Institutional Trading and Asset Pricing

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Abstract

The relation between beta and average return is strong and positive on days with high institutional trading activity. In contrast, on normal days, this relation is negative and statistically significant. Days with interest rate announcements also exhibit the positive relation. However, we show that the effect of institutional trading is the primary driver of the upward sloping security market line on announcement days. We explore potential explanations and find that our findings are most consistent with the leverage-constraints hypothesis.

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1. Introduction

Recent research has revisited the issue of the insignificant relation between beta and expected return. Frazzini and Pedersen (2014) suggest that the flat relation could be attributed to leverage constraints and show that a portfolio that is long low-beta stocks and short high-beta stocks is profitable. Savor and Wilson (2014) show that the relation is conditional on news announcement and document a positive relation on days with macroeconomic announcements. In this paper, we add to this recent debate and present new evidence on this relation. Using a unique Finnish dataset that records daily trading activities of all financial institutions, we find strong evidence that on days with high institutional trading volume, beta is positively related to average return. On other days, this relation is not just flat, but significantly negative. This finding cannot be attributed to size, book-to-market, momentum, short-sales constraints, liquidity effects or news announcements. Our results are most consistent with the leverage theory as put forth by Frazzini and Pedersen (2014).

We obtain data on all stocks listed on the Nasdaq OMX Helsinki Exchange over the period 1995-2011 from Euroclear Finland Ltd. (Euroclear). This dataset contains full records of all trades conducted by institutions aggregated at a daily level. We construct our measure of institutional trading (IT) activity as the fraction of total trading volume by all institutions over total market volume, and label day t as a high institutional trading day (High-IT) when the fraction of institutional trading volume on that day exceeds its average over the past quarter. We find that, on High-IT days, an increase in beta by one is associated with a significant increase in average return of about 7 basis points (bps). In contrast, on Low-IT days, we observe a significant reduction in average daily excess return of approximately 8 bps. These findings hold for beta-sorted portfolios, for size and book-to-market ratio (BM) portfolios, for industry portfolios as well as for individual stocks. The results are not driven by well-known institutional trading behaviors such as the January and turn-of-month effects (Sikes, 2014) or by Nokia's stock, which is by far the dominant and most liquid stock in the Finnish market.[1]

One possible explanation for our findings is the announcement effect documented by Savor and Wilson (2014). They show that the slope of the security market line (SML) is significantly different on days with interest rate announcements by the U.S. Federal Open Markets Committee (FOMC) versus non-announcement days. We confirm these findings in Finland using the European Central Bank (ECB) interest rate announcements. We find that, after controlling for announcement days, the positive relation between beta and average return on High-IT days remains strong and positive. Thus, our results are not a manifestation of the announcement effect. We further examine which effect is stronger and whether the IT effect can potentially explain the announcement effect. We find that the announcement effect on the CAPM disappears when we exclude High-IT days from the sample: the SML is flat on both announcement days and non-announcement days. These findings indicate that the IT effect is much stronger and drives the upward sloping SML on announcement days.

We explore three potential mechanisms that could link the institutional trading effect to the relation between beta and average return, namely the short-sale constraints hypothesis, the investor disagreement effect, and the leverage-constraints hypothesis. Firstly, days with High-IT activity may also be times when short-sales constraints are less binding, causing the market to be more efficient. Under this hypothesis, we should observe that the IT effect is stronger on the selling side of institutions' trades. We find that the effect of institutional trading is strong on High-IT buying days and very weak on Low-IT selling days, suggesting that the short-sale constraints hypothesis does not explain our findings.

The second potential explanation for our findings could be that High-IT days are

[1]We also replicate our main findings using Thomson Reuters' quarterly 13F holdings data for the U.S. markets. Using ten beta-sorted portfolios as test assets, we find that the implied market risk premium is higher on High-IT quarters than on Low-IT quarters, though the difference is weakly significant. The weak results are primarily attributable to the fact that quarterly holdings miss out important information in the high-frequency (daily) trade of institutions. We view this result as strong support for our use of Finnish daily institutional trading data as well as a robustness test that our findings do not seem specific to the Finnish market. The results using the 13F holdings data are reported in Appendix B.

also times when there is weak aggregate investor disagreement. Hong and Sraer (2014) argue that high beta stocks are more sensitive to disagreement among investors about the future of the economy, and show that the relation between beta and average return exhibits an inverted U-shape curve on days with strong disagreement. Motivated by Dzielinski and Hasseltoft (2014), we proxy for investor disagreement by news dispersion (defined as the daily standard deviation of firm-specific news tone scores provided by Thomson Reuters). In line with Hong and Sraer (2014), we find that the relation between beta and average return is significantly negative on days with strong investor disagreement. However, we find that the difference in the SML between High- and Low-IT days remains robust after controlling for investor disagreement.

Finally, we test whether the leverage-constraints hypothesis can explain our findings. Frazzini and Pedersen (2014) argue that, when investors are faced with leverage constraints, they overweigh high beta stocks, and therefore require lower average returns on those stocks. They show that the betting-against-beta (BAB) premium represents the degree of leverage constraints in the market. While institutions trade more intensively when the leverage constraint is low, High-IT days may suggest a rise in margin requirements because an increase in IT (particularly buying) activity can use up the existing funding credit in the market over time. If so, we expect a negative relation between High-IT and BAB return as well as a positive relation between lagged High-IT and BAB return. Our time-series regressions of BAB on those IT variables show that the coefficient on High-IT day is indeed negative and the coefficient on lagged High-IT day is positive. Hence, our findings in this paper are most in line with Frazzini and Pedersen (2014).

We further explore the relation between High-IT and BAB return by relating it with the relation between BAB and the TED spread (a proxy of funding conditions). Similar to Frazzini and Pedersen (2014), we find that an increase in the TED spread is associated with lower contemporaneous BAB return. When we interact the High-IT dummy with the TED spread, we find that the coefficient on this interaction term is positive. Since a high TED spread suggests that investors' funding constraints are worsening, an increase in IT (particularly buying) reduces the existing funding credit in the market over time, thereby increasing the risk that margin requirements are higher. Those results again indicate that the High-IT effect is consistent with the leverage-constraints hypothesis.

This study joins a large literature including Barber et al. (2009), Grinblatt and Titman (1989, 1993), Daniel et al. (1997), Grinblatt et al. (1995), and others to shed a positive light on the effect of institutional trading. These studies generally suggest that institutions are informed and their trades can improve intraday price discovery. Our study offers an asset pricing perspective to this literature by linking the IT effect to the relation between beta and average return. Our findings should not be interpreted to imply that the performance of institutions can be explained by the CAPM as it is not the objective of this paper to take side on this inconclusive debate.[2] Our goal is to show that the prediction of the CAPM relation is supported when (for whatever reason) there is systematically High-IT activity in the market.

Though related, this study is different from Frazzini and Pedersen (2014) in at least three important aspects. Firstly, we employ daily trading data for all institutions while they use quarterly holdings data. Using daily institutional trades gives us a more timely and accurate estimate of beta. As our data cover all institutions on the Finnish market, we can examine the effect of aggregate institutional trading on the relation between beta and average return. Furthermore, we are also able to separately study the buying and selling sides of institutional trading, which help distinguish various competing hypotheses. Secondly, the scope of our study is different. Their focus is to explore the implication of leverage constraints through the BAB portfolio. Our study is one of the first to document the stark contrast in risk premium between high and low institutional trading days. The findings suggest that institutions act as one of the channels through which leverage constraints affect the CAPM prediction. Furthermore, since individual investors typically take the opposite side of institutional trades, the results also indicate that the CAPM fails miserably when retail investors trade intensively. Thirdly and most importantly, Frazzini and Peder-

[2]Lewellen (2011) finds that institutions do not possess stock-selection skills and their performance can be explained by book-to-market and momentum factors.

sen (2014) do not consider the effect of macroeconomic announcements documented in the contemporaneous study of Savor and Wilson (2014). The announcement effect could be considered as evidence against the profitability of the BAB portfolio because the security market line is upward sloping on announcement days. We provide a reconciliation between those two studies via the effect of institutional trading.

2. Data and empirical methodology

In this section, we discuss the unique feature of our data for the Finnish market that offers daily trading records of all institutions. This gives us a comparative advantage over other U.S.-based asset pricing studies that have to rely on quarterly institutional holdings data. We then discuss the methodology that we use through out this study.

2.1. Data

This study employs the daily trading record of financial institutions for Finnish stocks from Euroclear. The daily frequency gives this study an important advantage over prior research that uses lower frequency data (e.g., mutual funds holdings or 13F quarterly institutional holdings data). Moreover, the database contains trades by all institutions (identified by a unique number of each institution aggregated at the daily level) while most U.S. data only cover large institutions (small financial firms do not file 13Fs). These features of our database allow us to compute a timely measure of the systematic impact of institutional trading. To trade on this exchange, investors must register with Euroclear, and be given a unique account. Our data consist of 187 stocks listed on the Nasdaq OMX Helsinki exchange between 1995 and 2011.[3]

We collect daily stock prices, dividends, capitalization adjustment, and the num-

[3] Exchange-traded funds (EFT) have a negligible effect on our results because, in Finland, ETFs are not as popular as in the U.S.. In 2006, there were only two ETFs listed on the Finnish market. Grinblatt and Keloharju (2001) provide a detailed description of the Euroclear database and its classification between institutions and retail investors. Their data cover two years of 1995 and 1996 for 16 largest Finnish stocks. More recently, Berkman, Koch, and Westerholm (2014) analyze a subset of under-aged accounts in this dataset.

ber of shares outstanding from Compustat Global.[4] Book values of equity are obtained from WorldScope. For tests that use the central bank's interest rate announcement, we collect scheduled days of monetary policy announcements from the European Central Bank (ECB) website from 1999 when the ECB was officially established.[5] Although tests that employ ECB announcement days are limited to the sample period between 1999 and 2011, the daily frequency of our data gives us well over 3100 trading days, with about 370,000 of stock-days observations over this shorter period. All returns are in euros, and excess returns are above the government bond yield obtained from Datastream. Betas are computed with respect to the value-weighted market return.

< INSERT TABLE 1 HERE >

Table 1 reports summary statistics for the Finnish market. The number of firms listed on the Helsinki exchange increases from an average of 79 firms per year with an average market capitalization (price times number of shares outstanding) of 389.9 million euros at the beginning of the sample to 140 firms per year with an average market capitalization of 1095.5 million euros in the final years. In total, there are 187 unique firms in the database between 1995 and 2011. The average fraction of institutional trading volume (over the total market volume) increases from 19.6% in the first five years to 37.9% in the last four years of the sample. There is also a sharp increase in sell volume by institutions after 2008 (that includes the Global Financial Crisis period). Between 2008 and 2011, institutions' sell fraction (over the total market volume) is 25.1%, which is almost double the sell fraction earlier years. The number of trading accounts held by institutions increases from 563 in the first subperiod to 722 in the third subperiod, but then decreases to 656 for the last subperiod (2008-2011). Due to the substantial rise in the trading volume in the last

[4]Following Ince and Porter (2006) and Griffin et al. (2010), filters are applied on individual stock returns in order to eliminate data errors. Specifically, returns that are greater than 100% in one day is treated as missing. If daily return that is greater than 20% and then reversed immediately in the following day, then returns on both days are treated as missing.

[5]`https://www.ecb.europa.eu/press/govcdec/mopo/previous/html/index.en.html, accessed 14 October 2014.`

subsample, we ensure in one of the robustness tests that our results are not specific to this subperiod.

2.2. Empirical methodology

The main object of our analysis is aggregate institutional trading (IT) volume, defined as the total trading volume by all institutions across all stocks normalized by the total market trading volume at the end of the day. We determine a day to be having high institutional trading (High-IT day) when that day's IT fraction is higher than its average over the past quarter.[6] One can think of our measure as a time-series dummy variable that takes a value of one on High-IT days and zero otherwise. There are 1598 High-IT days over the sample period. In some of the tests, we separately examine institutions' buying volume (abbreviated as High-IT buying) and selling volume (abbreviated as High-IT selling). However, except where the hypothesis explicitly requires separate examinations of buy and sell, all tests employ institutions' total trading volume (abbreviated simply as High-IT) and all measures are scaled by total market trading volume.

Our main empirical tests employ the two-pass Fama and MacBeth (1973) procedure for the CAPM and then examine the coefficient estimate on High- and Low-IT days.[7] Firstly, we estimate stock betas using one-year rolling regressions, adjusting for the potential effect of non-synchronous trading by using Dimson (1979) sum beta. Specifically, we run the regression $R_t = \alpha + \beta_0 R_{M,t} + \beta_1 R_{M,t-1} + \beta_2 \sum_{k=2}^{4} R_{M,t-k}/3 + \epsilon_t$, where R_t and $R_{M,t}$ are excess returns on an asset and the market index, respectively. The Dimson sum beta is then $\beta_0 + \beta_1 + \beta_2$.[8] The test assets are four beta-sorted portfolios, nine Fama and French size- and BM-sorted portfolios, five industry portfolios, and individual stocks.

We form nine size- and BM- sorted portfolios in the spirit of Fama and French (1993). Stocks are first sorted into three groups on the basis of their size (market

[6]The results are robust to using the window of one year (see the Appendix A).

[7]This methodology is similar to that of Fama and French (1992) and Savor and Wilson (2014) and is standard in the literature.

[8]Our results are robust to using no Dimson adjustment.

capitalization) at the end of June of each year. Big stocks are those in the top 30% of the market cap for the Finnish market and small stocks are those in the bottom 30%. Independently, stocks are also sorted into three groups on the basis of their book-to-market (BM) ratios. We use book values for the fiscal year ending in calendar year $t-1$, while market cap is for the end of December in calendar year $t-1$. The nine size-BM portfolios are thus the intersections of three size and three BM portfolios.

Due to the small size of the Finnish market, we are unable to form 25 portfolios as in studies conducted in the U.S. markets. Sorting stocks into three bins helps to maintain a certain level of diversification in each portfolio as well as the power of our tests.[9] For similar reasons, we form four beta-sorted portfolios and five industry portfolios using the Fama and French's SIC classifications.[10] Except for the beta-sorted portfolio that is rebalanced monthly, all other portfolios are rebalanced on a yearly basis. Our main empirical tests employ all portfolios as the left-hand side variable, bringing the number of assets to a total of 18 portfolios in a test. Using portfolios as test assets gives more precise estimates of market betas than those from individual stocks (Fama and French, 1992).

In the second-stage regression, we run the following cross-sectional regressions:

$$R^H_{i,t+1} = \gamma^H_0 + \gamma^H_1 \hat{\beta}_{i,t} \tag{1}$$

$$R^L_{i,t+1} = \gamma^L_0 + \gamma^L_1 \hat{\beta}_{i,t} \tag{2}$$

where $\hat{\beta}_{i,t}$ is the asset i's stock market beta for period t estimated in the first stage; $R^H_{i,t+1}$ is the excess return on the test asset on high institutional trading days (High-IT or High).

As we are interested in studying the marginal effect of High-IT days on the rela-

[9] Sorting stocks into fewer bins may cause the difference in performance across the portfolios to be larger as can be seen by some extreme portfolio returns in Figure 1. Although there is no reason to exclude those portfolios as we have already applied filters to our returns data, in unreported tests, we attempted to do so in the FM regression analysis and our main results do not qualitatively change.

[10] The classification is downloaded from Ken French's website $http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html$.

tion between beta and average return, we emphasize the difference in the coefficient estimate of $\gamma_1^H - \gamma_1^L$. Standard errors are computed using the Newey-West method.

Similar to Savor and Wilson (2014), we also estimate separately the following panel regression to test the difference in implied market risk premia between High-IT days and Low-IT days:

$$R_{i,t+1} = \gamma_0 + \gamma_1 \hat{\beta}_{i,t} + \gamma_2 High_{t+1} + \gamma_3 \hat{\beta}_{i,t} High_{t+1} \tag{3}$$

where $High_t$ is a dummy variable that equals one for High-IT days and zero otherwise. We compute clustered standard errors by date, which adjust for the cross-sectional correlation of the residuals. The coefficient of interest is γ_3, which shows the difference in the coefficient on betas between High- and Low-IT days. We report rolling betas in all tables that are estimated using all data over the past one year. Section 3.6 shows that the difference in betas that are estimated separately for samples of High- and Low-IT days is not economically and statistically significant to affect our results.

3. Results

Our empirical analysis focuses on the difference in market risk premia between High- and Low-IT days ($\gamma_1^H - \gamma_1^L$ in regressions (1) and (2)). We first summarize our findings in Figure 1. We formally report regression results from various portfolios in Table 2. We then employ individual stock returns as test assets. We confirm that our results are not due to a specific sample period, the January effect, or the turn-of-month effect.

3.1. Beta, book-to-market, size, and industry portfolios

Figure 1 summarizes our findings. We use one year daily returns to estimate market betas for four beta-sorted and five industry portfolios. The figure plots average excess returns on those nine portfolios against their average estimated betas. The upper graph shows the relation on High-IT days while the lower graph plots the relation on Low-IT days. There is a striking difference between the two graphs. The graph for Low-IT days shows a strong, negative relation between beta and average return. An increase in beta by one is associated with a statistically significant reduction in average daily excess return of approximately 6 basis points (bps) per day, with an associated t-statistic above three. In stark contrast, on High-IT days, the relation between beta and average return is positive. An increase in beta by one is associated with an increase in expected return of about 35bps per day.[11] Interestingly, these results suggest that beta risk becomes important only when institutions trade intensively.

Table 2 formally reports results for regressions (1) and (2) using the Fama-MacBeth procedure (the left-hand side). Panel A shows the results for four beta-sorted portfolios. On Low-IT days, the slope coefficient on beta γ_1^L is negative 7.4bps per day (t-statistic = 2). Thus, there is a significant and negative relation between beta and average return on Low-IT days. This result contrasts with the prediction of the CAPM, but is consistent with the vast majority of the literature. The asset pricing literature generally agrees that this relation is flat (see Fama and French (2014) for a review). Frazzini and Pedersen (2014) show that the flat beta creates an arbitrage opportunity for an investor, who is not leverage constrained, to buy low-beta assets and sell high-beta assets. Frazzini and Pedersen call this portfolio betting-against-beta (BAB) portfolio, which they use as a proxy for leverage constraints. Our results show that on Low-IT days, this relation is not just flat, but also downward sloping, suggesting that such trading strategy is even more profitable on Low-IT days.

There is a stark contrast between High- and Low-IT days. On High-IT days, the slope γ_1^H is positive 7.3bps per day with an associated t-statistic of 2.6, significant at the 1% level. This positive slope is consistent with the prediction of the CAPM and that beta risk is priced on High-IT days. Thus, the BAB portfolio would earn a negative return on these days. The bottom row of panel A formally tests the difference

[11] It is also interesting that the two extreme portfolios on the right-hand side of the graph exhibit contrasting performances on High- and Low-IT days. Savor and Wilson (2014) also document similar results on days with macroeconomic announcements versus non-announcement days. The difference in performance between these and the rest of portfolios may reflect that fact that, due to the small size of the Finnish market, we form fewer portfolios than other U.S. studies. The slope of the security market line is still apparent when we exclude those portfolios.

in the slope coefficient between High- and Low-IT days. The average coefficient on High-IT days is 14.7bps higher than that on Low-IT days, with a significant associated t-statistic of 3.2.

The right-hand side of panel A presents results from pooled regression (3) that tests the difference in the slope coefficient between High- and Low-IT days. Consistent with the Fama-MacBeth regression results, the coefficient on the interaction between High-IT days and beta (High*Beta) is positive and statistically significant (2.8bps, with a t-statistic of 4.7 adjusted for clustering by trading day). Thus, beta is a much more important systematic risk on High-IT days. Notice that when we control for the interaction term, the coefficient on High-IT dummy is insignificant. This suggests that the return difference of various beta-sorted portfolios across High- and Low-IT days is attributable to their portfolio betas.

Panel B adds five industry portfolios to the test and brings the total of test portfolios to nine. Consistently, we see that High-IT days exhibit strong positive relation between beta and average return. The coefficient on beta is positive 7.6bps, which is statistically significant at the 1% level. On the other hand, this coefficient is negative 8bps on Low-IT days. The pooled regression shows that a positive coefficient on the interaction term (High*Beta) of 18.9bps (t-statistic = 3.72). This suggests that adding five industry portfolios to the set of test assets does not change our conclusions that beta risk is much more important on High-IT days.

Panel C further raises the hurdle by including nine size-BM portfolios as additional test portfolios to panel B. Having more test portfolios can increase the power of our tests and strengthen our conclusions. The slope coefficient on beta is positive 7bps on High-IT days with an associated t-statistic of 2.8, significant at the 1% level. On Low-IT days, the slope is again significant and negative 8.2bps. The difference in the slope on beta between High- and Low-IT samples is 15bps with an associated t-statistic of 3.5. In the pooled regression, the coefficient on the interaction term is also positive and significant. Consequently, we conclude that the CAPM is supported in the data on High-IT days, but rejected on Low-IT days. We particularly note the significantly higher slope of beta on High-IT days than on Low-IT days.

< INSERT TABLE 2 HERE >

3.2. Excess returns on individual stocks

In this subsection, we test whether beta can explain returns on individual stocks and whether the slope on beta is still higher on High-IT days than on Low-IT days. In Table 3, we separately report results from Fama-MacBeth regressions for High-IT and Low-IT days as well as pooled regressions of realized excess return on a stock's market beta. Panels A and B include beta as the only explanatory variable. Panels C and D add log(size), log(BM), and past one-year returns as additional controls. We further control for turnover in panels E and F as a proxy for liquidity. Turnover is defined as the average daily trading volume over the past year divided by the number of shares outstanding. On each day t, we then rank stocks based on their turnover and use the rank ($Turn$) as an additional control in both Fama-MacBeth regression (panel E) and pooled regression (panel F).[12] In panels G and H, we repeat the full regressions with all controls, but exclude the Nokia from the sample. Over our sample period, Nokia is the most liquid and largest firm by market capitalization. Thus, panels G and H ensure that our results are not driven by this particular stock. Since the estimation error is higher for individual stocks than for portfolios, we emphasize the sign of the coefficient and the difference in the coefficient on beta between High- and Low-IT days.

< INSERT TABLE 3 HERE >

Panel A shows that, on High-IT days, the relation between beta and return is still positive 3.9bps with an associated t-statistic of 1.8, significant at the 10% level. The lower statistical significance reflects the estimation uncertainty when the test asset is individual stock return. In contrast, on Low-IT days, the slope coefficient on beta

[12] As a robustness test, we also proxy for the level of liquidity of a stock by the number of occurrences of zero returns over the past year. This liquidity proxy is in the spirit of Lesmond et al. (1999). Intuitively, stocks that were more illiquid over the past year should have more zero returns than those that were traded more frequently. Griffin et al. (2010) show that, in smaller and emerging markets, this type of measure captures the illiquidity and transaction costs better than other measures. Our conclusions do not change.

is negative 7.8bps (t-statistic = -3.2), significant at the 1% level. The difference in the slope on High- and Low-IT days (last row) is positive 11.7bps, which is statistically significant at the 1% level. In panel B, the coefficient on the interaction term (High*Beta) is also significantly positive. Thus, our conclusions that the implied market risk premium is much higher on High-IT days than Low-IT days still hold for individual stocks.

In panels C and D, we include log(size), log(BM), and past one-year returns as additional controls to the basic model. On High-IT days, the coefficient on beta is still positive and marginally significant. In contrast, on Low-IT days, the coefficient on beta is significantly negative. Again, the difference in the slope on beta between two samples remains statistically significant and positive. Consistent with the U.S. evidence, size is significantly negatively related to average returns. However, value stocks do not outperform growth stocks in Finland. Panel D shows that including size, BM, and past returns does not affect the positive coefficient on the interaction term (High*Beta).

Another confounding effect that may affect the trade of financial institutions is liquidity. As institutions tend to hold liquid stocks that have more efficient prices, the significant difference in the coefficient on beta between high- and Low-IT days may be a manifestation of the liquidity effect: Low-IT days may represent days with low liquidity in the market and therefore stock prices are less efficient. We argue that liquidity does not seem to significantly affect our results for two reasons. Firstly, Boehmer and Kelly (2009) show that, in their intraday analysis, institutions' trade enhances market efficiency that is beyond the effect of liquidity provision itself. Secondly, the effect of liquidity, if any, would be larger for selling than for buying activity of institutions. As we show in the next section, our results are driven by the buying, rather than selling, side of institutional trades.

Nevertheless, we attempt to control for turnover (proxy for liquidity) in panels E and F of Table 3. The coefficient on $Turn$ is positive but insignificant. Including $Turn$ does not change our conclusions. On High-IT days, the coefficient on beta is positive 4bps whereas, on Low-IT days, this coefficient is negative 7.7bps (t-statistic

= -2.82). This leads to the average difference in the slope between High- and Low-IT days of 12bps (t-statistic = 3.1). The pooled regression in panel F shows consistent results that the implied risk premium is much higher on High-IT days even after controlling for known firm characteristics.

Panels G and H repeat the regressions in panels E and F, but exclude Nokia from the sample. Our findings are not driven by the dominant stock of Nokia. The coefficient on beta is still positive on High-IT days whereas, on Low-IT days, it is significantly negative. The difference in the implied market risk premium between High- and Low-IT days also remains positive and statistically significant.

3.3. Macroeconomic announcements

Savor and Wilson (2014) find that the relation between beta and average return is strong and positive on days when there is scheduled interest rate announcement from the U.S. FOMC. This relation on non-announcement days, in contrast, is flat. Savor and Wilson argue that existing theories cannot offer explanations as to why the relation in beta risk and average returns as predicted by the CAPM only holds on announcement days.

Figure 2 confirms the findings of Savor and Wilson (2014) by separately plotting the SML on ECB monetary policy announcement days and non-announcement days between 1999 and 2011. Similar to their study, we find a positive relation between beta and average returns on announcement days. Non-announcement days, on the other hand, exhibit the well-documented negative relation. Though this announcement effect is still a puzzle in their study, one may be concerned that the effect of institutional trading is a manifestation of ECB announcement effects. The analysis in this subsection has two parts. In the first part, we start by showing in Figure 3 that the announcement effect cannot explain our findings. In the second part, we examine which effect is stronger by running regressions on various combinations of High-IT and announcement days in Table 4.

< INSERT FIGURE 2 HERE >

If the effect of institutional trading is a manifestation of the announcement effect, then we should not see the upward sloping SML on High-IT days because announcement days are now excluded from the data. Figure 3 shows clearly that the positive relation between beta and average returns is still present on High-IT days. On Low-IT days, beta is negatively related to average returns. Consequently, our results cannot be explained by macroeconomic announcements.[13]

< INSERT FIGURE 3 HERE >

Having confirmed that our results are distinct from the macroeconomic announcement effect, it would be interesting to examine whether the effect of institutional trading is stronger and can potentially explain the puzzle of Savor and Wilson (2014). Table 4 formally reports regression results for various test portfolios that are separately estimated on High- and Low-IT days, conditioned on those days being announcement or non-announcement days. Panel A reports results for total IT volume. As we are also interested in finding out which side of institutional trades drive the announcement effect, we separately present estimation results for IT buying volume in panel B and IT selling volume in panel C. As before, we define a day to High-IT buying (selling) if day t's buying volume (scaled by total market volume) is greater than its average over the past quarter.

Panel A1 contrasts the slope coefficient on beta on days that are both High-IT total volume and having announcements (abbreviated as "Yes" day) versus all other days (abbreviated as "No" day). (One can think of our "Yes" day as a time-series dummy variable that takes the value of one if the day is High-IT and an announcement day and zero otherwise ("No" day)). On Yes days, the coefficient on beta is positive and statistically significant. In contrast, on normal ("No") days, the relation between beta and average return is flat. The difference in betas between two samples is thus positive and significant as shown in the last row of panel A1 as well as the interaction

[13]Lucca and Moench (2014) document a drift on the day before FOMC announcement. In unreported robustness tests, we exclude both ECB day and pre-ECB day. Our conclusions do not change: the upward sloping SML is still strong on High-IT days even after excluding both days from the analysis. Thus, the results are not a manifestation of the effect of interest rate announcements.

term in the pooled regression.

Panel A2 considers days that are both Low-IT and having announcement (Yes day) versus all other days (No day). Thus, this panel is meant to study the effect of macroeconomic announcements when the day is also Low-IT. If the announcement effect is robust and strong, we should see a significant and positive coefficient on "Yes" days. Surprisingly, the effect of macroeconomic announcements becomes statistically insignificant. Although the coefficient on beta is still positive on announcement days and negative on non-announcement days, they are both small and insignificant. The difference in beta between two types of days is also statistically insignificant (t-statistic = 1.2). The pooled regression also shows similar results with the coefficient on the interaction term between announcement day dummy and beta is almost zero. Consequently, when the day is a Low-IT day, the CAPM is still not supported even if it has macroeconomic announcements.

For completeness, panel A3 examines days that are High-IT and having no announcement (Yes day) versus "No" days. This panel therefore tests whether the effect of institutional trading is still robust even when the day does not have any macroeconomic announcement. High-IT days indeed exhibit a positive relation between beta and average return while, on other days, this relation is significantly negative. Although the intercept is on High-IT days is positive and statistically significant, we show shortly that this is caused by the selling side of the institutions' trade. The last row of panel A3 reports the difference in the slope on beta between High- and Low-IT days, which is positive 25bps with an associated t-statistic of 2.7. In pooled regression results, the coefficient on the interaction term (High*Beta) is also positive and statistically significant. Consequently, these results show that the effect of High-IT days is stronger than the macroeconomic announcement effect.

< INSERT TABLE 4 HERE >

Panel B repeats the analysis for institutional buying volume, rather than total volume. The general conclusion from panel B is that the results in panel A are even stronger when we employ IT buying volume. Specifically, panel B2 contrasts the slope on beta between Yes days (with Low-IT and announcement) and No days (all other days). The results show that the effect of macroeconomic announcements becomes insignificant when the announcement day is also a Low-IT day. The relation between beta and average return is flat for all types of days and the difference in slope of beta between announcement and non-announcement days is statistically zero. In pooled regression, the coefficient on the interaction term between announcement day dummy and beta is again insignificantly different from zero.

Panel B3 shows that the effect of High-IT buying days is robust to the control of announcement days. On Yes days (with High-IT and no announcement), the relation between beta and average return is strongly positive even though the day does not have macroeconomic announcements. The intercept is statistically insignificant from zero. In contrast, on other days, the slope coefficient on beta is negative 16bps with an associated t-statistic of -2.5. The difference in the slope between High- and Low-IT days is positive 28bps, which is statistically significant at the 1% level. The pooled regression estimate shows consistent results that the implied market risk premium is much higher on High-IT days than on Low-IT days.

Panel C replicates the findings in Panel A using institutional selling volume, rather than total volume. Panel C1 considers days that are High-IT selling and having announcements versus all other days (No days). If the announcement effect is strong and robust, we should see a significant and positive coefficient on beta on Yes days. Interestingly, the Fama-MacBeth regression shows that the slope coefficient on beta is flat on all types of days even though the day has announcement. The difference in the slope between Yes and No days is 3bps with an insignificant t-statistic of 0.9. Although the pooled regression shows that the coefficient on the interaction term is still positive and significant, it is much weaker than the corresponding estimate in panel B1.

Panel C2 examines days that are High-IT selling, but having no announcements (Yes days) versus all other days (No days). Again, on Yes days, the coefficient on beta is insignificant, though positive, even though the day has interest rate announcement. The difference in the coefficient on beta between Yes and No days is positive and statistically significant. The slightly higher significance comes from the fact that days with low selling volume can be associated with high buying volume, and therefore the results partly pick up the effect of the buying side. Panel C3 shows that when there is no announcement, High-IT selling days do not exhibit a strong, positive relation between beta and average return. These results suggest that the effect of institutional trading on the CAPM relation is attributable to the buying, not selling, activity.

In short, this subsection has shown that the effect of institutional trading (particularly buying) is a bigger driver of the upward sloping SML on macroeconomic announcement days. If the announcement effect is a puzzle as argued by Savor and Wilson (2014), then the explanation can be traced to the high institutional trading activity.

3.4. Turn-of-month and January effects

To examine whether our results are due to the institutional trading regularity throughout the calendar year as institutions are known to pursue window dressing behavior (Sikes, 2014), we exclude days that are turn-of-month from the analysis. Figure 4 contrasts the SML between high- and Low-IT days that exclude turn-of-month days. High-IT days still exhibit the positive relation between beta and average return while Low-IT days show the negative relation. On High-IT days, an increase in beta of the portfolio by one is associated with an rise in average return of 35bps per day (t-statistic = 7.02). On Low-IT days, an increase in beta by one is associated with a decrease in average return of 7bps per day (t-statistic = -3.8). These results suggest that the turn-of-month behavior is not the explanation.

< INSERT FIGURES 4 and 5 HERE >

To complete the analysis, Figure 5 also plots similar graphs that exclude the month of January in order to account for the well-known January effect (Sias and Starks, 1997). Again, outside January, High-IT days still show strong support for the CAPM while Low-IT days indicate the CAPM failure in explaining the average return. On High-IT days, an increase in beta of the portfolio by one is associated with an rise in average return of 27bps per day (t-statistic = 5.14). On Low-IT days, an increase in beta by one is associated with a decrease in average return of 5.5bps per day (t-statistic = -2.9). We conclude that regularities in stock returns throughout the calendar year cannot explain our findings.

3.5. Subsample analysis: pre- and post-2008

The summary statistics in Table 1 show that there is an increase in trading volume of institutions over the period between 2008 and 2011 that covers the Global Financial Crisis. Consequently, this subsection examines whether our results are attributable to this later period by looking at two subsamples: pre- and post-2008.

< INSERT TABLE 5 HERE >

Table 5 reports results from Fama-MacBeth regressions and pooled regressions that are estimated using samples before (panel A) and after 2008 (panel B). As before, estimates are reported separately for High- and Low-IT days and test assets are four beta-sorted, nine size-BM, and five industry-sorted portfolios. The general conclusion is that the difference in implied market risk premium between High- and Low-IT days remains positive and statistically significant in all subsamples. In panel A, on High-IT days, the slope on beta is positive 14bps with an associated t-statistic of 2.1. On Low-IT days, the slope is negative 6bps, though statistically insignificant. The difference in the coefficient on beta between two samples is 21bps with a significant associated t-statistic of 2.6. The pooled regression also shows that the coefficient on the interaction term is positive 26bps (t-statistic = 6.1).

We see a similar picture in panel B for the period between 2008 and 2011. The relation between beta and average return is still strong and positive on High-IT days while this relation is significantly negative on Low-IT days. The pooled regression also shows that the implied market risk premium is much higher on High-IT days than on Low-IT days. Consequently, the effect of institutional trading is not specific to a subsample period.

3.6. Betas on High- versus Low-IT trading days

Betas in the analysis above are estimated using data of both high and Low-IT trading days. As pointed out by Savor and Wilson (2014), this method may bias our results because betas are not conditioned on the type of day. The difference in average returns between High- and Low-IT days can be driven by the difference in betas on those days, and not because of high institutional trading per se.

In order to rule out this possibility, we follow Savor and Wilson (2014) to examine the difference in betas that are estimated separately using either data on High-IT days or Low-IT days. We should expect to see this difference in betas to be small. Table 6 reports those betas for four beta-sorted portfolios (panel A) and nine size-BM portfolios (panel B). We also present the average beta on Low-IT days as a reference point.

< INSERT TABLE 6 HERE >

For beta-sorted portfolios in panel A, betas on High-IT days are lower than those on Low-IT days, though the difference is not significant for any of the portfolios. Panel B shows average estimates for nine size- and BM-sorted portfolios. The average beta on High-IT days is smaller than that on Low-IT days in all portfolios, but again the difference is statistically insignificant.

In short, this subsection has shown that, similar to the findings of Savor and Wilson (2014), using the same data to estimate betas on both High- and Low-IT days does not affect our findings. In unreported results, we can also confirm that our conclusions are robust to using individual stocks as test assets.

4. Discussion of other potential explanations

This section examines various mechanisms through which High-IT could affect the relation between beta and average return. Specifically, we investigate three potential candidates: the short-sale constraints hypothesis, the investor disagreement effect, and finally the leverage-constraints hypothesis.

4.1. Short-sale constraints hypothesis

In this subsection, we examine whether short-sale constraints can explain our findings. High-IT days could be times when short-sale constraints are less binding and therefore stocks are priced more efficiently on those days. Nagel (2005) uses quarterly institutional holdings (13F) in the U.S. and argues that stocks with high institutional holdings are easier to short sell. In an intraday analysis, Boehmer et al. (2008) and Boehmer and Wu (2013) find that short selling activities tend to be more informed and enhance price discovery. Although our data do not allow us to identify short sales, under this hypothesis, we should observe that the IT effect is stronger on the selling side of institutional trading. Consequently, we separately examine institutions' buying volume and selling volume. As before, we label a day to High-IT buying (selling) if day t's buying volume (scaled by total market volume) is greater than its average over the past quarter. We then repeat the exercise in Table 2 that runs Fama-MacBeth regressions and pooled regressions to test the difference in the slope coefficient on beta between High- and Low-IT days. (Even though subsection 3.3 also separately examine buying and selling volume, those results are conditioned on announcement days.)

< INSERT TABLE 7 HERE >

Panel A of Table 7 reports regression results for High- and Low-IT buying days. On High-IT days, the coefficient on beta is positive for all test portfolios, ranging from 8bps to 8.7bps with associated t-statistics ranging from 2.8 to 3. These coefficients are even more significant than those reported in Table 2 for IT total trading volume. The picture is reversed on Low-IT days with all coefficients on betas are significantly negative. This leads to the difference in the slope between High- and Low-IT buying days to be significantly positive. In all test portfolios, this difference is about 17bps and the associated t-statistic all above 3. Consistently, the pooled regression shows that the coefficient on the interaction between High-IT buying days and beta (High*Beta) is all positive and t-statistic (clustered by trading day) above 5. Consequently, our results are stronger on High-IT buying days.

Panel B of Table 7 reports regression results for High- and Low-IT selling days. The general picture arises from this panel is that the stark contrast in the slope on beta between High- and Low-IT selling days becomes statistically insignificant and economically small. On High-IT days, the slope on beta in Fama-MacBeth regresions is economically small, though positive. For the test using all portfolios in panel B3, the intercept is even statistically significant on High-IT selling days. The pooled regression, however, shows positive and significant coefficient on the interaction term (High*Beta). Nevertheless, the magnitude is much smaller and weaker than that in panel A for IT buying volume.

In short, Table 7 shows that the effect of institutional trading is strong on High-IT buying days and very weak on Low-IT selling days. Thus, our results in the previous section are driven by the buying side of institutional trades, suggesting that the short-sale constraints hypothesis is not the explanation. These findings that the IT effect is stronger for the buying side are in fact intuitive. When institutions buy, they tend rely more on the analysis of risk and return and could be using the standard capital asset pricing model. On the other hand, their sales rely more on other factors that are less likely to be because of the risk level of the stock.[14]

4.2. Investor disagreement and the CAPM

Hong and Sraer (2014) offer another theoretical explanation for the failure of the CAPM. They argue that high beta stocks are more sensitive to disagreement among investors about the future of the economy. Consequently, in times with high disagreement (such as the crisis period), those stocks experience stronger disagreement about their expected returns. This, together with the short-sale constraints that are more binding during the crisis, causes the optimists to outweigh the pessimists in their

[14] A related hypothesis that may explain our findings is liquidity: High-IT days may represent times when liquidity in the market is high, and therefore stocks are priced more rationally. This hypothesis is unlikely the explanation because we show in the previous section that our results are robust to the control of liquidity. Moreover, if the liquidity effect drives our results, we should also see stronger results on High-IT selling days because selling relies more on the liquidity in the market. As shown in Table 7, the effect of institutional trading is driven by the buying side, suggesting that liquidity is unlikely the explanation.

trading impact on those stocks. Consequently, when macroeconomic disagreement is sufficiently large, the expected return on high beta stock exhibits an inverted U-shape curve: it initially increases and then decreases with beta.

We view that investor-disagreement hypothesis does not seem to be the explanation. Since investor disagreement tends to be larger during the crisis period, we could see that the IT effect is driven by the subsample after 2008. Our subsample analysis in subsection 3.5 shows that the IT effect before 2008 is as strong as that after 2008. Nevertheless, this subsection attempts to formally test whether High-IT days are simply a manifestation of times when the aggregate investor disagreement is relatively low.

Empirically, Hong and Sraer (2014) employ the dispersion (standard deviation) in analyst forecasts of the earnings-per-share (EPS) long-term growth rate (LTG) that is similar to Yu (2011). In our context, the disadvantage of this measure is its very low frequency and there is also little variation in analyst forecast over time. This is not suitable for our tests, which use daily returns. Consequently, we employ the measure of aggregate news tone dispersion that is similar in spirit to Dzielinski and Hasseltoft (2014) as a proxy of investor disagreement.

We collect news data from Thomson Reuters News Analytics (TRNA) that systematically quantifies the tone of firm-specific news for Finnish firms between 2003 and 2011 (2267 trading days). For every news item, TRNA provides the probability that a news item has good, neutral, or negative tone (the three scores sum to one). For each news article, we compute a unified tone score as the difference between good and bad score.[15] On each day t, we then compute news tone dispersion as the standard deviation of the tone score of all articles on that day. Finally, we define a day to have high news dispersion if the day's tone dispersion is greater than the average dispersion over the past one month. As TRNA is reasonably comprehensive, approximately 90% of the trading days have news and on average there are 52 news articles per day. The average news dispersion is 0.48 per day and 1260 days are defined as

[15]We use all news items, but our results are robust to examining news with the relevance score of one, which means that the firm's ticker code is mentioned in the headline or title of the news article.

having high news dispersion (strong investor disagreement).

Dzielinski and Hasseltoft (2014) find that this news dispersion is strongly associated with, and can even drive the analyst disagreement of Yu (2011). Using this measure allows us to construct a timely measure of investor disagreement. The theory of Hong and Sraer (2014) predicts an upward sloping security market line on days with low investor disagreement, which is proxied by low news dispersion. We confirm their theory using the Finnish data and the new measure of investor disagreement. Figure 6 plots the SML on weak- and strong-disagreement days. On days with strong disagreement (the lower graph), the SML is downward sloping: an increase in beta by one is associated with 14% lower average return per day, with the associated t-statistic of 5.8. In contrast, on weak disagreement days, the relation between beta and average return is positive. An increase in beta by one is associated with 5% increase in average return, with a significant associated t-statistic at the conventional level.

It should be noted again that our goal is to test whether High-IT days are also times when investor disagreement is relatively weak. It is, therefore, beyond the scope of this study to conduct a full test of the theory of Hong and Sraer (2014). To achieve our goal, we fix the day to have weak investor disagreement, and examine the difference in the slope of the SML on High- and Low-IT days. To be distinct from the effect of investor disagreement, we should still observe the contrasting difference in the SML between the two types of days. Figure 7 shows that, even on days with a low level of disagreement, the relation between beta and average return is still negative when there is low institutional trading. On High-IT days, the SML is upward sloping, suggesting a robust positive relation. These findings indicate that the High-IT effect is distinct from the effect of investor disagreement.[16]

[16] In unreported results, we also find that the relation between beta and average return is still positive and strong on High-IT days, even though the day has strong investor disagreement.

4.3. The effect of leverage constraints

In this subsection, we examine another theory that can potentially explain our findings: the leverage-constraints theory. Frazzini and Pedersen (2014) argue that the relation between beta and average return is flat because investors are constrained in the leverage that they can take. By taking advantage of this flat security market line, they find that a market-neutral betting-against-beta (BAB) portfolio that buys low-beta stocks and sells high-beta stocks earns a positive average return in the U.S. and international markets (including Finland). More importantly, they show that the BAB factor can proxy for the degree of leverage constraints.

If High-IT days represent times when the overall leverage constraint in the market is worsening, then we should observe a negative relation between High-IT and BAB and a positive relation between BAB and lagged High-IT. Model 1 of Table 8 reports results from the time-series regression of BAB return on a dummy variable of High-IT days (abbreviated as High) and its lagged measure.[17] The coefficient on High is negative 23bps with a significant associated t-statistic of -4.1. In other words, the BAB portfolio, on average, earns 23bps less when there is a large contemporaneous increase in institutional trading volume. Moreover, the coefficient on lagged IT dummy is positive 8bps per day, though not statistically significant. Since BAB represents the leverage constraint, this negative relation between High-IT (an increase in institutional buy over time) and BAB could mean that High-IT is associated with times when leverage constraints in the market are worsening (or margin requirements are increasing).[18] The results are consistent with a central prediction of Frazzini and Pedersen's theory: the future BAB premium increases when funding constraints become more binding.

[17]Recall that High-IT day is defined as the difference between today's IT volume and its average over the past quarter. Thus, High-IT day accounts for the contemporaneous increase in volume. Frazzini and Pedersen (2014) also examine the quarterly holdings of individual institutions. Their focus is to show that institutions tend to hold high-beta stocks, and not to examine the effect of their trades on the test of the CAPM. We obtain returns on the BAB factor from Lasse Heje Pedersen's website `http://www.lhpedersen.com/data.`

[18]Low-IT days are therefore just the opposite, which suggests that leverage constraints are currently binding, and hence the BAB return is higher.

In order to further test whether the leverage-constraints hypothesis can explain High-IT effects, we follow Frazzini and Pedersen (2014) to examine the relation between BAB and the TED spread as a proxy of funding conditions. We tailor the TED definition to the Finnish market by defining this spread to be the difference between three-month EURIBOR (Euro interbank offered rate) and the yield on five-year Finnish government bond. The sample period is between 1996 and 2011. For the interbank rate before 1999, we use HELIBOR (Helsinki interbank offered rate).[19]

Two caveats of using the TED spread as a proxy of funding constraints are in order. Firstly, even though we call it TED, it is tailored to the Finnish market. For studies in the U.S., the TED is measured as the difference between three-month Eurodollar LIBOR and three-month U.S. Treasury rate. We employ the Euribor, which is similar to the LIBOR, but more relevant for Finland. Since daily yield on three-month Finnish government bond is not available, we use the yield on five-year government bond as a proxy for the risk-free rate. Though the principle in constructing the TED spread is maintained, the mismatch in maturity may reduce the power of our tests. However, as we show shortly, the results are still qualitatively consistent with Frazzini and Pedersen (2014). The second caveat is that the interpretation of the TED spread is subject to debate. As we employ the return on the BAB factor from Frazzini and Pedersen (2014), we follow their interpretation of the TED spread. Specifically, a high TED spread indicates that funding constraints are worsening.

< INSERT TABLE 8 HERE >

Model 2 of Table 8 shows the basic regression of BAB return on the contemporaneous change in the TED spread (today TED spread minus the lagged TED spread)

[19] Our measure is not based on Eurodollar LIBOR, which is part of the abbreviation of the TED. Nevertheless, we call it TED for short and to be comparable with other studies. As a robustness test, we also run regressions of BAB on the U.S. TED spread defined as the difference between three-month Eurodollar LIBOR and three-month T-Bill. The sign on the coefficients does not change, but the statistical significance is much smaller. We attribute this weaker result to the possible market fragmentation between the U.S. and the Finnish market. Frazzini and Pedersen (2014) employ the U.S. TED spread to run monthly time-series regressions for all countries aggregated together, not specifically for Finland.

and the lagged TED spread. Consistent with Frazzini and Pedersen (2014), the coefficients on these two controls are negative, though only the change in TED spread is statistically significant. Frazzini and Pedersen (p. 16) interpret these negative coefficients as "a high TED spread could indicate banks are credit-constrained and that banks tighten other investors' credit constraints over time, leading to a deterioration of BAB returns over time (if investors do not foresee this)."

In Model 3, we add the dummy variable for High-IT days and interact it with the TED variable. Coefficients on the change in TED spread and the lagged TED spread are still negative. The relation between the contemporaneous increase in IT volume (High) and BAB remains negative and statistically significant. The coefficient on the interaction between lagged High and lagged TED in Model 3 is positive. Although this coefficient is not statistically significant, by comparing with the coefficient on the lagged TED spread (-1.52%), its magnitude of positive 1.64% per day is economically high. The next coefficient of interest in this model is that of the interaction term between High and the change in TED spread. It is positive and statistically significant. Following Frazzini and Pedersen's interpretation of the TED spread, the positive coefficient on the interaction term has an interesting economic meaning. Since a high TED spread suggests investors' leverage constraints become more binding, an increase in IT (particularly buying) reduces the existing funding credit in the market over time. When banks tighten investors' credit and margin requirements are rising over time, BAB returns are higher. In Model 4, we further control for lagged BAB return and lagged market return and the conclusions do not qualitatively change.

In short, this subsection has shown that the IT effect seems to be consistent with the leverage-constraints hypothesis of Frazzini and Pedersen (2014). When margin requirements rise, the required future BAB return rises (the coefficient on lagged High is positive), and the contemporaneous realized BAB return becomes negative (the coefficient on High, which accounts for the contemporaneous increase in IT volume, is negative). Consistently, when we interact High (lagged High) with the TED measure (lagged TED), coefficients on interaction terms are all positive – suggesting higher required BAB premium following an increase in margin requirements over time. These results show that High-IT days can be times when there is an increase in leverage constraints, and hence the relation between beta and average return is positive.

5. Conclusion

By employing a comprehensive dataset of daily institutional trading, this study is one of the first to directly link the effect of institutional trading (IT) to the relation between beta and average return. We find that this relation is strong and positive on days when there is high institutional trading (High-IT). On Low-IT days, however, this relation is negative and statistically significant. Moreover, the difference in market risk premium between High- and Low-IT days is positive and statistically significant. These findings hold for various test portfolios and for individual stocks. The results are not driven by specific subsample period, the January effect, or the turn-of-month effect. Our results are unlikely to be explained by the short-sale constraints hypothesis, the liquidity effect, or the effect of aggregate investor disagreement. We show that the IT effect is, however, most consistent with the leverage-constraints hypothesis of Frazzini and Pedersen (2014).

Savor and Wilson (2014) show that days with interest rate announcement from the central bank also exhibit the positive relation between beta and average return. Their findings, thus, point out days when the CAPM relation is not consistent with the leverage-constraints theory of Frazzini and Pedersen (2014), which is established to explain the flat SML. Our study offers a new perspective to those equivocal findings. First, we show that the IT effect is not a manifestation of the announcement effect. Second, we find that announcement days only show the positive relation when it is accompanied by High-IT buying activity. Third, the IT effect is a stronger phenomenon that is present even on days without interest rate announcements. We are therefore able to offer an explanation for the puzzle of Savor and Wilson (2014) based on the Finnish data. The results show that, in order for announcements to enhance the CAPM relation, they have to induce institutional buying. This high IT buying activity is, in turn, consistent with the prediction of the leverage-constraints hypothesis

(if a rise in IT buying volume is associated with rising leverage constraints.)

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Figure 1: Capital asset pricing model on high and low institutional trading

Average excess returns for four beta-sorted and five industry portfolios on high and low institutional trading (IT) days. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted (value-weighted) portfolios, nine value-weighted size-BM portfolios, and five value-weighted industry portfolios. Day t has Low-IT volume (scaled by total market volume) when IT volume at t is greater than the average IT volume over the past quarter. The first graph shows the relation between beta and average return on High-IT days while the second graph is on days with Low-IT. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is between 1996 and 2011. Individual stocks' betas are corrected for potential asynchronous trading using the Dimson method. This figure shows that the relation between beta and average return is much higher and more positive on High-IT days (first graph) whereas, on Low-IT days (second graph), the relation is significantly negative.

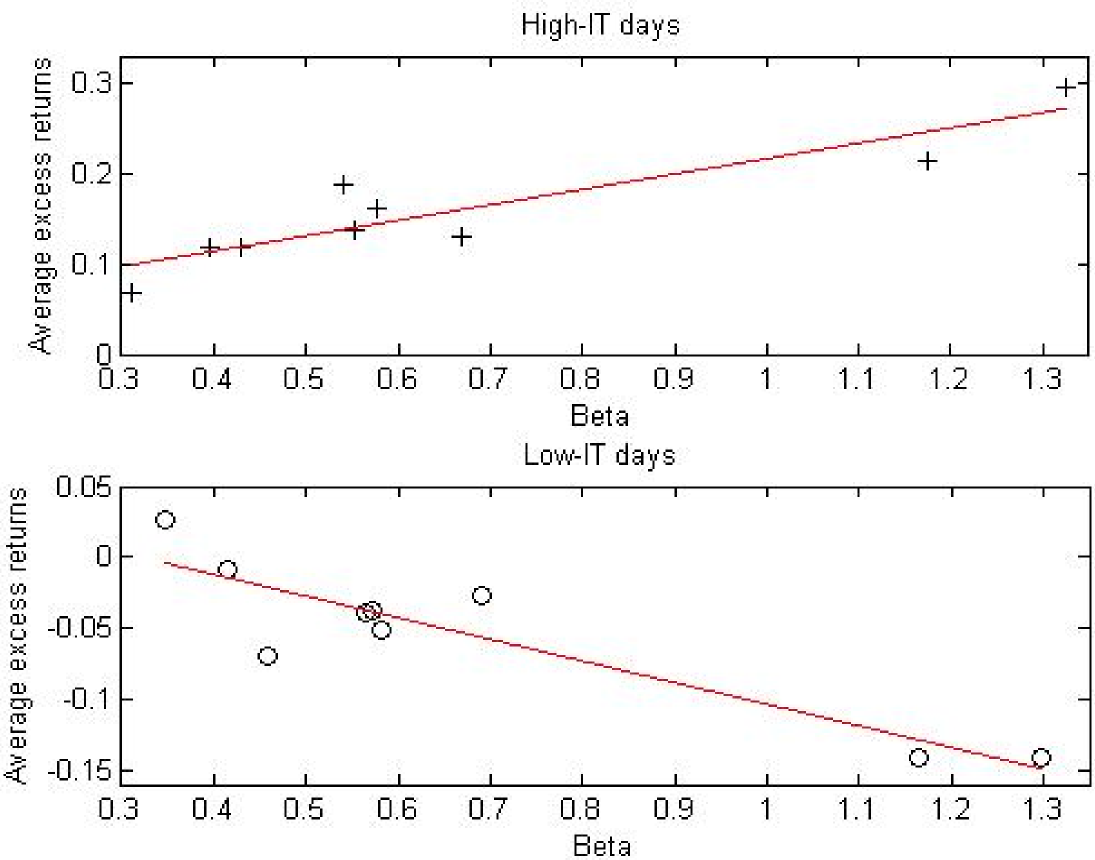


Figure 2: Capital asset pricing model on announcement and non-announcement days

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on ECB announcement versus non-announcement days. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. The first graph shows the relation between beta and average return on days with ECB monetary policy decision. The second graph presents similar line on non-announcement days. The implied ordinary least squares estimates of the security market line for each type of day are also plotted. The sample period is between 1999 and 2011 (the ECB was formally established in 1999). Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure shows that, consistent with Savor and Wilson (2014), the relation between beta and average return is much more positive on monetary announcement days than on normal days.

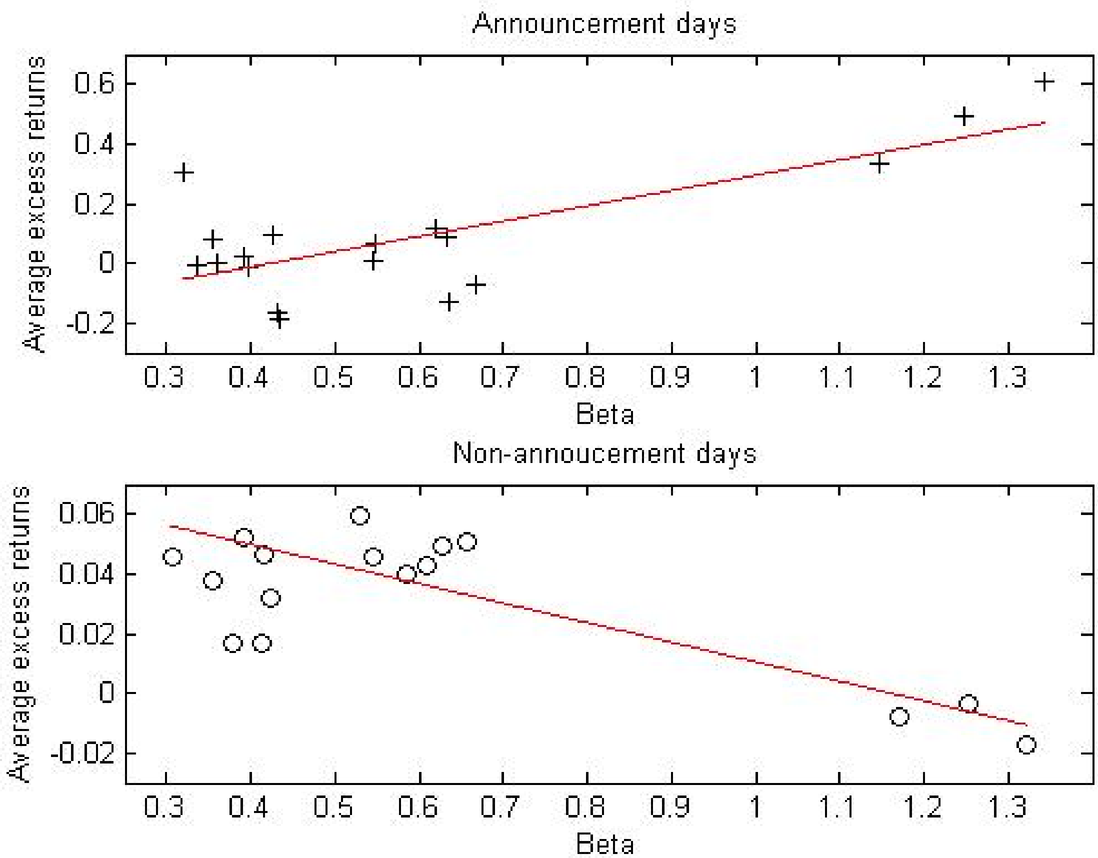
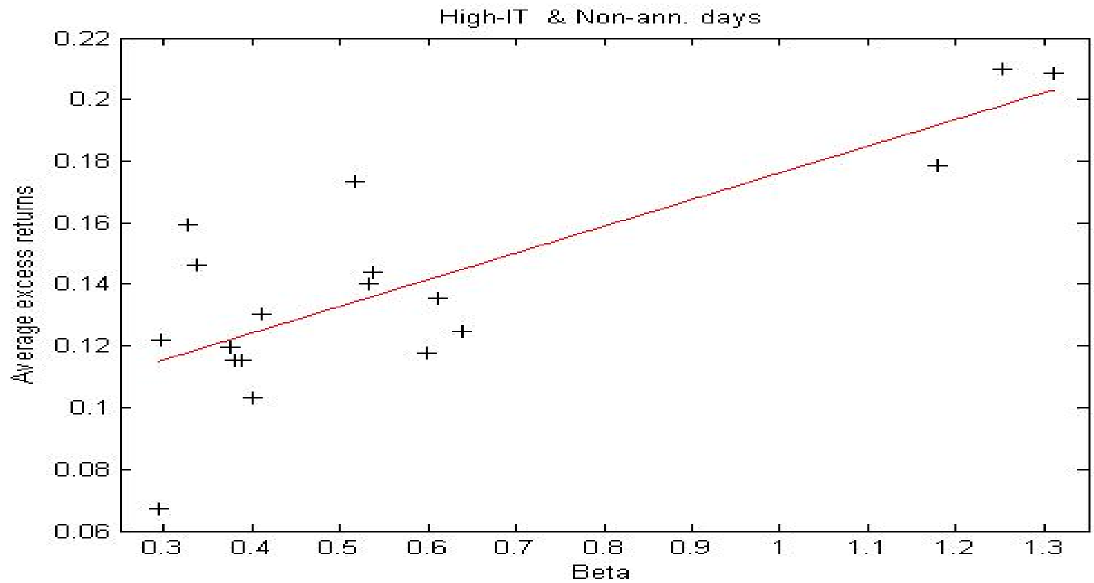


Figure 3: Capital asset pricing model – Non-announcement days

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on High- and Low-IT days accounting for the ECB announcement effect. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. The first graph shows days with High-IT volume but no ECB monetary policy decision. The second graph presents the relationship between excess returns and betas on days with Low-IT volume and no announcement. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is between 1999 and 2011 (the ECB was formally established in 1999). Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. The purpose of this figure is to show that, even when the day has no macroeconomic announcement, the difference in the risk premium between High- and Low-IT days remains robust. Consequently, the effect of institutional trading is not a manifestation of announcement effects.



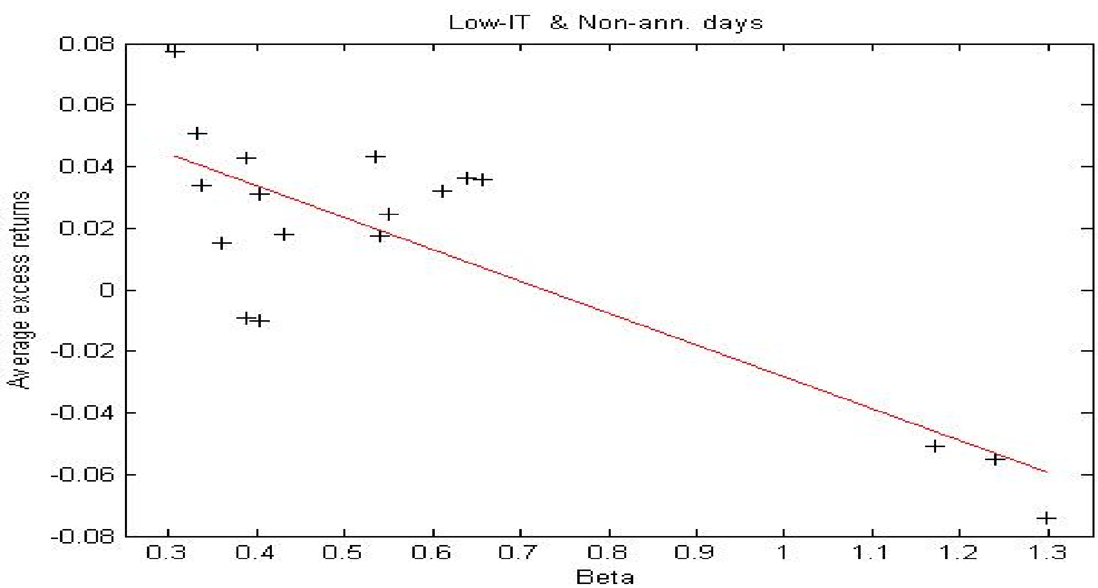


Figure 4: Capital asset pricing model on non-turn-of-month days

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on High- and Low-IT days accounting for the turn-of-month effect. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. The first graph shows days with High-IT total volume but not the turn-of-month day. The second graph presents the relationship between excess returns and betas on days with Low-IT total volume and not the turn-of-month day. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is between 1996 and 2011. Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure shows that, after excluding turn-of-month days, the difference in the risk premium between High- and Low-IT days remains robust.

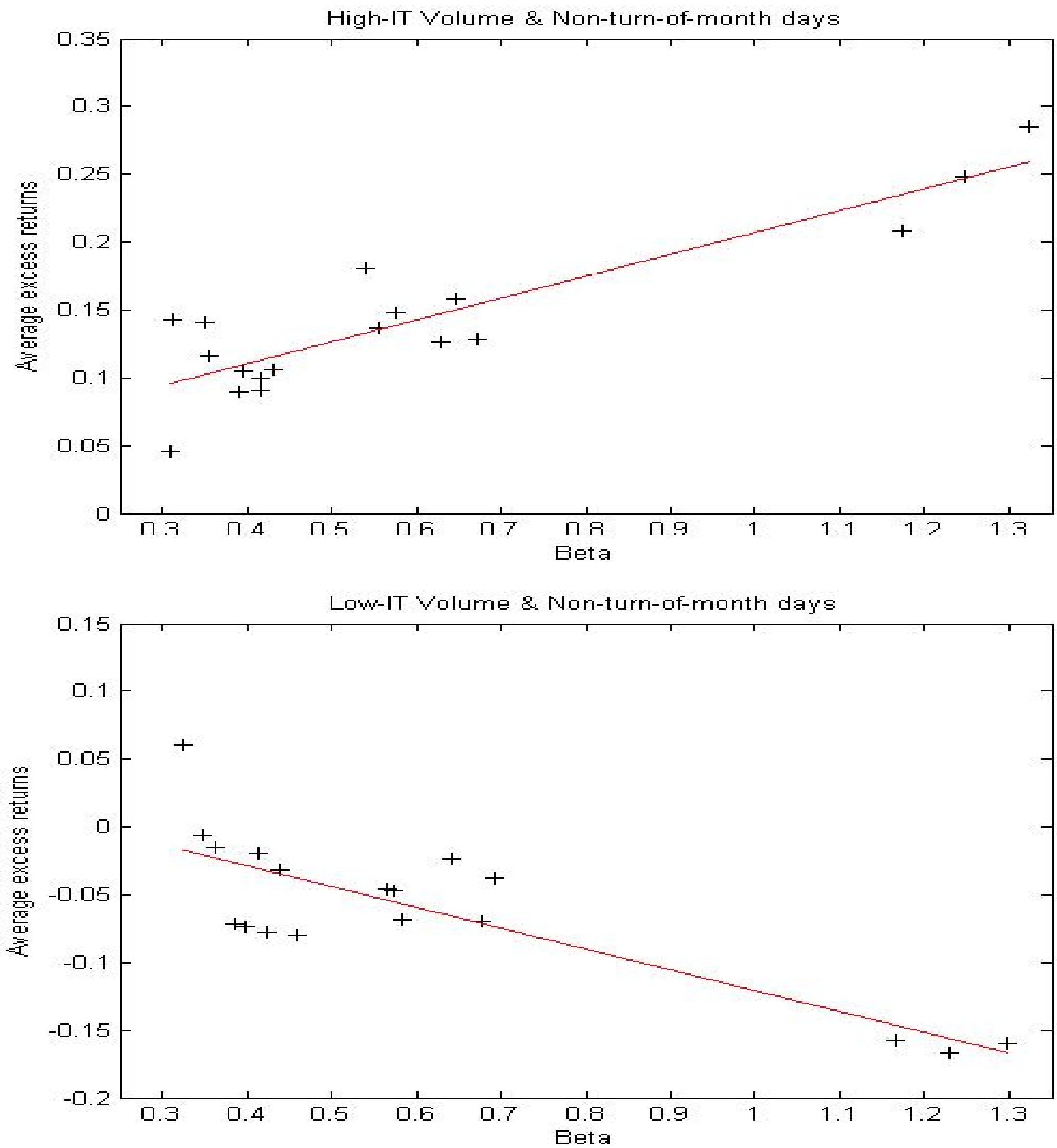
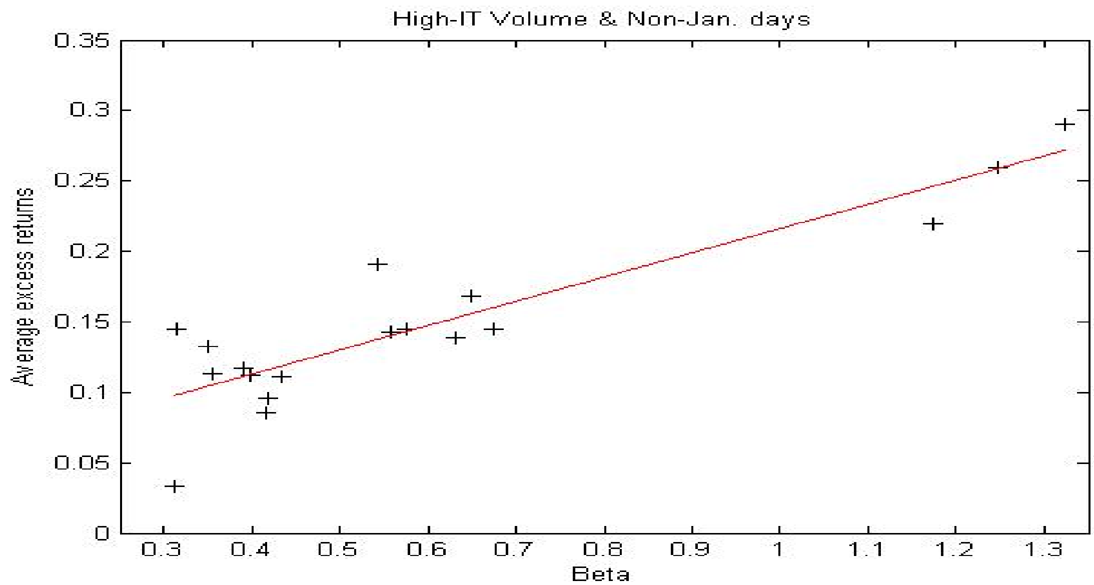


Figure 5: Capital asset pricing model on non-January days

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on High- and Low-IT days accounting for the January effect. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. The first graph shows days with High-IT volume but not in January. The second graph presents the relationship between excess returns and betas on days with Low-IT volume and not January days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is between 1996 and 2011. Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure shows that, after excluding January, the difference in the risk premium between High- and Low-IT days remains robust.



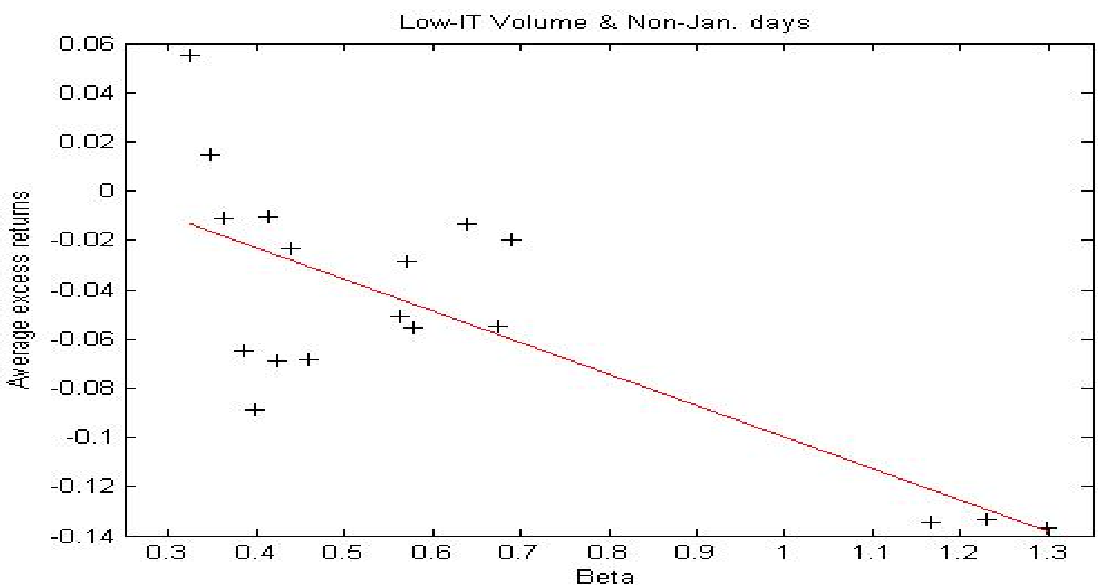


Figure 6: Capital asset pricing model on days with high or low degree of investor disagreement Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on high and low investor-disagreement days accounting for the ECB announcement effect. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. A day t has strong investor disagreement if the cross-sectional standard deviation of news tone on day t is higher than its average over the past month. Dzielinski and Hasseltoft (2014) show that high news dispersion is associated with strong investor disagreement. The first graph shows days with weak investor disagreement. The second graph presents the relation between excess returns and betas on days with strong investor disagreement. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is daily frequency between 2003 and 2011 (the news dataset starts in 2003). Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure provides evidence for Hong and Sraer's (2014) theory that the relation between beta and average return is negative (positive) when the aggregate investor disagreement is strong (weak).

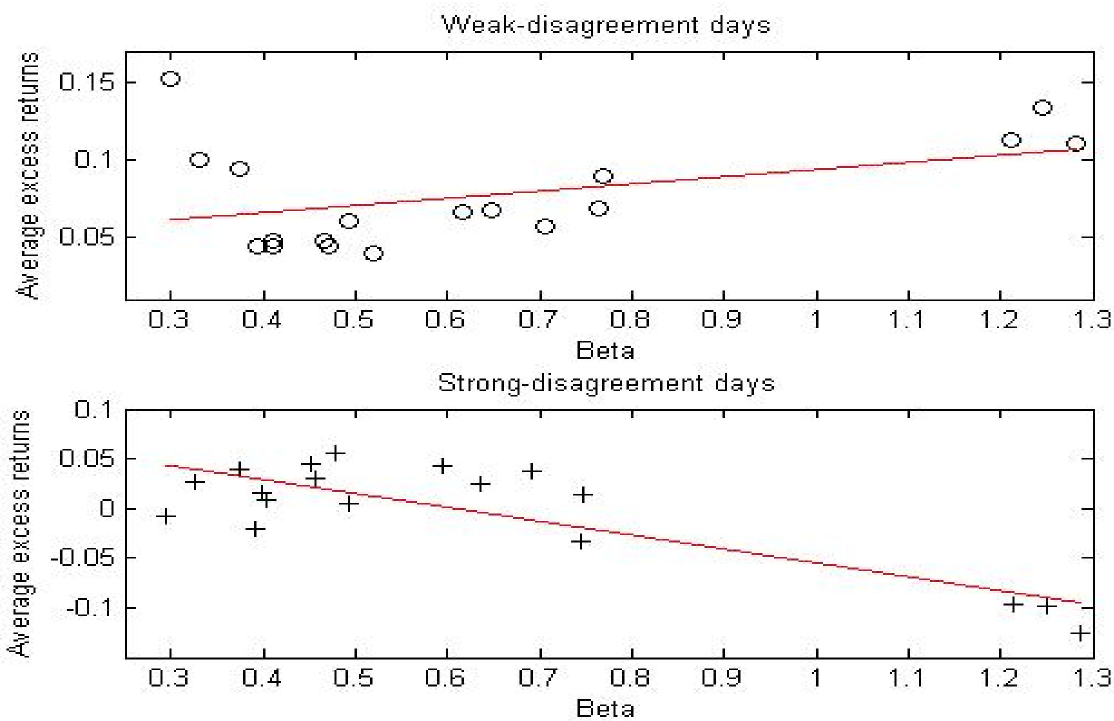
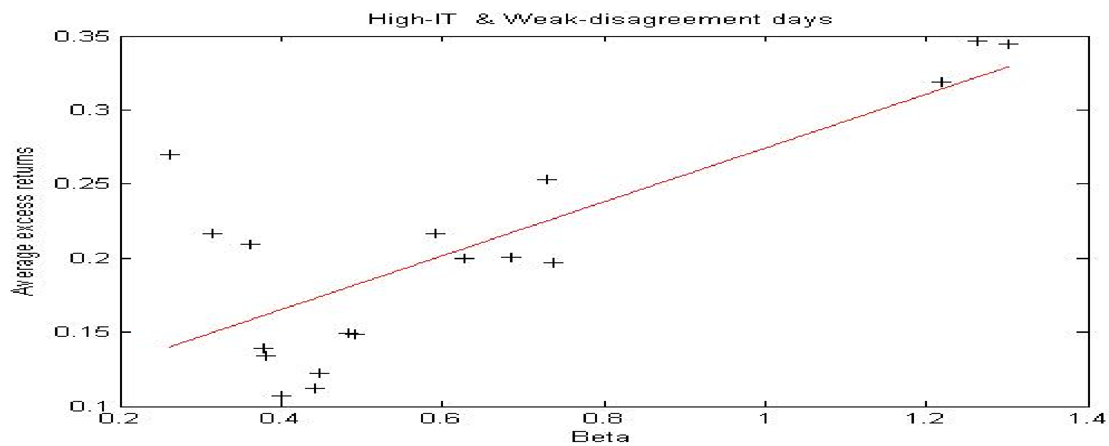


Figure 7: Capital asset pricing model on various types of day – institutional trading and investor disagreement

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on High- and Low-IT days accounting for the ECB announcement effect. This figure plots average daily excess returns (in percentages) against market betas for four beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. A day t has strong investor disagreement if the cross-sectional standard deviation of news tone on day t is higher than its average over the past month. Dzielinski and Hasseltoft (2014) show that high news dispersion is associated with strong investor disagreement. The first graph shows days with High-IT volume and weak disagreement in the news. The second graph presents the relationship between excess returns and betas on days with Low-IT volume and weak disagreement in the news. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is daily frequency between 2003 and 2011 (the news dataset starts in 2003). Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure shows that, even when the day has weak (low) aggregate investor disagreement, the distinction of the IT effect between High- and Low-IT days remains robust.



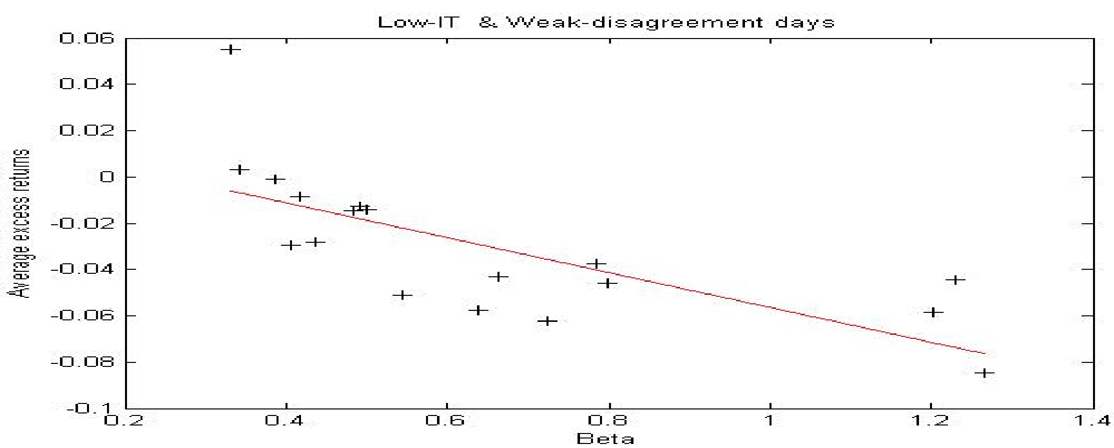


Table 1: Summary statistics for Finnish market between 1995 and 2011

This table reports summary statistics for the Helsinki stock exchange between 2 January 1995 and 30 December 2011. "Mean Firms" are the average number of firms. "Mean ME" is the average market capitalization in millions of euros (price times number of shares outstanding). "Mean Fraction of Total IT Volume" is the average fraction of trading volume by financial institutions over the total market volume. "Mean Fraction of Sell Volume" is the average fraction of sell volume by financial institutions over the total market volume. "Number of Accounts" is the count of unique accounts held by financial institutions.

Year Period	Mean Firms	Mean ME ('000,000)	Mean Fraction of Total IT Volume	Mean Fraction of Sell Volume	Number of Accounts
1995-1999	79	389.868	0.196	0.123	563
2000-2003	138	1767.843	0.169	0.104	643
2004-2007	141	1335.035	0.232	0.128	722
2008-2011	140	1095.511	0.379	0.251	656

Table 2: Daily excess returns on days of high and low institutional trading

This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios. Estimates are computed for days with high institutional trading (High-IT days or High) and other days (Low-IT days or Low). Day t has Low-IT volume (scaled by total market volume) when IT volume at t is greater than the average IT volume over the past quarter. The difference in the coefficient between high- and Low-IT days is reported in the last row of each panel. There are 1598 days with High-IT volume. The right-hand side panel reports estimates from pooled regression of excess returns on betas, High-IT day dummy, and interaction between beta and High-IT (High*Beta). Panel A shows results for four beta-sorted (value-weighted) portfolios. Individual stocks' betas are adjusted for potential asynchronous trading effects using Dimson's method. Panel B presents results for four beta-sorted and five value-weighted industry portfolios. Panel C reports results for nine value-weighted size-BM portfolios, four beta-sorted portfolios, and five industry portfolios. The sample period is between 1996 and 2011 (we lost one year to form portfolios). t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering by trading day. Betas are estimated using data of both high and Low-IT days. This table shows that the difference in the coefficient on beta between High- and Low-IT days is always positive and statistically significant.

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	High	High*Beta	Avg. R^2
Panel A: four beta-sorted portfolios								
High	0.00013	0.00073	0.24	0.00068	−0.00186	0.000258	**0.00283**	0.53
	(0.77)	(2.61)		(1.62)	(−4.54)	(0.42)	**(4.69)**	
Low	0.00011	−0.00074	0.31					
	(0.54)	(−2.00)						
High − Low	0.00002	**0.00147**						
	(0.08)	**(3.18)**						
Panel B: four beta-sorted and five industry portfolios								
High	0.00011	0.00076	0.16	0.00095	−0.00120	−0.00070	**0.00189**	0.39
	(0.65)	(2.83)		(3.19)	−3.67	−1.51	**(3.72)**	
Low	0.00016	−0.00080	0.20					
	(0.50)	(−1.80)						
High − Low	−0.00005	**0.00156**						
	(−0.14)	**3.20**						
Panel C: four beta-sorted, nine size & BM portfolios, and five industry portfolios								
High	0.00019	0.00070	0.11	0.00060	−0.00173	0.00022	**0.00296**	0.37
	(1.41)	(2.81)		(1.88)	(−7.19)	(0.46)	**(8.40)**	
Low	0.00017	−0.00082	0.14					
	(0.72)	(−2.26)						
High − Low	0.00003	**0.00152**						
	(0.12)	**3.50**						

Table 3: Daily excess returns for individual stocks on days of high and low institutional trading

This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios. Estimates are computed for days with high domestic institutional trading (High-IT days or High) and other days (Low-IT days or Low). Day t has Low-IT volume (scaled by total market volume) when IT volume at t is greater than the average IT volume over the past quarter. The difference in the coefficient between High- and Low-IT days is reported in the last row of each panel. There are 1598 days with High-IT volume. The right-hand side panel reports estimates from pooled regression of excess returns on betas, High-IT day dummy, and interaction between beta and High-IT days (High*Beta). Panels A and B show results for beta as the right-hand side variable in Fama-MacBeth regressions and pooled regressions, respectively. Panels C and D are similar to the first two panels, but include $log(size)$, BM, and past one-year returns as additional controls. Panels E and F include liquidity rank (LIQ) as an additional control. This liquidity measure is constructed based on the occurrence of zero returns over the past year. The sample period is between 1996 and 2011 (we lost one year to form portfolios). Panels G and H repeat the regressions in Panels E and F, but excluding Nokia, which is the largest firm on the Finnish market. t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering by trading day. This table shows that, for individual stocks, the coefficient on beta on High-IT days is higher than on Low-IT days.

Panel A: beta only (Fama-MacBeth regressions)					
Type of day	Beta				Avg. R^2
High	0.00039				0.02
	(1.80)				
Low	−0.00078				0.02
	(−3.20)				
High − Low	**0.00117**				
	(3.52)				
Panel B: beta and interaction with High-IT (Pooled regressions)					
	Beta	High	High*Beta		Avg. R^2
	−0.00123	0.00058	**0.00242**		0.09
	(−6.59)	(1.52)	**(8.68)**		
Panel C: size, BM, and past returns as controls (Fama-MacBeth regressions)					
Type of day	Beta	Size	BM	Past one-year	Avg. R^2
High	0.00044	−0.00008	−0.00009	−0.02032	0.04
	(1.81)	(−2.59)	(−3.13)	(−1.18)	
Low	−0.00077	−0.00007	−0.00007	0.00026	0.05
	(−2.85)	(−2.29)	(−2.19)	(1.43)	
High − Low	**0.001205**	−0.00001	−0.00002	−0.02058	
	3.214	(−0.02)	(−0.40)	(−1.76)	

Table 3 continued.

Type of day	Beta	Size	BM	Past one-year	Turn	High	High*Beta	Avg. R^2
Panel D: size, BM, and past returns as controls (Pooled regressions)								
	Beta	Size	BM	Past one-year		High	High*Beta	Avg. R^2
	−0.00165	−0.00016	0.00002	0.00015		0.00020	**0.00280**	0.09
	(−8.01)	(−4.74)	(1.26)	(0.70)		(0.50)	**(9.51)**	
Panel E: size, BM, past returns, and liquidity as controls (Fama-MacBeth regressions)								
Type of day	Beta	Size	BM	Past one-year	Turn			Avg. R^2
High	0.00041	−0.00008	−0.00009	−0.01801	0.00413			0.04
	(1.88)	(−2.85)	(−3.15)	(−1.05)	(0.76)			
Low	−0.00077	−0.00007	−0.00007	0.00028	−0.00001			0.06
	(−2.82)	(−2.21)	(−2.19)	(1.51)	−0.20			
High − *Low*	**0.00118**	−0.00001	−0.00002	−0.01829	0.00415			
	(3.14)	(−0.28)	(−0.38)	(−1.73)	(0.58)			
Panel F: size, BM, past returns, and liquidity as controls (Pooled regressions)								
	Beta	Size	BM	Past one-year	Turn	High	High*Beta	Avg. R^2
	−0.00168	−0.00017	0.00002	0.00014	0.00007	0.00019	**0.00281**	0.09
	(−8.03)	(−4.68)	(1.24)	(0.68)	(0.90)	(0.49)	**(9.52)**	
Panel G: size, BM, past returns, and liquidity as controls (Fama-MacBeth regressions) – excluding Nokia								
Type of day	Beta	Size	BM	Past one-year	Turn			Avg. R^2
High	0.00039	−0.00009	−0.00010	−0.01746	0.00419			0.04
	(1.78)	(−2.96)	(−3.26)	(−1.02)	(0.77)			
Low	−0.00078	−0.00007	−0.00008	0.00028	−0.00001			0.06
	(−2.79)	(−2.24)	(−2.32)	(1.53)	(−0.08)			
High − *Low*	**0.001171**	−0.00002	−0.00002	−0.01773	0.00419			
	(3.10)	(−0.32)	(−0.31)	(−1.69)	(0.50)			
Panel H: size, BM, past returns, and liquidity as controls (Pooled regressions) – excluding Nokia								
	Beta	Size	BM	Past one-year	Turn	High	High*Beta	Avg. R^2
	−0.00168	−0.00018	0.00001	0.00014	0.00008	0.00020	**0.00280**	0.09
	(−7.84)	(−4.68)	(0.33)	(0.69)	(0.94)	(0.50)	**(9.26)**	

Table 4: Daily excess returns on various day types

This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios on High- and Low-IT days accounting for the ECB announcement effect. Day t has High-IT volume when IT volume (scaled by market volume) on day t is greater than its average over the past quarter. "Announcement days" are days when the ECB announced monetary policy decisions. "Yes" represents days that have the characteristics displayed in the heading whereas "No" represents days that do not have any or both of the characteristics displayed in the heading. For example, in panel A1, a day is a "Yes" day when it has both High-IT and announcement; otherwise, it is a "No" day. The difference in the coefficient on beta between Yes and No days is reported in the last row of each panel. The right-hand side panel reports estimates from pooled regression of excess returns on betas, Yes day dummy, and interaction between beta and Yes (Yes*Beta). Test assets are four beta-sorted, nine size-BM portfolios, and five industry portfolios. Panel A reports results for IT total volume. Panels B and C break the analysis into buying and selling volume, respectively. t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering by trading day. This table shows that the effect of announcements becomes insignificant with the day is a Low-IT day, suggesting that the effect of IT is stronger and driving the announcement effect of Savor and Wilson (2014). The results also indicate that the effect of ECB announcements only improves the relation between average return and beta when the announcement is accompanied by High-IT, particularly buying (panel B).

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	Yes	Yes*Beta	Avg. R^2
Panel A: IT total volume								
Panel A1: High-IT and announcement days								
Yes	−0.00123	0.00555	0.31	0.00073	−0.00064	−0.00139	**0.00558**	0.36
	(−0.73)	(2.45)		(3.05)	(−3.56)	(−0.95)	**(5.10)**	
No	0.00055	−0.00055	0.26					
	(1.90)	(−1.15)						
$Yes - No$	−0.00178	**0.00607**						
	(−1.20)	**(2.19)**						
Panel A2: Low-IT and announcement days								
Yes	−0.00150	0.00287	0.31	0.00083	−0.00061	−0.00097	**0.00001**	0.37
	(−0.94)	(0.73)		(2.38)	(−1.63)	(−0.47)	**(0.01)**	
No	0.00056	−0.00046	0.26					
	(1.93)	(−1.03)						
$Yes - No$	−0.00206	**0.00333**						
	(−1.44)	**(1.25)**						
Panel A3: High-IT and non-announcement days								
Yes	0.00063	0.00106	0.26	0.00058	−0.00151	0.00031	**0.00236**	0.36
	(2.04)	(1.84)		(1.88)	(−6.35)	(0.65)	**(6.55)**	
No	0.00040	−0.00139	0.27					
	(0.93)	(−2.10)						
$Yes - No$	0.00023	**0.00245**						
	(0.47)	**(2.71)**						

Table 4 continued.

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	Yes	Yes*Beta	Avg. R^2
Panel B: IT buying volume								
Panel B1: High-IT buying and announcement days								
Yes	−0.00159	0.008189	0.33	0.00076	−0.00072	−0.00265	**0.00874**	0.37
	(−1.20)	(2.254)		(3.18)	(−3.97)	(−1.78)	**(7.78)**	
No	0.00056	−0.000589	0.26					
	(1.93)	(−1.32)						
Yes − No	−0.00215	**0.00878**						
	(−1.43)	**(3.12)**						
Panel B2: Low-IT buying and announcement days								
Yes	−0.00117	0.00067	0.30	0.00074	−0.00052	−0.00165	**0.00096**	0.36
	(−0.75)	(0.20)		(3.08)	(−2.87)	(−1.19)	**(0.92)**	
No	0.00055	−0.00040	0.26					
	(1.90)	(−0.87)						
Yes − No	−0.00172	**0.00107**						
	(−1.23)	**(0.407)**						
Panel B3: High-IT buying and non-announcement days								
Yes	0.00028	0.001250	0.26	0.00090	−0.00170	−0.00041	**0.00276**	0.37
	(0.84)	(2.11)		(2.85)	(−7.12)	(−0.87)	**(7.66)**	
No	0.00066	−0.00157	0.26					
	(1.64)	(−2.48)						
Yes − No	−0.00038	**0.00282**						
	(−0.78)	**(3.13)**						

Table 4 continued.

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	Yes	Yes*Beta	Avg. R^2
Panel C: IT selling volume								
Panel C1: High-IT selling and announcement days								
Yes	−0.00113	0.00234	0.31	0.00072	−0.00055	−0.00110	**0.00235**	0.36
	(−0.62)	(0.90)		(3.00)	(−3.05)	(−0.73)	**(2.08)**	
No	0.000541	−0.00043	0.26					
	(1.90)	(−0.95)						
$Yes - No$	−0.00167	**0.00278**						
	(−1.09)	**(0.98)**						
Panel C2: Low-IT selling and announcement days								
Yes	−0.00157	0.00565	0.32	0.00078	−0.00069	−0.00299	**0.00651**	0.36
	(−1.13)	(1.33)		(3.26)	(−3.80)	(−2.17)	**(6.23)**	
No	0.00056	−0.00055	0.26					
	(1.93)	(−1.24)						
$Yes - No$	−0.00213	**0.00620**						
	(−1.54)	**(2.39)**						
Panel C3: High-IT selling and non-announcement days								
Yes	0.00090	0.000309	0.261	0.00043	−0.00106	0.00062	**0.00132**	0.36
	(2.53)	(0.53)		(1.40)	(−4.47)	(1.30)	**(3.67)**	
No	0.00021	−0.000854	0.262					
	(0.56)	(−1.44)						
$Yes - No$	0.000697	**0.00116**						
	(1.45)	**(1.29)**						

Table 5: Daily excess returns on High- and Low-IT volume: subsample analysis

This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios in two subsamples: before and after 2008. Estimates are computed for days with high domestic institutional trading (High-IT days or High) and other days (Low-IT days or Low). Day t has Low-IT volume (scaled by total market volume) when IT volume at t is greater than the average IT volume over the past quarter. The difference in the coefficient between high- and Low-IT days is reported in the last row of each panel. The right-hand side panel reports estimates from pooled regression of excess returns on betas, High-IT day dummy, and interaction between beta and High-IT (High*Beta). Test assets are nine value-weighted size-BM portfolios, four beta-sorted portfolios, and five industry portfolios. The sample period is between 1996 and 2011. Panel A uses sample before 2008 while the data in Panel B are after 2008. t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering by trading day. Betas are estimated using data of both high and Low-IT days. This table shows that the difference in the coefficient on beta between High- and Low-IT days is always positive and statistically significant.

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	High	High*Beta	Avg. R^2
Panel A: four beta-sorted, nine size-BM portfolios, and five industry portfolios, pre-2008								
High	0.00053	0.00143	0.26	0.00089	−0.00142	−0.0001	**0.00261**	0.29
	(1.41)	(2.09)		(2.50)	(−4.85)	(−0.01)	**(6.13)**	
Low	0.00030	−0.00064	0.141					
	(0.99)	(−1.36)						
High − Low	0.00024	**0.00207**						
	(0.55)	**(2.67)**						
Panel B: four beta-sorted, nine size-BM portfolios, and five industry portfolios, post-2008								
High	0.00018	0.00186	0.25	0.00016	−0.00249	0.00011	**0.00424**	0.29
	(0.317)	(2.06)		(0.26)	(−6.31)	(0.12)	**(7.05)**	
Low	−0.00013	−0.00124	0.15					
	(−0.38)	(−2.48)						
High − Low	0.00031	**0.00310**						
	(0.51)	**(2.80)**						

Table 6: Market betas by type of day

This table reports the difference in betas that are estimated in two separate samples: High-IT days and Low-IT days. Panel A uses four beta-sorted portfolios as the left-hand side assets while panel B uses nine size-BM portfolios. β_H is estimated using sample of days with High-IT volume while β_L is estimated using days with Low-IT volume only. t-statistics of the differences, which are computed using Newey-West standard errors with five lags, are reported in parentheses. This table shows that the difference in betas between two samples is not economically and statistically strong to explain the difference in expected returns on high and Low-IT days. This suggests that using all data to estimate betas as in previous tables does not badly affect our results.

Panel A: four beta-sorted portfolios				
Beta	Low	2	3	High
β_L	0.7735	0.7742	0.7750	0.7751
$\beta_H - \beta_L$	−0.0306	−0.0312	−0.0371	−0.0500
	(−0.31)	(−0.31)	(−0.37)	(−0.50)

Panel B: nine size-BM portfolios				
Beta		Low	Medium	High
β_L	*Small*	0.7742	0.7732	0.7731
$\beta_H - \beta_L$		−0.0267	−0.0289	−0.0283
		(−0.27)	(−0.29)	(−0.28)
β_L	*Medium*	0.7735	0.7718	0.7724
$\beta_H - \beta_L$		−0.0283	−0.0278	−0.0290
		(−0.28)	(−0.28)	(−0.29)
β_L	*Big*	0.7728	0.7741	0.7740
$\beta_H - \beta_L$		−0.0290	−0.0306	−0.0307
		(−0.29)	(−0.31)	(−0.31)

Table 7: Daily excess returns on days of high- and low-institutional buy and sell

This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios on high- and low-IT buying and selling days (rather than total IT volume as in previous tables). Estimates are computed for days with high institutional trading (High-IT days or High) and other days (Low-IT days or Low). Day t is a High-IT day when IT buy (sell) volume (scaled by total market volume) at t is greater than its average over the past quarter. The difference in the coefficient between High- and Low-IT days is reported in the last row of each panel. The right-hand side panel reports estimates from pooled regression of excess returns on betas, High-IT day dummy, and interaction between beta and High-IT (High*Beta). Panel A shows the estimate for buying volume (scaled by total market volume) while Panel B shows the results for selling volume (scaled by total market volume). t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering trading day. Betas are estimated using sample of both high and Low-IT days. This table shows that the difference in the coefficient on beta between High- and Low-IT days is driven by the buying side of institutional trading.

	Fama-MacBeth regression			Pooled regression				
Type of day	Intercept	Beta	Avg. R^2	Intercept	Beta	High	High*Beta	Avg. R^2
Panel A: High- versus Low-IT buying days								
Panel A1: four beta-sorted portfolios								
High	0.00002	0.000868	0.250	0.001062	−0.002206	−0.00055	**0.00352**	0.53
	(0.10)	(2.97)		(2.50)	(−5.35)	(−0.87)	**(5.85)**	
Low	0.00022	−0.00087	0.30					
	(1.09)	(−2.41)						
High − Low	−0.00021	**0.00174**						
	(−0.80)	**(3.78)**						
Panel A2: four beta-sorted and five industry portfolios								
High	0.00006	0.000802	0.17	0.00095	−0.00193	−0.00067	**0.00357**	0.39
	(0.33)	(2.77)		(2.45)	(−5.80)	(−1.17)	**(7.34)**	
Low	0.00021	−0.00084	0.20					
	(0.73)	(−2.04)						
High − Low	−0.00015	**0.001643**						
	(−0.48)	**(3.36)**						
Panel A3: four beta-sorted, nine size & BM portfolios, and five industry portfolios								
High	0.000077	0.00080	0.12	0.00095	−0.00200	−0.00056	**0.00353**	0.37
	(0.54)	(3.03)		(2.99)	(−8.32)	(−1.19)	**(10.02)**	
Low	0.00029	−0.000925	0.14					
	(1.32)	(−2.72)						
High − Low	−0.00021	**0.00173**						
	(−0.90)	**(3.99)**						

Table 7 continued.

Type of day	Fama-MacBeth regression: Intercept	Beta	Avg. R^2	Pooled regression: Intercept	Beta	High	High*Beta	Avg. R^2
Panel B: High- versus Low-IT selling days								
Panel B1: four beta-sorted portfolios								
High	0.00018	0.00029	0.25	0.00070	−0.00120	0.00015	**0.00139**	0.53
	(1.06)	(1.04)		(1.67)	(−2.95)	(0.25)	**(2.31)**	
Low	0.00006	−0.00029	0.30					
	(0.29)	(−0.80)						
High − Low	0.000125	**0.00059**						
	(0.49)	**(1.28)**						
Panel B2: four beta-sorted and five industry portfolios								
High	0.00030	0.00017	0.17	0.00041	−0.00071	0.000432	**0.00098**	0.39
	(1.42)	(0.56)		(1.05)	(−2.15)	(0.76)	**(2.01)**	
Low	−0.00003	−0.00021	0.19					
	(−0.11)	(−0.52)						
High − Low	0.000330	**0.00038**						
	(1.04)	**(0.77)**						
Panel B3: four beta-sorted, nine size & BM portfolios, and five industry portfolios								
High	0.00036	0.000129	0.12	0.00046	−0.00084	0.00046	**0.00104**	0.37
	(2.22)	0.500		(1.44)	(−3.50)	(0.97)	**(2.94)**	
Low	0.00001	−0.00025	0.14					
	(0.05)	(−0.74)						
High − Low	0.000349	**0.00038**						
	(1.48)	**(0.89)**						

Table 8: Time-series regression results

This table presents results from time-series regressions. The left-hand side variable is return on betting-against-beta (BAB) factor downloaded from Lasse Heje Pedersen's website. Frazzini and Pedersen (2014) use BAB to proxy for leverage constraints in the market; the higher the BAB the more binding leverage constraints. The BAB portfolio is constructed by sorting stocks in the market to either low-beta or high-beta group. Stocks are weighted by their ranked betas and the portfolio goes long low-beta stocks and short high-beta stocks. BAB portfolios are rebalanced every calendar month. The explanatory variables are High-IT day dummy, the TED spread, and other controls. A day is high-IT when the IT volume (scaled by total market volume) on day t is higher than its average over the past quarter. (It thus represents for the contemporaneous increase in IT volume.) We compute TED for the Finnish market in a similar spirit to the TED spread in the U.S. literature. It is the difference between three-month Euribor (Euro interbank offered rate) and the yield on Finnish government bond. The sample period is between 1996 and 2011. For interbank rate before 1999, we use Helibor (Helsinki interbank offered rate). t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses.

This table first confirms the findings of Frazzini and Pedersen (2014) that the coefficients on contemporaneous change TED and lagged TED are negative. Frazzini and Pedersen argue that, if a high TED spread indicates that the funding constraint is worsening, then a high TED spread suggests that banks are credit-constrained and that banks tighten other investors' credit constraints over time, leading to lower BAB returns over time. If an increase in IT (High) also means that margin requirements are rising, then the IT effect is consistent with the leverage-constraints hypothesis. Model (1) indeed shows that the coefficient on lagged High is positive and the contemporaneous increase in IT volume (High) is negative. In Models (3) and (4), the coefficient on the interaction term of High and TED spread is positive.

Left-hand side: BAB return	(1)	(2)	(3)	(4)
Intercept	0.0014	0.0008	0.0020	0.0021
	(3.43)	(2.01)	(3.75)	(3.92)
High	**-0.0023**		**-0.0023**	**-0.0023**
	(−4.05)		(−4.03)	(−4.09)
Change in TED spread		**-0.0079**	**-0.0315**	**-0.0317**
		(−3.46)	(−4.99)	(−5.05)
High*Change TED spread			**0.0271**	**0.0275**
			(4.01)	(4.09)
Lagged TED spread		**-0.0090**	**-0.0152**	**-0.0180**
		(−0.24)	(−0.29)	(−0.35)
Lagged High*Lagged TED spread			**0.0164**	**0.0255**
			(0.22)	(0.35)
Lagged High	**0.0008**		**0.0007**	**0.0005**
	(1.42)		(0.88)	(0.67)
Lagged BAB return				−0.0909
				(−4.86)
Lagged market return				−0.0273
				(−1.85)
Adjusted R^2	0.01	0.01	0.02	0.02

Appendices

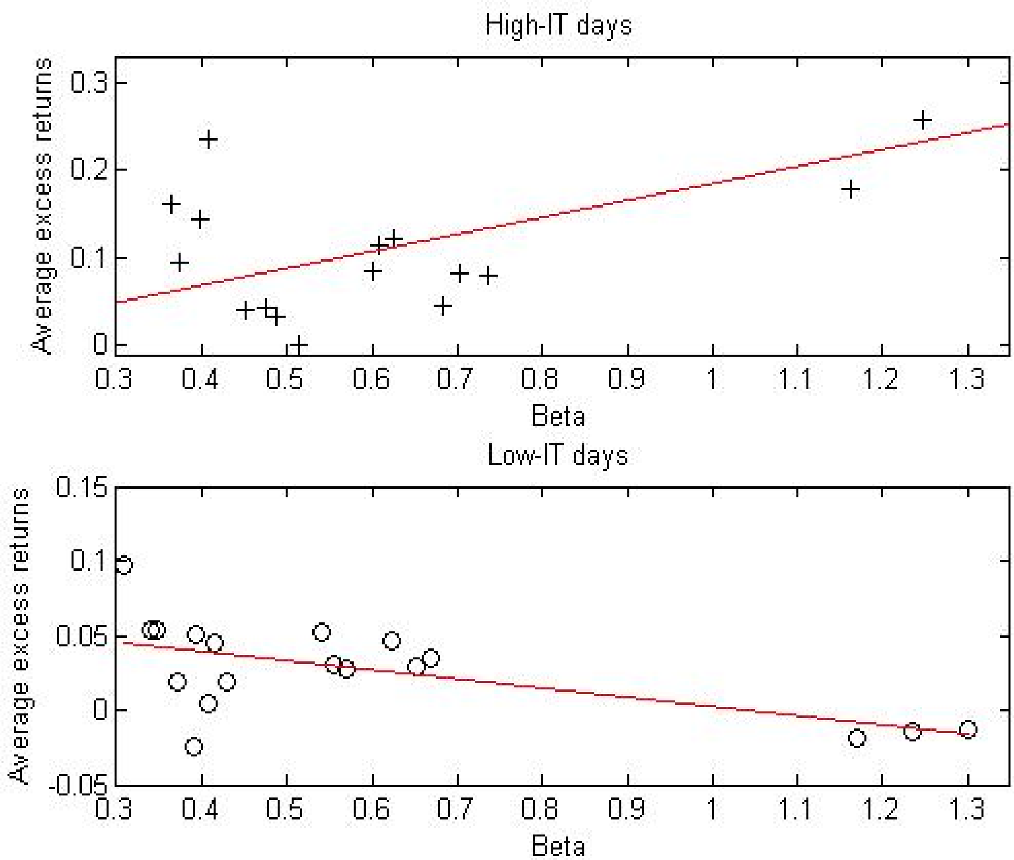
A. Capital asset pricing model between High- and Low-IT days (one-year window)

In the main text, we report results from High- and How-IT days that are defined on the basis of the past quarter. In this appendix, we use the window of one year as the basis to determine a High- or Low-IT day. Specifically, a day has High-IT when the fraction of institutional trading volume over the market volume is greater than its average over the past year.

Figure A.1 plots the security market line for four beta-sorted, nine size-BM, and five industry portfolios. The relation between beta and average return is still much higher and positive on High-IT days. An increase in beta by 0.5 is associated with a statistically significant increase in daily excess return of 9.7bps per day. In contrast, this relation is significantly negative on Low-IT days (second graph). An increase in beta by 0.5 leads to a reduction in average excess return of 3.1bps per day (t-statistic = -3.1). We thus conclude that our results are not sensitive to the choice of window length to define High- or Low-IT days. In untabulated results, we also repeat the estimation for the level institutional volume (without scaling by market volume). The difference in implied market risk premium between High- and Low-IT days remains significant.

Figure A.1: Capital asset pricing model on High- and Low-IT volume days

Average excess returns for four beta-sorted, nine size-BM, and five industry portfolios on High and Low-IT volume. This figure plots average daily excess returns (in percentages) against market betas for three beta-sorted portfolios, nine size-BM portfolios, and five industry portfolios. The first graph shows days with high-IT volume (days with the fraction of IT volume greater than the average past one-year volume). The second graph presents the relationship between returns and betas on low-IT volume days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample period is between 1996 and 2011 (we lost one year to form portfolios). Betas to form portfolios are corrected for potential asynchronous trading using the Dimson method. This figure shows that the relation between beta and average return is much higher and more positive on High-IT days (first graph) than that on Low-IT days (second graph).



B. U.S. 13F quarterly holdings data

In this appendix, we attempt to replicate our findings using Thomson Reuters 13F quarterly holdings data for the U.S. markets between quarter 1, 1980 to quarter 1, 2014. In each quarter, we compute aggregate change in holdings of all 13F institutions scaled by the total trading volume in that quarter. As before, we determine a quarter to be High-IT when the fraction of institutional volume is higher than its average over the past year. We collect monthly market data for all U.S. common equities (share codes of 10 and 11) from Center for Research in Security Prices (CRSP). We estimate pre-ranking betas for individual stocks by regressing 60 months of excess returns on excess market returns (adjusting for potential non-synchronous trading using Dimson's sum beta). We form ten value-weighted portfolios on the basis of individual stocks' monthly betas. The High-IT dummy is then a monthly time-series dummy variable that takes the value of one in months of High-IT quarters. We repeat the Fama-MacBeth regression and pooled regression as in Table 2 and report results in Table B.1.

Before we move to the results, it is worth noting that we employ 13F holdings data to mainly show that the High-IT effect does not seem to be specific to the Finnish market. The primary disadvantage of 13F holdings data (that motivates us to use a much comprehensive and high-frequency Finnish dataset) is its very low frequency. Since the quarterly frequency of 13F data does not capture the timely trade of institutions, the power of our tests would be significantly reduced, and any inference would have to rely on the sign and magnitude of the coefficient rather than its statistical significance.

Panel A of Table B.1 reports the estimate from Fama-MacBeth regressions. Portfolio betas in each month is estimated by running 60-month rolling window regression of excess portfolio returns on excess market returns. On High-IT quarters, the coefficient on beta is positive 27bps whereas, on Low-IT quarters, this coefficient is negative 35bps. The difference in the coefficient on beta between two types of day is 63bps (t-statistic = 1.8). The pooled regression shows a similar picture that the coefficient on the interaction term (High*Beta) is positive 58bps with an associated t-statistic of 2.5. Compared with the Finnish results in Table 2, the magnitude of these coefficients is higher, and hence economically significant. These findings show that, even with the U.S. quarterly holdings data, the implied market risk premium is much higher on High-IT quarters.

Our view is that these out-of-sample tests using quarterly U.S. data confirm our main conclusions and show that the High-IT effect is not specific to the Finnish market. These results strongly suggest that the particular institutional settings of the Finnish market do not seem to be driving our findings.

Table B.1: Excess returns on quarters of high and low institutional trading: U.S. 13F holdings data
This table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for ten beta-sorted portfolios using CRSP data. Estimates are computed for quarters with high institutional trading (High-IT or High) and other quarters (Low-IT or Low). Using data from Thomson Reuters 13F holdings data, we compute aggregate change in institutional holdings scaled by total market trading volume per quarter. Quarter t has Low-IT volume (scaled by total market volume) when the aggregate change in quarterly holdings at t is greater than the average IT volume over the past year (four quarters). Betas are estimated by running 60-month rolling window of excess returns on excess market returns (with Dimson's adjustment). The difference in the coefficient between high- and Low-IT quarters is reported in the last row of each panel. Panel B reports estimates from pooled regression of excess returns on betas, High-IT quarter dummy, and interaction between beta and High-IT (High*Beta). The sample period is between Q1-1984 and Q1-2014. t-statistics, which are computed using Newey-West standard errors with five lags, are reported in parentheses. For pooled regressions, standard errors are corrected for clustering by month. Betas are estimated using data of both high and Low-IT months. This table shows that the difference in the coefficient on beta between High- and Low-IT quarters is positive and though not statistically significant. The weak power of our tests is because quarterly holdings do not capture the timely trade of institutions and also because quarterly beta estimates are less precise.

Panel A: Fama-MacBeth regression

Type of day	Intercept	Beta	Avg. R^2
High	0.00040	0.002791	0.25
	(0.20)	1.040	
Low	0.006491	−0.003520	0.27
	(3.56)	−1.19	
High − Low	−0.00609	**0.00631**	
	(−2.55)	**(1.80)**	

Panel B: Pooled regression

Intercept	Beta	High	High*Beta	Avg. R^2
0.00979	−0.00368	−0.00491	**0.00583**	0.74
(2.31)	(−2.23)	(−0.81)	**(2.45)**	