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), during pessimistic sentiment periods (Antoniou, Doukas, and Subrahmanyam, 2016), 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 realised excess returns are linearly and positively proportional to their CAPM beta. Under rational expectations, such realised return is often used as a proxy for the conditional expected return formed on the previous day. Our finding therefore implies that when trading is more balanced in the cross-section, the expected return increases proportionally with beta, just as the CAPM suggests. We label these days with the smallest one-trading-daylagged turnover skewness as *post-balance-trading days* (hereafter PBTDs) and depict our main finding in Figure 1. The plot suggests that there exists a linear and positive risk-return trade-off on PBTDs (represented by red round dots), whereas it remains mostly flat on other days (represented by blue triangles). The CAPM implied market price of risk (the slope of SML) is 57 and -1.03 bps per day, respectively, on PBTDs and other days (non-PBTDs). 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 confirm the main finding from Fig 1. In the Fama-MacBeth analysis with value-weighted portfolios, the CAPM implied market price of risk on PBTDs is 54.17 bps per day and is significant at the 1% level, compared to -0.36 bps per day on non-PBTDs that is not statistically different from zero. When using equally-weighted portfolios, the CAPM implied market price of risk on PBTDs is 47.89 bps per day and is significant at the 5% level, compared to -2.75 bps per day on non-PBTDs that is significant at the 5% level. 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, respectively, from our sample and show that the strong positive riskreturn relationship is still present on PBTDs and the difference in the CAPM implied market price of risk on PBTDs 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

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

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 PBTDs 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 PBTDs, on which both overnight and intraday periods exhibit positive SML slopes.

In attempt to understand why investors appear to require large and positive compensation for bearing beta risk when trading is more balanced in the cross-section, we first follow Savor and Wilson (2014) and discuss the possibility that our results can be explained by factor models. Savor and Wilson (2014) discuss and reject the hypothesis that their results could be explained by a CAPM model with time-varying market premium across macro-announcement and non-announcement days or an unconditional two-factor model, on the basis that the CAPM betas are identical across the two types of days while the difference in market premium (on the two types of days) cannot be explained by that in the market variance. Examining the CAPM betas as well as the market return-to-variance ratio on PBTDs and non-PBTDs, we also reject such theoretical possibility in our setting. Particularly, we show that the CAPM beta averaged across test portfolios is statistically identical on both PBTDs and non-PBTDs. Furthermore, while there is an increase in market variance on PBTDs compared to non-PBTDs, we show that the increase in market premium is much more dramatic, to a degree that cannot be fully explained by the difference in the market variance. These observations allow us to reject unconditional factor models with one or two factors following the logic set out by Savor and Wilson (2014). We cannot reject the possibility that our results could be explained by models with three or more factors. However, such models would require the existence of risk factors that are related to how balanced trading is in the cross-section and present on PBTDs while largely disappear on non-PBTDs. To the best of our knowledge, we are not aware of such risk factors being proposed in the existing literature.

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

²See 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)).

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

trading volume, a natural concern is the time varying information, such as those about technology 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 PBTDs 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 in the cross-section.

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 (PBTDs). 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 PBTDs and discusses two potential explanations. Section 5 concludes.

⁵For 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 2022.⁶ 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%.⁷ 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 PBTDs

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:

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

⁶Since the pre-ranking betas are estimated from the past one year (as detailed in Section 3), most of our analyses has an effective sample period from July 1963 to December 2022.

 $^{^{7}}$ This further removes 0.012% of the data. Our main results remain unchanged if these observations are retained in the sample.

one-trading-day lagged γ as PBTDs (post-balance-trading days). More specifically, in our main 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. As we will show in Section 3.8, our main finding remains qualitatively unchanged if we define a larger portion of the days as PBTDs by relaxing the 1% threshold.

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 PBTD, compared with that on a matched non-PBTD. 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 PBTD with one or more non-PBTDs 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 Stocks A and B (as labelled in Figure 2) being extensively traded on the day preceding 14 August 2007, yielding a turnover of 27.4% and 60.8%.⁸ We argue that the existence of

⁸An investigation shows that the company issued Stock A (PERMNO 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 Stock B (PERMNO 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/

such intensively traded stocks with unusually large turnover compared to their peers is a primary signal of imbalanced trading activity, which may affect the cross-sectional pricing of stocks. This could be due, for example, to that 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.]

To further illustrate the relationship between balanced trading activity and our measure of turnover skewness, in Table 2, we divide all the trading days in our sample into five groups based on their cross-sectional skewness of turnover (γ), and then, within each group, we report the time series means for the 25th, 50th, 75th, 90th, 99.99th and 100th percentiles of the cross-section of turnover.

Generally, it is observed that the time-series average of each percentile increases with γ , yet a closer look suggests that the cross-group difference remains fairly small up to the 99th percentile before surging to a much higher level for the 99.99th and 100th percentiles. For example, the largest cross-group difference is only 0.07% (0.12% - 0.05%) for the 25th percentile and increases monotonically across percentiles to 2.22% (4.66% - 2.44%) for the 99th percentile. However, this difference becomes much larger to 14.22% (19.89% - 5.67%) for the 99.99th percentile and 44.43% (53.23% - 8.80%) for the maximum turnover in the cross-section, i.e., the 100th percentile. This observation implies that the cross-sectional distribution of turnover does not vary much across γ groups up to the 99th percentile, but it looks very differently across the groups in the far right tail (e.g., 99.99th and 100th percentiles). That is, our measure is largely driven by the existence of stocks that are intensively traded.

[Table 1 about here.]

idUSWEN0379 and https://www.reuters.com/article/idUSN13323428, for details).

2.3. Exploratory analysis

Table 1 reports the summary statistics. The cross-sectional mean (μ) of one-trading-day lagged turnover is on average 0.59% in our sample period for PBTDs, higher than 0.43% for Non-PBTDs (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 PBTDs 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 PBTDs have the smallest average standard deviation (0.80%), which is not surprising given that the skewness on these days is the smallest. Again, the average standard deviation of turnover on days preceding other types of days is roughly the same (0.95% to 1.02%), 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 1.95% 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 PBTDs, 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 3.77 for PBTDs, whereas it ranges from 4.25 to 76.49 for all other days, with a mean of 12.89. The minimum skewness of 2.40 shows that the cross-sectional distribution of turnover is by nature right-skewed.

[Table 2 about here.]

3. Main Results

3.1. Beta-sorted portfolios

To formally establish the difference in the CAPM implied market price of risk on PBTDs 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 30 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 using daily data over the past year but updated at a daily frequency. 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 3 about here.]

The left-hand side of Panels A and B in Table 3 report the Fama-MacBeth results for value- and equally-weighted beta-sorted portfolios, respectively. We observe that, for the value-weighted portfolios, one unit of risk (β) bear is compensated by 54.17 bps per day on PBTDs. This astonishing (CAPM implied) 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 -0.33. The Welch's t-statistic between the estimated λ 's on the two types of days is 4.97, accompanied with a significantly higher compensation of 54.53 bps per day for one unit of beta risk on PBTDs versus other days. The average R^2 for the two types of days is 49% and 48%, respectively. These results echo our finding in Figure 1 that on PBTDs an upward sloping security market line is observed. Our results also hold for the equally-weighted beta-sorted portfolios. The estimated λ is 47.89 (-2.75) bps and significant at the 5% (1%) level on PBTDs (other) days with a significant difference of 50.63 bps (t-statistic = 4.87) between the two types of days. The average R^2 is 60% for PBTDs 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 equally-weighted portfolios, respectively:

$$r_{j,t+1} = \alpha + \lambda \hat{\beta}_{j,t} + \xi_1 D_{j,t}^{PBTDs} + \xi_2 \hat{\beta}_{j,t} D_{j,t}^{PBTDs} + \epsilon_{j,t},$$
(4)

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

Results shown in the right-hand side of Panels A and B in Table 3 largely confirm our evidence from the Fama-MacBeth regressions. 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 equally-weighted cases, ξ_2 is economically large and statistically significant, with a point estimate of 55.90 (*t*-statistic = 3.15) and 50.46 (*t*-statistic = 2.78) for each case, respectively. This is consistent with our Fama-MacBeth evidence that the CAPM implied market price of risk is positive and significantly larger on PBTDs.

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 PBTDs 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 3 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 50.28 bps (t-statistic = 2.63) is close to our estimate when using only the beta-sorted portfolios. Similarly, we also observe a statistically insignificant λ on other days (-0.75 bps with a t-statistic of -0.69), as in the case with only the beta-sorted portfolios. The difference in the CAPM implied market price of risk between the two types of days is 51.02 bps with a t-statistic of 4.67. Moving to the pooled regressions, again we have similar results as in Panels A and B. For example, the slope of the interaction term is 62.44 with a t-statistic of 2.58, confirming a large and significant difference in the CAPM implied market price of risk between the two types of days.

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 3 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 40.72 bps and a *t*-statistic of 2.55. The difference in the slope coefficient between the two types of the day is 42.85 bps (*t*-statistic = 5.84).

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 PBTDs 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 valueweighted 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 PBTDs using the 1% threshold over these three sub-periods, respectively. As shown in the left-hand side of Table 4, the difference in the slope coefficient (λ) between PBTDs and other days is observed across all three periods, with the estimated difference being 27.12 bps, 40.51 bps, and 125.60 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 (26.05, 40.40, and 125.40 bps) while statistical significance appears in the first and last twenty-year windows with a *t*-statistic of 1.76 and 2.54, respectively. The slight reduction in statistical significance is somewhat expected given that there are now only around 50 PBTDs in each sub-period. What important here is that the difference in the estimated market price of risk between PBTDs and other days are still positive and significant while the R^2 still ranges between 40% to 60% in all subperiods. Furthermore, we also report results for the pooled regressions in the right-hand side of Table 4, 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 34.85 (t-statistic = 2.17), 70.98 (t-statistic = 1.78), and 120.63 (t-statistic = 2.59), respectively.

[Table 4 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 PBTDs, implying that our results is unlikely to be dominated by these announcement days. To formally test this implication, we delete $r_{j,t+1}$ in Regressions (3) and (4) if t + 1is a macroeconomic announcement day (as defined in Savor and Wilson (2013, 2014)) and LEADs (as defined in Chan and Marsh (2022)); and repeat our Fama-MacBeth analysis.

[Table 5 about here.]

Panels A and B in Table 5 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 PBTDs is 54.08 bps (t-statistic = 2.67) whereas it is not statistically different from zero (point estimate of -1.27 with a t-statistic of -1.09) on other days. There's also a significant difference of 55.35 bps (t-statistic = 4.67) 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 52.48 bps (t-statistic = 2.84) on PBTDs while being again insignificant on other days. The difference between the two types of days on λ is 53.21 bps that is associated with a t-statistic of 4.85.

The main conclusion remains unchanged in the pooled regressions, as suggested by a significant slope coefficient of the interaction term of 56.02 (54.84) with a *t*-statistic of 2.92 (3.06) when we discard the macro-announcement days (LEADs) from our sample.

The estimated (CAPM implied) market price of risk on PBTDs 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 PBTDs is about 7 (5) times larger than that is documented on the macro-announcement days (LEADs). This discrepancy in the estimated market price of risk corresponds to the difference in the market premium on PBTDs, macro-announcement days, and LEADs. For example, in Table 8, we observe a market premium of 40.49 bps per day on PBTDs, compared to 6.99 and 13.54 bps on the macro-announcement days and LEADs, respectively, over our sample period.

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 $r_{j,t+1}$ in Regressions (3) and (4) if t + 1 is a Friday and repeat our analysis. The results shown in Panel C of Table 5 confirm that our finding of a positively sloped security market line on PBTDs 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 43.02 bps (*t*-statistic = 1.97) on these days and, more importantly, the difference between PBTDs and other days is 42.58 bps that is significant at the 1% level (*t*-statistic = 3.33). Again, the pooled regressions echo the Fama-MacBeth evidence through a statistically significant estimate of ξ_2 (42.37, *t*-statistic = 2.08).

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:

$$r_{i,t}^{N} = \frac{1+r_{i,t}}{1+r_{i,t}^{I}} - 1,$$
(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 PBTDs and other days, respectively.

[Table 6 about here.]

As shown in Table 6, we observe a positive and statistically significant λ over the night for both PBTDs (40.90 bps, t-statistic = 1.86) and other days (7.20 bps, t-statistic = 7.87). This is consistent with the finding of Hendershott et al. (2020) that the security market line is upward sloped after trading hours. However, λ flips signs during the intraday period (as documented in Hendershott et al. (2020)) only on non-PBTDs but not on PBTDs. When focusing on the intraday period, particularly, we obtain large and positive λ estimate of 27.50 bps on PBTDs, albeit being statistically insignificant with a t-statistic of 0.92. In contrast, it is -7.35 bps with a significant t-statistic of -4.76 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 PBTDs and other days, respectively. While there is a considerable difference between the two periods on non-PBTDs, as suggested by a point estimate of 14.54 bps with a t-statistic of 8.10, it is not statistically different from zero on PBTDs (13.40 bps with a t-statistic of 0.36). Our results suggest that, unlike on non-PBTDs, the beta-return relationship mostly positive and does not flip signs across both intraday and overnight periods.

3.8. Alternative Thresholds in PBTDs Identification

Finally, one might be concerned about our identification of PBTDs as being days ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover. As we have discussed above, the reason we adapt this 1% threshold is that the cross-section of turnover is by nature right-skewed and we are focusing on only the days that are less so. However, in this sub-section we show that our results remains qualitatively if we relax this threshold when identifying PBTDs.

[Table 7 about here.]

In Table 7, we report the CAPM implied market price of risk for PBTDs and its difference between PBTDs and non-PBTDs when PBTDs are identified using thresholds 2%, 3%, 4%, 5%, 6%, 7%, 8%, 9%, and 10%. That is, we redefine PBTDs as being days ranked in the bottom 2%, 3%, 4%, 5%, 6%, 7%, 8%, 9%, and 10%, respectively, by the cross-sectional skewness of one-trading-day-lagged individual stock turnover and repeat our main analysis. As it is shown, the significant positive relationship between expected returns and betas can be observed for thresholds up to 3%. However, if we focus on the difference in the estimated slope of the SML between PBTDs and non-PBTDs, the statistical significance can be observed for thresholds up to 8%. This result suggests that our main finding that there exists a positive beta-return relationship on PBTDs whereas no such relationship can be observed for non-PBTDs is not sensitive to the threshold of 1% that is used to identify PBTDs in our main analysis.

4. Discussion

4.1. Risk factor models

We have seen so far that there exists a robust linear and positive relationship between CAPM betas and average returns on PBTDs, but not non-PBTDs (on average). Here we discuss the possibility that this result can be explained by risk factor models. Our discussion draws heavily on that in Savor and Wilson (2014).

In Savor and Wilson (2014), the authors discuss the possibility of using factor models to explain their finding that the CAPM holds on the macro-announcement days but not on the other days. Their discussion starts by rejecting the hypothesis that the CAPM model with time-varying market premium holds on both types of days. Simply put, the authors illustrate that by writing returns in logarithmic form and aggregating them over periods with arbitrary length across both types of days, one should not observe that the CAPM holds only on the macro-announcement days but not on the non-macro-announcement days while no such beta-return relationship is observed at a time-aggregating level, which is something we know from existing literature. With an additional condition that the return-to-variance ratio of the market is significantly different on the two types of days (a central result of Savor and Wilson (2013)), the authors further reject the hypothesis that an unconditional two-factor model can explain their results.⁹

We therefore compare the CAPM beta and return-to-variance ratio of the market across PBTDs and non-PBTDs. Specifically, we first compute the mean of the post-ranking betas across the 45 test portfolios used in Section 3.2 on PBTDs and non-PBTDs, respectively, and study the difference across the two types of days. We do not run a time-series regression of test portfolio returns on the market with an interaction term of a PBTD dummy and the market because we fear that the estimation could be potentially unreliable due to the fact that we have only 150 PBTDs versus around 15,000 non-PBTDs in our sample. We then compute the mean and standard deviation of market excess returns across the two types of days, which allows us to study the return-to-variance ratio of the market.

[Table 8 about here.]

As shown in Table 8, the average post-ranking beta across the 45 portfolios is 1.014 on PBTDs, versus 0.943 on non-PBTDs, yielding a marginal difference of 0.071 with a *t*-statistic of 1.45. Therefore, the CAPM beta is statistically identical on both PBTDs and non-PBTDs, an analogous result as in Savor and Wilson (2014) that leads us to reject the single-factor CAPM model with varying market premium.

We then turn our attention to unconditional two-factor models. Unlike in Savor and Wilson (2014), Table 8 shows that the standard deviation of market excess return increases from 100.9 bps per day on non-PBTDs to 201.9 bps per day on PBTDs, which implies that the market variance is about 4 times higher on PBTDs. However, compared to non-PBTDs, the market premium is much larger on PBTDs, to an extent that cannot be explained by the difference in market variance. For example, the observed market premium on PBTDs is 40.49 bps per day, which is about 16.6 times larger than the 2.27 bps per day observed

⁹We refer readers to Sections 4.1.1 and 4.1.2, and Online Appendix of Savor and Wilson (2014) for detailed discussions.

on non-PBTDs. With this additional observation, we can reject the hypothesis that an unconditional two-factor model can explain our results, following the same logic set out in Savor and Wilson (2014).

Finally, we note, as in Savor and Wilson (2014), we cannot reject the possibility that our results could be explained by factor models with three or more factors. However, such model would require the existence of risk factors that are related to how balanced trading is in the cross-section and present on PBTDs while largely disappear on non-PBTDs, which make up most of our sample period. To the best of our knowledge, we are not aware of such risk factors being proposed in the existing literature.

4.2. Intensively-traded stocks

So why does there exist such a strong beta-return relationship that is in line with the theory on PBTDs but not on other days, which 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-PBTDs relative to PBTDs. The presence of such "outliers" would drive the turnover skewness on that day to a large level, thus differentiate that day from the PBTDs. 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 9 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 PBTDs. For example, the estimated market

price of risk (λ) monotonically decreases from -3.76 bps (t-statistic = -2.91) when focusing on the top 20% of the stocks by turnover to -6.86 bps (t-statistic = -4.46) 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-PBTDs, with λ again monotonically decreasing from -4.43 bps (t-statistic = -3.46) when focusing on the top 20% of the stocks by turnover to -7.68 bps (t-statistic = -5.00) when focusing on the top 5% of the stocks. However, the beta-return relationship remain significantly positive on PBTDs, even among relatively high turnover stocks on those days. Specifically, the estimated λ increases from 62.94 bps (t-statistic = 2.61) to 73.44 bps (t-statistic = 3.01) across the samples that comprise top 5%, 10%, 15%, and 20% of the stocks by turnover. This is not surprising since on PBTDs 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-PBTDs, thus the positive risk-return trade-off is not distorted.

[Table 9 about here.]

5. Conclusion

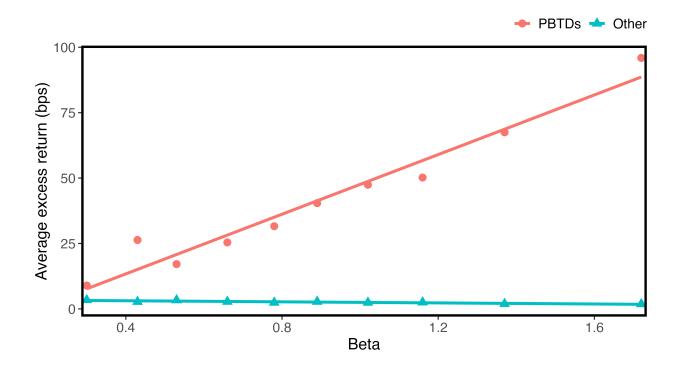
Using the skewness of individual stock turnover in the cross-section as a measure of how balanced the trading activity is, we study the beta-return relationship in the US stock market. We provide evidence that when the distribution of trading is more balanced across stocks, investors are compensated on the next trading day 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 betasorted 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 post-ranking betas are statistically identical across both post-balance-trading days (PBTDs) and non-post-balance-trading days (non-PBTDs). With a further observation that the market premium is significantly larger on PBTDs and cannot be fully explained by the corresponding increase in market variance, we reject the theoretical possibility that our results can be explained by unconditional factor models with one or two risk factors.

Finally, we explore the nature of PBTDs 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 investors' disagreement.

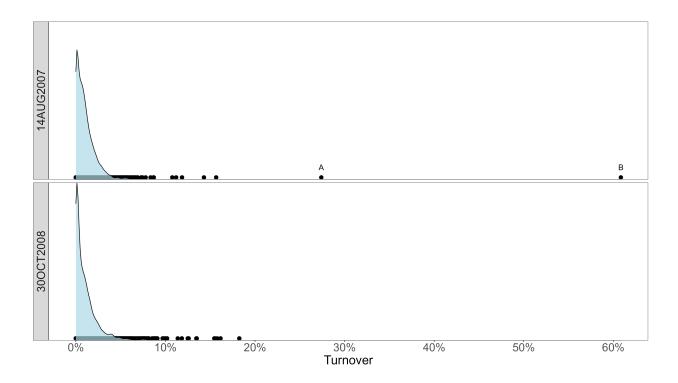
Figures

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



This figure plots average daily excess returns again market betas for 10 beta-sorted valueweighted portfolios on post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (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 PBTDs and Other days: An illustrative example



This figure plots the distribution density as well as the dot plot for the cross-section of onetrading-day-lagged turnover on 14 August 2007 and 30 October 2008, respectively. 30 October 2008 is selected from the post-balance-trading days (PBTDs), 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-PBTDs. 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 PBTD with one or more non-PBTDs 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 most heavily traded stocks with the highest lagged turnover on 14 August 2007 using the letters "A" (permno 87756) and "B" (permno by their corresponding PERMNO (a unique stock level identifier assigned by CRSP), respectively.

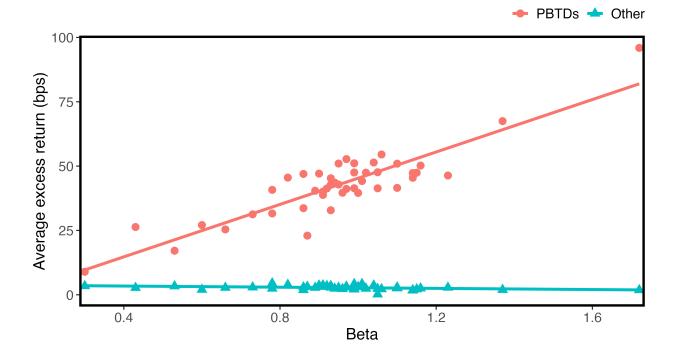


Fig. 3: Daily excess returns for beta-sorted, 25 Fama-French, and 10 industry portfolios

This figure plots average daily excess returns again market betas for 10 beta-sorted valueweighted 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 post-balancetrading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (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

μ (ξ) μ (ξ) μ (ξ) Derroam 0.39 0.57 0.04 0.01 <	Type of day	Mean	$\operatorname{Std.Dev}$	Min	P1	P25	P50	P75	P99	Max	Ν
BTDs 0.20 0.57 0.08 0.11 0.10 0.29 0.23 2.27 150 254 257 150 0.04 0.04 0.15 0.25 0.77 1.67 2.57 159 254 0.24 0.23 0.23 0.24 0.25 0.25 0.77 1.67 2.57 2.59 254 0.24 0.23 0.24 0.23 0.24 0.25 0.25 0.25 0.25 0.25 0.25 0.25 0.25) 11	%)				
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$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	ther	0.43	0.38	0.04	0.06	0.15	0.26	0.75	1.68	3.28	14829
$ \begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	Iacro-ann.	0.43	0.38	0.04	0.07	0.15	0.25	0.77	1.67	2.57	1939
$ \begin{array}{rrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrrr$	EADs	0.83	0.31	0.28	0.29	0.71	0.81	0.93	2.41	2.79	264
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Iondays	0.44	0.41	0.04	0.06	0.15	0.25	0.73	1.90	3.28	2853
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$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Vednesdays	0.44	0.37	0.05	0.07	0.15	0.26	0.76	1.66	2.65	3052
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	EADs	1.95	0.96	0.54	0.61	1.37	1.80	2.32	6.51	7.04	264
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	Iondays	0.97	0.91	0.07	0.13	0.32	0.57	1.46	4.10	6.32	2853
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hursdays1.020.960.090.140.340.591.554.297.763014ridays1.020.940.090.140.340.601.554.337.482994BTDs3.770.402.402.413.483.854.124.254.251432ther1.2897.134.257.8910.9315.5237.6858.141939ther1.2.606.914.207.7110.9315.5237.6858.141939ther1.2.605.914.207.7110.9315.5237.6858.14306ther1.2.907.382.404.147.8510.7815.7939.5064.882853heresdays1.2.907.382.944.137.7310.6515.73306heresdays1.2.907.382.411.3316.7640.7158.14306heresdays1.2.537.093.2576.49294306heresdays1.2.537.092.474.137.7310.6515.7439.66heresdays1.2.537.092.471.3010.6615.5439.6057.51306heresdays1.2.537.092.474.137.7310.6515.4439.6057.51306hereseries summary statistics of the cross-sectional mean(μ)36.7640.7158.14306hereseries	Vednesdays	0.99	0.94	0.08	0.13	0.32	0.57	1.52	4.24	7.49	3052
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BTDs 3.77 0.40 2.40 2.47 3.48 3.85 4.12 4.25 4.25 150 ther 12.80 7.13 4.25 4.63 7.89 10.93 15.86 39.29 76.49 14829 Eacro-ann. 12.60 6.91 3.10 4.20 7.71 10.83 15.52 37.68 58.14 1939 Eacro-ann. 12.60 5.91 3.10 4.20 7.71 10.83 15.52 37.68 58.14 1939 Eacro-and 14.56 5.88 $3.3.8$ 4.53 10.16 14.09 18.51 32.66 34.00 264 for 34.00 264 for 32.90 7.57 3.09 4.24 4.14 7.78 10.78 15.79 39.50 64.88 2853 hursdays 12.39 6.74 2.94 4.44 7.78 10.76 15.54 39.50 57.29 3014 fidays 12.50 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 fidays 12.53 7.09 2.47 4.13 7.73 10.65 15.44 38.25 7.649 2.94 fidays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 39.50 57.29 3014 fidays 12.53 7.09 2.47 4.13 7.73 10.65 15.44 38.25 7.649 2.94 fidays (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annouccement days (Macro-ann., as defined in Savor and Wilson (2014)), fing earning announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and firent weekdays. In the columns, we report the mean, standard deviation (π), and skewness (γ) of one-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annous days (Macro-ann., as defined in Savor and Wilson (2014)), fing earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and firent weekdays. In the columns, we report the mean, standard deviation (π), and skewness (γ) of one-trading days (PBTDs), and the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the Λ of the period from January 2001 to December 2022), and firend weekdays. In the columns, we report the time-series of the cros-sectional statistics. Daily individual	ridays	1.02	0.94	0.09	0.14	0.34	0.60	1.55	4.33	7.48	2994
BTDs 3.77 0.40 2.40 2.47 3.48 3.85 4.12 4.25 4.25 4.25 150 ther 12.89 7.13 4.25 4.03 76.49 14829 facto-ann. 12.60 6.91 3.10 4.20 7.71 10.83 15.52 37.68 58.14 1939 EADs 14.56 5.88 $3.3.8$ 4.53 10.16 14.09 18.51 32.66 34.00 264 64.88 2853 tondays 12.90 7.57 3.38 4.53 10.16 14.09 18.51 32.66 34.00 264 64.88 2853 tondays 12.90 7.57 3.09 4.25 7.89 10.16 11.33 16.76 40.71 58.14 3066 7.57 305 tondays 12.60 6.93 3.29 4.44 7.85 10.78 15.79 39.50 64.88 2853 tondays 12.50 6.73 3.29 4.44 7.78 10.76 15.54 30.50 76.49 3014 tondays 12.60 6.93 3.29 4.44 7.78 10.76 15.54 39.50 76.49 3056 tondays 12.60 tonduced the time-series summary statistics of the cross-sectional mean (μ) standard deviation (σ), and skewness (γ) of one-trading days (PBTDs), time das those transformed to the bottom 1% by γ , Non-PBTDs (Other), Macro-annoucement days (Macro-ann., as defined in Savo and Wilson (2014)), time das those reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading days (PBTDs), time das those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annoucement days (Macro-ann., as defined in Savo and Wilson (2014)), time das those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annoucement days (Macro-ann., as defined in Savo and Wilson (2014)), time das those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annoucement days (Macro-ann., as defined in Savo and Wilson (2014)), time das those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annous percentiles from the 1st (P1) to the theorem beat of the cross-sectional statistics. Daily individual stock turnover is measured in the columns, we report the mean, standard deviation (Std.Dev), minimu (Min), various percentiles from the 1st (P1) to the theorem beach and theorem beach an	l						λ				
ther 12.89 7.13 4.25 4.63 7.89 10.93 15.86 39.29 76.49 14829 facro-ann. 12.60 6.91 3.10 4.20 7.71 10.83 15.52 37.68 58.14 1939 EADs 14.56 5.88 3.3.8 4.53 10.16 14.09 18.51 32.66 34.00 264 foundays 12.90 7.38 2.40 4.14 7.85 10.78 15.79 39.50 64.88 2853 uesdays 12.90 7.37 3.09 4.25 7.89 11.33 16.76 40.71 58.14 3066 hursdays 12.50 6.74 2.94 4.33 7.80 10.80 15.53 37.22 57.57 3052 hursdays 12.60 6.93 3.2.9 4.44 7.78 10.76 15.54 39.50 64.88 2994 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 39.50 67.99 2994 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 39.50 67.99 2094 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 39.50 67.49 2994 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 38.25 76.49 2994 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 38.25 76.49 2994 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.54 38.25 76.49 2994 ridays the time-series summary statistics of the cross-sectional mean (μ) , standard deviation (σ) , and skewness (γ) of one-trading day ridays the time-series summary statistics of the cross-sectional mean (μ) , standard deviation (σ) , and skewness (γ) of one-trading day ridays the time-series summary statistics of the cross-sectional mean (μ) , standard deviation (σ) , and skewness (γ) of one-trading day ridays the time-series summary statistics of the cross-sectional mean (μ) , standard deviation (σ) , and skewness (γ) of one-trading day ridays those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2011 to December 2022, including post-balance-trading days (PBTDs), ding earnings announcement days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured herewore the result of ang (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured herewore and the result of ang (N) for the time-series of the cr	BTDs	3.77	0.40	2.40	2.47	3.48	3.85	4.12	4.25	4.25	150
Iacro-ann.12.60 6.91 3.10 4.20 7.71 10.83 15.52 37.68 58.14 1939 EADs 14.56 5.88 3.38 4.53 10.16 14.09 18.51 32.66 34.00 264 Iondays 12.90 7.58 3.38 4.53 10.16 14.09 18.51 32.66 34.00 264 Iondays 12.90 7.57 3.09 4.25 7.89 11.33 16.76 40.71 58.14 3065 Vednesdays 12.59 6.74 2.94 4.33 7.80 10.80 15.54 39.50 64.88 2365 hursdays 12.59 6.74 2.94 4.33 7.78 10.76 15.44 39.50 57.29 3014 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.44 38.25 76.49 294 stable reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading days (PBTDs), dime das those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann, as defined in Savor and Wilson (2014)), dime das ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann, us defined in Savor and Wilson (2014)), dime darmings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from J anuary 2001 to December 2022), and the rest for the ine-series under evek days. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 15 (P) to the for the time	ther	12.89	7.13	4.25	4.63	7.89	10.93	15.86	39.29	76.49	14829
EADs 14.56 5.88 3.38 4.53 10.16 14.09 18.51 32.66 34.00 264 100 doubdys 12.90 7.38 2.40 4.14 7.85 10.78 15.79 39.50 64.88 2853 10.80 12.30 7.57 3.09 4.25 7.89 11.33 16.76 40.71 58.14 3066 76 163.88 12.59 57.57 3052 57.57 3052 1648 12.59 12.59 12.59 6.74 2.94 4.33 7.80 10.80 15.53 37.22 57.57 3054 16 12.53 12.50 57.29 3014 110 12.53 12.50 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 110 12.53 12.53 7.09 2.47 4.13 7.73 10.65 15.44 39.50 57.29 3014 110 12.53 12.53 7.09 2.47 4.13 7.73 10.65 15.44 39.50 57.29 3014 110 12.53 12.53 12.54	lacro-ann.	12.60	6.91	3.10	4.20	7.71	10.83	15.52	37.68	58.14	1939
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	EADs	14.56	5.88	3.38	4.53	10.16	14.09	18.51	32.66	34.00	264
uesdays 13.36 7.57 3.09 4.25 7.89 11.33 16.76 40.71 58.14 3066 Vednesdays 12.59 6.74 2.94 4.33 7.80 10.80 15.53 37.22 57.57 3052 rulesdays 12.60 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 ridays 12.60 6.93 2.47 4.13 7.73 10.65 15.44 39.50 57.29 3014 30.15 is table reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading-day-ged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including post-balance-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and for the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the (P9), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured to the time-series of the cross-sectional statistics. Daily individual stock turnover is measured by the time-series of the cross-sectional statistics. Daily individual stock turnover is measured by the time-series of the cross-sectional statistics. Daily individual stock turnover is measured by the time-series of the cross-sectional statistics. Daily individual stock turnover is measured by the time-series of the cross-sectional statistics. Daily individual stock turnover is measured to the time-series of the cross-sectional statistics. Daily individual stock turnover is measured to the time-secience of the cross-sectional statistics. Daily individual stock turnover is measured to the time-secience of the cross-sectional statistics. Daily individual stock turnover is measured to the time-secience of the cross-sectional statistics. Daily individual stock turnover is measured to the time-secience of the cross-sectional statistics	$\mathbf{Iondays}$	12.90	7.38	2.40	4.14	7.85	10.78	15.79	39.50	64.88	2853
Vednesdays 12.59 6.74 2.94 4.33 7.80 10.80 15.53 37.22 57.57 3052 hursdays 12.60 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 ridays 12.60 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 ridays 12.60 6.93 2.47 4.13 7.73 10.65 15.44 38.25 7.6.49 2994 riday is table reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading-day-ged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including post-balance-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-annoucement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and ferent weekdays. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the the (P99), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured	uesdays	13.36	7.57	3.09	4.25	7.89	11.33	16.76	40.71	58.14	3066
hursdays 12.60 6.93 3.29 4.44 7.78 10.76 15.54 39.50 57.29 3014 ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.44 38.25 76.49 2994 his table reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading-day- ged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including post-balance-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and ferent weekdays. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the th (P99), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured	Vednesdays	12.59	6.74	2.94	4.33	7.80	10.80	15.53	37.22	57.57	3052
ridays 12.53 7.09 2.47 4.13 7.73 10.65 15.44 38.25 76.49 2994 his table reports the time-series summary statistics of the cross-sectional mean (μ), standard deviation (σ), and skewness (γ) of one-trading-day- ged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including post-balance-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and ferent weekdays. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the th (P99), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured	Thursdays	12.60	6.93	3.29	4.44	7.78	10.76	15.54	39.50	57.29	3014
his table reports the time-series summary statistics of the cross-sectional mean (μ) , standard deviation (σ) , and skewness (γ) of one-trading-day- ged individual stock turnover for different types of days from 01 July 1963 to 31 December 2022, including post-balance-trading days (PBTDs), fined as those ranked in the bottom 1% by γ , Non-PBTDs (Other), Macro-announcement days (Macro-ann., as defined in Savor and Wilson (2014)), ding earnings announcement days (LEADs, as defined in Chan and Marsh (2022), over the period from January 2001 to December 2022), and Ferent weekdays. In the columns, we report the mean, standard deviation (Std.Dev), minimum (Min), various percentiles from the 1st (P1) to the th (P99), maximum (Max), and number of days (N) for the time-series of the cross-sectional statistics. Daily individual stock turnover is measured	ridays	12.53	7.09	2.47	4.13	7.73	10.65	15.44	38.25	76.49	2994
	his table repc gged individu: fined as those ading earning: fferent weekda th (P99), max	rts the time al stock turr ranked in th s announcen yys. In the c cinum (Max	-series summa over for different a bottom 1% L nent days (LE ₄ columns, we rep t), and number	ry statistics c ant types of α by γ , Non-PB ADs, as defin out the mear of days (N) f	of the cross-se days from 01 TDs (Other), ted in Chan i a, standard dd	ectional mean July 1963 to Macro-annoi and Marsh (2 eviation (Std. eries of the cr	(μ) , standard 31 December uncement days (022), over the Dev), minimu oss-sectional i	1 deviation (c 2022, includi 8 (Macro-ann. e period from m (Min), var statistics. Dai	r), and skewn ng post-balar , as defined in January 200 ious percentil ly individual	ess (γ) of one nee-trading da is Savor and W 1 to Decemb- es from the 1s stock turnove	-trading-day- ws (PBTDs), ws (2014)), er 2022), and et (P1) to the r is measured

Table 1: Summary statistics of turnover

γ	Ν	P25	P50	P75	P90	P99	P99.9	Max
Low	2996	0.05%	0.16%	0.36%	1.09%	2.44%	5.67%	8.80%
2	2996	0.06%	0.17%	0.38%	1.23%	3.17%	9.14%	15.24%
3	2996	0.09%	0.23%	0.48%	1.50%	3.95%	13.65%	25.14%
4	2996	0.12%	0.29%	0.60%	1.76%	4.66%	19.89%	41.30%
High	2995	0.09%	0.25%	0.52%	1.51%	3.75%	16.12%	53.23%

Table 2: Average percentiles of turnover by cross-sectional skewness

All the trading days are first ranked by their cross-sectional skewness of turnover (γ) and then divided equally into five groups. Reported are the number of observations (N) and time-series means of the 25th, 50th, 75th, 90th, 99.9th and 100th (Max) percentiles for the cross-section of turnover for each of the five groups. Our sample ranges from 01 July 1963 to 31 December 2022.

Type of day Intercept	٢	Ave R^2		-	ξ1	ξ2	D2
		D	Intercept	<	•	10	11
		Panel P	Panel A: Ten beta-sorted portfolios (value-weighted)	rtfolios (value-weig	hted)		
PBTDs -10.40	54.17^{***}	0.49	3.90***	-1.47	-13.84	55.90^{***}	0.002
(-1.06)	(2.96)		(5.42)	(-1.27)	(-1.44)	(3.15)	
Other 2.96^{***}	-0.36	0.48					
	(-0.33)						
$PBTDs - Other -13.36^{**}$	54.53^{***}						
(-2.02)	(4.97)			:	Ĩ		
		Panel B:	Panel B: Ten beta-sorted portfolios (equally-weighted)	tfolios (equally-wei	ghted)		
PBTDs 3.82	47.89^{**}	0.60	8.80^{***}	-4.07^{***}	-3.53	50.46^{***}	0.002
(0.44)	(2.43)		(12.18)	(-3.36)	(-0.31)	(2.78)	
Other 7.54^{***}	-2.75***	0.54					
(16.28)	(-2.67)						
PBTDs - Other -3.72	50.63^{***}						
(-0.79)	(4.87)						
	Panel	C: Ten beta-sorted, 25 size/BM sorted, and 10 industry portfolios (all value-weighted)	25 size/BM sorted, ar	d 10 industry port	folios (all value-we	ighted	
PBTDs -8.32	50.28^{***}	0.28	3.56^{***}	-0.83	-20.38	62.44^{**}	0.001
(-0.68)	(2.63)		(3.68)	(-0.65)	(-1.51)	(2.58)	
Other 3.36***	-0.75	0.25					
	(-0.69)						
PBTDs - Other -11.68*	51.02^{***}						
(-1.69)	(4.67)						
			Panel D: Individual stocks	dual stocks			
PBTDs 10.04	40.72^{**}	0.031	8.82^{***}	-3.77***	5.27	49.67^{***}	0.0001
(1.27)	(2.55)		(15.23)	(-4.82)	(0.41)	(2.77)	
Other 6.99***	-2.13^{***}	0.014					
(16.44)	(-2.96)						
PBTDs - Other 3.05	42.85^{***}						
(0.71)	(5 84)						

Table 3: Daily excess returns on PBTDs and non-PBTDs

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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 of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the former being updated monthly and the latter daily. Panel B reports results for the equally-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. *, **, and *** represent significance levels at 1%, 5%, and 10%, 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 respectively.

		117 0						
	rama-ivlacibeth	cpetn			4	roolea regression	110	
Type of day	Intercept	Y	${ m Avg}\;R^2$	Intercept	Y	ξ1	ξ_2	R^{2}
			Pane	Panel A: 01 July 1963 to 30 June 1983	3 to 30 June	1983		
PBTDs	-8.58	26.05^{*}	0.41	3.07***	-1.61	-17.45*	34.85** (2.17)	0.001
Other	(-0.98) 2.61***	(1.70)	0.48	(3.30)	(01.1-)	(-1.14)	(2.17)	
PBTDs - Other	(3.66) -11.19 (-1.58)	(-0.82) 27.12^{**} (2.09)						
			Pane	Panel B: 01 July 1983 to 30 June 2003	3 to 30 June ;	2003		
PBTDs -	5.29	40.40	0.50	4.20^{***}	-2.16	-18.24	70.98*	0.002
	(0.42)	(1.25)		(3.45)	(-1.01)	(-0.94)	(1.78)	
Other	2.83^{***} (2.90)	-0.11 (-0.06)	0.46					
PBTDs - Other	2.46	40.51^{**}						
	(0.25)	(2.23)	Panel (Panel C: 01 July 2003 to 31 December 2022	o 31 Decembe	er 2022		
PBTDs	-30.67	125.40^{**}	0.60	4.75^{***}	-1.30	-31.32	120.63^{**}	0.005
Other	(-1.13) 340^{**}	(2.54)-0.20	0.50	(3.30)	(-0.58)	(-1.13)	(2.59)	
	(2.22)	(-0.08)						
PBTDs - Other	-34.16^{**} (-2.17)	125.60^{***} (5.22)						
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 post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading- day-lagged individual stock turnover, and Non-PBTDs (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 PBTDs dummy $(D_{j,t}^{PBTDs})$ and an interaction term between this dummy and market beta, and run the following regression: $\tau_{j,t+1} = \alpha + \lambda \hat{\beta}_{j,t} + \xi_1 D_{j,t}^{PBTDs} + \xi_2 \hat{\beta}_{j,t} D_{j,t}^{PBTDs} + \epsilon_{j,t}$, where $D_{j,t}^{PBTDs}$ is a dummy variable that takes value of 1 for portfolio j on PBTDs and 0 on other days. In parentheses, the <i>t</i> -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 estimated using a one-year rolling window, with the <i>common by the test portfolio</i> on that of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the <i>common by the test portfolio</i> on that of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the <i>common by the test portfolio</i> on that of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the <i>common by the test portfolio</i> on that of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with t	stimates from the beta-sortec for post-balanc l stock turnover or the pooled re g regression: lummy variable eviation of the eviation of the egressions. Por test portfolio o	Fama and Macl l value-weightec e-trading days (r, and Non-PBT gression, we ad $r_{j,t+}$ that takes valu- time-series estin- tions are const tfolios are const the individual n that of the m	Beth (1973) regr d portfolios in di PBTDs), defined [Ds (Other). Th d an PBTDs dur $1 = \alpha + \lambda \hat{\beta}_{j,t} + \xi$ e of 1 for portfoli mates for the Fa ructed by sorting stock on that of arket. Both pre- * *** and *** w	MacBeth (1973) regressions (left-hand side) and pooled regressions (right-hand side) of daily excess ghted portfolios in different sample periods from 01 July 1963 to 31 December 2022. Estimates are ays (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading- PBTDs (Other). The third row in each Panel reports the difference in the means of estimates on the e add an PBTDs dummy $(D_{j,t}^{PBTDs})$ and an interaction term between this dummy and market beta, $r_{j,t+1} = \alpha + \lambda \hat{\beta}_{j,t} + \xi_1 D_{j,t}^{PBTDs} + \xi_2 \hat{\beta}_{j,t} D_{j,t}^{PBTDs} + \epsilon_{j,t}$, value of 1 for portfolio j on PBTDs and 0 on other days. In parentheses, the <i>t</i> -statistics are computed to estimates for the Fama-MacBeth regressions whereas clustered standard errors (by trading day) are constructed by sorting individual stocks into 10 portfolios based on their pre-ranking betas, estimated dual stock on that of the market. Post-ranking betas are estimated using a one-year rolling window, with the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the	side) and pool riods from 01 (1 the bottom 19 1 Panel reports and an interacti $D_{j,t}^{PBTDs} + \epsilon_{j,t}$ 1 0 on other da essions whereas into 10 portfor ranking betas betas are estir	led regressions (July 1963 to 31 % by the cross-se the difference i on term between ys. In parenthes ys. clustered stand dios based on th are then similar nated using a or	right-hand side) December 2022. cctional skewness a the means of e a this dummy ar ithis dummy ar es, the <i>t</i> -statistic lard errors (by the lard errors (b) the lard e	of daily excess Estimates are of one-trading- stimates on the id market beta, are computed rading day) are etas, estimated regressing daily ndow, with the
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Type of day	Intercept	Y	Avg R^2	Intercept	X	ξ1	ξ2	R^2
				Panel A: Macro-ann. excluded	nn. excluded			
PBTD _s	-10.73	54.08^{***}	0.48	3.89^{***}	-1.98	-14.29	56.02^{***}	0.002
	(96.0-)	(2.67)		(5.00)	(-1.59)	(-1.29)	(2.92)	
Other	3.26^{***}	-1.27	0.48					
	(4.61)	(-1.09)						
PBTDs - Other	-14.00^{*}	55.35^{***}						
	(-1.95)	(4.67)		; ; ; ;	•			
ľ				Panel B: LEADs excluded)s excluded			
$PBTD_{S}$	-10.42	52.48^{***}	0.49	4.10^{***}	-1.93*	-14.21	54.84^{***}	0.002
	(-1.07)	(2.84)		(5.71)	(-1.67)	(-1.50)	(3.06)	
Other	3.12^{***}	-0.73	0.48					
	(4.73)	(-0.67)						
PBTDs - Other	-13.54^{**}	53.21^{***}						
	(-2.05)	(4.85)						
				Panel C: Fridays excluded	ys excluded			
PBTDs _	-8.72	43.02^{*}	0.50	2.78^{***}	-1.04	-8.98	42.37^{**}	0.001
	(-0.80)	(1.97)		(3.37)	(-0.78)	(-0.91)	(2.08)	
Other	1.57^{**}	0.44	0.49					
	(2.08)	(0.36)						
PBTDs - Other	-10.28	42.58^{***}						
	(-1.34)	(3.33)						
	(+0.1-)	(0.00)						
This table reports estimates from Fama and MacBeth (1973) regressions (left-hand side) and pooled regressions (right-hand side) of daily excess returns	stimates from Fa	uma and MacBet	$\ln (1973) regressi$	ons (left-hand side) and pooled reg	ressions (right-	hand side) of dail	y 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	u-sorted value-w s defined in Sav	eighted portfolic or and Wilson (os from 01 July 1 2014)), leading ϵ	963 to 31 Decembrance	er 2022 using di nent days (LEA	fferent samples vDs, as defined	excluding Macro in Chan and Ma	-announcement sh (2022), over
the period from January 2001 to December 2022), or Fridays. Estimates are computed separately for post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (Other). The	uary 2001 to Dé bottom 1% by	scember 2022), \dot{c} the cross-section	r Fridays. Estim	, or Fridays. Estimates are computed separately for post-balance-trading days (PBTDs), defined as ional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (Other). The	separately for ged individual	post-balance-tr stock turnover,	ading days (PBT and Non-PBTD	'Ds), defined as s (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 PBTDs dummy (D_{P}^{PBTDs}) and an interaction term between this dummy and market beta, and run the following regression:	nel reports the elevation term	difference in the between this du	means of estima mmv and marke	he means of estimates on the two types of day. For the pool dummy and market beta, and run the following regression:	es of day. For tl e following regr	ne pooled regree ession:	ssion, we add an]	PBTDs dummy
(-j,t)					0			
		$r_{j,t+}$	$_{1}=\alpha +\lambda \hat{\beta}_{j,t}+.$	$r_{j,t+1} = \alpha + \lambda \hat{\beta}_{j,t} + \xi_1 D_{j,t}^{PBTDs} + \xi_2 \hat{\beta}_{j,t} D_{j,t}^{PBTDs} + \epsilon_{j,t},$	$D_{j,t}^{PBTDs} + \epsilon_{j,t}$			
where $D_{j,t}^{PBTDs}$ is a dummy variable that takes value of 1 for portfolio j on PBTDs and 0 on other days. In parentheses, the t-statistics are computed	dummy variable	that takes valu	e of 1 for portfol	io j on PBTDs and	1 0 on other day	s. In parenthe	ses, the <i>t</i> -statistic	s are computed
using the standard deviation of the time-series estimates for the Fama-MacDeth 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	levlation of the regressions. Por	tfolios are const	mates for the Fa tructed by sortin	g individual stocks	into 10 portfo	clustered stand lios based on th	lard errors (by u leir pre-ranking b	radıng day) are etas, estimated · · · ·
by regressing darive excess returns of the individual stock on that of the market. Fost-ranking betas are then simularly computed by regressing darive excess returns of the test portfolio on that of the market. Both pre- and post-ranking betas are estimated using a one-year rolling window, with the	excess returns o test portfolio o	t the individual on that of the m	stock on that of arket. Both pre-	the market. Post- and post-ranking	ranking petas ablas ablas ablas ablas ablasment ablasment between an estim	are then similar nated using a o:	'ly computed by l ne-year rolling wi	regressing daily ndow, with the
former being updated monthly and the latter daily. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.	d monthly and	the latter daily.	*, **, and *** 1	epresent significar	ce levels at 1%	, 5%, and 10%,	respectively.	

Table 5: Daily excess returns on PBTDs and non-PBTDs: Excluding Macro-ann./LEADs/Fridays

Type of day	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2
	Pa	nel A: PBT	'Ds	Р	anel B: Othe	er
Overnight	-15.80 (-1.64)	40.90^{*} (1.86)	0.64	-3.54^{***} (-7.14)	7.20^{***} (7.87)	0.49
Intraday	-5.90 (-0.38)	27.50 (0.92)	0.56	8.27*** (8.21)	-7.35*** (-4.76)	0.48
Over - Intra	-9.89 (-0.55)	$13.40 \\ (0.36)$		-11.82^{***} (-10.52)	$ \begin{array}{c} 14.54^{***} \\ (8.10) \end{array} $	

Table 6: Daily intraday/overnight returns on PBTDs and non-PBTDs

This table reports estimates from Fama and MacBeth (1973) regressions for the intraday and overnight periods, respectively. Estimates are computed separately for post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and non-PBTDs (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 using a one-year rolling window, with the former being updated monthly and the latter daily. The sample period covers from 01 July 1992 to 31 December 2022. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

	2%	3%	4%	5%	9%9	7%	8%	9%	10%
PBTD _s	23.11^{**}	17.99^{**}	10.98	8.52	8.18	7.44	6.96	5.49	4.42
	(2.12)	(2.08)	(1.56)	(1.44)	(1.58)	(1.58)	(1.64)	(1.40)	(1.22)
PBTDs - Other	23.39^{***}	18.36^{***}	11.24^{**}	8.77*	8.51^{*}	7.80^{*}	7.36^{*}	5.83	4.71
	(2.99)	(2.86)	(2.01)	(1.75)	(1.85)	(1.82)	(1.82)	(1.52)	(1.29)
This table reports the CAPM implied market price of risk obtained from Fama and MacBeth (1973) regressions. Daily excess returns	the CAPM	implied mark	et price of ris	sk obtained f	rom Fama aı	nd MacBeth ((1973) regress	sions. Daily e	xcess returns
are regressed on betas for the beta-sorted value-weighted portfolios, which are constructed by sorting individual stocks into 10 portfolios	stas for the b	eta-sorted val	ue-weighted	portfolios, wł	nich are const	ructed by sor	ting individu	al 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	ranking beta	s, estimated b	y regressing	daily excess r	eturns of the	individual sta	ock on that o	f 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-	uilarly compu	ted by regres	sing daily ex	cess returns	of the test p	ortfolio on th	iat of the ma	rket. Both pr	e- and post-
ranking betas are estimated using a one-year rolling window, with the former being updated monthly and the latter daily. Estimates are	estimated usi	ng a one-year	rolling winde	ow, with the i	former being	updated mor	ithly and the	latter daily. F	lstimates are
computed separately for post-balance-trading days (PBTDs) and Non-PBTDs (unreported in the table). From left to right, respectively,	ily for post-bi	alance-trading	; days (PBTI	Ds) and Non-	PBTDs (unre	ported in the	e table). Fron	n left to right,	respectively,
PBTDs are identified as those ranked in the bottom 2%, 3%, 4%, 5%, 6%, 7%, 8%, 9%, and 10% by the cross-sectional skewness of	fied as those	ranked in the	${}^{\circ}$ bottom 2%	, 3%, 4%, 59	%, 6%, 7%, 8	3%, 9%, and	10% by the α	cross-sectional	skewness of
one-trading-day-lagged individual stock turnover. The table reports the average slope coefficient of beta and its significance for PBTDs	gged individu	al stock turn	over. The tal	ble reports th	ne average slc	pe coefficient	of beta and	its significanc	e for PBTDs

as well as the difference between PBTDs and Non-PBTDs (Other). *t*-statistics are reported in parentheses. The sample period covers from 01 July 1963 to 31 December 2022. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

	Thresholds in PBTDs Identification
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Type of day	$\mu_m \text{ (bps)}$	σ_m (bps)	Avg. β
PBTDs	40.49	201.9	1.014^{***} (29.82)
Other	2.27	100.9	0.943^{***} (27.35)
PBTDs - Other	38.23^{***} (4.55)		0.071 (1.45)

Table 8: Market premium, realised volatility, and average post-ranking betas on PBTDs and non-PBTDs

This table reports the time-series mean (μ_m) and standard deviation (σ_m) of daily market premium, and average post-ranking betas for post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and non-PBTDs (Other). Post-ranking betas are averaged across the 10 beta-sorted, 25 size and value, and 10 industry portfolios. *t*-statistics are reported in parentheses. The sample period covers from 01 July 1963 to 31 December 2022. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

Top percentiles Intercept	Intercept	K	Avg R^2	Intercept	Y	Avg R^2	Intercept	Y	Avg R^2
	Par	Panel A: All d	lays	P	Panel B: Other	er	Pa	Panel C: PBTDs	Ds
20%	13.29^{***}	-3.76***	0.36	13.50^{***}	-4.43***	0.36	-6.49	62.94^{***}	0.37
	(11.97)	(-2.91)		(12.24)	(-3.46)		(-0.31)	(2.61)	
15%	15.05^{***}	-4.19^{***}	0.33	15.25^{***}	-4.89***	0.33	-4.54	64.94^{***}	0.33
	(12.60)	(-3.17)		(12.85)	(-3.73)		(-0.21)	(2.70)	
10%	17.54^{***}	-5.22***	0.29	17.82^{***}	-5.98***	0.29	-9.70	69.73^{***}	0.29
	(12.75)	(-3.75)		(13.02)	(-4.33)		(-0.41)	(2.79)	
5%	22.11^{***}	-6.86***	0.23	22.40^{***}	-7.68***	0.23	-6.06	73.44^{***}	0.23
	(12.83)	(-4.46)		(12.99)	(-5.00)		(-0.25)	(3.01)	
This table reports estimates from Fama and MacBeth (1973) regressions of daily excess returns on betas for the beta-sorted	ts estimates	from Fama	and MacBe	th (1973) reg	ressions of	daily excess	returns on be	etas for the	beta-sorted
value-weighted portfolios from 01 July 1963 to 31 December 2022 using stocks with turnover cross-sectionally ranked in different	ortfolios from	1 01 July 19	63 to 31 Dec	ember 2022 u	sing stocks	with turnove	r cross-section	nally ranked	in different
top percentiles. Estimates are computed	Istimates are		separately fc	r all days, po	st-balance-t	trading days	separately for all days, post-balance-trading days (PBTDs), defined as those ranked in	fined as thos	e ranked in

The third row in each Panel reports the difference in the means of estimates on the two types of day. In parentheses, the

the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (Other).

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 using a one-year

rolling window, with the former being updated monthly and the latter daily. *, **, and *** represent significance levels at 1%,

5%, and 10%, respectively.

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High
regressions:
Fama-MacBeth
Table 9:

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Appendix A. Additional Tables

Type of day	Intercept	λ	Avg R^2	Intercept	λ	Avg R^2
	Panel A: 1964 - 2011			Panel B: 2001 - 2019		
PBTDs	-15.32 (-1.29)	68.48^{***} (3.16)	0.48	-30.80 (-1.09)	116.89^{**} (2.26)	0.60
Other	3.01^{***} (5.38)	-1.06 (-0.96)	0.48	4.36^{***} (4.17)	-1.84 (-0.91)	0.50
PBTDs - Other	-18.32*** (-3.23)	69.54^{***} (6.23)		-35.17*** (-3.27)	$118.73^{***} \\ (5.71)$	

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

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 post-balance-trading days (PBTDs), defined as those ranked in the bottom 1% by the cross-sectional skewness of one-trading-day-lagged individual stock turnover, and Non-PBTDs (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 using a one-year rolling window, with the former being updated monthly and the latter daily. *, **, and *** represent significance levels at 1%, 5%, and 10%, respectively.

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