Slow trading and stock return predictability

Matthijs Lof
Aalto University School of Business

Matti Suominen
Aalto University School of Business

10/15/2015

Abstract

Market returns predict the future abnormal returns on small and illiquid stocks, implying attractive dynamic investment strategies for investors investing in the size premium or in small and illiquid stocks either directly or through exchange traded funds. We provide evidence that this return predictability is due to institutional investors' trading patterns: When rebalancing their portfolios the institutional investors initially buy (sell) relatively more the large and liquid stocks. In the case of illiquid stocks they split their orders over several days to avoid excessive price impact, thus inducing predictability in stocks returns. We provide evidence that some hedge funds exploit this return predictability.

Keywords: Liquidity, return predictability, institutional investors, hedge funds

JEL classification: G12

Both authors are from the Aalto University School of Business. Address: P.O. Box 21230, Aalto 00076, Finland, e-mails: matthijs.lof@aalto.fi and matti.suominen@aalto.fi; tel.: +358-50-4014448 (Matthijs) and +358-50-5245678 (Matti); fax: +358-9-43138678. We thank Ioanid Rosu, David Solomon and Geoffrey Tate and seminar participant at Aalto University for helpful comments and Antti Lehtinen for research assistance.

1. Introduction

Returns on large and liquid stocks predict the returns on small and illiquid stocks (See e.g. Lo and MacKinlay (1990) and Chordia and Swaminathan (2000)). We demonstrate the economic significance of these 'return spillovers' by suggesting various attractive trading strategies exploiting the predictability. We provide evidence that hedge funds are positively exposed to these strategies. Finally, we find that the return spillovers originate partly from the trading patterns of large institutional investors: While these institutions execute trades in large liquid stocks swiftly, consistent with Vayanos (2001) they split their trades in small illiquid stocks over several days to avoid excessive price impact.

Returns on the static size premium, i.e. a portfolio that is long in small stocks and short in large stocks, have been rather weak, in particular in recent decades[1]. In this paper we show that the size premium is however highly profitable when timed correctly. Exploiting the return spillovers from large to small stocks, we propose strategies that are long in the size premium following periods with positive market returns and short in the size premium following periods with negative market returns. With daily, weekly, and even monthly portfolio adjustment these strategies yield positive highly attractive abnormal risk-adjusted returns. Even low-cost versions of such strategies that rely only on long positions in small-cap exchange traded funds (ETFs) yield positive abnormal returns.

---

[1] Asness et al. (2015) however find a stronger and more robust size premium when controlling for various "quality" factors of firms.

While earlier research has argued that the predictability of small-stock returns can be due to informed traders trading in the more liquid stocks and the information therefore being first revealed in the liquid stocks, see e.g. Chordia, Sarkar, and Subrahmanyam (2011), we provide evidence of a supplementary force behind the return predictability. Our results suggest that the return predictability is partly due to institutional investors' trading patterns: When rebalancing their portfolios the large investors initially buy (sell) relatively more the large stocks, where they can quickly increase or reduce their overall risk exposure. In the case of the small stocks, in turn, they split their orders over several days. When the institutions have large buying or selling needs both in the liquid and illiquid stocks this leads to predictability in stocks returns. This result provides evidence supporting for the model by Vayanos (2001), who finds that investors optimally slow down trades in small illiquid stocks to avoid price impact. Consistent with this theory, we find that the returns spillovers are larger during periods when market liquidity is low.

This paper is organized as follows. Section 2 presents the data. In Section 3 we document the lead-lag relation between large capitalization stock returns and small market capitalization stock returns. In Section 4 we show also that this predictability implies highly attractive trading strategies, some of which can be executed with low cost ETFs. We provide here also evidence that this lead lag relation is stronger in illiquid markets. In Section 5 we investigate the lead-lag relations in trading volume and provide evidence that the observed return predictability can be related to institutional investors' trading patterns. In section 6 we demonstrate that some hedge funds exploit the return predictability by increasing their exposure to the small stocks after good returns in the stock market. Section 7 concludes the paper.

2. Data

We obtain daily returns and trading volumes (number of shares traded multiplied by the closing price) from the CRSP daily stock file for all common stock listed on NYSE, AMEX and NASDAQ over the period 1964-2014 (12711 days, 2657 weeks, 607 months). We disregard the most infrequently traded stocks by only considering stocks that had positive trading volume on at least 200 days in the previous calendar year. We adjust for delisting bias by including delisting returns from the CRSP daily event file.[2]

Stocks are sorted into deciles sorted by size (from large to small), measured by market capitalization at the last trading day of June of the previous calendar year. For each decile, we compute value-weighted average returns, and total trading volume. For most of the analysis of trading volume, the portfolios are aggregated into large-cap (decile 1, 2 and 3), mid-cap (decile 4, 5, 6 and 7) and small-cap (decile 8, 9 and 10) portfolios. Besides sorting on size, we also sort stocks on Amihud's illiquidity measure of the previous calendar year.

We 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

---

[2] When the delisting return is missing, and the delisting is performance-related, we follow Shumway (1997) by imposing a return of -30%.

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). It has been used extensively in recent 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 volume in CRSP.

From the ANcerno data, we obtain buying and selling volume at the level of the individual institutions and calculate the aggregate level buying and selling volumes daily for large-, mid-, and small-cap stocks. The analysis with ANcerno data covers the period 2006-2010, for which we can identify institutions and obtain reliable matching with stock characteristics obtained from CRSP.

3. A lead-lag relation in large/small stock returns

Table 1 presents dynamic cross-correlations $correlation(R_{X,t-1}, R_{Y,t})$ describing the lead-lag relations between daily, weekly and monthly returns on different size deciles. The lead-lag predictability from large stocks to small stocks (upper diagonal part of the table) is clearly larger than the reverse predictability from small stocks to large stocks. The statistical significance of this predictability is assessed by means of Granger Causality tests. First we run bivariate vector autoregressions (VAR) for all possible combinations of size deciles including calendar dummies. We then test whether returns in each size decile predicts (Granger causes) returns in other deciles, controlling for the deciles' own lags and calendar effects. Shaded areas in Table 1 indicate that the null hypothesis (No Granger causality) is rejected at the 5% level mainly when we test predictability from larger market capitalization deciles to smaller market capitalization deciles (i.e.: in the upper diagonal part of the table). Our finding of Granger causality does not only apply to the tails, but holds over the entire size distribution. In line with the findings in Lo and MacKinlay (1990) and Chordia and Swaminathan (2000), therefore, we find that the returns of larger stocks predict returns of smaller stocks at Daily, Weekly and Monthly frequencies.

<TABLE 1 HERE>

In Table 2 we show additional evidence related to the lead-lag relations in the stock market, now from stock market returns to the returns on large and small stocks. Similarly as Chordia & Swaminathan (2000) we first perform a test for a lead-lag relation that was originally presented in Dimson (1979). We regress the difference of returns of the smallest and largest size deciles (the size premium: $R_{size,t}$) on the value weighted market return ($R_{M,t}$) and its five leads and lags:

$$R_{size,t} = \alpha + \sum_{i=-5}^{5} \beta_i \, R_{M,t+i} + \epsilon_t$$

According to Dimson (1979) a negative contemporaneous beta and positive sum of lagged betas implies that large stocks adjust more rapidly to market wide new information than small stocks. Table 2 reports the results and shows that we find indeed positive sums of lagged betas on all frequencies, and negative contemporaneous betas for daily and weekly returns. Returns of small caps therefore react with a lag to value-weighted average market returns. This result is consistent with Table 1, as the value weighted average market return is mostly determined by large stocks.

<TABLE 2 HERE>

In line with the previous, in Table 3 we document systematic return predictability from market returns to size factor returns - and Amihud ILLIQ factor returns - using a yet different methodology. It presents the time-series averages of coefficient estimates from cross-sectional Fama-Macbeth regressions, where stock returns are explained with the three Fama-French factors and the Amihud ILLIQ factor. In addition to the unconditional time series averages, Table 3 presents also the average factor slope coefficients conditional on the sign of the previous month's market return. As the results in Table 3 show, the size premium prevails only following good stock market returns in the previous month. Similarly the Illiquidity premium is most dominant following good market returns.

<TABLE 3 HERE>

4. Time Variation in the Size Premium

Having confirmed the return predictability in small stocks we consider whether this predictability can be utilized in trading. We find highly attractive trading strategies on small stocks, and on the size premium (small minus big portfolio) conditioning on the historical stock market returns. In Figure 1 we show the returns on a dynamic trading strategy that makes use of the lead lag relationship between market returns and size premium. The first part of the figure shows the cumulative returns to investing in the long short portfolio that is long in the small and short the large stocks (size premium) only on days following a positive market return, and only on days following a negative market return. For comparison we plot also the cumulative returns to a continuous investment in the size premium in this figure. [3]

<FIGURE 1 HERE>

The second part of Figure 1 shows the cumulative returns to a dynamic long-short strategy, which we call spillover strategy (returns from large stocks spilling over to small stocks), that is long the size premium following days, weeks or months with positive market returns but short the size premium following days, weeks or months with negative market returns. Finally, the third part of Figure 1 shown the returns to these strategies if we skip one day following the signal prior to taking positions. The returns are highly attractive even in the monthly rebalanced portfolio despite skipping one day after the signals, providing evidence that these returns are not merely due to infrequent trading of securities.

Average returns, Sharpe-ratios and risk adjustment based on the Fama-French-Carhart 4 factor model for the spillover strategy are given in Table 4. The spillover strategy does not only yield high returns, the returns are not strongly correlated with the risk factors, leading to large alphas. Results are again qualitatively similar with daily, weekly and monthly

[3] In the Appendix (Figure A1), we reproduce the first part of Figure 1 with weekly and monthly reblancing, and allowing for a one-day skip after the signal prior to taking positions.

portfolio rebalancing, and remain largely intact after replacing the size premium ("10-1") portfolio by the "9-2" portfolio that is long in the 9th decile of stocks sorted by size and short the 2nd decile of stocks sorted by size. This shows that the result is a market wide phenomenon and is not solely driven by the tails of the distributions.

<TABLE 4 HERE>

Next, as our spillover strategy might have large trading costs, we consider below also the returns to an alternative, easily implementable ETF spillover trading strategy on ETFs on Russell 2000 or on other small market capitalization stock ETFs. Here we compare the returns to a long only strategy of holding ETFs only during months after positive or negative market returns. The strategy of buying ETFs only after positive market returns yields significantly higher risk-adjusted returns than a buy-and-hold strategy on the same ETFs (the annualized Carhart 4 factor alpha being 6% compared to -1% on average from a simple Buy-and-Hold strategy over the same period and -6% for a strategy that invests in the ETFs only following months with negative market returns). The long-only spillover strategy in ETFs provides alpha for investors even after transaction costs as it is with monthly adjustment and the trading costs in ETFs especially for institutional investors are negligible.

<TABLE 5 HERE>

Our results imply that there is significant time variation in the size premium and returns on small and illiquid stocks. Our results based on ETFs strongly suggest that investors could have utilized this time variation in expected returns in their portfolio management as the differences in risk adjusted expected returns easily outweigh the costs of trading.

Next, let us look at time variation in our spillover strategy returns. Table 6 shows the results from regressing the returns on our daily spillover strategies on the aggregate time-varying liquidity measure by Pastor and Stambaugh (2003), γ_t. Both contemporaneous and lagged liquidity measures significantly predict spillover returns negatively: return spillovers are larger during and following periods of illiquidity. Table 6 further shows that this negative correlation between return spillovers and liquidity holds for both components of the spillover strategy: Liquidity reduces the size premium on days following a positive market return, while liquidity increases the size premium on days following a negative market return.

<TABLE 6 HERE>

These result support the idea that the return predictability is caused by the investors' delayed trading of small illiquid stocks as was argued in the introduction. During periods of low liquidity, slowing down the trading of illiquid stocks may be more desirable or even inevitable. As a result, the return predictability increases during these illiquid periods, leading to higher returns on our spillover strategy. In the next section, we provide evidence that institutional investors indeed delay the trading of small and illiquid stocks.

5 Source of predictability: lead-lag relations in volume

5.1. Effect of aggregate level volume shocks

The predictability in small stocks' abnormal returns has been attributed in the previous research to the fact that small stocks and large stocks are traded at different times (e.g. Chordia, Sarkar, and Subrahmanyam, 2011 and Badrinath et al., 1995). Given this, we first study whether there are volume spillovers from market volume to the volume of small stocks in the sense that trading volume of small-cap stocks reacts with a delay to a market volume shock. We define a market volume shock as the log-difference in total market trading volume (from CRSP) and average trading volume over the previous 3 months:

$$VolShock_{M,t} = \log\left(\frac{TotalMarketVol_t}{\frac{1}{n}\sum_{j=1}^{n} TotalMarketVol_{t-j}}\right), \qquad (1)$$

where *n=63* (daily data), *n=13* (weekly data) or *n=3* (Monthly data). We are interested in how the relative volume of small stocks and large stocks responds to general market volume shocks. Instead of considering the trading volume in all 10 size deciles, we now divide the stocks into three groups based on their market capitalization: large-cap stocks (size deciles 1, 2 and 3), mid-cap stocks (deciles 4, 5, 6 and 7) and small-cap stocks (decile 8, 9 and 10). Our main variable of interest is the daily fraction of the total market wide trading volume that occurs in these three groups of stocks (for instance, what fraction of daily volume takes place in small-cap stocks on any given day).

In panel A of Table 7 we regress daily changes in these three fractions of total trading volume (i.e., fractions of large-cap, mid-cap, and small-cap trading volume) on the market volume shock of the previous day. Market volume shock was defined in Equation (1) above. Results in Panel A of Table 6 show that a positive market volume shock predicts an increase in the share of trading in small-cap stocks and mid-cap stocks during the next day, while a decrease in the relative volume of large-cap stocks. This suggests a volume spillover from market trading volume to small stocks' trading volume in the sense that the relative volume of small stocks increases after a day of abnormally high market trading volume. Similar results are obtained with weekly or monthly frequencies (available upon request). The right side of panel A shows the results from the same three regressions using a shorter sample period (2006-2010). The results are qualitatively similar, but less significant.

<TABLE 7 HERE>

These results are consistent with hypothesis that the lead-lag patterns from large stock to small stock returns could be caused by the traders first trading the large stocks following news and the small stocks only later.

To examine further the channels in volume spillovers from large stocks to small stocks and the role of institutions in creating these predictive patterns, we study the ANcerno transaction data. First, we look at the aggregate institutional buying and selling volumes. Similar to the previous we compute aggregate institutional buying or selling shocks. First, in line with Equation (1), we calculate the institutions' buy and sell volumes relative to their three months moving averages, using ANcerno transaction data (and take the logarithm of these variables). After this, to identify the buying and selling shocks that are specific to institutional investors, we regress these measures on the Market volume shock, $VolShock_{M,t}$, defined in (1). Our aggregate institutional buying shocks $BuyVolShock_{Inst,t} = \varepsilon^{Buy}_{Inst,t}$ are then defined by the residual from the regression:

$$\log\left(\frac{TotalInstitutionalBuyVol_t}{\frac{1}{n}\sum_{j=1}^{n} TotalInstitutionalBuyVol_{t-j}}\right) = \delta_1 + \delta_2 VolShock_{M,t} + \varepsilon^{Buy}_{Inst,t} \qquad (2)$$

Similarly, we run the following regression for the sell side volumes:

$$\log\left(\frac{TotalInstitutionalSellVol_t}{\frac{1}{n}\sum_{j=1}^{n} TotalInstitutionalSellVol_{t-j}}\right) = \delta_1 + \delta_2 VolShock_{M,t} + \varepsilon^{Sell}_{Inst,t}, \qquad (3)$$

and define an aggregate institutional sell shocks as the residual from this regression: $SellVolShock_{Inst,t} = \varepsilon^{Sell}_{Inst,t}$.

We then run regressions to explain daily changes in the relative institutional Buy and Sell volumes in large-, mid-, and small-cap stocks on both the institutional buying and selling shocks (2-3) as well as the aggregate market volume shock that was defined Equation (1). Panel B of Table 7 shows the results of these regressions. It seems that institutional buying and selling volume shocks have similar volume spillovers as total market volume shocks had in Panel A of Table 6: Following institutional buy (sell) shocks, the relative buying (selling) of mid-cap and small-cap stocks increases, while the buying (selling) of large-cap stocks declines. Interestingly, the composition of institutional trading volume does not respond significantly to a general market volume shock, only to the institution specific buy and sell volume shocks.

5.2. Effect of institution specific buy and sell volume shocks

Finally, we disaggregate the ANcerno trading volume into institution-specific buy and sell volumes and derive measures of institutions specific buy and sell volume shocks. More precisely, we derive institution-specific buy and sell volume shocks by regressing (logs of) the ratios of institution-specific buy or sell volumes to their three month averages on Market volume shock (1) and aggregate institutional Buy and Sell shocks (2-3) as defined below:

$$\log\left(\frac{BuyVol_{i,t}}{\frac{1}{n}\sum_{j=1}^{n} BuyVol_{i,t-j}}\right) = \delta_1 + \delta_2 VolShock_{M,t} + \delta_3 BuyVolShock_{Inst,t} + \delta_4 SellVolShock_{Inst,t} + \varepsilon_{i,t}^{Buy} \qquad (4)$$

and

$$\log\left(\frac{SellVol_{i,t}}{\frac{1}{n}\sum_{j=1}^{n} SellVol_{i,t-j}}\right) = \delta_1 + \delta_2 VolShock_{M,t} + \delta_3 BuyVolShock_{Inst,t} + \delta_4 SellVolShock_{Inst,t} + \varepsilon_{i,t}^{Sell} \qquad (5)$$

An institution specific buy shock for institution i is defined as the residual from the regression (4): $BuyVolShock_{i,t}$ = $\varepsilon_{i,t}^{Buy}$ and a Sell shock for institution i is defined as the residual from the regression (5): $SellVolShock_{i,t}$ = $\varepsilon_{i,t}^{Sell}$.

When looking at institution-level buying and selling data, the results, presented in Table 8, show strong evidence that institutions buy (sell) first large liquid stocks and later small illiquid stocks. The relative volume of institutional mid cap and small cap buying (selling) increases after an idiosyncratic volume shock to institution-specific aggregate buying (selling) activity. In these regressions we control for market wide volume shocks and aggregate institutional buy and sell shocks. The responses to these aggregate shocks are far smaller in both magnitude and significance than the volume-spillovers at the institution specific level.

<TABLE 8 HERE>

The lead-lag patterns in volume and returns seem to be therefore at least partially driven by the same traders buying first large stocks and then small stocks. This somewhat contradicts with Badrinath et al. (1995), who claim that the predictability is driven by institutions trading before non-institutional traders. It is however exactly in line with the model by Vayanos (2001), which predicts that large traders execute trades slowly, to reduce price impact.

Finally we identify from ANcerno data all sequences in which an institution is a net seller or buyer of stocks for multiple subsequent days. We identify 31190 of such buying sequences and 30530 selling sequences for a total of 464 institutions, over the period 2006-2010 (After 2011, client codes are not available in ANCERNO). For each day of the sequence, we compute the institution-specific buy (sell) volume in large-cap, mid-cap and small-cap stocks as percentages of total institution-specific buy (sell) volume. These percentages are regressed on the day of the sequence, i.e. on the duration of the sequence up to that point. The results of these panel regressions are presented in table 9.

<TABLE 9 HERE>

The results in table 9 show that as an institutional buying sequence proceeds, the relative buying volume of large-cap stocks for that institution decreases, while the relative volume of mid-cap and small-cap stocks increases. This confirms our earlier finding that institutions buy first large liquid stocks and then only later small illiquid stocks, inducing spillovers in both volume and returns from large to small stocks. Looking at selling sequences, the results are qualitatively similar, although smaller in magnitude and insignificant.

6 Hedge Funds' exposure to the spillover strategy returns

We examine if the hedge funds in the TASS-Lipper data with investment styles Equity Market Neutral and Equity Long-Short are exposed to our Spillover strategy. That is, whether some hedge funds time their exposure to the size premium. Our sample runs from January 1994 until June 2014.

More precisely, we look at a long/short spillover strategy that is long in small stocks and short in large stocks during days following a positive market return over the past five days, while reversing to being long in large stocks and short in small stocks following a negative market return over the past five days. We also look at a long-only spillover strategy that consists only of the long part of the above spillover strategy. We then perform a similar analysis as Jylhä et al. (2014) by running time-series regressions where we regress hedge funds' returns on these spillover strategies' returns, controlling for the seven Fung and Hsieh (2004) risk factors and the Sadka (2006) liquidity shock. Finally, to allow some time for the hedge funds to trade we look at the returns to this spillover strategy not only immediately after its formation, but after skipping one to five days.

<TABLE 10 HERE>

We find in line with our expectation that some hedge funds seem to be timing their size premium investments to benefit from the return predictability that arises as small stock returns lag the market returns. The percentage of hedge funds in the Equity Market Neutral and Equity Long-Short investment styles that have a statistically significant exposure to the Spillover strategy's return on the next day after portfolio signals is 6%, roughly same as the amount of hedge funds that have a negative exposure to the Spillover strategy. Both percentages exceed the 2.5% that would be expected without any relation between hedge funds returns and the returns on the Spillover strategy. When we look at the returns to the

Spillover strategy portfolio after skipping some days following the signals we find that more hedge funds are positively exposed to the Spillover strategy returns. Overall the percentage of funds with positive exposure to the spillover strategy's returns on zero to five days after the signals is nearly 22%, higher than the corresponding figure for the funds with negative exposure to the spillover strategy which is 17%.

When we look at the hedge funds exposure to the long only spillover strategy the evidence is clearer. Now more than 30% of hedge funds have a positive exposure to at least one of the Spillover strategy return series, in contrast to only 9% that have a negative exposure to those return series.

These positive exposures to the spillover strategy that we find and the fact that the hedge funds' exposure to Spillover strategy rises gradually after the signals are clear evidence to us that some hedge funds time their investments in small stocks to take benefit of the return spillovers.

7 Conclusion

In this paper we investigate the lead-lag relations between liquid and illiquid stocks and the predictability of the size premium. We find that small stocks and the size premium (long-short portfolio) perform well after positive market returns or high returns to large and liquid stocks. This predictability implies the existence of attractive trading strategies to trade the size premium, or just illiquid stocks or ETFs. Consistent with the idea that the return predictability is due to slow trading by institutions, we document similar spillovers in volume. We find also that individual institutions trade first liquid and then illiquid securities contributing to the volume and return spillovers. Finally, we show evidence that abnormally many hedge funds are exposed to the spillover strategy suggesting that some hedge funds dynamically time their size premium investments to take advantage of the return predictability.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1), 31-56.

Asness, C. S., Frazzini, A., Israel, R., Moskowitz, T. J., & Pedersen, L. H. (2015). Size Matters, if You Control Your Junk. Working paper.

Badrinath, S. G., Kale, J. R., & Noe, T. H. (1995). Of shepherds, sheep, and the cross-autocorrelations in equity returns. *Review of Financial Studies*, *8*(2), 401-430.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57-82.

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2011). Liquidity dynamics and cross-autocorrelations. *Journal of Financial and Quantitative Analysis*, 46(03), 709-736.

Chordia, T., & Swaminathan, B. (2000). Trading volume and cross-autocorrelations in stock returns. *Journal of Finance*, 913-935.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, *7*(2), 197-226.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), 55-84.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607-636.

Fung, W. and Hsieh, D. (2004) Hedge fund benchmarks: a risk based approach, *Financial Analyst Journal* 60, 65–80.

Jylhä, P., Rinne, K., & Suominen, M. (2014). Do Hedge Funds Supply or Demand Liquidity?. *Review of Finance*, 18(4), 1259-1298.

Lo, A. W., & MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction?. *Review of Financial studies*, *3*(2), 175-205.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, 111(3), 642-685.

Puckett, A., & Yan, X. S. (2011). The interim trading skills of institutional investors. *The Journal of Finance*, 66(2), 601-633.

Sadka, R. (2006) Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk, *Journal of Financial Economics* 80, 309–349.

Vayanos, D. (2001). Strategic trading in a dynamic noisy market. *Journal of Finance*, 131-171.

Tables and Figures

Table 1: Cross-Correlations and Granger Causality

This table reports the lead-lag relations *correlation*($R_{X,t-1}$,$R_{Y,t,}$), where X is the size decile on the left and Y is the size decile on top. Positive entry in upper diagonal indicates that Large leads Small and in the lower diagonal that Small leads Large. The shaded areas indicate Granger Causality at the 5% significance level. Rejection frequencies of no Granger causality (*H0*: X does not Granger cause Y) at 1%, 5% and 10% are reported at the bottom of each Panel separately for the upper diagonal (Large -> Small) and Lower diagonal (Small -> Large) entries. Granger Causality tests are computed from a bivariate Vector Autoregressive Model (VAR) for Daily/Weekly/Monthly returns for each combination of different Size deciles including month and weekday (for daily data) dummies on the right hand side. Lag length of the VAR is selected by Bayesian Information Criteria (maximum 5 lags). Granger test statistics are estimated with a Heteroscedasticity and Autocorrelation Consistent covariance matrix.

A: Daily

X\Y	Large	P2	P3	P4	P5	P6	P7	P8	P9	Small
Large	.	0.13	0.12	0.12	0.11	0.11	0.14	0.22	0.25	0.25
P2	0.01	.	0.12	0.11	0.11	0.11	0.15	0.24	0.28	0.28
P3	0.01	0.12	.	0.11	0.11	0.11	0.15	0.25	0.28	0.29
P4	0.01	0.10	0.10	.	0.10	0.10	0.14	0.24	0.28	0.29
P5	0.00	0.10	0.09	0.09	.	0.10	0.14	0.24	0.28	0.29
P6	0.00	0.09	0.09	0.09	0.09	.	0.14	0.24	0.28	0.30
P7	0.00	0.08	0.09	0.09	0.09	0.10	.	0.24	0.29	0.30
P8	0.00	0.09	0.10	0.11	0.12	0.13	0.17	.	0.30	0.32
P9	0.00	0.08	0.10	0.11	0.12	0.14	0.18	0.26	.	0.33
Small	-0.01	0.07	0.07	0.09	0.10	0.12	0.16	0.24	0.29	.

Rejection Frequency	1%	5%	10%
Upper diagonal	0.80	0.93	0.93
Lower diagonal	0.33	0.44	0.56

B: Weekly

X\Y	Large	P2	P3	P4	P5	P6	P7	P8	P9	Small
Large	.	0.03	0.05	0.08	0.09	0.10	0.13	0.18	0.21	0.21
P2	-0.05	.	0.05	0.09	0.11	0.13	0.16	0.21	0.25	0.26
P3	-0.05	0.03	.	0.08	0.10	0.13	0.16	0.22	0.26	0.27
P4	-0.05	0.02	0.04	.	0.10	0.12	0.16	0.22	0.26	0.27
P5	-0.04	0.04	0.05	0.09	.	0.13	0.17	0.23	0.27	0.29
P6	-0.05	0.03	0.04	0.08	0.10	.	0.17	0.22	0.27	0.29
P7	-0.06	0.01	0.03	0.06	0.09	0.11	.	0.21	0.26	0.28
P8	-0.07	0.01	0.03	0.06	0.09	0.11	0.16	.	0.26	0.29
P9	-0.06	0.01	0.03	0.07	0.09	0.11	0.16	0.22	.	0.30
Small	-0.08	-0.01	0.01	0.05	0.07	0.10	0.14	0.20	0.25	.

Rejection Frequency	1%	5%	10%
Upper diagonal	0.42	0.64	0.69
Lower diagonal	0.00	0.09	0.16

C: Monthly

X\Y	Large	P2	P3	P4	P5	P6	P7	P8	P9	Small
Large	.	0.08	0.10	0.12	0.12	0.13	0.15	0.17	0.19	0.22
P2	0.06	.	0.12	0.15	0.16	0.17	0.20	0.24	0.27	0.29
P3	0.06	0.10	.	0.14	0.16	0.17	0.19	0.24	0.27	0.30
P4	0.06	0.10	0.10	.	0.14	0.15	0.18	0.24	0.27	0.29
P5	0.04	0.08	0.09	0.11	.	0.15	0.17	0.23	0.26	0.29
P6	0.04	0.08	0.07	0.10	0.11	.	0.15	0.21	0.24	0.27
P7	0.04	0.08	0.08	0.11	0.12	0.14	.	0.21	0.25	0.27
P8	0.04	0.07	0.07	0.09	0.11	0.13	0.15	.	0.25	0.28
P9	0.04	0.08	0.08	0.10	0.12	0.13	0.15	0.20	.	0.27
Small	0.03	0.06	0.05	0.07	0.08	0.10	0.11	0.17	0.20	.

Rejection Frequency	1%	5%	10%
Upper diagonal	0.00	0.20	0.38
Lower diagonal	0.00	0.00	0.07

Table 2: Dimson regressions

This table shows the contemporaneous beta β_0 and sum of lagged betas $\beta_{-5:-1}$ from Dimson (1979) regressions of the daily/weekly/monthly spread between small and large stock returns on contemporaneous value-weighted market returns and five lags and leads of market returns. Heteroscedasticity and Autocorrelation Consistent standard errors are shown in italics below the coefficients.

Daily		*Weekly*		*Monthly*	
β_0	$\beta_{-5:-1}$	β_0	$\beta_{-5:-1}$	β_0	$\beta_{-5:-1}$
-0.362 ***	0.616 ***	-0.057	0.721 ***	0.273 ***	0.386 ***
0.007	*0.016*	*0.042*	*0.069*	*0.064*	*0.117*

Table 3: Fama-MacBeth regressions

This table reports the result of Fama-MacBeth regressions of monthly stock returns on Beta, Size, Book-to-Market and Amihud Illiquidity. Panel A reports the full-sample time-series average of the slopes from the monthly cross-sectional regressions. Panel B shows the subsample time-series averages conditional on the sign of the value-weighted market return during the previous month. T-statistics based on Heteroscedasticity and Autocorrelation Consistent standard errors are shown below the coefficients in italics.

A: Full sample	*BETA*	*SIZE*	*B/M*	*ILLIQ*
Time-series average	2.3680	-0.3890	2.0750 ***	1.5130 ***
	0.91	*-1.06*	*2.86*	*3.51*
B: Conditional	***BETA***	***SIZE***	***B/M***	***ILLIQ***
($R_{M,t-1} > 0$)	8.2190 ***	-1.8350 ***	2.6980 ***	2.3150 ***
	2.78	*-4.05*	*3.04*	*4.29*
($R_{M,t-1} < 0$)	-6.9720 *	1.9180 ***	1.0800	0.2320
	-1.83	*3.45*	*1.00*	*0.32*

Table 4: Spillover strategy

This table reports annual returns, annualized Sharpe-ratios and results from a Fama-French-Carhart 4-factor regression for a strategy that is long in small stocks and short in large stocks during periods following a positive market return, while reversing to being long in large stocks and short in small stocks 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 and 10th size deciles, with daily, weekly, or monthly portfolio adjustments. Columns 4 to 6 show the same results based on trading the 2nd and 9th size deciles. The final column shows a passive annually adjusted strategy that is long in the 10th decile and short the 1st decile of stocks sorted by size (Size premium). Adjustments/year refers to the average number of portfolio adjustments the strategy requires annually. This includes the first period of the year when the stocks are sorted on size, and all periods following a change of sign of the market return. Sample: 1964-2014. T-statistics based on Heteroscedasticity and Autocorrelation Consistent standard errors are shown below the coefficients in italics.

	Spillover strategy			"9-2" Spillover strategy			Size
	Daily	*Weekly*	*Monthly*	*Daily*	*Weekly*	*Monthly*	Premium
Return	52 %	41 %	21 %	20 %	27 %	13 %	4 %
Sharpe Ratio	2.86	2.12	0.94	1.70	1.98	0.85	0.28
α	0.48 ***	0.43 ***	0.23 ***	0.23 ***	0.27 ***	0.14 ***	0.00
	14.70	*9.41*	*6.85*	*7.39*	*7.85*	*6.03*	*0.01*
Mkt-Rf	-0.30 ***	-0.15	-0.10	-0.20 ***	-0.02	-0.03	-0.03
	-3.88	*-1.30*	*-1.17*	*-4.11*	*-0.22*	*-0.57*	*-0.62*
SMB	0.00	0.46 **	0.24	-0.08	0.25 **	0.16	1.82 ***
	0.02	*2.58*	*1.33*	*-0.97*	*2.44*	*1.34*	*21.44*
HML	0.10	0.08	-0.01	-0.05	-0.03	0.00	0.26 **
	0.77	*0.44*	*-0.04*	*-0.53*	*-0.21*	*0.03*	*2.28*
MOM	-0.30 ***	-0.17	-0.20 **	-0.21 ***	-0.01	-0.15 **	0.02
	-4.38	*-1.31*	*-2.01*	*-3.72*	*-0.08*	*-2.14*	*0.31*
adj R^2	0.11	0.06	0.02	0.08	0.02	0.02	0.64
adjustments/year	113.6	25.9	6.5	113.6	25.9	6.5	1

Table 5: ETF strategies

This table reports the annual return, Sharpe ratio (SR) and Fama-French-Carhart 4-factor alpha for various small-stock ETFs. The first three columns are based on a static long position in the ETF, while columns 4 to 6 are based on a strategy that is long in the ETF only during months following a positive value weighted market return, and in cash (with zero interest) in other months. The final 3 columns are based on a strategy that is long in the ETF only during months following a negative value weighted market return, and in cash (with zero interest) in other months. T-statistics based on Heteroscedasticity and Autocorrelation Consistent standard errors are shown in italics below the alpha estimates.

	all months			(RM,t-1 > 0)			(RM,t-1 < 0)		
	Return	SR	α	Return	SR	α	Return	SR	α
ISHARES-RUSSELL-2000	8 %	0.49	0.00	9 %	0.73	0.05 *	-1 %	0.03	-0.05 *
from 2000-06 (T=169)			*0.11*			*1.92*			*-1.82*
SPDR-RUSSELL-SMCAP-COMPL	10 %	0.60	0.02	10 %	0.82	0.07 **	0 %	0.07	-0.04
from 2005-12 (T=103)			*1.39*			*2.11*			*-1.25*
PROSHARES-ULTRA-RUSSELL2000	3 %	0.30	-0.07 ***	12 %	0.55	0.07	-8 %	-0.07	-0.14 *
from 2007-02 (T=89)			*-3.93*			*0.94*			*-1.66*
SPDR-S&P600-SMALL-CAP	10 %	0.58	0.02 **	10 %	0.78	0.06 *	0 %	0.08	-0.04
from 2005-12 (T=103)			*2.06*			*1.85*			*-1.21*
VANGUARD-SMALL-CAP	10 %	0.60	0.02 ***	9 %	0.72	0.05 *	1 %	0.15	-0.03
from 2004-02 (T=125)			*2.88*			*1.70*			*-1.00*
ISHARES-MORNINGSTAR-SMALL-CP	10 %	0.58	0.01	9 %	0.71	0.05	1 %	0.15	-0.04
from 2004-08 (T=119)			*1.02*			*1.61*			*-1.09*
WISDOMTREE-INTL-SMALLCAP-DIV	6 %	0.40	-0.01	7 %	0.56	0.05	-1 %	0.03	-0.05
from 2006-07 (T=96)			*-0.14*			*1.17*			*-1.25*
PROSHARES-ULTRA-SMALLCAP600	7 %	0.37	-0.02	13 %	0.58	0.09	-6 %	-0.02	-0.12
from 2007-02 (T=89)			*-1.09*			*1.25*			*-1.49*
SPDR-S&P-INTL-SMALL-CAP	2 %	0.22	-0.04	5 %	0.42	0.03	-3 %	-0.08	-0.07
from 2007-05 (T=86)			*-1.01*			*0.78*			*-1.60*

Table 6: Spillover returns and Liquidity

This table reports the results from regressing the monthly returns from the spillover strategy and its various components on the Pastor-Stambaugh (2003) Aggregate Liquidity Measure (γ). The first column shows the effect of the monthly liquidity measure γ on contemporaneous monthly returns of the spillover strategy with daily adjustment. The second columns show the predictive power of the previous month's liquidity. Columns 3 and 4 show the effects of contemporaneous and lagged liquidity on the size premium, on days following a positive market return. Columns 5 and 6 show the effects of contemporaneous and lagged effect on the size premium, on days following a negative market return. Columns 7 and 8 show the effects of contemporaneous and lagged effect on the size premium on all days. Sample: 1964-2014. T-statistics based on Heteroscedasticity and Autocorrelation Consistent standard errors are shown below the coefficients in italics.

	Spillover strategy	Spillover strategy	Size premium ($R_{M,t-1} > 0$)	Size premium ($R_{M,t-1} > 0$)	Size premium ($R_{M,t-1} < 0$)	Size premium ($R_{M,t-1} < 0$)	Size premium	Size premium
intercept	0.03 ***	0.03 ***	0.02 ***	0.02 ***	-0.01 ***	-0.02 ***	0.01 **	0.00
	11.28	*12.11*	*8.04*	*8.51*	*-6.31*	*-7.25*	*2.00*	*1.19*
γ_t	-0.39 ***		-0.13 ***		0.23 ***		0.11 **	
	-8.49		*-3.83*		*6.63*		*2.10*	
γ_{t-1}		-0.13 ***		-0.03		0.10 ***		0.06
		-3.21		*-1.05*		*2.98*		*1.25*
adj R^2	0.20	0.02	0.13	0.00	0.03	0.02	0.01	0.00

Table 7: Aggregate Volume spillovers

Panel A is based on CRSP data and shows using regression analysis the effect of a market wide volume shock on the changes in small-cap, mid-cap, and large-cap trading volumes. Small-cap, mid-cap, and large-cap trading volumes are measured as percentages of total market volume. The market volume shock $Vol_{M,t}$ is defined as the log-difference between total market volume on day *t* and the average volume over the previous three months. The right hand side of Panel A shows the same three regressions for a shorter sample period. *Panel B* shows the effects of aggregate institutional buy- and sell-shocks as well as the effect of the market-wide volume-shock on the daily changes in aggregate institutional buying and selling volumes in small-cap, mid-cap, and large-cap stocks. The institutional Buy and Sell shocks, $BuyVolShock_{Inst,t}$ and $SellVolShock_{Inst,t}$, are defined in a similar way as the Market volume shock $VolShock_{M,t}$ in Panel A using total aggregate institutional buying and selling volumes. The Buy and Sell shocks are however orthogonalized w.r.t. the Market volume shock $VolShock_{M,t}$. The Market volume shock $VolShock_{M,t}$ is the same as in Panel A. The institutions' buy and sell volumes and the aggregate buy and sell volume shocks are based on ANcerno data. Buy and sell volumes in the size terciles are measured as percentages of total buy or sell market volumes. T-statistics based on Heteroscedasticity and Autocorrelation Consistent standard errors are shown in italics below the coefficients.

A: Market Volume (CRSP)

	Fractions of Market Volume			*Fractions of Market Volume*		
	Large Cap	Mid Cap	Small Cap	Large Cap	Mid Cap	Small Cap
$VolShock_{M,t-1}$	-0.68 ***	0.53 ***	0.15 ***	-0.13	0.10	0.04 **
	-11.40	*10.50*	*7.59*	*-1.45*	*1.18*	*2.28*
Weekday dummies	yes	yes	yes	yes	yes	yes
Month dummies	yes	yes	yes	yes	yes	yes
Period	1964-2014	1964-2014	1964-2014	2006-2010	2006-2010	2006-2010
Observations	12711	12711	12711	1259	1259	1259

B: Aggregate Institutional Buy and Sell Volume (ANCERNO)

	Fractions of Aggregate Institutional Buy Volume			*Fractions of Aggregate Institutional Sell Volume*		
	Large Cap	Mid Cap	Small Cap	Large Cap	Mid Cap	Small Cap
$BuyVolShock_{Inst,t-1}$ (Aggregate)	-2.70 ***	2.63 ***	0.07	0.04	-0.02	-0.02
	-5.03	*5.02*	*1.58*	*0.09*	*-0.04*	*-0.87*
$SellVolShock_{Inst,t-1}$ (Aggregate)	0.00	0.02	-0.02	-2.75 ***	2.64 ***	0.11 ***
	0.00	*0.04*	*-0.37*	*-5.99*	*5.81*	*4.28*
$VolShock_{M,t-1}$ (Total market)	0.29	-0.27	-0.02	-0.36	0.36	0.00
	0.83	*-0.79*	*-0.57*	*-1.37*	*1.37*	*0.06*
Weekday dummies	yes	yes	yes	yes	yes	yes
Month dummies	yes	yes	yes	yes	yes	yes
Period	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010
Observations	1259	1259	1259	1259	1259	1259

Table 8: Institutional Volume spillovers

This table shows the effects of institution specific buy- and sell-shocks, aggregate institutional buy- and sell-shocks (defined in Panel B of Table 5) as well as the effect of the market-wide volume-shock (defined in Panel A of Table 5) on the daily changes in institution specific buying and selling volumes in small-cap, mid-cap, and large-cap stocks. The institution-specific Buy (Sell) shock $BuyVolShock_{i,t}$ ($SellVolShock_{i,t}$) is defined as the log-difference between total buy (sell) volume on day t by institution i in deviation from the average buy volume over the previous three months (Source: ANcerno) and are orthogonalized w.r.t. the market volume shock and aggregate institutional buy and sell volume shocks. T-statistics based on standard errors clustered at the institution level are shown in italics below the coefficients.

	Fractions of Institution-specific Buy Volume			*Fractions of Institution-specific Sell Volume*		
	Large Cap	Mid Cap	Small Cap	Large Cap	Mid Cap	Small Cap
$BuyVolShock_{i,t-1}$ (Institution-specific)	*-3.93* ***	*3.62* ***	*0.31* ***	*0.19* ***	*-0.13* **	*-0.06* ***
	-53.61	*50.00*	*14.24*	*2.95*	*-2.10*	*-3.61*
$SellVolShock_{i,t-1}$ (Institution-specific)	*0.35* ***	*-0.29* ***	*-0.06* ***	*-3.68* ***	*3.33* ***	*0.35* ***
	5.74	*-4.85*	*-4.12*	*-50.41*	*45.95*	*15.09*
$BuyVolShock_{Inst,t-1}$ (Aggregate)	*-1.50* ***	*1.40* ***	*0.11*	*-1.86* ***	*1.80* ***	*0.07*
	-3.02	*2.82*	*1.09*	*-3.90*	*3.78*	*0.74*
$SellVolShock_{Inst,t-1}$ (Aggregate)	*0.20*	*-0.25*	*0.06*	*0.38*	*-0.25*	*-0.13*
	0.47	*-0.63*	*0.64*	*0.83*	*-0.54*	*-1.59*
$VolShock_{M,t-1}$ (Total market)	*-0.95* **	*0.85* **	*0.11*	*-1.49* ***	*1.42* ***	*0.06*
	-2.53	*2.31*	*1.25*	*-3.66*	*3.48*	*0.66*
Institution fixed effects	yes	yes	yes	yes	yes	yes
Weekday fixed effects	yes	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes	yes
Period	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010
T (days)	1259	1259	1259	1259	1259	1259
N (institutions)	466	466	466	466	466	466

Table 9: Buy and Sell sequences

This table shows how institution specific Buy or Sell volume in large-cap, mid-cap and small-cap stocks evolves during an institution-specific buying or selling sequence. A buying (selling) sequence is defined as a period of at least two days during which a specific institution is a net buyer (seller) for each consecutive day. Large-cap, mid-cap and small-cap buy or sell volume are expressed as a percentage of total buy or sell volume by that specific institution during the same day (Source: ANcerno). These percentages are regressed on a variable "Day of sequence" that measures the number of trading days since the beginning of the sequence. T-statistics based on standard errors clustered at the institution level are shown in italics below the coefficients.

	Fractions of Buy Volume during Buy sequences			*Fractions of Sell Volume during Sell sequences*		
	Large-Cap	Mid-cap	Small-cap	Large-Cap	Mid-cap	Small-cap
Day of sequence	-0.215 ***	0.204 ***	0.011	-0.066	0.057	0.008
	-4.13	*4.01*	*1.23*	*-0.91*	*0.75*	*0.73*
Institution fixed effects	yes	yes	yes	yes	yes	yes
Weekday fixed effects	yes	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Period	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010	2006-2010
Number of institutions	464	464	464	458	458	458
Number of Sequences	31190	31190	31190	30530	30530	30530

Table 10: Hedge Fund Exposure

This table presents the summary statistics of the coefficients from regressing hedge funds' monthly returns on the returns to a long/short spillover strategy, or on the returns to a long-only spillover strategy, while controlling for the seven Fung and Hsieh (2004) risk factors and the Sadka (2006) liquidity shock. The long/short spillover strategy is long in small stocks and short in large stocks during days following a positive market return over the past five days, while reversing to being long in large stocks and short in small stocks following a negative market return over the past five days. The long-only spillover strategy consists only of the long part of the spillover strategy. We consider 6 alternative versions of the strategies allowing for zero up to five days being skipped following the signal prior to taking positions.

"Mean" gives the average of the coefficients for all funds, "Negative" ("Positive") gives the proportion of coefficients that are significantly negative (positive) at a 5% level using Heteroscedasticity and Autocorrelation Consistent standard errors. For means, the t-statistics for the test of zero mean are given in italics. For the proportion of negatives and positives, the figures in italics are z-statistics testing whether the proportion is equal to 2.5%, which it would be under no exposure to the spillover strategy. Figures significant at a 5% level are depicted in bold. "Cumulative" after *i* days shows the cumulative percentage of funds that have a statistically significant exposure to at least one of the spillover strategies with at most *i* days skipped following the signal prior to taking positions. The sample includes all hedge funds in the TASS database with investment style "Long/Short Equity" or "Equity Market Neutral" over the period January 1994 to June 2014.

	Long/Short spillover strategy					*Long-only spillover strategy*				
				Cumulative					Cumulative	
	Mean	Negative	Positive	Negative	Positive	Mean	Negative	Positive	Negative	Positive
0 days	-0.01	5.5 %	5.8 %	5.5 %	5.8 %	0.06	3.7 %	12.8 %	3.7 %	12.8 %
	-1.69	*4.14*	*4.45*			*7.56*	*1.97*	*9.63*		
1 day	0.00	4.3 %	5.5 %	8.4 %	9.6 %	0.07	3.7 %	17.1 %	5.5 %	20.4 %
	0.77	*2.78*	*4.14*			*9.78*	*1.97*	*12.11*		
2 days	0.01	4.2 %	7.3 %	10.9 %	13.5 %	0.07	3.3 %	15.6 %	6.4 %	23.5 %
	2.03	*2.65*	*5.74*			*9.69*	*1.37*	*11.26*		
3 days	0.03	3.0 %	7.5 %	12.6 %	17.9 %	0.09	3.2 %	17.9 %	6.9 %	27.7 %
	5.63	*0.87*	*5.91*			*11.85*	*1.20*	*12.56*		
4 days	0.02	3.8 %	7.7 %	14.9 %	20.9 %	0.08	3.5 %	17.4 %	7.9 %	29.3 %
	5.07	*2.11*	*6.08*			*11.37*	*1.68*	*12.28*		
5 days	0.01	3.8 %	5.4 %	17.0 %	22.4 %	0.07	3.7 %	14.3 %	8.6 %	30.8 %
	2.32	*2.11*	*4.04*			*10.19*	*1.97*	*10.55*		

Figure 1: Spillover strategy

The black line in Figure 1A shows the cumulative returns on a passive strategy that is long in small stocks and short in large stocks (Size premium). Figure 1A shows also the cumulative returns to the Size premium separately following positive (blue) and negative (red) market returns. Figure 1B shows the cumulative returns on daily (red), weekly (purple) and monthly (green) spillover strategies that are long in small stocks and short in large stocks during periods following a positive market return, while reversing to being long in large stocks and short in small stocks following a negative market return. Figure 1C shows the cumulative returns to the daily, weekly, and monthly spillover strategies when one day is skipped following the signal prior to taking positions.

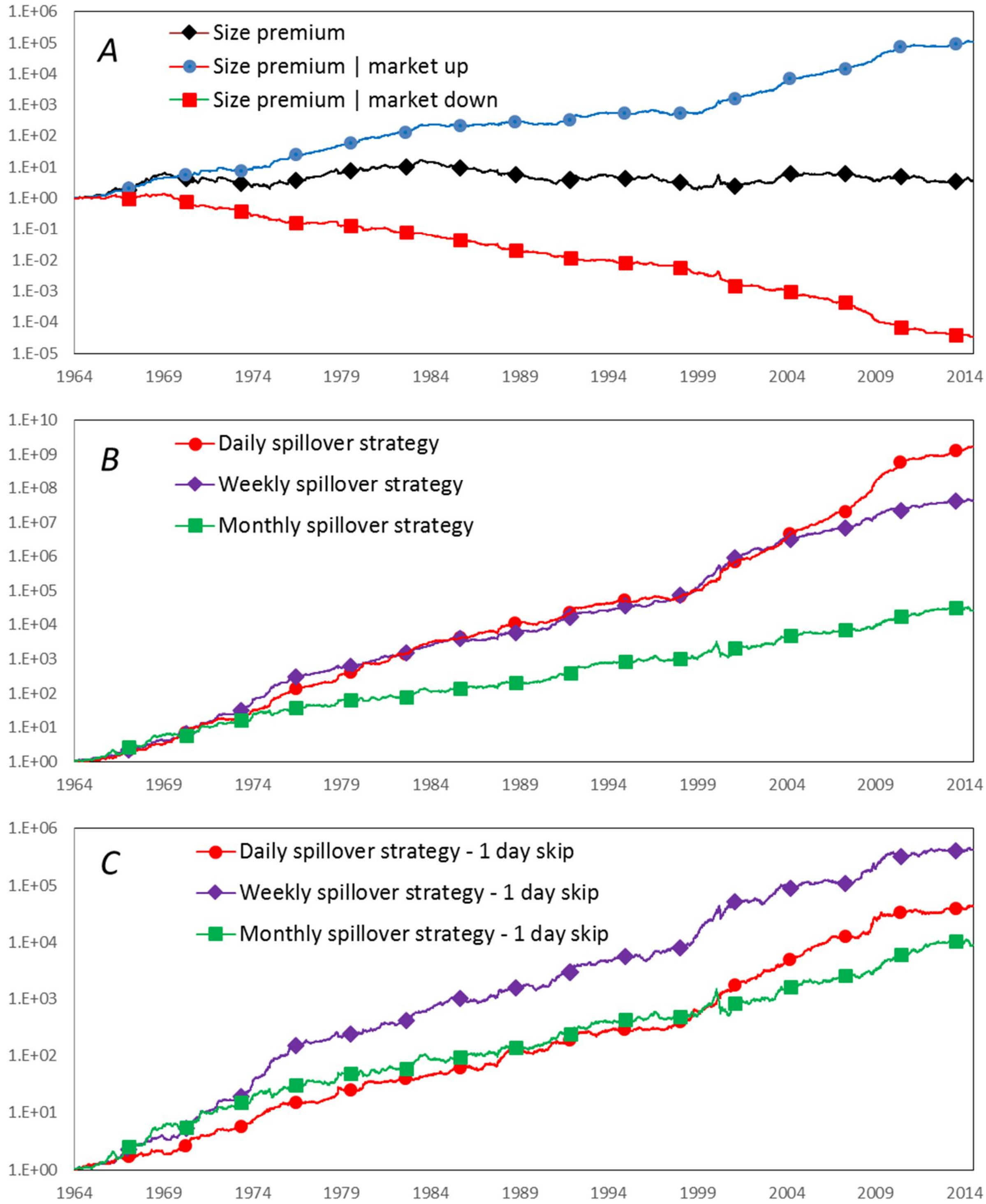

Figure A1: Return Spillovers on weekly and monthly frequency

The black line shows the cumulative returns on a passive strategy that is long in small stocks and short in large stocks (Size premium). Each figure shows also the cumulative returns to the Size premium separately following positive (blue) and negative (red) market returns. These plots are reproductions of Figure 1.A with the difference that the rebalancing is not daily, but weekly (left column) and monthly (right column). The bottom plots show the result when one day is skipped after the signal prior to taking positions.