large stocks	77 %	70 %	69 %	68 %	68 %
Small-Large	11 % ***	9 % ***	7 % ***	6 % ***	5 % ***
	(13.3)	(6.2)	(3.8)	(4.5)	(4.0)

B: Daily percentage of split trades	Small stocks		Large stocks	
	Buy	Sell	Buy	Sell
	$\%split_{t+1}$	$\%split_{t+1}$	$\%split_{t+1}$	$\%split_{t+1}$
Intercept	0.591 ***	0.586 ***	0.381 ***	0.566 ***
	(15.60)	(16.88)	(12.34)	(21.00)
AR(1)	0.333 ***	0.338 ***	0.505 ***	0.241 ***
	(7.76)	(8.72)	(12.66)	(6.99)
$R_{VW,t}$	0.313 **	-0.306 **	0.164	-0.200 *
	(2.36)	(-3.1)	(1.29)	(-1.66)
Observations	2765	2765	2765	2765
Adj. R^2	0.111	0.115	0.255	0.058

Table 8: Mutual fund scandal and changes in 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 fund's 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 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 parentheses 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 USD (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)	(1.7)	(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)	(0.6)
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 USD (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)	(7.3)	(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)	(-2.2)	(-3.82)	(-3.41)	(-1.23)
Observations	312	312	312	312	312	312
Fund fixed effects	yes	yes	yes	yes	yes	yes

Table 9: Mutual fund flows and return predictability

Based on quarterly snapshots of mutual fund ownership and monthly fund flows, we sort stocks each month into terciles by the stock's ownership-weighted inflows normalized by the stock's market capitalization. This table reports monthly returns, alphas from a CAPM regression (α_{CAPM}) and from a Fama-French-Carhart 4-factor regression ($\alpha_{4-Factor}$) for value-weighted portfolios including stocks in the inflow and outflow terciles of small (deciles 1-5) and large (deciles 6-10) stocks separately. Panel A reports "in-sample" returns on portfolios during the month in which the flows are realized. Panel B reports returns on portfolios sorted by flows in the prior month. t-statistics are reported below the coefficients in parentheses and are based on Newey-West standard errors. The sample period is 1990-2014.

A: Contemporaneous flows	Small stocks			Large stocks		
	Inflow	Outflow	In-Out	Inflow	Outflow	In-Out
Monthly Return	1.1 %	0.2 %	0.9 %	1.1 %	-0.1 %	1.1 %
α_{CAPM}	0.5 % **	-0.4 % **	1.0 % ***	0.6 % ***	-0.7 % ***	1.3 % ***
	(2.58)	(-2.17)	(6.94)	(5.36)	(-4.24)	(5.22)
$\alpha_{4\text{-}Factor}$	0.3 % ***	-0.6 % ***	0.9 % ***	0.5 % ***	-0.7 % ***	1.3 % ***
	(5.2)	(-4.99)	(7.43)	(4.97)	(-4.27)	(5.52)

B: Lagged flows	Small stocks			Large stocks		
	Inflow	Outflow	In-Out	Inflow	Outflow	In-Out
Monthly Return	0.9 %	0.5 %	0.4 %	0.6 %	0.7 %	-0.2 %
α_{CAPM}	0.4 % *	-0.1 %	0.5 % ***	0.1 %	0.1 %	0.0 %
	(1.92)	(-0.44)	(3.03)	(0.87)	(0.9)	(-0.23)
$\alpha_{4\text{-}Factor}$	0.2 % ***	-0.2 % *	0.4 % ***	0.0 %	0.1 %	-0.1 %
	(2.63)	(-1.93)	(3.18)	(0.43)	(0.97)	(-0.49)

Table 10: Ownership commonality and delayed adjustment of returns

At the end of June of each year, we regress the daily, weekly, and monthly returns on stock i, R_{it}, on contemporaneous and lagged value-weighted market returns, $R_{VW,t}$, and ownership-commonality weighted returns, $R_{FCAP,i,t}$, over a sample of one year:

$$R_{i,t} = \alpha_i + \beta_{i0} R_{VW,t} + \vartheta_{i0} R_{FCAP,i,t} + \beta_{i1} R_{VW,t-1} + \vartheta_{i1} R_{FCAP,i,t-1} + \varepsilon_{i,t}$$

Ownership-commonality weighted returns are the daily risk-adjusted 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 table reports the sample averages of the estimated parameters for small stocks (deciles 1-5) and large stocks (deciles 6-10) separately. The final column shows the differences in mean coefficients for small and large stocks. t-statistics are reported in parentheses and are based on two-way clustered standard errors at year and firm level. The sample period is 1980-2014.

	Daily			Weekly			Monthly		
	Small	Large	SML	Small	Large	SML	Small	Large	SML
β_0	0.783	1.006	-0.223	0.937	1.095	-0.158	1.211	1.146	0.065
	(26.1)	(60.62)	(-10.77)	(34.46)	(74.14)	(-6.44)	(38)	(47.47)	(1.65)
ϑ_0	1.269	0.737	0.532	1.319	0.750	0.569	1.430	0.707	0.722
	(67.39)	(17.93)	(12.62)	(56.31)	(18.1)	(12.4)	(27.48)	(16.15)	(10.35)
β_1	0.021	0.007	0.013	0.050	-0.024	0.074	0.042	-0.023	0.066
	(4.04)	(1.49)	(1.47)	(6.77)	(-4.44)	(6.19)	(2.15)	(-1.45)	(2.11)
ϑ_1	0.103	-0.035	0.138	0.129	-0.078	0.207	0.081	-0.070	0.151
	(9.71)	(-4.32)	(8.28)	(8.92)	(-6.59)	(8.99)	(2.53)	(-2.42)	(2.74)
R^2	0.125	0.249		0.200	0.323		0.459	0.515	