Balanced Trading Activity and Asset Pricing

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Abstract

Measuring how balanced the trading activity is in the cross-section via the skewness of individual stock turnover, we show that the relationship between beta and expected return is linear and significantly positive when trading is more balanced. This effect is robust to a variety of test portfolios as well as different sub-samples. It is not driven by the positive beta-return relationship on macroeconomic announcement days, leading earnings announcement days, or Fridays. We explore and discuss two plausible explanations that are related to risk-based and behavioural models.

JEL classification: G12, G14.

Keywords: CAPM; Trading volume; Security market line.

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1. Introduction

The slope of the security market line (SML) gives the cross-sectional market price of risk in the setting of the CAPM (Sharpe, 1964; Lintner, 1965), which has wide practical implications ranging from corporate decision-making to investors' performance evaluation. Since the seminal work of Black, Jensen, and Scholes (1972), there has been consensus that this slope is too flat and even negative in the data (see, e.g., Baker, Bradley, and Wurgler, 2011). This directly contradicts the core principle of risk-based asset pricing models, where investors expect a positive return to compensate for taking on (undiversifiable) risk, thus challenging the practical use of the CAPM (Fama and French, 2004). Recently, however, it has been realised that this slope does appear to be positive during specific episodes, such as months preceded by low inflation (Cohen, Polk, and Vuolteenaho, 2005), when the initial margin requirement is low (Jylhä, 2018), on macroeconomic announcement days (Savor and Wilson, 2014) and leading earnings announcement days (Chan and Marsh, 2022), or when the exchange is closed (Hendershott, Livdan, and Rösch, 2020). In this paper, we expand upon this strand of literature by showing that the market price of risk implied by the CAPM is significantly positive when the cross-sectional distribution of trading activity is more balanced.

We capture trading activity of individual stocks by their turnover and study the dynamics between its cross-sectional skewness, as a measure of how balanced the trading activity is in the cross-section, and the slope of SML. We show that on days ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, the average returns are linearly and positively proportional to their CAPM beta. We label these days as *balanced trading days* (BTDs) and depict our main finding in Figure 1. The plot suggests that there exists a linear and positive risk-return trade-off on BTDs (represented by red round dots), whereas it remains mostly flat on other days (represented by blue triangles). The estimated market price of risk (the slope of SML) is 54.96 and -1.00 bps per day, respectively, on BTDs and other days. This implies that the market price of risk seems to be distorted on most of the days when there are some stocks are traded much more intensively than others.

[Fig. 1 about here.]

Following Savor and Wilson (2014), Hendershott et al. (2020), and Chan and Marsh (2022), we formally test this implication in a Fama-MacBeth (Fama and MacBeth, 1973) setting. We start with ten beta-sorted test portfolios and show that the estimated market price of risk on BTDs is 50.57 (44.99) bps per day and is significant at the 1% (5%) level, compared to an estimate of -0.36 (-2.71) bps per day from all other days that is not statistically different from zero, when the testing portfolios are value-weighted (equal-weighted). Our result holds not only for the ten beta-sorted portfolios, but also for a variety of test portfolios including the 25 size and book-to-market portfolios as well as the 10 industry portfolios, of which the data are downloaded from Kenneth French's Data Library.[1] The effect is also robust during different sub-sample periods and when the risk-return trade-off is estimated directly from individual stocks.

To ensure our result is not driven by the findings of Savor and Wilson (2014) and Chan and Marsh (2022), we exclude macroeconomic announcement days and leading earnings announcement days from our sample and show that the strong positive risk-return relationship is still present on BTDs and the difference between BTDs and other days is virtually unchanged. Furthermore, we study our effect in absence of Fridays, on which Birru (2018) argue that a positive beta-return relationship can be observed due to high mood of investors, and find that our results are not driven by Fridays. Finally, we repeat the main analysis of Hendershott et al. (2020) respectively on BTDs and other days and show that their finding of coexistence of an upward-sloping SML over the night and a downward-sloping SML during the day cannot be observed on BTDs, on which both overnight and intraday periods exhibit positive slopes.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

In attempt to understand why investors appear to be compensated by a large and positive return for bearing beta risk on BTDs but not on other days, we first consider the existence of an extra factor that is priced primarily on BTDs but not on other days. Savor and Wilson (2013) document a larger market premium on macroeconomic announcement days than other days and propose an explanation where investors are compensated for bearing not only market risk, but also risk of "*learning that the economy is performing worse than expected*". Savor and Wilson (2014) discuss the possibility that a multi-factor model consists of a factor corresponding to news about future market variance and generates different cross-sectional beta-return relationship at different times. If our BTDs happen to be days on which investors expect to learn news about some state variables, then the betas could potentially capture the increased risk associated with learning such news. Studying the market premium, risk-free rate, percentage change in implied variance, and realised volatility on both BTDs and other days, we reject the hypothesis that our results are driven by the increased risk from learning news about state variables on BTDs. Particularly, we show that although the market premium is significantly larger on BTDs than other days (38.03 bps versus 2.29 bps), the realised volatility is also much larger on BTDs than other days (201.3 bps versus 100.9 bps), implying the higher market premium we observe on BTDs is largely a result of increased market variance. Furthermore, we illustrate that the risk-free rate is higher on BTDs than non-BTDs, contradicting the implication of lower risk-free rate on BTDs if the model of Savor and Wilson (2013) were applied in our setting. Finally, we show that the percentage change in implied volatility is virtually the same across BTDs and non-BTDs and the difference is statistically zero, whereas, based on the model of Savor and Wilson (2013), it is predicted to be a drop on BTDs if our effect was driven by an increased risk of leaning news released on BTDs.

We then turn our attention to the most intensively-traded stocks in the cross-section, i.e., the stocks with the highest turnover, whose presence represents largely unbalanced trading activity (thus large turnover skewness) on a given day. We show that the compensation for bearing one unit of beta risk among these stocks is strongly negative, suggesting the possibility that the cross-sectional risk-return trade-off is distorted by the trading of these stocks. In the disagreement literature, higher trading volume is often considered as a signal of larger belief dispersion among investors.[2] Our results could therefore imply that the heterogeneous beliefs of investors distort the otherwise positive risk-return trade-off on most of the days, echoing the intuition in Hong and Sraer (2016), albeit the disagreement in their model is at the aggregate level.

Our main contribution is twofold. First, we link trading volume with the market price of risk. In basic economics, both quantity and price are determined simultaneously in equilibrium, yet the literature in asset pricing is often separate from those on trading volume, due perhaps to the famous no-trade theorems.[3] Indeed, as John Cochrane points out, trading volume plays essentially zero role in the canonical asset pricing models and remains what he regards as The Great Unsolved Problem of Financial Economics.[4] Our study sheds light on the relationship between trading volume and cross-sectional market price of risk by showing that when trading activity is more balanced in the cross-section, i.e., when there are fewer stocks being more intensively traded than most of their peers, the traditional wisdom of positive risk-return relationship emerges. The evidence we document suggests that this relationship could be severely distorted when some stocks in the cross-section are intensively traded but the rest are much less so. Second, we study asset pricing implications of trading volume by extracting information from the third moment in the cross-section. A difficulty when working with such a complicated measure as trading volume is that its information contents can be multi-dimensional. When studying different periods in time identified by trading volume, a natural concern is the time varying information, such as those about tech-

[2]See Hong and Stein (2007) for a survey on the trading volume implications of disagreement models. See also Medhat and Schmeling (2021) and Han, Huang, Huang, and Zhou (2022) for recent examples of associating trading volume with belief dispersion in empirical studies.

[3]An exception is the research on disagreement and financial market, which speaks directly to both asset prices and their trading volume (see Hong and Stein (2007)). However, as far as we are aware, there's little empirical study investigating directly the relationship between trading volume and market price of risk.

[4]`https://www.johnhcochrane.com/research-all/volume-and-information`.

nology advancements (e.g., the implementation of electronic trading platforms), conveyed by trading volume. Our approach of extracting information from the third moment in the cross-section ensures the identification of BTDs is less affected by biases induced by such time-varying information.

Our paper is related to the long-standing literature on the behaviour of SML. In testing the CAPM of Sharpe (1964) and Lintner (1965), Black et al. (1972), among others, find that SML is too flat compared to what the model suggests. This flat SML is rationalised in Black (1972) where the assumption of unlimited risk-free borrowing in the original CAPM is scrapped. Indeed, practitioner are often constrained as to how much they can lever and thus are forced to overweight risky assets. Building on this observation, Frazzini and Pedersen (2014) further extend Black (1972) from risk-free borrowing constraints to broader funding constraints and develop a model wherein there exists a negative relationship between alpha and expected return in the cross section. This story of leverage constraints is empirically supported by Jylhä (2018). A recent alternative explanation of the flat SML is given by Andrei, Cujean, and Wilson (2023), in which the CAPM holds for investors but appears flat to empiricists due to the variation in expected returns over time as well as across investors.

However, SML is not always flat and does behave well in some time periods. For example, Tinic and West (1984) find evidence that there exists a positive risk-return relationship in January but not in other months. Savor and Wilson (2014) show that SML exhibits a positive slope, just as the theory suggests, on macroeconomic announcement days while it remains flat on other days. Similar results can also be found on major corporate earnings announcement days, as documented in Chan and Marsh (2022). At a more granular level, Hendershott et al. (2020) present evidence that SML is upward-sloping out of trading hours when the market is closed while a downward-sloping SML can be observed when the market is open. Contributing on this strand of literature, we show that the CAPM implied market price of risk is linear and significantly positive when trading activity is more balanced distributed in the cross-section and argue that this effect is unlikely to be caused by revelation of news as has been studied in the existing literature.

While the aforementioned idea of leverage constraints may accommodate a flat SML and even a negative beta-*alpha* relationship (e.g., Frazzini and Pedersen, 2014), it cannot generate a downward-sloping SML that features a negative beta-*expected return* relationship that has been documented in the literature.[5] This is also argued in Hong and Sraer (2016) and Buffa, Vayanos, and Woolley (2022). How could a downward-sloping SML be reconciled then? Hong and Sraer (2016) and Buffa et al. (2022) provide theoretical understanding of the issue from heterogeneous-belief and institutional-friction perspectives, respectively. In Hong and Sraer (2016), short-sale restricted investors disagree on the expected common factor in future cash flows, and this disagreement increases with beta. When the disagreement is large enough, the pessimistic investors sideline from trading high beta assets leaving them overpriced and thus commanding low expected returns. On the other hand, the Buffa et al. (2022) model features investors with varying constraints as to how much they can deviate from a benchmark (e.g. quasi-indexers) and shows such institutional constraints amplifies the overpricing of high-beta stocks. Unlike Hong and Sraer (2016), this model generates a downward-sloping SML without requiring short-sale constraints. In our paper, we show that the beta risk is negatively priced among most intensively-traded stocks, a phenomenon that could be potentially reconciled with such behavioural or institutional friction frameworks.

The remainder proceeds as follows. Section 2 describes our sample and defines balanced trading days (BTDs). Section 3 presents the main findings and illustrates they are robust using a variety of test portfolios and sub-samples. Section 4 explores the nature of BTDs and discusses two potential explanations. Section 5 concludes.

[5]For example, Baker et al. (2011) show that in the post-1968 period high-beta stocks are actually associated with low average returns, compared to their low-beta peers. In a study of money illusion in the stock market, Cohen et al. (2005) show that the slope of SML negatively comoves with inflation, being negative in months with highest preceding inflation. Furthermore, as mentioned already, Hendershott et al. (2020) illustrate that SML is downward-sloping during trading hours.

2. Data and Exploratory Analysis

2.1. Data

Our data is from the Center for Research in Security Prices (CRSP) and contains daily observations for the US common stocks (with CRSP share codes of 10 or 11) traded on the NYSE, AMEX, or NASDAQ (those with CRSP exchange codes of 1, 2, or 3) from 01 July 1962 to 31 December 2022. To mitigate distortions induced by missing data, we remove a stock-day observation if the stock price, return, or share of outstanding is missing. As for extreme values, we follow Hendershott et al. (2020) and delete observations with a daily return greater than 1000%. In addition, we also discard an observation if the turnover is larger than 100%.[6] To ensure the records of trading volume from NASDAQ is comparable to that from NYSE and AMEX, we follow the literature (Gao and Ritter, 2010; Medhat and Schmeling, 2021; Han et al., 2022) and apply a deflator of 2.0 prior to February 2001, 1.8 from February 2001 to December 2001, and 1.6 from January 2002 to December 2003.

2.2. Definition of BTDs

In order to measure how balanced the trading activity is in the cross-section, on each trading day we compute the skewness (γ) of individual stock turnover:

$$\gamma = \frac{\frac{1}{N}\sum_{i=1}^{N}(TO_i - \mu)^3}{\left[\frac{1}{N}\sum_{i=1}^{N}(TO_i - \mu)^2\right]^{3/2}}, \tag{1}$$

where N is the number of stocks in the cross-section, TO_i is the turnover for stock i, and μ is the cross-sectional mean of individual turnover. We then define days with the smallest one-trading-day lagged γ as BTDs (balanced trading days). More specifically, in our main

[6] This further removes 0.012% of the data. Our main results remain unchanged if these observations are retained in the sample.

analysis we rank all trading days by their one-trading-day lagged γ and focus on the different asset pricing implications between the bottom 1% of the days and the rest. The rather uneven division of our sample is a direct result of the fact that the skewness of cross-sectional turnover is always positive (see Table 1) and largely so on most of the days, implying that the number of days with relatively balanced trading activities is by nature small.

To illustrate the "balanced trading activity" that we are capturing via skewness, in Figure 2 we give an example by depicting the cross-sectional distribution of one-trading-day-lagged turnover on a selected BTD, compared with that on a matched non-BTD. Specifically, the two days are selected as follows. First, for each day in our sample, we compute the cross-sectional mean and standard deviation (rounded up to two decimal places) of one-trading-day-lagged turnover. Second, we match each BTD with one or more non-BTDs based on the computed mean and standard deviation. Finally, we find the pair that gives us the largest difference in the skewness of one-trading-day-lagged turnover, after controlling for the mean and standard deviation.

As it is shown in Figure 2, while the cross-section of one-trading-day-lagged turnover on both days have the same mean (1.07%) and standard deviation (1.48%), their skewness are distinct. Particularly, the distribution of one-trading-day-lagged turnover on 14 August 2007 exhibits fatter right tail than that on 30 October 2008. This is mainly a result of the stocks with Permanent Company Number (PERMNO, a unique stock level identifier assigned by CRSP) of 87756 and 89684 being extensively traded on the day preceding 14 August 2007, yielding a turnover of 27.4% and 60.8%.[7] We argue that the existence of such intensively traded stocks with unusually large turnover compared to their peers is a primary signal of

[7] An investigation shows that the company issued the stock with PERMNO of 87756, the SCO Group, lost a court case against IBM to the copyright claims of Linux, which is of significant value to their core business, on Friday, 10 August 2007 (see https://www.reuters.com/article/novell-unix/update-2-sco-loses-court-case-key-to-linux-claims-idUKN1031204220070811, for details). Reacting to the revelation of the news, trading volume surged on Monday, 13 August 2008. Moreover, the unusual trading volume of the stock with PERMNO of 89684 appears to be related to the aborted takeover of its issuer, Accredited Home Lenders Holding Co., by Lonestar and associated legal battles that were announced in the window around the weekend prior to Monday, 13 August 2008 (see https://www.reuters.com/article/idUSWEN0379 and https://www.reuters.com/article/idUSN13323428, for details).

unbalanced trading activity. Such stocks may have drawn excessive attention or other scarce resources of investors and thus distort the pricing of risk in the entire cross-section. This is what we aim to test in our main analysis that follows.

[Fig. 2 about here.]

2.3. Exploratory analysis

Table 1 reports the summary statistics. The cross-sectional mean (μ) of one-trading-day lagged turnover is on average 0.58% in our sample period for BTDs, higher than 0.43% for Non-BTDs (other days), 0.43% for macro-announcement days (Savor and Wilson, 2014), and 0.41% to 0.44% for different weekdays. This suggests that despite the right tail being less extreme in the cross-section of turnover, the aggregate engagement in trading activities on days preceding BTDs is in fact higher, while it is virtually the same across days preceding macro-announcement days and different weekdays. In terms of the cross-sectional variation of one-trading-day lagged turnover, our BTDs have the smallest average standard deviation (0.80%), which is not surprising given that the skewness on these days is the smallest. Again, the difference in the average standard deviation on days preceding other types of days is roughly the same (0.94% to 1.01%), with the exception of the leading earnings announcement days (LEADs, as defined in Chan and Marsh (2022)), for which a larger average standard deviation of 1.93% is observed. Turning attention to our key variable γ, which is the cross-sectional skewness of one-trading-day lagged turnover, we observe that it is significantly lower on BTDs, as it should be, and remain virtually the same on all other types of days. For example, the time-series of one-trading-day lagged γ ranges from 2.40 to 4.25 (which is our 1% breakpoint) with a mean of 3.75 for BTDs, whereas it ranges from 4.25 to 62.18 for all other days, with a mean of 12.83. The minimum skewness of 2.40 shows that the cross-sectional distribution of turnover is by nature right-skewed.

[Table 1 about here.]

3. Main Results

3.1. Beta-sorted portfolios

To formally establish the difference in market price of risk on BTDs and that on other days, as suggested by Figure 1, we follow the literature and run Fama-MacBeth (Fama and MacBeth, 1973) and pooled regressions, starting with the beta-sorted portfolios. As in Hendershott et al. (2020), we sort individual stocks at the end of each month m into 10 test portfolios based on their pre-ranking betas that are obtained from daily data over the past year, with minimum 15 available observations:

$$r_{i,t} = \alpha_i + \beta_{i,m} r_{M,t} + \epsilon_{i,t}, \tag{2}$$

where $r_{i,t}$ and $r_{M,t}$ are excess returns of individual stock i and the market, respectively, at date t. Post-ranking betas for the 10 test portfolios are then estimated similarly at the end of each month using daily data over the past year. In the Fama-MacBeth regressions, the excess returns of the test portfolios are regressed on their post-ranking betas on each day t:

$$r_{j,t+1} = \alpha_t + \lambda_t \hat{\beta}_{j,t} + \epsilon_{j,t}, \tag{3}$$

where $r_{j,t+1}$ is the excess return for the test portfolio j at date $t+1$, $\hat{\beta}_{j,t}$ is its corresponding estimate of the post-ranking beta estimated using information from the past one year up to t, and λ_t is the variable of interest at date t.

[Table 2 about here.]

The left-hand side of Panels A and B in Table 2 report the Fama-MacBeth results for value- and equal-weighted beta-sorted portfolios, respectively. We observe that, for the value-weighted portfolios, one unit of risk (β) bear is compensated by 50.57 bps per day on BTDs. This astonishing market price of risk is significant at the 1% level. In contrast, the average risk compensation on other days is statistically zero, as suggested by the point estimate of -0.36 bps with an insignificant t-statistic of -0.34. The Welch's t-statistic between the estimated λ's on the two types of days is 4.67, accompanied with a significantly higher compensation of 50.93 bps per day for one unit of risk on BTDs versus other days. The average R^2 for both types of days is 48%. Moreover, the CAPM implied risk-free rate (the intercept) is statistically insignificant on BTDs but significant at the 1% level with a point estimate of 3 bps on other days, which leads to a difference in the implied risk-free rate of -12.22 bps between BTDs and other days. These results echo our finding in Figure 1 that on BTDs an upward sloping security market line is observed.

Our results also hold for the equal-weighted beta-sorted portfolios. The estimated λ is 44.99 (-2.71) bps and significant at the 5% (1%) level on BTDs (other) days with a significant difference of 47.71 bps (t-statistic = 4.59) between the two types of days. Similar to the value-weighted case, our analysis implies a significant positive risk-free rate of 7.61 bps on days other than BTDs, but a statistically zero risk-free rate on BTDs. The average R^2 is 60% for BTDs whereas it is 54% on other days.

As in Savor and Wilson (2014), Hendershott et al. (2020), and Chan and Marsh (2022), we also fit a pooled regression for both value-weighted and equal-weighted portfolios, respectively:

$$r_{j,t+1} = \alpha + \lambda\hat{\beta}_{j,t} + \xi_1 D^{BTDs}_{j,t} + \xi_2 \hat{\beta}_{j,t} D^{BTDs}_{j,t} + \epsilon_{j,t}, \tag{4}$$

where $D^{BTDs}_{j,t}$ is a dummy variable that takes value of 1 for portfolio j on BTDs and 0 on other days.

Results shown in the right-hand side of Panels A and B in Table 2 largely confirm our evidence from the Fama-MacBeth regressions. For the value-weighted portfolios, the intercept is 3.89 bps (t-statistic = 5.35) on non-BTDs, which is 11.99 bps (but insignificant) lower on BTDs. For the equal-weighted portfolios, the intercept is 8.83 bps (t-statistic = 11.90) on non-BTDs, which is 0.49 bps (also insignificant) higher on BTDs. Our key coefficient of interest here is the slope of the interaction term, ξ_2, which gives the difference in market price of risk on the two types of days. In both value- and equal-weighted cases, ξ_2 is economically large and statistically significant, with a point estimate of 51.29 (t-statistic = 2.99) and 43.29 (t-statistic = 2.46) for each case, respectively. This is consistent with our Fama-MacBeth evidence that the market price of risk is positive and significantly larger on BTDs.

3.2. *Size, book-to-market, and industry portfolios*

To confirm the robustness of our findings, following Savor and Wilson (2014), Hendershott et al. (2020), and Chan and Marsh (2022), we add the 25 size, book-to-market, and industry portfolios to our analysis and re-examine the beta-return relationship on the two types of days. First of all, we re-plot this relationship as in Figure 1 but using instead the 45 portfolios. Figure 3 shows clearly that the beta-return relationship is positive on days with small lagged turnover skewness whereas it remains flat for other days. Specifically, we plot average r_{t+1} against full-sample post-ranking betas of the test portfolios for BTDs and other days and find a positive sloped security market line for the former (red dots) and a virtually flat security market line for the latter (blue triangles).

[Fig. 3 about here.]

Panel C of Table 2 presents results for the Fama-MacBeth and pooled regressions, respectively, using the 45 value-weighted test portfolios. In the Fama-MacBeth regressions, the estimated λ of 46.85 bps (t-statistic = 2.50) is close to our estimate when using only the beta-sorted portfolios. Similarly, we also observe a statistically insignificant λ on other days (-0.78 bps with a t-statistic of -0.73), as in the case with only the beta-sorted portfolios. The difference in the market price of risk between the two types of days is 47.63 bps with a t-statistic of 4.44. Moving to the pooled regressions, again we have similar results as in Panel A. For example, the implied risk-free rate is 3.60 bps on non-BTDs while the slope of the interaction term is 53.38 with a t-statistic of 2.31.

3.3. Individual stocks

Next, we turn to the robustness of our results when individual stocks are used in the analysis. To do so, we run Fama-MacBeth and pooled regressions of excess returns to individual stocks on their betas that are estimated and updated at the end of each month using daily data from the past year. The right-hand side of Panel D in Table 2 presents results for the Fama-MacBeth regressions. As in the case with various beta- and characteristic-sorted portfolios, the estimated slope coefficient is positive and statistically significant with a point estimate of 33.85 bps and a t-statistic of 2.31. The difference in the slope coefficient between the two types of the day is 36.19 bps (t-statistic = 5.16). Similar to the results from the beta-sorted equal-weighted portfolios, we observe a negative slope coefficient on non-BTDs of -2.34 bps (t-statistic = -3.34), suggesting a slightly downward sloping security market line on these days.

3.4. Sub-period analysis

Having established our main findings with various beta- and characteristic-sorted portfolios as well as individual stocks, we now turn our attention to the robustness of our results in the time-series, starting with a sub-period analysis. This is important to our study since, unlike Savor and Wilson (2014); Hendershott et al. (2020), and Chan and Marsh (2022), our BTDs are not pre-scheduled but picked up via an ex-ante variable, i.e., the cross-sectional skewness of turnover on the previous trading day. Therefore, it is important to examine whether our results are driven by a particular economic episode.

To this end, we repeat our analysis in three 20-year sub-periods using beta-sorted value-weighted portfolios. More specifically, we partition our sample into sub-periods of 01 July 1963 to 30 June 1983, 01 July 1983 to 30 June 2003, and 01 July 2003 to 31 December 2022 and re-identify BTDs using the 1% threshold over these three sub-periods, respectively. As shown in the left-hand side of Table 3, the difference in the slope coefficient (λ) between BTDs and other days is observed across all three periods, with the estimated difference being 28.99 bps, 40.67 bps, and 119.18 bps (all of which are significant at the 1% or 5% levels), respectively. Moving on to the estimates of λ itself, we obtain a positive estimate at a remarkable magnitude across all three periods (27.94, 40.37, and 119.06 bps) while statistical significance appears in the first and last twenty-year windows with a t-statistic of 1.93 and 2.42, respectively. The slight reduction in statistical significance is somewhat expected given that there are now only around 50 BTDs in each sub-period. What important here is that the difference in the estimated market price of risk between BTDs and other days are still positive and significant while the R^2 still ranges between 40% to 60% in all sub-periods. Furthermore, we also report results for the pooled regressions in the right-hand side of Table 3, which once again confirm that the difference in the slope of the security market line between the two types of days is robust in all three sub-periods, as suggested by a significant ξ_2 of 33.19 (t-statistic = 2.09), 70.76 (t-statistic = 1.76), and 114.36 (t-statistic = 2.58), respectively.

[Table 3 about here.]

3.5. Announcement days

Savor and Wilson (2014) document that a positive risk-return trade-off holds well, both in the time-series and cross-section, on the announcement days of important macroeconomic news such as inflation, unemployment, and interest rates. Chan and Marsh (2022) find evidence of a positively sloped security market line on leading earnings announcement days (LEADs). It is therefore important to control for their results and see if our findings are driven by these announcement days.

We have seen from Table 1 that, on average, the mean skewness of trading volume is 3.3 and 3.9 times larger on the macro-announcement days and LEADs, respectively, than that on BTDs, implying that our results is unlikely to be dominated by these announcement days. To formally test this implication, we respectively delete the macroeconomic announcement days, as defined in Savor and Wilson (2013, 2014), and LEADs, as defined in Chan and Marsh (2022), from our sample and repeat our analysis.

[Table 4 about here.]

Panels A and B in Table 4 report the evidence that our results remain virtually unchanged after excluding announcement days. With the macroeconomic announcement days excluded, for example, the estimated market price of risk on BTDs is 51.22 bps (t-statistic = 2.62) whereas it is not statistically different from zero (point estimate of -1.36 with a t-statistic of -1.18) on other days. There's also a significant difference of 52.58 bps (t-statistic = 4.53) in λ between the two types of days. Similar results can be observed when we exclude instead LEADs from the sample. For example, the estimated λ is 49.40 bps (t-statistic = 2.72) on BTDs while being again insignificant on other days. The difference between the two types of days on λ is 50.14 bps that is associated with a t-statistic of 4.61.

The main conclusion remains unchanged in the pooled regressions, as suggested by a significant slope coefficient of the interaction term of 53.48 (50.16) with a t-statistic of 2.90 (2.88) when we discard the macro-announcement days (LEADs) from our sample.

The estimated market price of risk on BTDs is remarkable in magnitude and larger than that has been documented on macro-announcement days and leading earnings announcement days. we show in Table A.1 of Appendix A that by repeating our analysis over the sample periods used in Savor and Wilson (2014) and Chan and Marsh (2022) (1964-2011 and 2001-2019), respectively, the estimated market price of risk on BTDs is about 7 (5) times larger than that is documented on the macro-announcement (leading earnings announcement) days.

3.6. Day of week effect

In examining the day of week effect of 19 anomalous strategies, Birru (2018) argues high-beta stocks are more affected by high mood of investors on Fridays and produce high returns, which results in a strategy that bets against the beta (e.g., Frazzini and Pedersen,

2014) earning negative profits on Fridays. To make sure our cross-sectional skewness of turnover does not simply pick up Fridays with strong sentiment in the market, we exclude all the Fridays from the sample and repeat our analysis. The results shown in Panel C of Table 4 confirm that our finding of a positively sloped security market line on BTDs is not driven by the change in mood on Fridays. Particularly, even without Fridays being included in the sample, we still observe a statistically significant λ of 37.75 bps (t-statistic = 1.80) on these days and, more importantly, the difference between BTDs and other days is 37.33 bps that is significant at the 1% level (t-statistic = 2.99). Again, the pooled regressions echo the Fama-MacBeth evidence through a statistically significant estimate of ξ_2 (39.63, t-statistic = 2.02).

3.7. Overnight vs intraday

Another potential concern about the robustness of our results is the different behaviour of the security market line across the overnight and intraday periods. Lou, Polk, and Skouras (2019) document that the betting-against-beta strategy earns its profit primarily from the intraday period contra the overnight period. Sequentially, Hendershott et al. (2020) find that the beta-return relationship is strongly negative during the day but positive over the night, of which the evidence is equally strong. To eliminate the possibility that our findings are a result of an unbalanced "tug-of-war" between overnight and intraday periods on days preceded by a small cross-sectional turnover skewness, we study the security market line separately for the two periods, as in Hendershott et al. (2020), on these days and other days.

Following Lou et al. (2019) and Hendershott et al. (2020), specifically, we assume major corporate events take place overnight and impute overnight returns ($r_{i,t}^N$) for stock i from its intraday returns:

$$r_{i,t}^N = \frac{1 + r_{i,t}}{1 + r_{i,t}^I} - 1, \tag{5}$$

where $r_{i,t}$ is the daily return for stock i from CRSP and $r_{i,t}^I$ is the intraday return for stock

i computed using the open and close prices on day t. We then perform the main analysis in Hendershott et al. (2020) to BTDs and other days, respectively.

[Table 5 about here.]

As shown in Table 5, we observe a positive and statistically significant λ for both BTDs (41.41 bps, t-statistic = 1.88) and other days (7.21 bps, t-statistic = 7.88). This is consistent with the finding of Hendershott et al. (2020) that the security market line is upward sloping over the night. However, λ flips signs during the intraday period (as documented in Hendershott et al. (2020)) only on non-BTDs but not on BTDs. When focusing on the intraday period, particularly, we obtain large and positive λ estimate of 14.60 bps on BTDs, albeit being statistically insignificant with a t-statistic of 0.49. In contrast, it is -7.22 bps with a significant t-statistic of -4.67 on other days, echoing the evidence documented in Hendershott et al. (2020). Most importantly, we compute the difference in λ between the overnight and intraday periods for BTDs and other days, respectively. While there is a considerable difference between the two periods on non-BTDs, as suggested by a point estimate of 14.42 bps with a t-statistic of 8.03, it is not statistically different from zero on BTDs (26.81 bps with a t-statistic of 0.73). Our results suggest that, unlike on non-BTDs, the beta-return relationship mostly positive and does not flip signs across both intraday and overnight periods.

4. Discussion

4.1. Market premium and "news-learning risk"

In the time-series, Savor and Wilson (2013) find that the market premium is multiple times higher on announcement days than other days. They propose a potential explanation of this effect in which investors are compensated for bearing not only market risk but also risk of "*learning that the economy is performing worse than expected*". In Savor and Wilson

(2014), the authors discuss the possibility that an unconditional multi-factor model with three or more factors (or a conditional two-factor model), of which one is associated with news about future market variance, can explain the different cross-sectional market price of risk on macro-announcement days and other days. In our case, there is in principle also such possibility that if for some reason investors expect to learn news about future market variance on BTDs.

To investigate such possibility, we compare and contrast the market premium, risk-free rate, implied volatility, and realised volatility, as in Savor and Wilson (2013), on BTDs and non-BTDs. Table 6 presents the results. First, we find the market premium is significantly larger on BTDs than other days, with a statistically significant difference of 35.73 bps (t-statistic = 4.25). While this is analogous to the finding of Savor and Wilson (2013) that the market premium is significantly larger on the macro-announcement days, we find the realised volatility is also significantly larger on BTDs. For example, the standard deviation of the market premium on BTDs is 201.3 bps, compared to 100.9 bps on other days, resulting in a difference of 100.4 bps. That is, the realised volatility is almost twice as large on BTDs. Unreported in the table, the F-statistic between the two standard deviation is 3.98 and suggests a statistical significance level of 1%. This an important distinction of our BTDs from macro-announcement days of Savor and Wilson (2013), on which the realised volatility is only slightly larger than non-macro-announcement. In other words, our evidence of significantly higher market premium on BTDs has weeker indicative power of additional state variable of which the risk is not captured by market volatility.

[Table 6 about here.]

In the model of Savor and Wilson (2013), the market-clearing risk-free rate is negatively related to investors' desired precautionary saving. As investors approach to macro-announcement days, increased uncertainty induced by the news-related state variable leads to an increase in the desired precautionary saving and thus a lower interest rate. While the authors find support evidence for macro-announcement days, we observe a significantly larger risk-free rate on BTDs (2.32 bps), compared to other days (1.71 bps). The difference between the two types of day is 0.61 bps with a t-statistic of 5.88. This evidence again implies that our BTDs are less likely to be associated with news-related state variables.

The last implication of the Savor and Wilson (2013) model we test for our BTDs is on the implied variance. In their model, the implied variance is expected to decrease on the macro-announcement days, which is empirically supported by the author. In our case, however, the change in implied variance on BTDs is positive and statistically indifferent from that on other days. For example, the daily percentage change in the implied variance, which is measured using the squared end-of-day value of the VIX Index, is 0.69% and 0.97% on BTDs and other days, respectively. The difference between the two types of day is statistically insignificant with a t-statistic of -0.12. Overall, our results suggest that despite showing similar empirical patterns in the risk-return trade-off, our effect on BTDs is unlikely driven by news-related state variables and therefore fundamentally different from the findings in studies like Savor and Wilson (2014) and Chan and Marsh (2022).

4.2. Intensively-traded stocks

So why does there exist such a strong beta-return relationship that is in line with the theory on BTDs but not on other days that account for the vast majority of the trading days? One obvious distinction between the two types of days is that there are more extremely active stocks on non-BTDs relative to BTDs. The presence of such "outliers" would drive the turnover skewness on that day to a large level, thus differentiate that day from the BTDs. In the disagreement literature, trading volume is often seen as a proxy for belief dispersion among investors. These "outliers" could therefore be seen as stocks with fundamentals on which investors largely hold divergent opinions. If this is the case, our results then imply that on most of the days the otherwise positive beta-return relationship could be potentially distorted by the disagreement among investors. We therefore investigate the risk-return trade-off among only these disagreed stocks.

On each day, we rank all the stocks in the cross-section by descending order based on their turnover and repeat our Fama-MacBeth analysis using only the stocks with highest turnover in the cross-section. Table 7 reports results using stocks in the top 5%, 10%, 15%, and 20%, respectively. As it is shown, the risk-return trade-off among the highest turnover stocks is significant and negative on all days except for BTDs. For example, the estimated market price of risk (λ) monotonically decreases from -3.73 bps (t-statistic = -2.90) when focusing on the top 20% of the stocks by turnover to -6.87 bps (t-statistic = -4.50) when focusing on the top 5% of the stocks, on all days as shown in Panel A. In Panel B, we observe a stronger negative beta-return relationship on non-BTDs, with λ again monotonically decreasing from -4.37 bps (t-statistic = -3.43) when focusing on the top 20% of the stocks by turnover to -7.67 bps (t-statistic = -5.04) when focusing on the top 5% of the stocks. However, the beta-return relationship remain significantly positive on BTDs, even among relatively high turnover stocks on those days. Specifically, the estimated λ increases from 59.37 bps (t-statistic = 2.48) to 72 bps (t-statistic = 2.97) across the samples that comprise top 5%, 10%, 15%, and 20% of the stocks by turnover. This is not surprising since on BTDs even relatively high turnover stocks do not deviate far from the median in the cross-section, implying that attention is more evenly distributed on these days than non-BTDs, thus the positive risk-return trade-off is not distorted.

[Table 7 about here.]

5. Conclusion

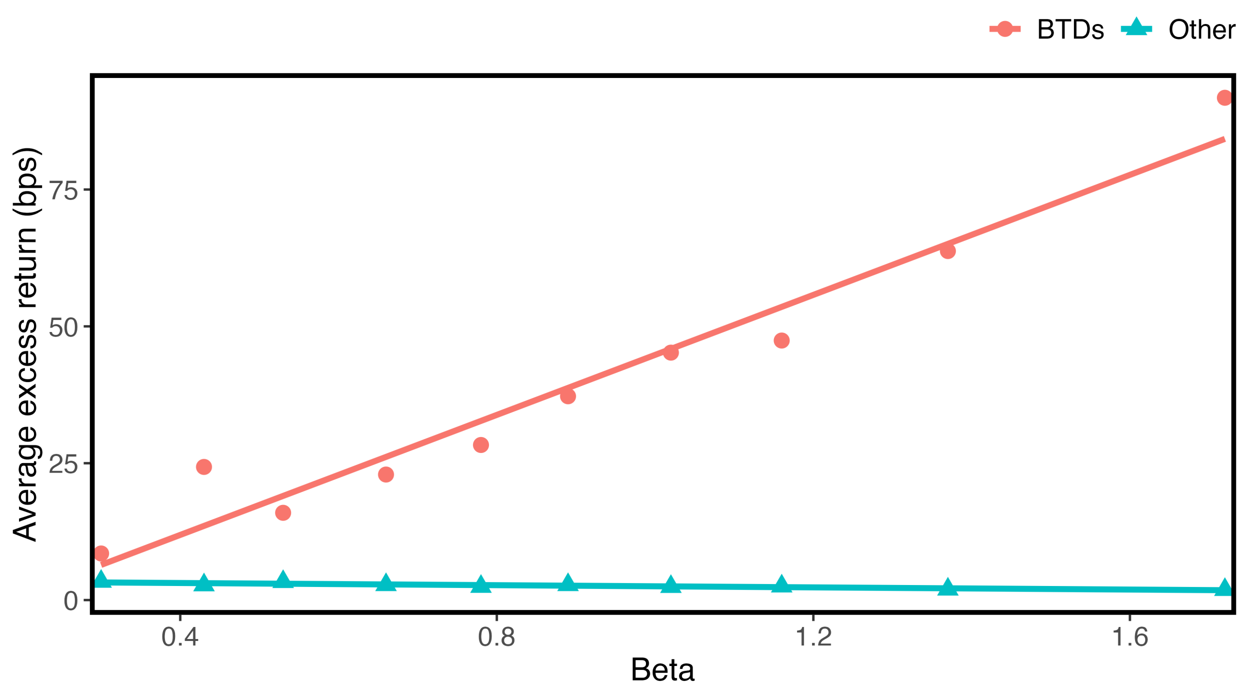
Using the skewness of individual stock turnover in the cross-section as a measure of how balanced the trading activity is, we study the beta-return relationship in the US stock market. We provide evidence that when the distribution of trading is more balanced across stocks, investors are compensated with a positive return for bearing beta risk and, on average, no such compensation is given on other days. The linear and positive beta-return relationship is robust to various test portfolios, ranging from beta-sorted portfolios to size, book-to-market portfolios and to industry portfolios. It also holds for different sub-sample periods as well as individual stocks. We further show that our effect is not driven by the positive beta-return relationship on certain days documented in existing literature, such as macroeconomic announcement days (Savor and Wilson, 2014), leading corporate announcement days Chan and Marsh (2022), or Fridays Birru (2018).

In addition, we observe that the market premium is significantly larger on our balanced trading days (BTDs). However, we also note that realized market volatility is higher during these periods. This suggests that, despite observing similar empirical patterns on BTDs, the phenomenon may be fundamentally different from what is documented on announcement days. We provide supporting evidence by demonstrating that the interest rate on BTDs is significantly larger, as opposed to smaller. This trend runs counter to the precautionary saving channel described in Savor and Wilson (2013). Furthermore, we show that the change in implied variance is neither negative nor statistically different from that observed on other days, in contrast to the pattern seen on announcement days.

Finally, we explore the nature of BTDs by examining the risk-return trade-off among the extremely active stocks, whose presence lead to unbalanced trading in the cross-section. We find that the beta-return relationship among these stocks are significantly negative. Seeing turnover as a proxy for heterogeneous beliefs, this pattern is conceptually consistent with the intuition described in Hong and Sraer (2016), albeit it is the aggregate disagreement that takes effect in their model. Our result therefore suggests that on most of the trading days the otherwise positive risk-return trade-off may be distorted by the trading of the most active stocks and this may be a result of investor disagreement.

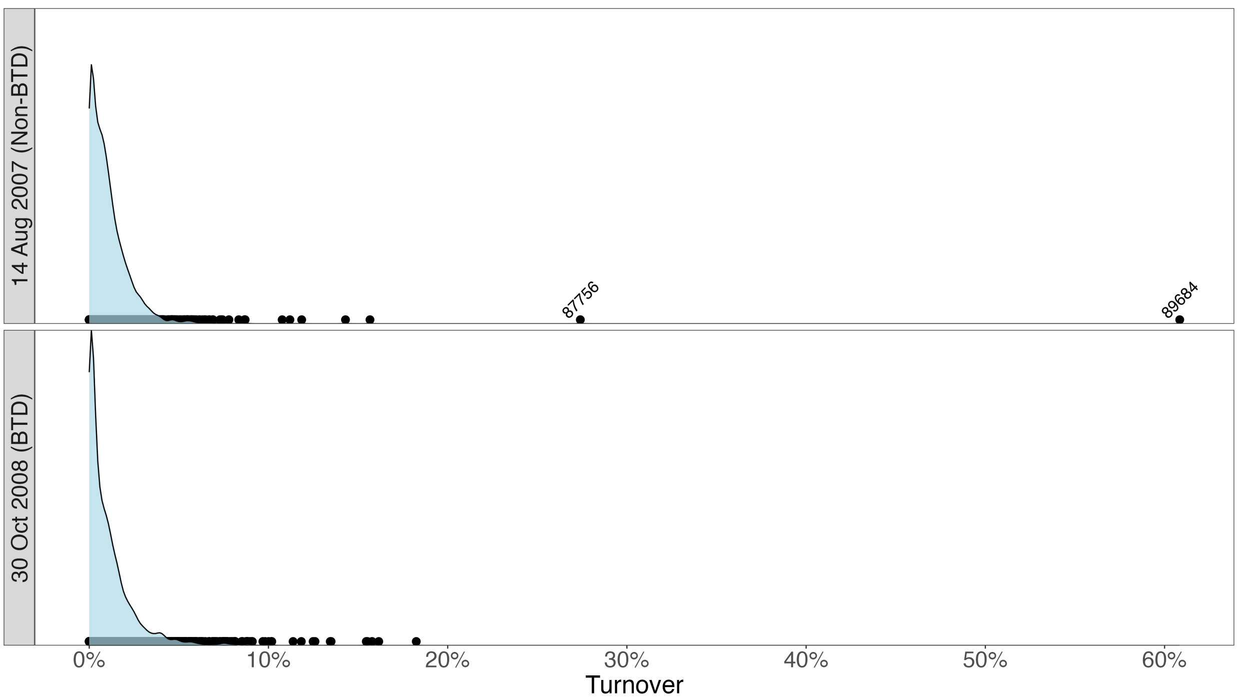
Figures

Fig. 1: Daily excess returns for beta-sorted portfolios



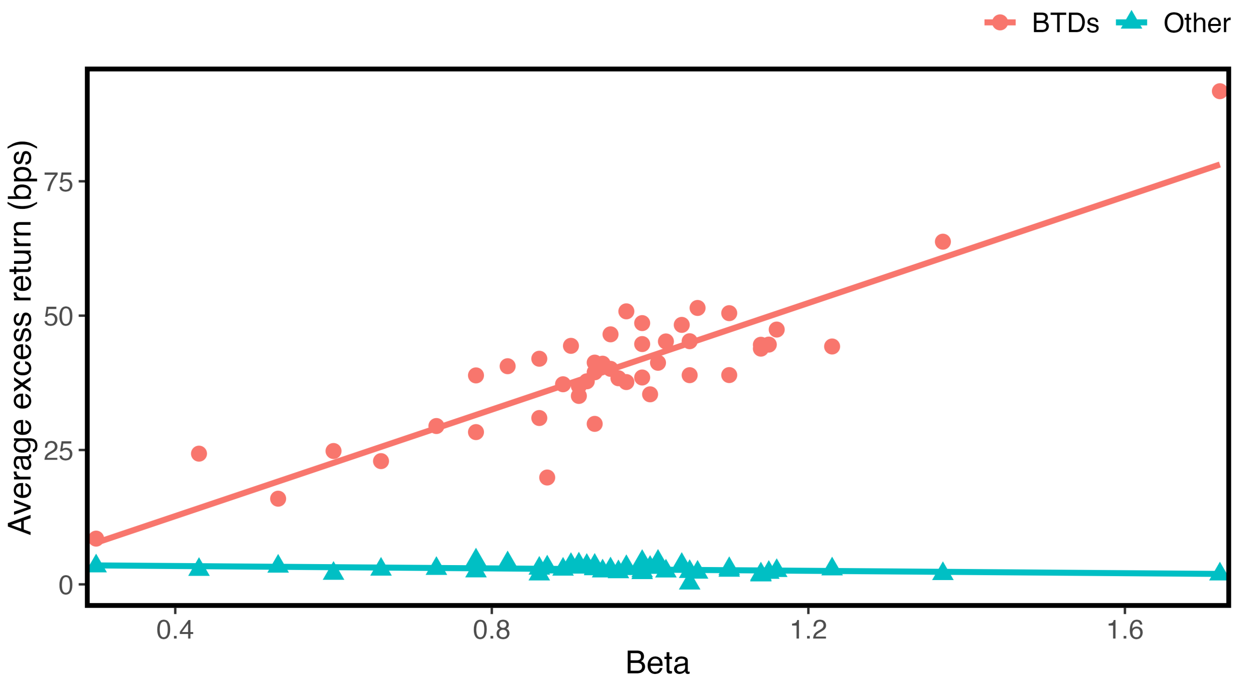
This figure plots average daily excess returns again market betas for 10 beta-sorted value-weighted portfolios on balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other), respectively. The sample period covers from 01 July 1963 to 31 December 2022. At the end of each month, portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, which are estimated by regressing daily excess returns of the individual stock on that of the market over the past one year. Post-ranking betas for each test portfolio are estimated using the full sample.

Fig. 2: Mean- and standard deviation-matched comparison between BTDs and Other days: An illustrative example



This figure plots the distribution density as well as the dot plot for the cross-section of one-trading-day-lagged turnover on 14 August 2007 and 30 October 2008, respectively. 30 October 2008 is selected from the balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, whereas 14 August 2007 is from the non-BTDs. Specifically, the two days are selected as follows. First, for each day in our sample, we compute the cross-sectional mean and standard deviation (rounded up to two decimal places) of one-trading-day-lagged turnover. Second, we match each BTD with one or more non-BTDs based on the computed mean and standard deviation. Finally, we find the pair that gives us the largest difference in the skewness of one-trading-day-lagged turnover, after controlling for the mean and standard deviation. For exposition purposes, we also label the two stocks with the highest lagged turnover on 14 August 2007 by their corresponding PERMNO (a unique stock level identifier assigned by CRSP).

Fig. 3: Daily excess returns for beta-sorted, 25 Fama-French, and 10 industry portfolios



This figure plots average daily excess returns again market betas for 10 beta-sorted value-weighted portfolios, as well as 25 size and book-to-market portfolios and 10 industry portfolios, of which the data are obtained from Kenneth French's Data Library, on balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other), respectively. The sample period covers from 01 July 1963 to 31 December 2022. At the end of each month, portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, which are estimated by regressing daily excess returns of the individual stock on that of the market over the past one year. Post-ranking betas for each test portfolio are estimated using the full sample.

Tables

Table 1: Summary statistics of turnover

Type of day	Mean	Std.Dev	Min	P1	P25	P50	P75	P99	Max	N
					μ (%)					
BTDs	0.58	0.57	0.08	0.11	0.20	0.28	0.93	2.32	2.77	150
Other	0.43	0.37	0.04	0.06	0.15	0.26	0.75	1.67	3.23	14829
Macro-ann.	0.43	0.38	0.04	0.07	0.15	0.25	0.77	1.67	2.55	1939
LEADs	0.83	0.30	0.28	0.29	0.71	0.81	0.92	2.38	2.77	264
Mondays	0.44	0.41	0.04	0.06	0.15	0.25	0.73	1.88	3.23	2853
Tuesdays	0.41	0.36	0.04	0.06	0.14	0.24	0.72	1.67	2.56	3066
Wednesdays	0.44	0.37	0.05	0.07	0.15	0.26	0.76	1.64	2.64	3052
Thursdays	0.44	0.37	0.05	0.06	0.16	0.27	0.77	1.65	2.77	3014
Fridays	0.44	0.37	0.04	0.07	0.16	0.27	0.77	1.63	2.55	2994
					σ (%)					
BTDs	0.80	0.80	0.12	0.14	0.27	0.39	1.24	3.23	4.23	150
Other	0.98	0.92	0.07	0.13	0.32	0.57	1.49	4.23	7.72	14829
Macro-ann.	0.98	0.95	0.08	0.14	0.31	0.54	1.49	4.30	7.34	1939
LEADs	1.93	0.94	0.55	0.61	1.37	1.79	2.24	6.43	6.93	264
Mondays	0.96	0.90	0.07	0.13	0.32	0.57	1.46	4.10	6.05	2853
Tuesdays	0.94	0.91	0.08	0.12	0.30	0.53	1.43	4.23	7.02	3066
Wednesdays	0.98	0.93	0.08	0.13	0.32	0.57	1.50	4.24	7.47	3052
Thursdays	1.01	0.94	0.09	0.14	0.34	0.59	1.54	4.25	7.72	3014
Fridays	1.01	0.93	0.09	0.13	0.34	0.59	1.54	4.30	7.34	2994
					γ					
BTDs	3.75	0.40	2.40	2.46	3.45	3.82	4.10	4.24	4.25	150
Other	12.83	7.08	4.25	4.62	7.86	10.86	15.79	39.08	62.18	14829
Macro-ann.	12.54	6.90	3.10	4.21	7.69	10.76	15.48	36.99	58.11	1939
LEADs	14.54	5.90	3.38	4.53	10.16	14.10	18.42	32.66	33.98	264
Mondays	12.86	7.33	2.40	4.13	7.85	10.75	15.78	39.44	60.42	2853
Tuesdays	13.29	7.55	3.01	4.23	7.86	11.24	16.62	40.17	58.11	3066
Wednesdays	12.53	6.69	2.94	4.30	7.77	10.77	15.49	36.50	57.54	3052
Thursdays	12.57	6.92	3.29	4.44	7.77	10.75	15.51	39.46	57.16	3014
Fridays	12.44	6.98	2.46	4.13	7.69	10.55	15.32	38.37	62.18	2994

This table reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading-day-lagged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including balanced trading days (BTDs), defined as those ranked in the bottom 1% by γ, Non-BTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), leading earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and different weekdays. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the 99th (P99), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured in percentage.

Table 2: Daily excess returns on BTDs and non-BTDs

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	λ	Avg R^2	Intercept	λ	ξ_1	ξ_2	R^2
			Panel A: Ten beta-sorted portfolios (value-weighted)					
BTDs	-9.22	50.57***	0.48	3.89***	-1.43	-11.99	51.29***	0.001
	(-0.92)	(2.82)		(5.35)	(-1.24)	(-1.27)	(2.99)	
Other	3.00***	-0.36	0.48					
	(4.56)	(-0.34)						
BTDs - Other	-12.22*	50.93***						
	(-1.85)	(4.67)						
			Panel B: Ten beta-sorted portfolios (equal-weighted)					
BTDs	4.73	44.99**	0.60	8.83***	-4.01***	0.49	43.29**	0.002
	(0.55)	(2.32)		(11.90)	(-3.30)	(0.04)	(2.46)	
Other	7.61***	-2.71***	0.54					
	(16.13)	(-2.64)						
BTDs - Other	-2.88	47.71***						
	(-0.60)	(4.59)						
			Panel C: Ten beta-sorted, 25 size/BM sorted, and 10 industry portfolios (all value-weighted)					
BTDs	-7.22	46.85**	0.27	3.60***	-0.83	-14.46	53.38**	0.001
	(-0.58)	(2.50)		(3.66)	(-0.65)	(-1.11)	(2.31)	
Other	3.45***	-0.78	0.25					
	(5.03)	(-0.73)						
BTDs - Other	-10.67	47.63***						
	(-1.54)	(4.44)						
			Panel D: Individual stocks					
BTDs	14.13*	33.85**	0.027	9.00***	-3.91***	12.03	39.22**	0.0001
	(1.71)	(2.31)		(14.99)	(-5.08)	(0.91)	(2.39)	
Other	7.23***	-2.34***	0.014					
	(16.76)	(-3.40)						
BTDs - Other	6.90	36.19***						
	(1.58)	(5.16)						

This table reports estimates from Fama and MacBeth (1973) regressions (left-hand side) and pooled regressions (right-hand side) of daily excess returns on betas for various test portfolios from 01 July 1963 to 31 December 2022. Estimates are computed separately for balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other). The third row in each Panel reports the difference in the means of estimates on the two types of day. For the pooled regression, we add an BTDs dummy ($D_{j,t}^{BTDs}$) and an interaction term between this dummy and market beta, and run the following regression:

$$r_{j,t+1} = \alpha + \lambda\hat{\beta}_{j,t} + \xi_1 D_{j,t}^{BTDs} + \xi_2\hat{\beta}_{j,t} D_{j,t}^{BTDs} + \epsilon_{j,t},$$

where $D_{j,t}^{BTDs}$ is a dummy variable that takes value of 1 for portfolio j on BTDs and 0 on other days. In parentheses, the t-statistics are computed using the standard deviation of the time-series estimates for the Fama-MacBeth regressions whereas clustered standard errors (by trading day) are used for the pooled regressions. Panel A reports results for the beta-sorted value-weighted portfolios that are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. Post-ranking betas are then similarly computed by regressing daily excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. Panel B reports results for the equal-weighted beta-sorted portfolios. Panel C adds the 25 size and book-to-market portfolios and the 10 industry portfolios, to the analysis. Panel D reports results for individual stocks, for which their pre-ranking betas as described above are used in the regressions. Their post-ranking betas are computed in the same way as those of the beta-sorted portfolios. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Table 3: Daily excess returns on BTDs and non-BTDs: Sub-sample analysis

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	λ	Avg R^2	Intercept	λ	ξ_1	ξ_2	R^2
Panel A: 01 July 1963 to 30 June 1983								
BTDs	-9.97	27.94*	0.40	3.12***	-1.63	-15.65	33.19**	0.001
	(-1.12)	(1.93)		(3.45)	(-1.12)	(-1.54)	(2.09)	
Other	2.62***	-1.05	0.48					
	(3.68)	(-0.80)						
BTDs - Other	-12.59*	28.99**						
	(-1.78)	(2.24)						
Panel B: 01 July 1983 to 30 June 2003								
BTDs	5.77	40.37	0.50	4.17***	-2.13	-17.81	70.76*	0.002
	(0.45)	(1.24)		(3.37)	(-1.01)	(-0.93)	(1.76)	
Other	2.97***	-0.30	0.46					
	(3.10)	(-0.17)						
BTDs - Other	2.80	40.67**						
	(0.29)	(2.26)						
Panel C: 01 July 2003 to 31 December 2022								
BTDs	-25.41	119.06**	0.60	4.74***	-1.29	-26.05	114.36***	0.005
	(-0.91)	(2.42)		(3.24)	(-0.58)	(-0.95)	(2.58)	
Other	3.43**	-0.12	0.50					
	(2.17)	(0.05)						
BTDs - Other	-28.84*	119.18***						
	(-1.82)	(4.99)						

This table reports estimates from Fama and MacBeth (1973) regressions (left-hand side) and pooled regressions (right-hand side) of daily excess returns on betas for the beta-sorted value-weighted portfolios in different sample periods from 01 July 1963 to 31 December 2022. Estimates are computed separately for balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other). The third row in each Panel reports the difference in the means of estimates on the two types of day. For the pooled regression, we add an BTDs dummy ($D_{j,t}^{BTDs}$) and an interaction term between this dummy and market beta, and run the following regression:

$$r_{j,t+1} = \alpha + \lambda\hat{\beta}_{j,t} + \xi_1 D_{j,t}^{BTDs} + \xi_2\hat{\beta}_{j,t}D_{j,t}^{BTDs} + \epsilon_{j,t},$$

where $D_{j,t}^{BTDs}$ is a dummy variable that takes value of 1 for portfolio j on BTDs and 0 on other days. In parentheses, the t-statistics are computed using the standard deviation of the time-series estimates for the Fama-MacBeth regressions whereas clustered standard errors (by trading day) are used for the pooled regressions. Portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. Post-ranking betas are then similarly computed by regressing daily excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Table 4: Daily excess returns on BTDs and non-BTDs: Excluding Macro-ann./LEADs/Fridays

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	λ	Avg R^2	Intercept	λ	ξ_1	ξ_2	R^2
Panel A: Macro-ann. excluded								
BTDs	-9.97	51.22***	0.47	3.90***	-1.97	-13.65	53.48***	0.002
	(-0.89)	(2.62)		(4.95)	(-1.59)	(-1.26)	(2.90)	
Other	3.37***	-1.36	0.48					
	(4.79)	(-1.18)						
BTDs - Other	-13.34*	52.58***						
	(-1.89)	(4.53)						
Panel B: LEADs excluded								
BTDs	-9.76	49.40***	0.48	4.08***	-1.87	-12.34	50.16***	0.001
	(-0.99)	(2.72)		(5.60)	(-1.63)	(-1.33)	(2.88)	
Other	3.16***	-0.74	0.48					
	(4.80)	(-0.69)						
BTDs - Other	-12.92*	50.14***						
	(-1.96)	(4.61)						
Panel C: Fridays excluded								
BTDs	-5.75	37.75*	0.49	2.76***	-1.01	-7.79	39.63**	0.001
	(-0.52)	(1.80)		(3.31)	(-0.76)	(-0.83)	(2.02)	
Other	1.60**	0.42	0.48					
	(2.13)	(0.34)						
BTDs - Other	-7.36	37.33***						
	(-0.97)	(2.99)						

This table reports estimates from Fama and MacBeth (1973) regressions (left-hand side) and pooled regressions (right-hand side) of daily excess returns on betas for the beta-sorted value-weighted portfolios from 01 July 1963 to 31 December 2022 using different samples excluding Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), leading earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), or Fridays. Estimates are computed separately for balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other). The third row in each Panel reports the difference in the means of estimates on the two types of day. For the pooled regression, we add an BTDs dummy ($D_{j,t}^{BTDs}$) and an interaction term between this dummy and market beta, and run the following regression:

$$r_{j,t+1} = \alpha + \lambda\hat{\beta}_{j,t} + \xi_1 D_{j,t}^{BTDs} + \xi_2\hat{\beta}_{j,t}D_{j,t}^{BTDs} + \epsilon_{j,t},$$

where $D_{j,t}^{BTDs}$ is a dummy variable that takes value of 1 for portfolio j on BTDs and 0 on other days. In parentheses, the t-statistics are computed using the standard deviation of the time-series estimates for the Fama-MacBeth regressions whereas clustered standard errors (by trading day) are used for the pooled regressions. Portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. Post-ranking betas are then similarly computed by regressing daily excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Table 5: Daily intraday/overnight returns on BTDs and non-BTDs

Type of day	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2
	Panel A: BTDs			Panel B: Other		
Overnight	-16.23*	41.41*	0.66	-3.55***	7.21***	0.49
	(-1.69)	(1.88)		(-7.16)	(7.88)	
Intraday	-1.35	14.60	0.58	8.23***	-7.22***	0.48
	(-0.09)	(0.49)		(8.14)	(-4.67)	
Over - Intra	-14.88	26.81		-11.78***	14.42***	
	(-0.82)	(0.73)		(-10.47)	(8.03)	

This table reports estimates from Fama and MacBeth (1973) regressions for the intraday and overnight periods, respectively. Estimates are computed separately for balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and non-BTDs (Other). Portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. For the intraday (overnight) period, post-ranking betas are then computed by regressing the intraday (overnight) returns on the market intraday (overnight) returns, as in Hendershott et al. (2020). Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. The sample period covers from 01 July 1992 to 31 December 2022. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Table 6: Market premium, risk-free rate, percentage change in implied variance and realised volatility on BTDs and other days

Type of day	μ_m (bps)	r_f (bps)	Δ_{VIX^2} (%)	σ_m (bps)
BTDs	38.03	2.32	0.69	201.3
Other	2.29	1.71	0.97	100.9
BTDs - Other	35.73***	0.61***	-0.27	
	(4.25)	(5.88)	(-0.12)	

This table reports the time-series mean of daily market premium (μ_m), risk-free rate (r_f), and percentage change in implied variance (Δ_{VIX^2}) for balanced trading days (BTDs) and non-BTDs (Other). In the last column, it also reports the time-series standard deviation of market premium (σ_m) for the two types of day. The percentage change in implied variance is computed as the daily percentage change in the squared end-of-day value of the VIX Index, which is a measure of constant, 30-day expected volatility of the US stock market, derived from real-time, mid-quote prices of S&P 500 Index call and put options. t-statistics are reported in parentheses. For μ_m, r_f, and σ_m, the sample period covers from 01 July 1963 to 31 December 2022, whereas for Δ_{VIX^2} it covers from 01 January 1990 to 31 December 2022. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Table 7: Fama-MacBeth regressions: High turnover stocks

Top percentiles	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2
	Panel A: All days			Panel B: Other			Panel C: BTDs		
20%	13.30***	-3.73***	0.36	13.47***	-4.37***	0.36	-3.62	59.37**	0.36
	(11.93)	(-2.90)		(12.18)	(-3.43)		(-0.17)	(2.48)	
15%	15.13***	-4.22***	0.33	15.30***	-4.88***	0.33	-1.24	61.39**	0.32
	(12.61)	(-3.22)		(12.84)	(-3.75)		(-0.06)	(2.54)	
10%	17.64***	-5.22***	0.29	17.89***	-5.94***	0.29	-6.91	66.24***	0.29
	(12.77)	(-3.78)		(13.03)	(-4.34)		(-0.28)	(2.66)	
5%	22.26***	-6.87***	0.23	22.55***	-7.67***	0.23	-6.23	72.20***	0.21
	(12.87)	(-4.50)		(13.03)	(-5.04)		(-0.26)	(2.97)	

This table reports estimates from Fama and MacBeth (1973) regressions of daily excess returns on betas for the beta-sorted value-weighted portfolios from 01 July 1963 to 31 December 2022 using stocks with turnover cross-sectionally ranked in different top percentiles. Estimates are computed separately for all days, balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other). The third row in each Panel reports the difference in the means of estimates on the two types of day. In parentheses, the t-statistics are computed using the standard deviation of the time-series estimates for the Fama-MacBeth regressions. Portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. Post-ranking betas are then similarly computed by regressing daily excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Appendix A. Additional Tables

Table A.1: Daily excess returns on BTDs and non-BTDs: Comparison with Savor and Wilson (2014) and Chan and Marsh (2022)

Type of day	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2
	Panel A: 1964 - 2011			Panel B: 2001 - 2019		
BTDs	-12.99	64.62***	0.46	-24.88	111.04**	0.60
	(-1.07)	(3.01)		(-0.86)	(2.17)	
Other	3.02***	-1.08	0.48	4.25***	-1.72	0.50
	(5.43)	(-0.98)		(3.99)	(-0.85)	
BTDs - Other	-16.02***	65.69***		-29.13***	112.76***	
	(-2.83)	(5.91)		(-2.66)	(5.42)	

This table reports estimates from Fama and MacBeth (1973) regressions of daily excess returns on betas for the beta-sorted value-weighted portfolios over the sample periods that are the same as in Savor and Wilson (2014) and Chan and Marsh (2022), respectively. Estimates are computed separately for balanced trading days (BTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-BTDs (Other). The third row in each Panel reports the difference in the means of estimates on the two types of day. In parentheses, the t-statistics are computed using the standard deviation of the time-series estimates for the Fama-MacBeth regressions. Portfolios are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated by regressing daily excess returns of the individual stock on that of the market. Post-ranking betas are then similarly computed by regressing daily excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated at the end of each month using a one-year rolling window and held unchanged for the subsequent month. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

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