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Asset pricing on earnings announcement days ☆

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ABSTRACT

Market betas have a strong and positive relation with average stock returns on a handful of days every year. Such unique days, defined as leading earnings announcement days (LEADs), are times when an aggregate of influential S&P 500 firms disclose quarterly earnings news early in the earnings season. The positive return-to-beta relation holds for various test portfolios, individual stocks, and Treasuries; and is robust to different data frequencies and testing procedures. On days other than LEADs, the beta-return relation is flat. We conclude that waves of early earnings announcements by large firms clustered on LEADs significantly influence asset pricing.

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1. Introduction

In the capital asset pricing model (CAPM), an asset's market risk exposure as measured by beta is linearly and positively related to its return expectations. Recent studies provide some new empirical evidence supporting this positive beta-return relation, but only in months of low inflation (Cohen et al., 2005), on macroeconomic announcement days (Savor and Wilson, 2014), when investor sentiment or disagreement about the stock market's prospects is low (Antoniou et al., 2016; Hong and Sraer, 2016), when borrowing constraints are slack (Jylha, 2018), when the beta-return relation is measured using a set of key accounting variables (Penman and Zhu, 2019), when investor attention or market predicted return is high (Da et al., 2020; Ben-Rephael et al., 2021; Hasler and Martineau, 2021), overnight while the market is closed (Hendershott et al., 2020), and in months after the U.S. midterm elections (Chan and Marsh, 2021).

Our study expands on this burgeoning literature by providing evidence that the market beta-return relation is linear and strongly positive across securities when an aggregate of large influential S&P 500 companies disclose corporate earnings news early in the earnings seasons. These leading earnings announcement days (LEADs) also happen to be times when institutional investors' attention is high. LEADs occur for only a handful of adjacent days per quar-

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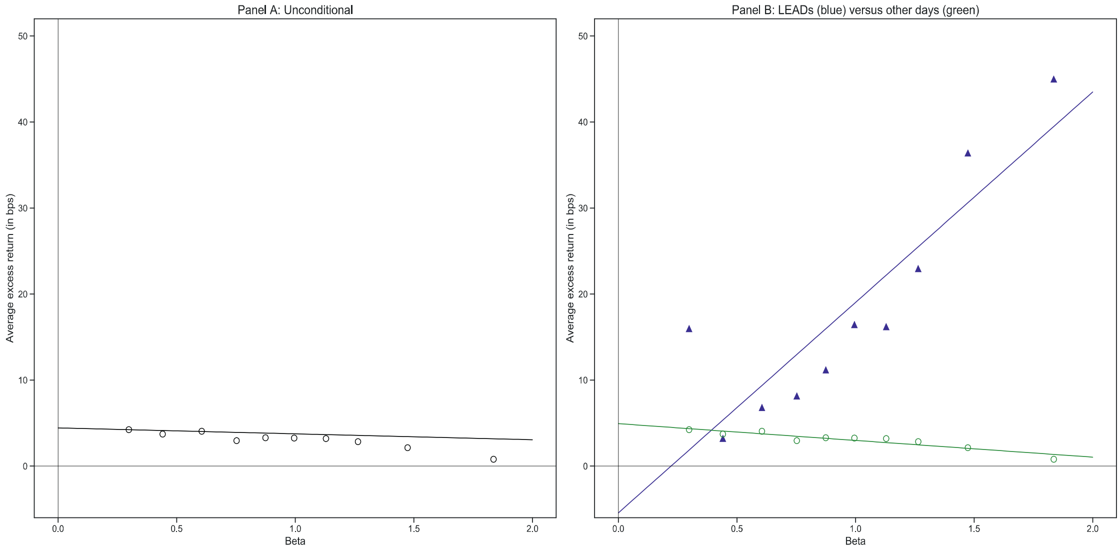

Fig. 1. Average excess returns for beta decile portfolios. This figure plots the average daily excess returns (expressed in basis points) against market betas for 10 value-weighted beta-sorted portfolios. Panel A plots the unconditional SML, and Panel B plots the conditional SMLs on LEADs (blue line with triangle markers) and on other days (green line with circle markers). For each test portfolio, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ter, and their timing is rather predictable. On days other than LEADs (i.e., "other days" or non-LEADs), the market beta-return relation is flat.[1]

Fig. 1 provides the key findings that motivate this study. As in Savor and Wilson (2014) and Hendershott et al. (2020), we use a 12-month rolling regression of daily of returns to estimate betas for US stocks. The stocks are grouped into ten value-weighted, beta-sorted portfolios, and average portfolio excess returns are plotted against average portfolio betas in Fig. 1. Panel A shows the unconditional fit of the security market line (SML) from 2001 to 2019. The line is mostly flat, suggesting that market betas do not explain average excess returns. This result, which is inconsistent with the CAPM, has been documented by Black et al. (1972), Fama and French (1992, 2004), and many others.

Panel B shows the SML separately for LEADs (blue line with triangle markers) and for other days (green line with circle markers). The blue SML shows that on LEADs, an increase in market beta of 1 is associated with an economically and statistically significant increase in average daily excess market returns of 24.47 basis points (bps). The result, however, is vastly different for other days: the green SML has a slight downward slope, where an increase in beta of 1 is associated with a reduction in stock excess returns of 1.95 bps. In addition, the intercept for the other-day SML is significantly positive (a finding that is inconsistent with the CAPM), while it is not statistically significant for LEAD returns.

We confirm that the positive beta-return relation on LEADs is a significant and robust phenomenon. It continues to hold when we perform the analysis using different test portfolios and US Treasuries, and for individual stocks after controlling for familiar firm characteristics such as size and book-to-market ratio. The results are also robust to whether we test using Fama and MacBeth (1973) or panel regressions, for sub-periods, and for betas estimated from high frequency (intraday) returns. Furthermore, the results are not driven by strategically early, or delayed, news releases by LEAD announcers, nor confounded by macro news announcements as per Savor and Wilson (2014), nor by the overnight return effect of Hendershott et al. (2020). We also show that the cross-section SML finding is accompanied by an increase in the market premium à la Roll (1977), whereby the average market premium on LEADs is seven times higher than on other days.

There are also pronounced shifts in the SML in the hours surrounding LEADs: a negative daytime SML on the day prior to LEADs is followed by a positive overnight SML just before the first "leading" trading day. On LEADs, the relation between average return and market beta is linear and mostly positive for all but the last trading hour, when the SML reverts to a flat slope. On the day following LEADs, the SML slope is negative. Finally, there appears to be a day-of-the-week effect for the positive beta-return relation: it occurs predominantly when earnings announcements are disclosed on Tuesday through Thursday in the LEAD week.

[1] Our use of an S&P 500-based definition of "influential announcers" is consistent with Bai et al. (2016) and Farboodi et al. (2020). They show that informational efficiency in prices has improved in recent years for S&P 500 stocks, inter alia because they are large companies. Both studies measure price informativeness by regressing future earnings on current stock prices of S&P 500 firms. In this study, on the other hand, we show that on LEADs, the entire cross-section of discount rates also changes. Taken together, the results suggest that price informativeness extends to that for cross-sectional discount rates for all stocks instead of just reflecting future earnings expectations for S&P 500 stocks.

To assess the economic significance of the findings, we analyze a hybrid "betting-on-and-against-beta" trading strategy that entails "betting-on-beta" (i.e., taking a long position in high-beta stocks and a short position in low-beta stocks) on LEADs, while switching to the familiar "betting-against-beta" strategy (i.e., buy low-beta stocks and sell high-beta stocks) on other days. This hybrid strategy earns a Sharpe ratio equal to 0.306 when annualized. This number is impressive, both in absolute terms and relative to other strategies: for example, the annualized Sharpe ratio generated by continuously betting-against-beta over the full sample period is three times lower at 0.113.[2] Overall, our results highlight the importance of corporate earnings announcements in asset pricing: market beta exposure is priced on LEADs after all and not on other days. In fact, one-third of the cumulative log excess market return in 2001–2019 is earned on LEADs alone, even though these LEADs account for only 5% of all trading days.

We explore three possible explanations for our results. First, our definition of LEADs entails a handful of days when an aggregate of influential S&P 500 companies are making an early wave of earnings announcements for the quarter. Thus, it is possible that LEAD announcements operate as a macro-level trigger for investor attention. Consistent with this interpretation, Hirshleifer and Sheng (2019) explore what constitutes a "news environment." They show that on days when macro news is released concomitantly with micro-level announcements, the former acts as an attention trigger for the latter, thereby driving the returns of individual (micro-level) stocks. Ben-Rephael et al. (2021) find that macro news is associated with micro-level risk premiums, and Da et al. (2020) report that high-beta stocks deliver higher average premiums than low-beta stocks when investor attention is high. On the other hand, it seems that attention to earnings announcements and associated media appearances, conference calls, and the like would, if important, already have been primed – "triggered" – at the time when the corresponding announcement date is scheduled, typically several days before the announcements, and mostly on the same day from year to year.

The second potential explanation for the LEAD effect on cross-sectional asset prices traces back to Black (1972), who proposes that an unconditional flat SML like we observe over the full sample period reflects market segmentation: leverage-constrained investors who cannot fully lever their portfolios are willing to pay more than predicted by the CAPM for risky stocks. This segment of leverage-constrained investors overweights high-risk assets, enabled by leverage-unconstrained investors who underweight them. The consequence is an equilibrium in which the prices of high-beta assets are higher and expected returns are lower, and prices of low-beta assets are lower and expected returns are higher, relative to the CAPM. This well-known segmentation model provides a basis for the "betting-against-beta" strategy. We discuss how the SML is upward sloping on LEADs if demand for the then-expensive leverage drops, and the size of the leverage-constrained segment of investors shrinks.

The third potential explanation for "on again" CAPM risk pricing on LEADs focuses on an increase in market risk on LEADs versus on other days. We show how the average realized betas change around earnings announcements in a way similar to Patton and Verardo (2012), and then provide evidence that the increase in average realized beta on LEADs is higher than that on other days. The shift (i.e., increase) in beta helps explain the positive cross-sectional return-beta relation, and a higher market premium on LEADs.[3] We interpret the increase in average betas for LEADs to be due to potential spillover of information to the cross-section of stocks in the wake of the "wave" of a quarter's announcements made by clusters of large firms. Savor and Wilson (2016) also explore the spillover of announcement information to future aggregate earnings growth. Two features of our results are that: (i) we observe the "early announcement LEAD effect" via a simple and transparent criterion for influential announcers, thus avoiding self-fulfilling choice and possible selection bias; and (ii) LEADs are days on which cross-sectional discount rates move systematically.[4]

Our study is related to Savor and Wilson's (2014) "tale of two days" where market exposure is priced on days when pre-scheduled key macroeconomic news is released, but not on other days. Chan and Marsh (2021) show that decreases in future economic policy uncertainty following pre-scheduled US midterm elections are likewise priced. Macroeconomic news announcements, Congressional election-related announcements, and LEAD earnings announcements all share two common attributes: they are pre-scheduled and "macro" in nature. The pre-scheduling ipso facto enables better trading strategies that utilize the timing at which possible insider information becomes known to the market. The LEAD announcements seem to pre-empt macro announcements insofar as the latter lose their importance once LEAD announcers are taken into account: we find no difference between the return-beta relation estimated on LEADs that happen also to overlap with macroeconomic news releases, and the return-beta relation on LEADs with no macro news.

We structure the paper as follows. In Section 2, we describe the data and procedure to identify LEADs. In Section 3, we analyze how stock prices behave differently on LEADs and on other days, and Section 4 provides additional tests. In Section 5, we discuss how our findings could be consistent with the three potential explanations outlined above. Finally, Section 6 concludes.

[2] Marsh and Pfleiderer (2016, exhibit 2) calibrate the betting-against-beta model of segmentation and find that it is consistent with premiums for low risk "value" stocks up to 60 bps when annualized.

[3] Penman (1990) suggests that the earnings announcement premium is a compensation for the additional cross-asset risk of information spillover of earnings news. Penman's (1990) work was proposed long before the sample period of the present study.

[4] Andrei et al. (2020) propose that it is discount rates as seen by the empiricist that move when differences in investor private information are "washed away" by public announcement (prior to that, each investor only observes the SML conditional on their private information sets and the empiricist sees only a conglomeration of them). Our framework differs insofar as the discount rate changes as seen by the empiricist are for a different set of stocks than the cluster of LEADers making the announcements.

2. Data and lead definition

The work by Savor and Wilson (2014) highlights the importance of pre-scheduled macro announcements made at the market level in asset pricing. The present study shows that pre-scheduled corporate earnings announcements are just as important at the aggregate level in asset pricing. To operationalize "aggregate," we identify a set of individual firms making corporate earnings announcements that collectively have the potential to "move" the market. We posit that, conditional on the concomitant earnings announcements released by market movers, exposure to the aggregate market moving news is priced cross-sectionally on announcement days. Market movers are large and influential, because all else equal, uncertainty about the informativeness of announcements made by smaller companies limits their influence, while there is also evidence of greater investor attention to earnings announcements made by large companies (Nekrasov et al., 2021). Indeed, clusters of large announcers in earnings week have virtually been institutionalized as the focus of media attention then; for example, Nasdaq lamented that: "…this week [September 4, 2020], there aren't enough major companies reporting to truly move the market."[5]

Amongst the large market movers, we expect early announcers to be inherently more influential because their announcements contain up-to-date information. "Strongest signal" announcements early in the quarterly earnings season are also regularly complemented by conference calls, media attention, interviews, and general "buzz" du jour sufficient to constitute a "macro" event for three or four jours. In other words, early influential announcements are plausibly signals or attention triggers.

To select early influential announcements, we begin by collecting quarterly earnings announcements for all the constituents of the S&P 500 index between January 2001 and December 2019, for a total of 4227 trading days. The 2001 starting date is motivated by studies such as Beaver et al. (2018, 2020), which document a considerable increase in information on earnings announcement days post-2000; a period of key accounting reforms, such as the Sarbanes-Oxley Act and Regulation Fair Disclosure. We extract earnings data from the Institutional Brokers' Estimate System (I/B/E/S) summary file, and we require that the S&P 500 announcers in our sample universe are listed on the NYSE, Amex or Nasdaq. Following convention, we remove a small number of earnings observations timestamped at 00:00:00 because these are likely I/B/E/S recording errors made especially in the early 2000s (deHaan et al., 2015). We further drop a handful of earnings news observations recorded on Saturdays, Sundays, and public holidays. Also, we follow Patton and Verardo (2012), Michaely et al. (2014), and deHaan et al. (2015) and assign news observations reported after the market has closed to the next trading day or overnight as appropriate for our analysis. The final sample has a total of 35,826 earnings announcements for constituents of the S&P 500 index.[6]

We then select "leading" earnings news from the pool of sample announcements. This procedure entails identifying leading earnings announcement days (LEADs) that are the days when "leading news" is reported. To this end, we use a method that is straightforward, transparent, and devoid of look-back bias: we select LEADs to be Tuesday through Thursday in the first week of reporting quarter q that has a minimum of 50 announcers (i.e., one-tenth of S&P 500 firms).[7] We label the LEAD announcers as LEADers. Put simply, our LEAD definition encompasses a single fraction of S&P 500 firms as announcers, thus ensuring that LEADers are, by construction, large but not otherwise specifically chosen, and their reported early earnings news is ex ante likely to be influential.[8] We omit Monday from our LEAD definition because firms rarely disclose earnings news on Monday (only about 5% of all S&P 500 firms' earnings reports in our sample were made between 0:00 am and 16:00 pm on Monday). As such, Monday announcements, if anything, are less influential. We also exclude Fridays from our LEADs due to general inattention and pre-weekend idiosyncrasies, and we provide the relevant discussion below.

Table 1 reports descriptive statistics of S&P 500 announcers reporting on two types of days: LEADs and other days. Panel A shows that there are on average 31 LEADers per day (i.e., about 93 from Tuesday through Thursday); this estimate is fourfold higher than the average number of other S&P 500 firms reporting on non-LEADs. In Panel B, we partition the news observations into different weekdays, for a total of 7138 news announcements on LEADs (i.e., about one-fifth of the final earnings sample) versus 28,688 news announcements on other days. Panel C tabulates, on a yearly basis, the total number of unique announcers on LEADs and on other days, and the cross-section median of variables such as market capitalization and analyst coverage. It is apparent from the panel that over the years, LEADers are, as desired, consistently larger and thereby attract more attention (with a slightly higher analyst following), than other S&P 500 announcers reporting on non-LEADs.

In Fig. 2, we plot the total number of LEADs identified in each reporting week. The online appendix presents the frequency distribution of LEADers and other S&P 500 announcers for each fiscal quarter. We can see that LEADers generally announce in week 3 or 4 in fiscal quarter one,

[5] https://www.nasdaq.com/articles/7-earnings-reports-to-watch-next-week-2020-09-04.

[6] Because of multiple data filters, our final sample consists of 35,826 news observations instead of 19 x 4 x 500 = 38,000 observations. We exclude, for example, Fannie Mae and Freddie Mac from the analysis because Compustat tags both stocks as traded over the counter since the start of our sample period (even though both firms were in actuality traded over the counter since mid 2010).

[7] Our LEADs are not always days with the largest number of announcers, and conversely, there are typically some large announcers reporting in advance of or following the LEAD clusters; nor do we seek to include all the popular attention-getters du jour (e.g., FAANG stocks).

[8] The online appendix tabulates 50 top frequent LEADers which include household names such as Apple Inc., AT&T, Boeing, IBM, and Johnson & Johnson, as well as several lesser known companies, such as Danaher and Nucor.

Table 1
Descriptive statistics of S&P 500 announcers.
This table reports descriptive statistics for S&P 500 announcers on LEADs and other days. Panel A reports the daily distribution of announcers, and Panel B reports the number of announcers each day between Monday and Friday. In Panel C, *Unique firms* is the number of announcers reporting in a given year, and *Mkt cap, B/M* and *# of analysts* report the respective cross-section median of market capitalization, firms' book-to-market ratios and number of analysts followings (all measured one quarter before the announcement date). The sample period covers January 2001 through December 2019.

Panel A: Daily distribution of announcers

	LEADs	Other days
Mean	31	8
Min	6	1
5 pctl	13	1
25 pctl	22	2
50 pctl	29	4
75 pctl	40	9
95 pctl	59	32
Max	73	70

Panel B: # of announcers in different weekdays

	LEADs	Other days
Monday	–	1719
Tuesday	1534	5767
Wednesday	2123	6538
Thursday	3481	8387
Friday	–	6277
Total	7138	28,688

Panel C: Descriptive statistics (per year)

	LEADs				Other days			
	Unique firms	Mkt cap ($ bil)	B/M	# of analysts	Unique firms	Mkt cap ($ bil)	B/M	# of analysts
2001	177	8.93	0.33	13	415	7.58	0.35	13
2002	167	9.63	0.35	14	423	7.36	0.39	14
2003	175	8.29	0.38	14	437	7.13	0.43	14
2004	191	10.88	0.35	16	428	9.03	0.37	14
2005	142	15.21	0.34	17	433	10.19	0.38	14
2006	182	15.11	0.31	16	450	11.36	0.36	14
2007	145	16.64	0.32	16	457	12.44	0.33	15
2008	198	11.68	0.37	14	458	9.56	0.4	14
2009	193	9.32	0.52	14	460	6.43	0.55	13
2010	189	12.07	0.43	17	463	8.91	0.46	15
2011	187	15.78	0.42	19	467	10.76	0.42	16
2012	153	14.67	0.42	19	469	11.95	0.42	17
2013	204	15.25	0.36	18	486	14.28	0.38	18
2014	207	20.04	0.32	19	488	16.77	0.33	18
2015	175	21.92	0.31	19	466	17.64	0.32	18
2016	153	20.17	0.35	19	489	17.46	0.34	18
2017	211	21.74	0.32	17	475	19.13	0.33	17
2018	191	24.26	0.29	17	481	19.92	0.33	17
2019	175	22.76	0.28	17	458	21.03	0.37	17
Avg	180	15.49	0.36	16.58	458	12.58	0.38	15.58

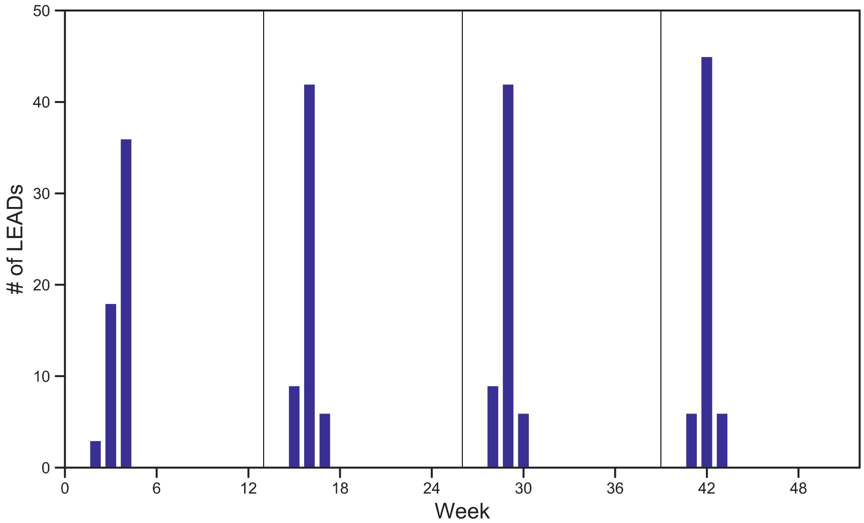

Fig. 2. LEADs in each quarter. In this figure, a typical year is equally partitioned into four fiscal quarters, each with 13 weeks. The number of days identified as LEADs are reported for each week-quarter. Since each quarter has three LEADs (Tuesday, Wednesday and Thursday), we have a total of 57 LEADs for each quarter over the 2001–2019 sample period (19 years).

and mainly in week 3 in the three remaining quarters. In fact, the identification of LEAD week is fairly predictable over the years, and it is concentrated as intended in early peak earnings weeks in January, April, July, and October.[9]

It is possible that the striking stock return differentials between LEADs and other days discussed below occur because LEADers strategically time their earnings announcements, in which case the strategic timing would become the leading information event. To check this possibility, we use a simple algorithm to project scheduled earnings dates for quarter q in year y based on the same reporting quarter-date as in the previous year y - 1. For example, if firm j reported on October 24, 2017, the algorithm predicts that the firm would release its fourth quarter earnings report around the same business day in the following fiscal year. Firm j is deemed to have strategically advanced its actual earnings reporting if it announced earlier than the expected date (i.e., October 24, 2018 in our example) by more than five business days. Using the same criteria, firm j is deemed to strategically delay its actual news reporting if it pushes back its announcement by more than five business days. The algorithm shows that only 205 (27) earnings announcements would have been advanced (delayed) to LEADs. With only 3% (205/6465) of the announcements having possibly been "sped up" to LEADs, and 0.4% (27/6465) delayed, we conclude that the distinct price dynamics observed on LEADs are unlikely caused by material strategic timing.[10] Also, we verify that there is no substantial disparity between earnings beats and earnings misses with effects that might be conflated with our LEAD analysis: of 7138 LEAD announcements, 68.2% beat the analyst consensus (and the remaining 31.8% missed or matched analyst forecasts) versus 65.9% beats during non-LEAD announcements. In other words, the earnings beats-to-misses ratio is almost identical on both types of days.

In summary, LEADers in this study are large constituents of the S&P 500 index, and they are early announcers. The aggregated early earnings news information reported by these announcers on LEADs influences and thus "leads" the reporting season. Finally, there is no evidence suggesting that LEADers strategically and systematically advance or delay the announcements of corporate earnings to LEADs.

[9] This regularity in the timing of LEADs identifies a "quarterly week 3 seasonality" (i.e., week 3 effect in each quarter), and a "quarterly weeks 4 and 3 seasonality" (i.e., week 4 effect in quarter one and week 3 effect in other quarters) in cross-sectional stock returns. To expand on the conjecture, the online appendix provides two separate SML plots for average returns in week 3 of each quarter (the "quarterly week 3 seasonality" effect), and average returns in week 4 in quarter one and week 3 in other quarters (the "quarterly weeks 4 and 3 seasonality" effect). The plots show that the implied market premium in the "quarterly week 3 seasonality" effect ("quarterly weeks 4 and 3 seasonality" effect) can be used as an expression for nearly 42% (65%) of the LEAD implied market premium. We are grateful to the referee for suggesting this implication.

[10] We omit announcements reported in the last four quarters because there are no matched expected-actual news announcements in the year beyond the 2019 end date of our sample. As such, we use 6465 instead of 7178 news observations in analyzing possible strategic announcements.

3. Relation between market betas and returns

3.1. Beta-sorted portfolios

We begin by constructing beta decile portfolios using stocks traded on the NYSE, Amex or Nasdaq from 2001 to 2019. We retrieve stock data from the Center for Research in Security Prices (CRSP) database, and we include all common stocks with CRSP share codes of 10 or 11.

In our initial set of tests, the daily pre-ranked betas of individual stock j are estimated using a 12-month rolling regression of the stock's daily excess returns on the market excess returns. At the start of each month, we sort the stocks into one of ten portfolios on the basis of their pre-ranking betas, and then calculate the daily value-weighted returns of each portfolio over the month. Post-ranking portfolio betas are calculated for each day using a 12-month rolling regression of the daily portfolio excess returns on the daily market excess returns. These value-weighted beta decile portfolios are our main test subjects, but we also consider other test assets, and the results (reported below) are robust.

Panel A of Fig. 1 plots average excess returns of the value-weighted beta decile portfolios on average market betas over the 2001–2019 sample period. The slope of the unconditional SML is mostly flat with a coefficient of −0.69 bps and a t-statistic of −2.38. The regression intercept, on the other hand, is statistically significant with an estimate of 4.44 bps and t-statistic of 14.40, and the R^2 is 42%. These results, which are inconsistent with the CAPM prediction, accord with prior studies, such as Black et al. (1972) and Fama and French (1992, 2004).

We then partition the unconditional SML into its conditional versions on LEADs and on other days. Panel B of Fig. 1 reports the findings. Following Savor and Wilson (2014) and Hendershott et al. (2020), we use unconditional portfolio betas averaged over the full sample period to plot both conditional SMLs in the panel. The blue SML shows a strong and positive linear relation between excess returns and market beta: on LEADs, a unit increase in beta is associated with a significant increase in daily average excess return of 24.47 bps (t-statistic = 5.14). The regression intercept has a modest negative estimate of −5.44 bps but the corresponding t-statistic is −1.07, rendering the negative estimate statistically insignificant. The regression R^2 is 77%, suggesting that the variation in the market beta explains a large portion of the cross-sectional excess return variation on LEADs. In sharp contrast, the slope of the green SML is −1.95 bps (t-statistic = −7.08), indicating a significantly negative implied market risk premium on other days. The regression intercept has a significantly positive estimate equal to 4.94 (t-statistic = 16.82), and the R^2 is 86%.

We now provide the first piece of evidence that the positive beta-return relation on LEADs is a robust phenomenon. Like Savor and Wilson (2014), we group all stocks into 50 value-weighted, beta-sorted portfolios and repeat the above analysis. Fig. 3 presents the SML results, with an almost identical finding. The blue SML shows a strongly linear and (almost) monotonically increasing slope: on LEADs, an increase in market beta of 1 is sig-

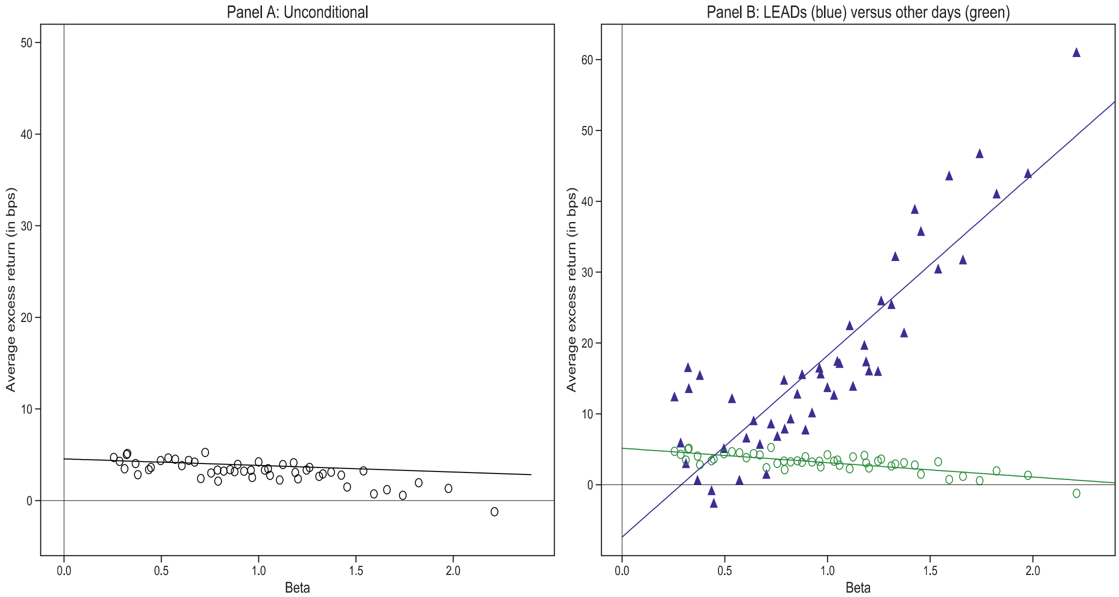

Fig. 3. Average excess returns for 50 beta-sorted portfolios. The figure plots the average daily excess stock returns (expressed in basis points) against market betas for 50 value-weighted, beta-sorted portfolios. Panel A plots the unconditional SML, and Panel B plots the conditional SMLs on LEADs (blue) and on other days (green). For each test portfolio, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

nificantly associated with an increase in average excess return of 25.63 bps (t-statistic = 12.91). The intercept is negative (–7.40 bps with t-statistic = –3.45) and the regression R^2 is 78%. On other days, the beta coefficient of the green SML is –2.04 bps (t-statistic = –8.42), implying a negative market risk premium on non-LEADs that lacks economic meaning. The non-LEAD intercept is significantly positive (5.15 bps with t-statistic = 19.74) and the regression R^2 is 60%. When LEAD and non-LEAD returns are pooled together, the resulting unconditional SML is largely flat with a beta coefficient of –0.72 bps (t-statistic = –3.12), the intercept is significantly positive (4.55 bps with t-statistic = 18.37), and the R^2 is 17%.

If the CAPM is considered as a restriction that the intercept is zero in the regression of portfolio excess returns on the market excess returns (Gibbons et al., 1989), the insignificant intercept for LEAD returns shown in Fig. 1 would be consistent with the CAPM, while the significantly positive intercept for non-LEAD returns is not. For LEAD returns, the GRS F-statistic for the hypothesis that the alphas of all the beta decile portfolios are jointly equal to zero is 1.75 (p-value = 0.07). This F-statistic is marginally significant at the 10% level, but it is still much lower than the GRS F-statistic estimated for other days (F-statistic = 3.03 with p-value = 0.001). Likewise, the GRS F-statistic for alphas of LEAD returns of the 50 beta-sorted portfolios shown in Fig. 3 is statistically insignificant at 1.23 (p-value = 0.16) versus a statistically significant F-statistic equal to 1.67 (p-value = 0.002) for non-LEAD returns. In short, the GRS test suggests that the CAPM captures the variation of average excess portfolio returns for LEADs, but the model is strongly rejected for non-LEADs.

As in Savor and Wilson (2014) and Hendershott et al. (2020), we push the analysis further by regressing the cross-section excess returns of portfolio i for LEAD day $t+1$ ($xr^L_{i,t+1}$) on the prior-day portfolio betas using the Fama and MacBeth (1973) regression:

$$xr^L_{i,t+1} = a^L + b^L \beta_{i,t} + \varepsilon^L_{i,t+1} \tag{1}$$

where $\beta_{i,t}$ is calculated from a 12-month rolling regression of excess returns of portfolio i on the daily market excess returns. Similarly, we estimate the Fama-MacBeth regression for other days as:

$$xr^O_{i,t+1} = a^O + b^O \beta_{i,t} + \varepsilon^O_{i,t+1} \tag{2}$$

The left-hand side of Panel A in Table 2 reports the Fama-MacBeth regression estimates and the corresponding t-statistics (in parentheses). Standard errors are calculated using the standard deviation of the time-series of coefficient estimates, but the significance levels barely change if we correct for heteroskedasticity and autocorrelation using Newey-West adjusted standard errors. The b^L coefficient estimate is 22.24 bps (t-statistic = 2.19); this value is close to the magnitude of the blue SML slope shown in Fig. 1. In economic terms, our finding means that on LEADs, stocks with a beta that is higher by one have a significantly higher average daily equity premium equal to 22.24 bps. In fact, this estimate is statistically indistinguishable from the 15.86 bps average risk premium of the aggregate market portfolio realized on LEADs over the 2001–2019 sample period (the t-test for the difference in means gives a t-statistic of 0.51). The LEADs intercept is slightly negative, but it is statistically insignificant (a^L = –2.62 with t-statistic = –0.50), and the average regression R^2 is 50%.

Table 2
Fama-MacBeth and panel regression results for various test portfolios.
This table reports the results from Fama-MacBeth and panel regressions of daily excess returns (expressed in basis points) on market betas for various test portfolios. The betas used to construct the portfolios are estimated using a 12-month rolling regression on daily excess returns. Panels A and B report the results for beta decile portfolios (value-weighted portfolios for Panel A and equal-weighted portfolios for Panel B). Panel C reports the results for 10 beta-sorted portfolios, 25 Fama and French size- and book-to-market sorted portfolios and 17 industry-sorted portfolios; all are value-weighted. The parenthesized t-statistics are estimated based on standard errors calculated using standard deviations of the time-series coefficient estimates (for the Fama-MacBeth regression) and standard errors clustered by days (for the panel regression). The sample period covers January 2001 through December 2019. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: 10 beta-sorted portfolios (value weighted)

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	β	Avg R^2	Intercept	B	D^{LEAD}	β x D^{LEAD}	R^2
LEADs	−2.62	22.24**	0.50	4.64***	−1.58	−11.31	27.35***	0.001
	(−0.50)	(2.23)		(3.48)	(−0.78)	(−1.59)	(2.63)	
Other days	4.46***	−1.60	0.51					
	(4.17)	(−0.77)						
LEADs - Other	−7.08	23.84**						
	(−1.44)	(2.50)						

Panel B: 10 beta-sorted portfolios (equal weighted)

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	β	Avg R^2	Intercept	β	D^{LEAD}	β x D^{LEAD}	R^2
LEADs	7.88**	13.12	0.64	9.29***	−3.96**	−4.50	19.50**	0.001
	(2.48)	(1.39)		(8.19)	(−2.28)	(−0.82)	(2.50)	
Other days	8.37***	−3.27	0.61					
	(10.50)	(−1.58)						
LEADs - Other	0.49	16.39*						
	(0.13)	(1.73)						

Panel C: 10 beta-sorted + 25 size/BM sorted + 17 industry portfolios

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	β	Avg R^2	Intercept	B	D^{LEAD}	β x D^{LEAD}	R^2
LEADs	−3.37	20.31**	0.21	2.98	0.09	−12.11	24.94***	0.001
	(−0.64)	(2.07)		(1.43)	(0.05)	(−1.23)	(2.58)	
Other days	4.38***	−1.44	0.23					
	(3.73)	(−0.70)						
LEADs - Other	−7.75	21.75**						
	(−1.44)	(2.29)						

A different finding emerges for the other days: b^O is –1.60 and the corresponding t-statistic is –0.77, making it statistically insignificant. That is, the Fama-Macbeth procedure suggests that the beta-return relation on other days is mostly flat. The net difference between b^L and b^O is 23.84 (t-statistic = 2.50), which indicates that the implied market risk premium is 23.84 bps higher on LEADs than on other days. The other-day regression intercept is positive and statistically significant (a^O = 4.46 with t-statistic = 4.17), and the average regression R^2 is 51%. The net LEADs-minus-other-days intercept is –7.08 but it is statistically insignificant (t-statistic = –1.44).

To explore further, we estimate the following panel regression modified from Savor and Wilson (2014):

$$xr_{i,t+1} = a + b_1\beta_{i,t} + b_2 D^{LEAD}_{t+1} + b_3\beta_{i,t} \times D^{LEAD}_{t+1} + \varepsilon_{i,t+1}, \quad (3)$$

where $xr_{i,t+1}$ is the excess return of portfolio i on all days, D^{LEAD}_{t+1} is a dichotomous variable equal to 1 on LEAD and 0 on other days, and the b_3 parameter directly captures the net difference in implied market risk premium on LEADs and on other days.

The right-hand side of Panel A in Table 2 reports the panel regression results, with the parenthesized t-statistics computed using standard errors clustered by trading days. The a and b_1 coefficient estimates are 4.64 bps and –1.58 bps, respectively; these values closely match the a^O and b^O estimates reported for the Fama-MacBeth regression. The b_3 coefficient is statistically significant at 27.35 bps (t-statistic = 2.63); this estimate is also close to the net difference of 23.84 bps obtained from the Fama-MacBeth procedure. The coefficient of the D^{LEAD} dummy variable, which captures the net “LEADs-minus-other-days” intercept, is –11.31. This number, although slightly below the –7.08 difference obtained using the Fama-MacBeth methodology, has a t-statistic of –1.59, making it statistically insignificant.

Panel A of Fig. 4 shows that our key result continues to hold for equal-weighted beta decile portfolios. The blue SML has a significantly positive slope on LEADs whereby an increase of one in market beta is associated with a 15.26 bps increase in average excess returns (t-statistic = 5.68). In contrast, the green SML has a signif-

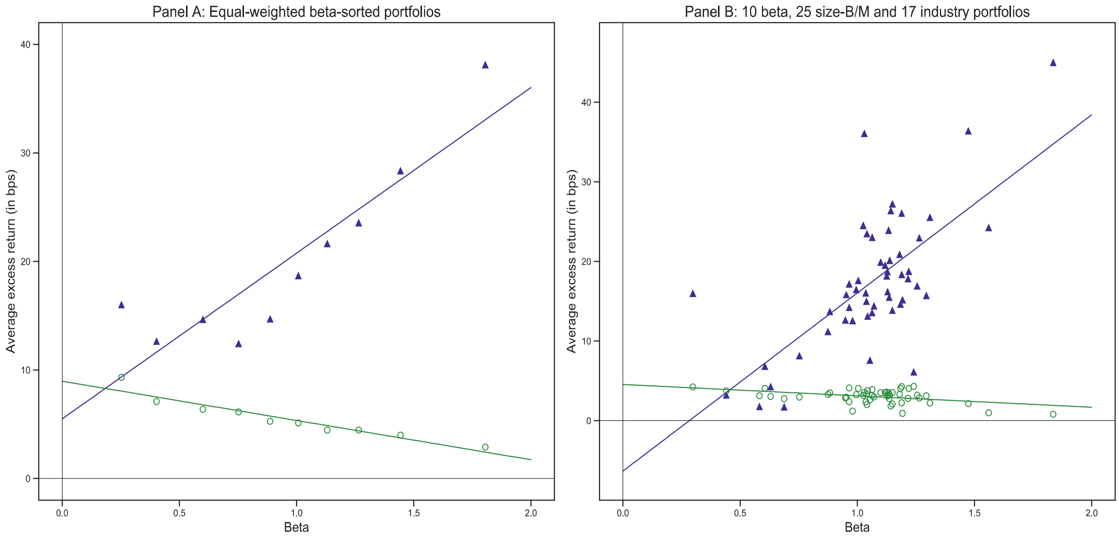

Fig. 4. Average excess returns for different test portfolios. Panel A plots the average daily excess returns (expressed in basis points) against market betas for 10 equal-weighted beta-sorted portfolios. Panel B presents analogous plots for 10 beta-sorted portfolios, 25 Fama and French size- and book-to-market sorted portfolios and 17 industry-sorted portfolios (all are value-weighted). In each panel, we plot the conditional SMLs on LEADs (blue) and on other days (green). For each test portfolio, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

icantly negative slope: on other days, an increase of one in market beta is associated with a reduction in average excess returns of 3.62 bps (t-statistic = –8.96). When we estimate the Fama-MacBeth and panel regressions, we get similar results, as reported in Panel B of Table 2. For the Fama-MacBeth test, the implied market risk premium on LEADs is 16.39 bps higher than on other days (t-statistic of the difference is 1.73). This finding is confirmed by the panel regression, where the difference between the risk premium on LEADs and on other days is 19.50 bps (t-statistic = 2.50).

Taken together, the key results presented in this section suggest that the cross-section of stock prices behave very differently on LEADs and on other (i.e., normal) days, since market betas of the same portfolios, which have a slightly negative (or rather flat) cross-sectional relation with returns during normal days, actually explain returns on LEADs.

3.2. Beta, size, book-to-market ratio and industry portfolios

Lewellen et al. (2010) advocate expanding the set of test portfolios to include those sorted on size and book-to-market ratio (B/M), because doing so provides a higher hurdle for accepting CAPM. To this end, we add 17 industry portfolios and 25 Fama and French size- and B/M-sorted portfolios to the 10 beta-sorted portfolios and repeat the earlier tests. We obtain the data for size, B/M, and industry portfolios from Kenneth French's online data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Panel B of Fig. 4 plots the average excess value-weighted returns on all 52 portfolios against market betas separately on LEADs and on other days. Once again, the blue SML has a strongly positive slope: a unit increase in beta is linearly related to an increase in average excess return of 22.38 bps (t-statistic = 6.77), implying a significantly positive market risk premium on LEADs. The intercept is negative, but it is only significant at the 10% level (–6.34 bps with t-statistic = –1.76), and the regression R^2 is 48%. On other days, the beta-return relation is strongly negative with an implied risk premium equal to –1.43 bps (t-statistic = –3.35), the SML intercept is positive (4.54 bps with t-statistic = 9.78) and the regression R^2 is nearly thrice lower (18%) relative to the LEAD's regression R^2 value.

We confirm the above finding through the Fama-MacBeth and panel regressions, with the results reported in Panel C of Table 2. For the Fama-MacBeth test, the implied market risk premium is significantly positive for LEAD returns (20.31 bps with t-statistic = 2.07) but it is negative for other-day returns (–1.44 bps with t-statistic = –0.70). The difference in implied market risk premiums for LEADs and other days is 21.75 bps (t-statistic = 2.29); this estimate is close to the LEAD-minus-other-days implied market risk premium estimated for the beta decile portfolios reported in Panel A of Table 2. The average R^2s are about 21%–23% for both LEAD and other-day returns. Using panel regression, the LEAD-minus-other-days implied market risk premium is equal to 24.94 bps (t-statistic = 2.58). The coefficient on the LEAD dummy is –12.11 but it is not statistically significant (t-statistic = –1.23).

3.3. Treasuries

Wachter and Zhu (2021) point out that pre-scheduled macro announcements contain informative news about

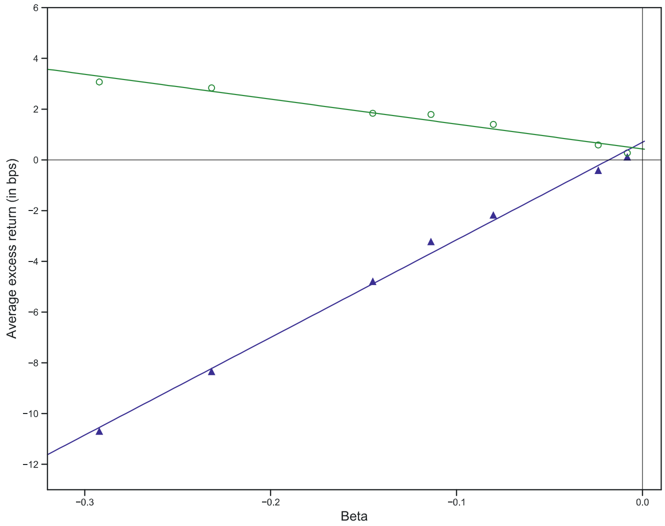

Fig. 5. Average excess returns for Treasuries. This figure plots the average daily excess returns (expressed in basis points) against market betas for US Treasuries with different maturities. The conditional LEAD-SMLs is in blue, and the other day-SML is in green. For each test portfolio, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. Constrained by data availability, the sample period used in the analysis covers January 2001 through December 2017. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

expected inflation, and thus Treasury bonds are potentially more exposed to scheduled news than are equities. Savor and Wilson (2014) provide empirical support to this hypothesis and show that the upward-sloping equity SML observed on macroeconomic news announcement days extends to U.S. Treasury bonds. Here, we confirm this general insight in the context of scheduled corporate earnings news. To this end, we retrieve US Treasury bonds with maturities of 1, 2, 5, 7, 10, 20, and 30 years from the CRSP Daily Treasury Fixed Term Indexes File.

Fig. 5 plots the average excess returns on Treasuries against market betas (calculated using a 12-month rolling regression) separately for LEADs and for other days. As the figure shows, Treasury returns have a relation with betas that is strikingly similar to that for equities: the linear blue SML slope is economically large and positive (38.50 bps with t-statistic = 34.89), implying a significantly positive risk premium on LEADs, while the magnitude of the intercept, although significant, is virtually zero (coefficient = 0.69 with t-statistic = 3.88). The regression R^2 is 99%, suggesting that variation in market betas explains almost all the variation in the average excess returns of the Treasuries on LEADs. On the other hand, the green SML has a significantly negative slope of –9.82 (t-statistic = –11.89). That is, on other ("normal") days, a negative risk premium estimate emerges, with an increase of one in market beta associated with a reduction in Treasury returns of about 10 bps.

3.4. Market premiums and trading strategies

We have documented a strong and positive cross-section relation between market betas and average returns for equities and Treasuries on LEADs. We now show that this cross-section finding has a counterpart at the aggregate market portfolio level, as Roll (1977) establishes that it must if the market is mean-variance efficient. That is, if a market proxy such as the CRSP index is ex post efficient, the linear relation will tautologically hold ex post with a slope equal to the ex post market index premium. Panel A of Table 3 provides evidence confirming this proposition: the average premium on the CRSP value-weighted market portfolio is seven times higher at 15.86 bps for LEADs versus 2.17 bps for other days. This 13.69 bps risk premium differential is economically large and statistically significant (t-statistic =1.75).

To reinforce the finding, Panel B of Table 3 reports the cumulative log excess returns of the CRSP market portfolio on different types of days. Cumulatively, the market outperformed the risk-free asset by 0.346 on LEADs versus 0.677 on the much larger number of other days. The 0.346 cumulative number is economically significant, since LEADs consist of only 228 out of 4779 trading days over the 2001–2019 sample period. In other words, of the unconditional log sum of 1.023, one-third is earned on LEADs alone even though the LEADs account for only 5% of all trading days.

We now explore several trading implications. First, we assess the performance of three alternative strategies: (i) invest in the aggregate market portfolio on LEADs and in the risk-free asset on other days; (ii) invest in the risk-free asset on LEADs and in the market portfolio on other days; and (iii) buy-and-hold the market portfolio between 2001 and 2019. Panel C of Table 3 reports the results. Strategy (i), which targets the LEADs effect, generates a daily mean and standard deviation of 0.013% and 0.253%, respectively. These values give a daily Sharpe ratio of 0.052, which when annualized, translates to a sizable estimate of 0.838. This number is about three times the annualized Sharpe ratio of 0.371 generated by strategy (ii), and twice

Table 3
Market premium and trading strategies.
Panel A reports average market risk premium for three types of days: LEADs, other days, and both types of days together, from January 2001 through December 2019. Panel B reports cumulative log excess returns earned by investing in the aggregate market portfolio. Panel C reports daily summary statistics (means, standard deviations and Sharpe Ratios) for three trading strategies: (i) invest in equities on LEADs and in the risk-free asset on other days; (ii) invest in the risk-free asset on LEADs and in equities on other days; and (iii) buy-and-hold equities over the full sample period. Panel D reports analogous statistics for the returns of two long-short trading strategies: (i) "betting-against-beta" strategy that takes a long (short) position on low (high) decile beta-sorted portfolio over the whole sample period; and (ii) the hybrid "betting-on-beta" strategy that takes a long (short) position on high (low) decile beta-sorted portfolio on LEADs and switch to the betting-against-beta strategy on other days. Both strategies (i) and (ii) in Panel D, however, are not beta neutral. Panel E reports the statistics for the analogous beta neutral long-short strategies.

Panel A: Market risk premium			
	LEADs	Other days	All days
Average (bps)	15.86	2.17	2.82
Panel B: Cumulative log excess returns			
	LEADs	Other days	All days
Cumulative returns	0.346	0.677	1.023
Panel C: Investing in the aggregatedmarket portfolio			
	(i)	(ii)	(iii)
Average (%)	0.013	0.026	0.034
Std deviation (%)	0.253	1.141	1.169
Sharpe Ratio	0.052	0.023	0.029

Panel D: Investing in long-short portfolio (not beta neutral)		
	Hybrid	Betting against beta
Average (%)	0.044	0.016
Std deviation (%)	2.284	2.284
Sharpe Ratio	0.019	0.007
Panel E: Investing in long-short portfolio (beta neutral)		
	Hybrid	Betting against beta
Average (%)	0.102	0.128
Std deviation (%)	2.375	2.375
Sharpe Ratio	0.043	0.054

the annualized Sharpe ratio of 0.468 earned from the buy-and-hold strategy (iii).

To the extent that high-beta stock returns eclipse those of low-beta stocks on LEADs, and low-beta stocks outperform their high-beta counterparts on other days, a hybrid "betting-on-and-against-beta" trading strategy that entails buying the high-beta (decile 10) value-weighted portfolio and selling the low-beta (decile 1) value-weighted portfolio on LEADs, and the reverse (viz. buying low-beta stocks and selling high-beta stocks) on other days, should yield an economically meaningful return. Panel D shows that this is indeed the case, with the betting-on-and-against-beta strategy earning a daily Sharpe ratio of 0.019, or 0.306 when annualized. This number is three times the Sharpe ratio earned by continuously betting-against-beta over the full sample period.

The long-short trading strategies reported in Panel D are not beta-neutral in the sense of Frazzini and Pedersen (2014). To address this issue, Panel E reports the beta-neutral version of the betting-on-and-against-beta strategy that encompasses the following beta-neutral betting-on-beta strategy on LEADs:

$$\frac{r_{10} - rf}{\beta_{10}} - \frac{r_1 - rf}{\beta_1},$$

where the subscript 1 (10) denotes low-beta (high-beta) portfolio, and reversing to the beta-neutral betting-against-beta strategy on other days:

$$\frac{r_1 - rf}{\beta_1} - \frac{r_{10} - rf}{\beta_{10}}.$$

We use the average post-ranking portfolio betas of 0.30 for β_1 and 1.84 for β_{10}. Panel D reports the findings. The Sharpe ratio for the beta-neutral betting-on-and-against-beta strategy is 0.043 per day, or 0.693 when annualized. This number, although lower than the beta-non-neutral betting-against-beta strategy over the full sample period (the Sharpe ratio is 0.871 when annualized), is still economically significant in an absolute sense.

4. Additional tests

4.1. Realized betas

So far, our results have been based on Fama-MacBeth beta estimates where both pre-ranking stock betas and post-ranking portfolio betas are calculated using a 12-month rolling regression with daily returns. We update the post-ranking portfolio betas every day, but some may question the wisdom of synchronizing updates that involve a rolling prior 12-month interval, albeit using daily returns, with a more dynamic time-series that involves return expectations conditional on earnings announcements.

To address such concerns, we repeat the earlier tests using daily betas estimated from high-frequency (i.e., intraday) stock returns. We use Refinitiv's Thompson Reuters Tick Historical database to extract stock prices every 25 min between 9:45am and 4:00pm, combined with the overnight return (calculated between 4:00pm on day t-1 and 9:45am on day t), for a total of 16 return components per day. The 9:45am starting time is chosen to mitigate issues related to illiquidity at the market open.

To keep the portfolio test analysis to a manageable level, we limit ourselves to S&P 500 constituents listed between 2001 and 2019. We end up forming realized beta decile portfolios using 668 unique stocks. For the market index, we rely on the S&P 500 index exchange traded fund (SPDR) with ticker symbol SPY. We estimate the daily realized beta for stock j as:

$$R\beta_{j,t} = \frac{\sum_{k=1}^{16} r_{j,t,k} r_{m,t,k}}{\sum_{k=1}^{16} r_{m,t,k}^2} \quad (4)$$

where $r_{j,t,k}$ refers to the 25-minute log returns on stock j during the k^{th} intraday period on trading day t and $r_{m,t,k}$ is

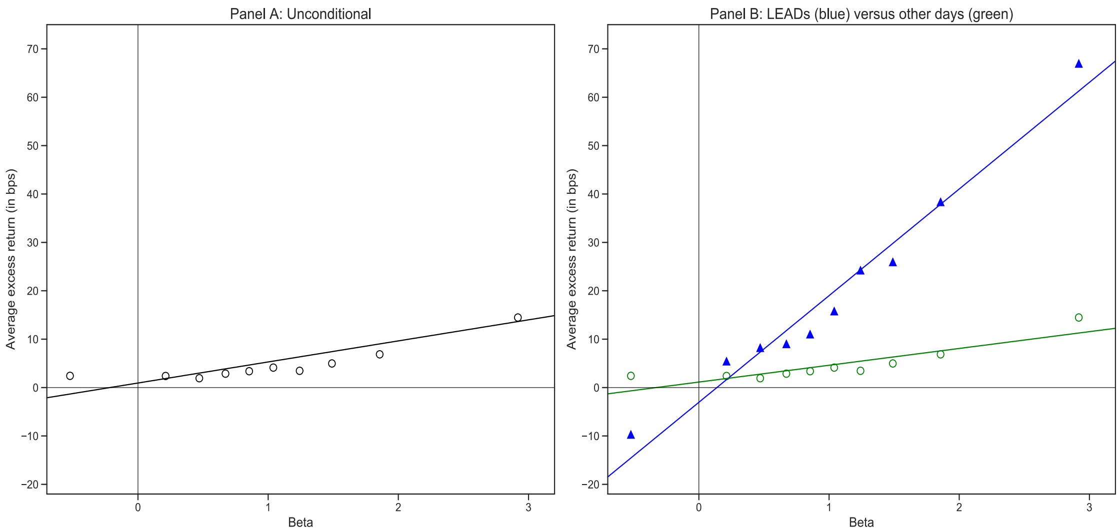

Fig. 6. Average excess returns for realized beta-sorted portfolios. This figure plots the average daily excess returns (expressed in basis points) against market betas for 10 value-weighted portfolios sorted on realized betas estimated using Eq. (4). Panel A plots the unconditional SML, and Panel B plots the conditional SMLs on LEADs (blue) and on other days (green). For each test portfolio, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the market log return.[11] This intraday beta estimation procedure deliberately follows Patton and Verardo (2012). We construct beta decile portfolios as follows: on each trading day, we calculate realized betas for stock j using Eq. (4) and group each stock into one of ten realized beta-sorted portfolios. We then use value-weights to average the realized betas and returns of individual stocks in each portfolio to produce daily estimates of portfolio beta and portfolio return.

As in the earlier figures, Fig. 6 shows the unconditional SML in Panel A, and the SMLs conditional on LEADs and on other days, separately, in Panel B. For all the SMLs, portfolio realized betas are averaged over the entire 2001–2019 sample period. Focusing first on Panel B, the blue SML shows a strong, approximately linear and positive, relation between average excess returns and realized beta with a slope equal to 22.04 bps (t-statistic = 15.34). This indicates a positive implied market risk premium on LEADs just as for the portfolios shown in Fig. 1. The intercept is slightly negative, but it is not statistically significant (–3.04 bps with t-statistic = −1.55), and the regression R^2 is 97%. On other days, the SML also has a positive slope, but its magnitude is relatively negligible (3.47 bps with t-statistic = 5.24), and the regression R^2 is 77%. When both conditional SMLs are combined, the resulting unconditional SML shown in Panel A has a slightly positive slope equal to 4.35 bps (t-statistic = 6.35). The intercept is 0.94 bps (t-statistic = 1.01) and the regression R^2 is 83%.

Table 4 reports the Fama-MacBeth and panel regression results for the realized beta decile portfolios. Once again, using the Fama-MacBeth procedure, the implied market risk premium for LEADs is economically and statistically significant at 23.45 bps (t-statistic = 2.39) and the intercept, although negative, is statistically indistinguishable from zero (–4.26 bps with t-statistic = –0.66). In contrast, the implied market risk premium on other days has a modest positive estimate equal to 5.86 bps (t-statistic = 2.98) and the regression intercept is slightly negative (–1.18 bps with t-statistic = –0.99). The LEAD-minus-other-day implied market risk premium is 17.59 bps with t-statistic equal to 1.76. The average regression R^2s are 61% and 52%, respectively, for LEAD returns and for other-day returns. Confirming the Fama-MacBeth findings, the panel regression shows that the difference in implied market risk premium between LEADs and other days is 14.20 bps with a t-statistic of 2.21. The regression coefficient on the realized beta in the panel regression is 1.59 but it is not statistically significant (t-statistic = 1.47).

The qualitative similarity between the SMLs presented in Fig. 1 (with betas estimated using a 12-month rolling regression on daily returns) and those in Fig. 6 (with realized betas derived from high-frequency returns) is not entirely surprising. To further explore the dynamics of realized betas around earnings news reported by LEADers and non-LEADers, we use the following specification modified from Patton and Verardo (2012):

$$R\beta_{i,t} = \alpha_i + \delta_t + \gamma^L_{-10} D^L_{i,t+10} + \cdots + \gamma^L_0 D^L_{i,t} + \cdots + \gamma^L_{10} D^L_{i,t-10}$$
$$\gamma^O_{-10} D^O_{i,t+10} + \cdots + \gamma^O_0 D^O_{i,t} + \cdots + \gamma^O_{10} D^O_{i,t-10} + \varepsilon_{i,t}, \quad (5)$$

where D^L_t s are dummy variables over the [−10, +10] event window days when LEADers make earnings announcements, D^O_t s are the equivalent dummy variables centered around non-LEADs when other S&P 500 announcers release earnings reports, and α_i and δ_t represent firm and year fixed-effects, respectively, to control for differences in

[11] Patton and Verardo (2012, Appendix I) show that when the sampling frequency is sufficiently high, the realized beta converges to the noisy but unbiased estimates of the true beta.

Table 4
Fama-MacBeth and panel regression results for realized beta-sorted portfolios.
This table reports the results from Fama-MacBeth and panel regressions of daily excess returns (expressed in basis points) on market betas for 10 value-weighted portfolios sorted based on realized betas. We form portfolios for each trading day, with stocks sorted according to realized beta estimated on a daily basis using Eq. (4). The parenthesized *t*-statistics are estimated based on standard errors calculated using standard deviations of the time-series coefficient estimates (for the Fama-MacBeth regression) and standard errors clustered by days (for the panel regression). The sample period covers January 2001 through December 2019. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	β	Avg R^2	Intercept	β	D^{LEAD}	β x D^{LEAD}	R^2
LEADs	−4.26	23.45**	0.61	3.15**	1.59	0.69	14.20**	0.001
	(−0.66)	(2.39)		(2.18)	(1.47)	(0.11)	(2.21)	
Other days	−1.18	5.86***	0.52					
	(−0.99)	(2.98)						
LEADs - Other	−3.08	17.59*						
	(−0.55)	(1.76)						

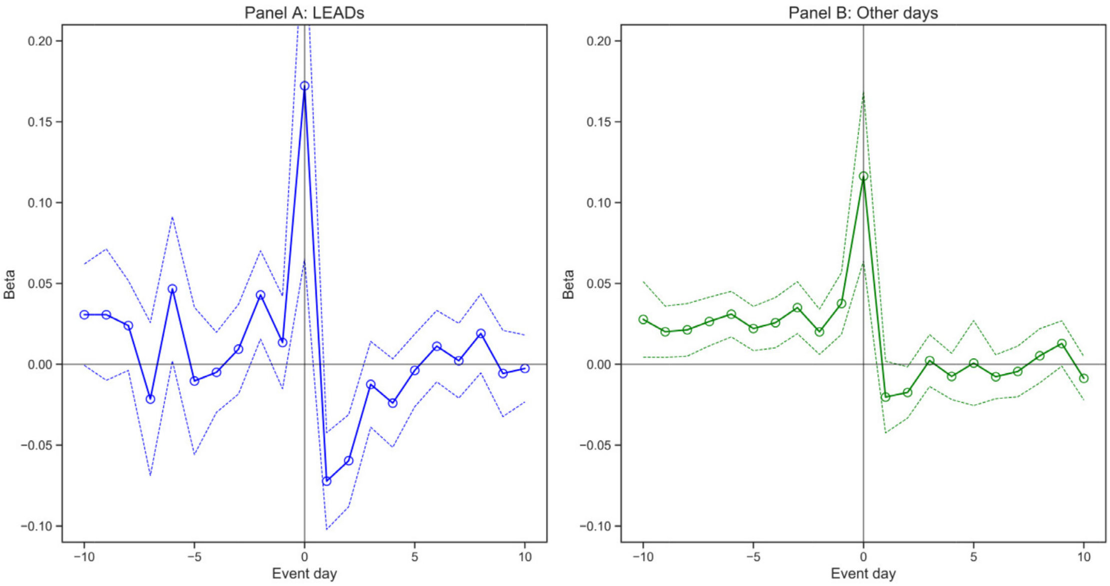

Fig. 7. Changes in realized beta around earnings news days. The figure plots the estimated changes in realized betas over the [−10, +10] event window when earnings news is released on LEADs (Panel A) and on other days (Panel B). Point estimates are marked with a solid line, and 95% confidence intervals (calculated from standard errors that clustered using two-way firm-year technique of Petersen (2009)) are plotted with dotted lines. To facilitate comparison, both panels have the same y-scale. The sample period covers 2001 through 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

betas across stocks and to capture changes in betas over time.

Savor and Wilson (2016) report a higher abnormal return for earnings announcing firms than for non-announcing firms, and that early (late) announcers deliver higher (lower) returns. They propose a risk-based explanation: investors superimpose aggregate information on firms' individual cash flow earnings news, thus generating a high conditional covariance between firm-level and market-level cash flow news (Savor and Wilson, 2016, pp. 83–84). To examine this proposition, we posit that beta increases with a larger magnitude on days when LEADers disclose early earnings news than on days when other later announcers make theirs. As such, our prediction is that in Eq. (5), $\gamma_0^L > 0$, $\gamma_0^O > 0$, and $\gamma_0^L > \gamma_0^O$.

Fig. 7 provides a visualization of a regression test of this prediction, with the full set of results available from the authors upon request. As can be seen, on LEADs realized betas constructed from 25-minute intraday pricing intervals increase significantly by 17.2% (*t*-statistic = 3.16), on average. On other earnings announcement days, the average realized beta also increases (relative to non-announcement days), but by a more modest magnitude of 11.6% (*t*-statistic = 4.34). When we consider both LEADs and other earnings news days together, the unreported coefficient on the day-0 dummy variable is 12.7% (*t*-statistic = 5.43); this number is slightly below the value of 16.2% obtained by Patton and Verardo (2012) for their 1996–2006 sample period.

To summarize, the increase in average realized beta on LEADs is consistent with variation in market exposures for stocks as a whole around the known timing of LEAD announcements (Patton and Verardo, 2012), as we would have expected when an aggregate of influential S&P 500 firms report early earnings news. At the same time, we observe an upward slope in the ratio of average returns to the increase in betas on LEADs, and per Roll (1977), a higher implied premium for the market exposure.

4.2. Overnight returns versus trading day returns

We have heretofore been analyzing daily close-to-close stock returns. However, Hendershott et al. (2020) document that stocks are priced such that their average excess returns are linearly and positively related to CAPM betas when the market is closed for trading, but the relation is negative during trading hours. In this section, we extend Hendershott et al. (2020) finding with an analysis as to whether overnight-versus-daytime asset pricing differs when LEADers make early earnings news announcements versus times when other announcers are making theirs.

Following Lou et al. (2019) and Hendershott et al. (2020), we split the close-to-close return on stock j for day t ($r_{jt}^{close-to-close}$) into close-to-open overnight return ($r_{jt}^{close-to-open}$) and open-to-close day return ($r_{jt}^{open-to-close}$). These components are related as:

$$\left(1+r_{jt}^{close-to-close}\right)=\left(1+r_{jt}^{close-to-open}\right)\left(1+r_{jt}^{open-to-close}\right) \tag{6}$$

We repeat the earlier tests on both close-to-open overnight return and open-to-close daytime return. Pre-ranking betas are estimated at the start of each month by regressing close-to-close returns of stock j on close-to-close market returns using a 12-month rolling regression. Stocks are sorted into one of the beta decile portfolios, portfolio returns are value-weighted and post-ranking portfolio betas are estimated differently for tables and figures: For tables, we follow Hendershott et al. (2020) and regress overnight returns of portfolio i on overnight returns of the market portfolio (constructed using value-weighted overnight returns of all individual stocks) using a 12-month rolling window. The daily post-ranking betas are used in the Fama-MacBeth and panel regression tests. For figures, we average the unconditional post-ranking beta of each portfolio i over the full sample period.

Panel A of Fig. 8 plots the SMLs at times when the market is closed for trading (i.e., overnight SMLs) on LEADs and on other days. Panel B presents the SMLs when the market is open for trading (i.e., daytime SMLs) for both types of days. Looking at the green SMLs in both panels, we first confirm the key finding of Hendershott et al. (2020): for non-LEAD "normal" days, market betas are positively related to overnight returns (slope = 4.45 bps with t-statistic = 8.03), but they are negatively associated with daytime returns (slope = –6.40 bps with t-statistic = –10.13). The regression R^2s for both daytime and overnight SMLs are around 90%.

The blue SMLs in both panels show that the positive relation between average overnight returns and market betas on LEADs is three times stronger than on other days: an increase in market beta of 1 on LEADs is associated with an increase in average overnight return of 12.52 bps (t-statistic of the slope coefficient is 8.41). The intercept is negative (estimate = –6.19 bps with t-statistic = –3.96), and the regression R^2 is 90%. What sets Fig. 8 apart from Hendershott et al. (2020) study is the daytime blue-SML: on LEADs, an increase in beta of 1 is positively associated with a 10.08 bps increase in average daytime returns (t-statistic = 3.09). The intercept is almost zero and the regression R^2 is 54%. We rationalize that for daytime returns, the difference in LEAD-SML and other day-SML is likely due to institutional investors closing out their announcement-event positions during the day following the announcement (except on Fridays when traders especially want to get "flat" well before the weekend illiquidity that occurs globally, and we have excluded Friday as a candidate "leading" day).

To explore further, we run two sets of Fama-MacBeth tests: first on LEADs, and then on other days. In each set of tests, we regress average day returns, and average overnight returns, separately, on market betas. This testing strategy allows the estimation of the difference in implied market risk premium between daytime and overnight SMLs on LEADs, and between daytime and overnight SMLs on other days.

Table 5 reports the results. Panel A shows that the average implied market risk premium during LEAD-overnight is positive and significant with a slope coefficient equal to 12.31 bps (t-statistic = 2.32). The implied market risk premium during trading hours on LEADs is also positive with an estimate equal to 10.80 bps, albeit with an insignificant t-statistic of 1.21. Together, the overnight-minus-daytime risk premium difference on LEADs is 1.51 bps; this estimate is never going to be significant, either economically or statistically (t-statistic of the difference is 0.14). On other days, the overnight implied market risk premium is significantly positive (4.71 bps with t-statistic = 4.53), but the implied market risk premium during trading hours is significantly negative (–6.11 bps with t-statistic = –3.47). The difference in risk premiums between both daytime and overnight SMLs is 10.82 with t-statistic of 5.30.

Overall, our finding reinforces the key insight of Hendershott et al. (2020): on "normal" days, the implied market risk premium is positive overnight, but it turns to negative when the market opens for trading. We extend the literature by showing that on LEADs, high-beta stocks earn higher returns, and low-beta stocks earn lower returns, as the CAPM predicts, and this finding holds for both daytime and overnight. Lou et al. (2019) identify a "tug of war" between day and overnight returns, and they hypothesize that different clienteles use different specialized trading strategies overnight and during the day. One obvious implication from our Fig. 8 is that during LEAD reporting weeks, Lou et al. (2019) "regular" clienteles are disrupted along with the patterns of information release (given the high concentration of after-hours releases) and the clienteles' trading strategies.

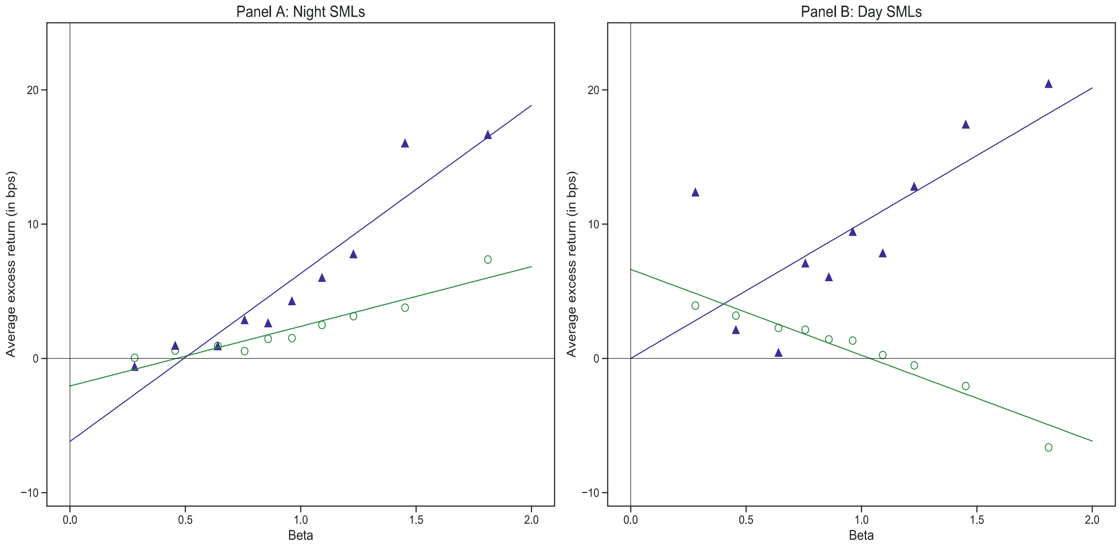

Fig. 8. Average excess returns for beta-sorted portfolios on day and overnight. Panel A plots the average daily excess returns estimated overnight (close-to-open) against market betas for 10 value-weighted beta-sorted portfolios, while Panel B presents the analogous plots for excess returns estimated during the day (open-to-close). In each panel, we compare the SMLs when earnings news is released on LEADs (blue) and on other days (green). We use the same full-sample beta estimate for all types of day, and we superimpose an ordinary least squares best fitted line for each type of day. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Fama-MacBeth regression results for returns on day and night.
This table reports the results for Fama-MacBeth regressions of daily excess returns on market betas for 10 value-weighted beta-sorted portfolios on LEADs (Panel A) and on other days (Panel B). In each panel, we report the results for excess returns during the trading day and overnight. The parenthesized t-statistics are estimated based on standard errors calculated using standard deviations of the time-series coefficient estimates. The sample period covers January 2001 through December 2019. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: LEADs			Panel B: Other days		
Type of day	Intercept	β	Avg R^2	Intercept	β	Avg R^2
Overnight	−5.15*	12.31**	0.43	−2.42***	4.71***	0.51
	(−1.91)	(2.32)		(−5.67)	(4.53)	
Day	−0.96	10.80	0.51	6.39***	−6.11***	0.49
	(−0.20)	(1.21)		(6.53)	(−3.47)	
Overnight - Day	−4.18	1.51		−8.81***	10.82***	
	(−0.77)	(0.14)		(−8.26)	(5.30)	

4.3. Weekday and intraday returns

We have explored how daytime and overnight SMLs behave distinctively on LEADs and on other days. It is worth repeating here that our analysis defines LEADs as occurring on Tuesday through Thursday in the first week of reporting quarter q that has a minimal aggregate of 50 S&P 500 announcers. We exclude Mondays and Fridays as possible LEADs given the evidence of weekend-induced effects on those days (e.g., Birru, 2018). To assess whether daytime and overnight Mondays and Fridays are indeed à priori different, we now examine the SMLs on weekdays separately.

The blue lines in Fig. 9 show, for LEAD week, the relation between beta and average day return, and the relation between beta and average overnight return. The figure shows that the relation is largely positive from Monday after the market has closed (Panel A2) to Thursday before the market closes (Panel D1). However, the SML is negative on Monday when the market is open (Panel A1), and from Thursday evening through to Friday (Panel D2 to Panel E2).[12] Recognizing traders' desire to minimize inventories going into Friday night and weekends, anecdotal Wall Street evidence is that unusual pricing behavior and negative returns can accompany major announcements on Fridays. Johnson and So (2018), p. 219 also provide complementary evidence that "...[financial] intermediaries demand greater compensation for providing [earnings announcement risk] liquidity to sellers, relative to buyers..."

The possibility that Monday and Friday market behavior is different also echoes Birru (2018), who attributes

[12] As noted earlier, firms rarely report earnings news between 0:00am and 16:00pm on Monday.

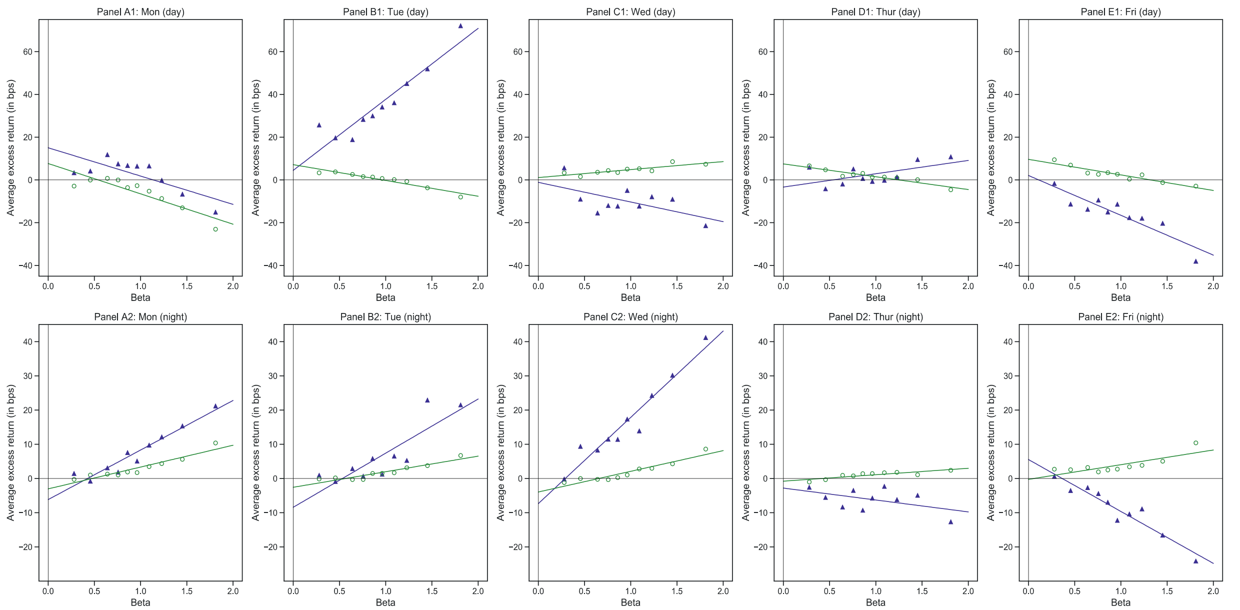

Fig. 9. Average day and night returns for beta-sorted portfolios on different weekdays. The top panels plot the average daytime returns against market betas for 10 value-weighted beta-sorted portfolios from Monday through Friday. The bottom panels present the analogous plots for average overnight returns. In each panel, we compare the SMLs when earnings news is released on LEADs (blue) and on other days (green). LEADs occur during midweek from Tuesday to Thursday, and the day- and night-SMLs presented in panels A1 and A2 (panels E1 and E2) are estimated on Monday prior to LEAD-Tuesday (on Friday following LEAD-Thursday). We use the same full-sample beta estimate for all types of day, and we superimpose an ordinary least squares best fitted line for each type of day. To facilitate comparison, the respective top (bottom) panels have the same y-scale. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a weekday seasonality in market anomalies to an upbeat mood on Fridays and downbeat blues on Mondays. That said, care must be taken in contrasting our finding to Birru's (2018): his results are based on day returns instead of the overnight returns that we have just analyzed, though we show below that our beta-return positive relation largely holds during the first half-hour of daytime trading on LEADs. DellaVigna and Pollet (2009) also analyze Friday announcements, and they report an under-reaction of stock prices to Friday announcements along with lower trading volume than that accompanying announcements on other days of the week. DellaVigna and Pollet (2009) attribute the under-reaction to investor distraction with non-work-related activities on Friday. As noted earlier, a greater under-reaction for higher beta stocks is another way of expressing our "non" result for Fridays. On the other hand, deHaan et al., 38) argue that "…attention to [earnings announcements] is no different on Fridays as compared to Monday – Thursdays" for their 2001–2011 sample period which overlaps our's. deHaan et al. (2015) suggest that managers attempt to hide bad information by reporting it on Friday when investor attention is typically lower. Their proposition would suggest the presence of bad earnings news on Fridays, but we find that there is nothing unusual about Friday earnings announcements in our sample: the ratio of earnings beats to misses is largely similar to that on other days.

Finally, we evaluate the intraday SML on LEADs by slicing the open-to-close returns into half-hourly intervals. Fig. 10 presents the finding. Unlike the earlier daytime SML analysis that relies on the 12-month rolling regression, the intraday SMLs in Fig. 10 are constructed using realized betas. Following Hendershott et al. (2020), we estimate the returns every half-an-hour, where the first interval covers 9:30 am to 10:00 am, and the final interval extends from 15:30 pm to 16:00 pm. For brevity, we aggregate the returns from 10:30 am to 15:00 pm, and present the average aggregated return-beta relation in Panel C of Fig. 10. Two observations emerge. First, Panel A shows a sharp upward-sloping SML between 9:30 am and 10:00 am.[13] Second, the average return-beta relation is mostly upward sloping throughout the day, except in the final trading hour when the slope of the SML is somewhat flat between 15:00 pm and 15:30 pm (Panel D), before turning to slightly negative between 15:30 pm and 16:00 pm when the stock market closes (Panel E).

4.4. Individual stocks

So far, the analysis of the beta-return relation has been focused on portfolios. The portfolio-level analysis, however, has a significant drawback: it could conceal a large amount of important cross-sectional information in the portfolio aggregation. To check this possibility, we now evaluate whether market betas explain returns across individual stocks on LEADs and on other days. To this end, we include all individual common stocks used in the earlier portfolio tests, except that, following convention, we require the stocks to have minimal price per share of \$2, and we remove stocks for which the daily return is above 200%. Finally, we match Compustat's data records (required to compute the stock's book-to-market ratio) with stock data retrieved from CRSP. We end up with 4267 stocks.

Panel A of Table 6 reports the findings for the Fama-MacBeth regression (as before, separately, for LEADs and for other days) and the panel regression of individual stock

[13] When analyzing Panel A, it is noteworthy that the beta-return relation could be noisy when trading begins at the start of the day, and more so after an overnight announcement.

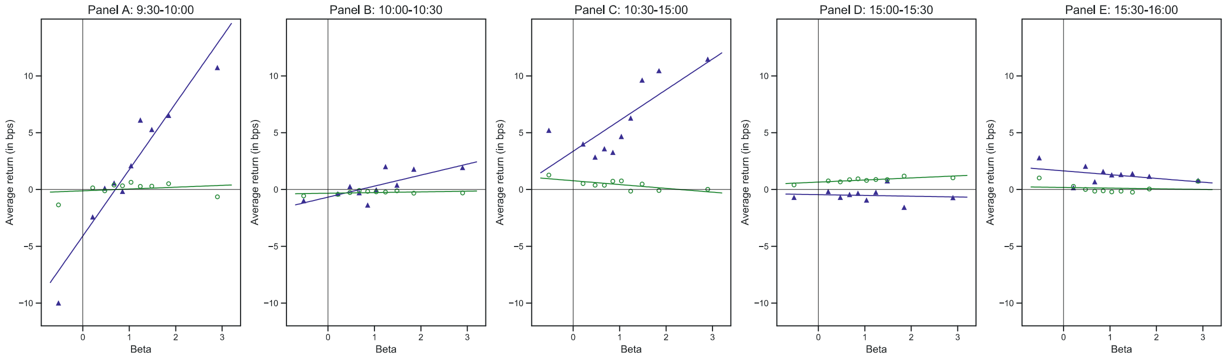

Fig. 10. Average intraday returns for realized beta-sorted portfolios. This figure plots the intraday average returns (expressed in basis points) against average realized betas for 10 value-weighted beta-sorted portfolios on LEADs (blue line) and on other days (green line). The panels show the SMLs for returns calculated for each 30-minute interval, except for Panel C which shows the SMLs estimated using aggregated returns between 10:30 and 15:00. We form portfolios every day, with stocks sorted according to realized beta estimated every day. For each plot, we use the same full-sample beta estimate for both types of day, and we superimpose an ordinary least squares best fitted line for each type of day. To facilitate comparison, all panels have the same y-scale. The sample period covers January 2001 through December 2019. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Fama-MacBeth and panel regression results for individual stocks.
This table reports the results from Fama-MacBeth and panel regressions of daily excess returns (expressed in basis points) for individual stocks. We require stocks to have a price per share of $2 and over. Panel A presents the regression results of daily excess returns on stock market betas only, and Panels B and C present the regression results after controlling for log market capitalization (Size), book-to-market ratios (BM) and cumulative returns over the past 12 months (PastRet). The parenthesized *t*-statistics are estimated based on standard errors calculated using standard deviations of the time-series coefficient estimates (for the Fama-MacBeth regression) and based on standard errors clustered by days (for the panel regression). The sample period covers January 2001 through December 2019. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Beta only

	Fama-MacBeth			Pooled regression				
Type of day	Intercept	β	Avg R^2	Intercept	β	D^{LEAD}	β x D^{LEAD}	R^2
LEADs	0.13	23.27**	0.036	6.43***	0.54	−12.91	27.35***	0.001
	(0.03)	(2.57)		(3.32)	(0.27)	(−1.47)	(2.68)	
Other days	5.71***	1.60	0.040					
	(4.93)	(0.84)						
LEADs - Other	−5.58	21.67**						
	(−1.06)	(2.49)						

Panel B: With firm characteristics as controls (Fama-MacBeth regression)

Type of day	Intercept	β	Size	BM	PastRet (x100)	Avg R^2
LEADs	18.57	29.31***	−2.12**	25.64***	0.75***	0.068
	(0.94)	(3.19)	(−2.28)	(5.39)	(11.24)	
Other days	40.70***	7.80***	−2.64***	20.61***	0.63***	0.074
	(4.55)	(3.93)	(−5.72)	(16.84)	(40.04)	
LEADs - Other	−22.13	21.51**	0.52	5.03	0.12	
	(0.55)	(2.36)	(0.25)	(0.90)	(1.63)	

Panel C: With firm characteristics as controls (pooled regression)

Intercept	β	Size	BM	PastRet (x100)	D^{LEAD}	β x D^{LEAD}	R^2
28.61***	5.31***	−2.04***	22.36***	0.50***	−14.60*	28.50***	0.004
(3.20)	(2.62)	(−5.25)	(8.51)	(9.03)	(−1.67)	(2.77)	

excess returns on market betas only. Quantitatively, the estimates are remarkably similar to the portfolio findings reported earlier for the value-weighted beta decile portfolios. Starting with the Fama-MacBeth regression, we can see that market betas are strongly and positively related to individual stock excess returns on LEADs, but the relation is mostly flat on other days: the implied market risk premium is 23.27 bps (t-statistic = 2.57) on LEADs versus 1.60 bps (t-statistic = 0.84) on other days. That is, the implied risk premium on LEADs is significantly higher than on other days by 21.67 bps (t-statistic of the difference is 2.49). This finding is confirmed using the panel regression to estimate the difference in market risk premium between both types of days: the difference is 27.35 bps (t-statistic = 2.68). In fact, this LEADs-minus-other-days risk premium difference is identical to the estimate obtained from the equivalent panel regression used in the portfolio analysis (see Panel A of Table 2).

We then add three control variables typically used in cross-section stock expected return analysis – log market capitalization (Size), book-to-market ratios (BM), and cumulative stock returns over the past 12-months (PastRet) – to market beta and re-run the Fama-MacBeth and panel regressions (see also Savor and Wilson, 2014). Panel B of Table 6 reports the Fama-MacBeth regression estimates, and Panel C presents the panel regression findings. We can see that the beta-return relation continues to hold. It is strongly positive on LEADs but is mostly flat on other days. The net difference in implied market risk premium on LEADs and on other days is 21.51 bps with a t-statistic of 2.36 for the Fama-MacBeth test, and it is higher at 28.50 bps with a t-statistic of 2.77 for the panel regression. The results for the control variables tabulated for both types of days are largely consistent with prior studies: size is strongly negatively related to stock excess returns, and BM and past 12-month returns have a strong and positive relation with average returns.

4.5. Robustness tests

Our key finding remains remarkably consistent when we partition the data into two su-period samples: the LEAD-SML has a slope coefficient of 27.46 bps (t-statistic $=$ 4.33) in the 2001–2009 sub-period, and 22.12 bps (t-statistic $=$ 4.57) in the 2010–2019 sub-period. The difference in the implied market risk premium between LEAD and other days is also similar across both sub-periods (30.64 bps in 2001–2009 vs. 25.51 bps in 2010–2019).

Savor and Wilson (2014) show that stock market beta is strongly related to average excess returns on days when key scheduled macroeconomic news, such as Federal Open Markets Committee (FOMC) interest rate decisions and inflation rate are released. Hirshleifer and Sheng (2019) suggest that on days when such macro news is released concomitantly with micro-level announcements, the former could operate as an attention trigger for the latter. From this viewpoint, it might be that our finding is confounded by macroeconomic news. However, LEADs rarely coincide with news arrivals for key macro variables. Between 2001 and 2019, only 8.8% (20/228) of the total number of LEADs also happen to be scheduled macro news announcement days. Also, there is virtually no difference, either statistically or economically, in the return-beta relation estimated on those LEADs that coincide with macro news release and on LEADs excluding macro news.

Nor are LEADs simply over-represented by days with a flood of announcements for constituents that are all implicitly assumed to have an equally important influence on investor expectations. To verify this contention, we redefine LEADs as (i) consecutive weekdays in the week that simply has the highest number of S&P 500 firms reporting in quarter q, and (ii) the top five non-consecutive days in quarter q with the highest number of announcers. We then repeat the earlier set of asset pricing tests on the value-weighted beta decile portfolios for the re-defined LEADs. These two experimental renditions of LEADs generate a conditional SML that is largely flat for (i), and that has a positive slope but with an inconsequential magnitude for (ii), suggesting that market betas do not explain average returns on days with simply “intense-by-count” earnings announcements. To save space, we report the robustness test results in the online appendix.

5. Explanations

5.1. LEADers as attention-getters

We define LEADs as a handful of adjacent early days in each quarter when prominent S&P 500 companies collectively make a first wave of scheduled earnings announcements and thus “lead” the earnings reporting seasons. This criterion for LEADs is designed to select influential announcements with minimal engineering. As noted at the outset, such announcements are likely ipso facto to be “attention getting.” Thus, our findings intersect with the growing number of studies that examines the relation between asset pricing and attention getting, and attention getting is possibly a candidate explanation for our results. For example, Ben-Rephael et al. (2017) show that macro news, including that for large firms in aggregate, is associated with micro-level risk premiums, while Da et al. (2020) find larger average premiums on high-beta stocks. Both studies attribute the higher premiums to the heightening of institutional investors’ attention on announcement day by using Bloomberg query scores as instruments for institutional attention.

If LEAD announcements are also attention getting, it is interesting to explore how they compare with the Bloomberg query scores. To provide insight on this, we use the query measure of institutional investor attention mentioned above that was developed by Ben-Rephael et al. (2017, 2021): the measure, termed “abnormal institutional attention (AIA),” relies on news-searching and news-reading on Bloomberg terminals. We check whether the AIA metric is higher on LEADs than on other days. Since Bloomberg terminal users are primarily institutional investors who have the financial resources to access the terminal, a heightening of AIA on LEADs could suggest that institutional investors pay closer attention to specific stocks on those unique LEADs than they do on other days.

To this end, we closely follow the procedure described by Ben-Rephael et al. (2017, 2021) in constructing the daily AIA metric. We construct a cross-section daily AIA for all S&P 500 constituents, and the online appendix shows that our result is robust when we use all constituent stocks in the Russell 3000 index. We do not only gauge institutional investors’ attention to specific announcers on day t; instead, we assess the attention given to (almost) all the stocks, since testing asset pricing models involves testing them all. We aggregate the AIAs across the S&P 500 firms to obtain *sumAIA* for day t. If *sumAIA* $=$ 100 on day t, for example, it means that Bloomberg terminal users (i.e., institutional investors) pay close attention to 100 firms on that specific day. All the numbers reported in Table 7 should be interpreted in the same way. For brevity, we detail the construction of *sumAIA* in the online appendix. Also

Table 7
Descriptive statistics of *sumAIA*.
This table reports descriptive statistics of daily counts of AIA (*sumAIA*) separately on LEADs and on other days. Limited by data availability, the sample period for the AIA measure covers February 2010 through December 2019. The historical data for Bloomberg's attention measure are missing from December 6, 2010 to January 7, 2011, and from August 17, 2011 to November 2, 2011.

	LEADs	Other days
Mean	116	81
Min	32	1
5 pctl	90	31
25 pctl	105	60
50 pctl	118	80
75 pctl	129	100
95 pctl	143	133
Max	160	311

in the online appendix, we plot the frequency distribution of the daily mean of *sumAIA* on both LEADs and non-LEADs for each reporting quarter *q*. Both Table 7 and the online appendix provide exploratory evidence that institutional investors' attention increases more on LEADs compared to other announcing days. On average, we find that institutional investors monitor 81 firms listed in the S&P 500 on non-LEADs, but this number increases 40% to 116 firms on days when LEADers report earnings news.

If the research motivation is to measure attention getting, it is plausible that LEADs are a stronger proxy than the AIA metric. For example, Hirshleifer and Sheng (2019, p. 3) find that: "…the attention trigger effect is more pronounced among large firms and firms with high analyst coverage." It is also entirely plausible that the causality could go from asset price changes on LEADs to AIA queries (i.e., sharp moves in stock prices induce queries rather than vice versa). Reverse causality seems even more likely when LEADs and risk premium shifts are occurring overnight while queries take place around say the beginning of the succeeding trading day. This is one reason why we define LEADs in terms of a clustering of firms, but then look at the structure of cross-sectional risk premiums at firm micro level. Moreover, we show that the attention-getting effect on premiums reverses the very next day. It is more plausible that a Wall Street attention span lasts at most a day (or even at most a New York minute!) than that it lasts for a whole week as in Ben-Raphael et al. (2021).

5.2. Reduced segmentation on LEADs

We next discuss a second framework that is consistent with the preceding evidence about asset pricing behavior on both non-LEADs and LEADs. This framework was suggested by Black (1972) and envisages a segment of investors who are constrained in borrowing. Frazzini and Pedersen (2014), and Marsh and Pfleiderer (2016) calibrate Black's model in which leverage-constrained investors overweight high-risk assets in their trading strategies. The overweighted high-risk assets are supplied by a leverage-unconstrained group of investors who underweight them while overweighting low-risk assets. The net result in normal non-LEADs times is an equilibrium in which the prices of high-risk assets are higher and expected returns lower (and conversely, low-risk assets are priced lower and expected returns are higher). As a result, we observe a flat SML in "normal" non-LEAD times.

However, as LEADs approach, daily betas and announcement risk increase. This reflects the potential asymmetries in information amongst investors about impending earnings numbers and earnings calls, accompanying guidance, and the like. The informational risk at announcement time for any one firm is accentuated by potential spillover of earnings surprises to other related stocks in which investors also have positions.

It becomes more expensive inter alia to short on announcement night/day. Johnson and So (2018) argue that these higher selling costs occur because market makers want to trade out of their securities inventories and be flat on announcement night. Selling on margin ("borrowing") can also be expensive. Thus, borrowing-constrained investors tend to reduce their expensive levered positions, particularly on LEADs where higher information spillover is more likely given our selection of clusters of leading influencers with large market cap. With the reduced segmentation, the Black SML "looks" increasingly like that for "representative" investors in a standard CAPM.

Regarding the CAPM-like pricing on LEADs, Roll (1977) shows that the linearity of ex post average returns in beta is tautological given the ex post efficiency of the market proxy. The efficiency of the market is not relevant in the Black segmented equilibrium on days other than LEADs: at those other times, neither borrowing-constrained nor borrowing-unconstrained investors hold the market, and the SML tends to be flat. The market clears with "discounts" for high-risk stocks and "premiums" for low-risk stocks (relative to the all-else-equal CAPM equilibrium expected returns).

We use both the CRSP and the S&P 500 indexes to proxy the market. On LEADs with pre-scheduled public announcements, the ex-post efficiency of both market proxies is plausibly higher: the considerable re-balancing in the market on announcement day arguably gets the average investor closer to efficiency (Gallagher et al., 2010; Lee and Zhu, 2018). In the segmented investor framework, in post-LEAD periods that are at the beginning of the next earnings announcement cycle, the difficulty of leveraging across the now-past announcements subsides, borrowing-constrained investors again push up the demand for risky assets with higher betas, and the SML again flattens out.

5.3. Market exposure and equilibrium risk premium on LEADs

We have provided evidence that average cross-sectional excess returns on portfolios of equities, Treasuries, and individual stocks are positively and linearly related to market betas on LEADs. We have also demonstrated a higher excess return on the aggregate market portfolio on LEADs. Taken together, these confirm Roll's (1977) proposition that the CRSP and SPDR market proxies that we have been using are at least approximately ex post efficient. That is, the linear return-beta relation holds tautologically ex post with a slope equal to the ex post market premium. We now show that the incremental increase that we reported above for the market return premium on LEADs is also consistent with a simple equilibrium where market risk increases on LEADs.

The daily average realized variance (calculated as the sum of squared 5-minute log returns) on the SPDR index is 1.62% on LEADs versus 1.38% on other days (i.e., on average, the daily market realized variance increases by 24 bps on LEADs). For an average investor with log utility (for which the one-period CAPM at issue here holds), the 24 bps rise in market variance is consistent with a 24 bps rise in market premium on LEADs, which in turn is remarkably close to the LEAD-minus-other day implied risk premium of 23.84 bps obtained from the Fama-MacBeth regression (see Table 2). In short, a LEAD announcement-risk explanation is also consistent with our results in an equilibrium.

6. Conclusion

In this study, we analyze the CAPM beta-return relation on days when large and influential firms disclose corporate earnings news announcements early in the earnings seasons. We label these unique days as leading earnings announcement days (LEADs). On LEADs, market beta exposure has a strong and positive linear cross-sectional relation to average excess returns, and this relation is statistically significant and economically meaningful. This key finding extends to various test portfolios, Treasuries, and individual stocks. It holds during overnight (daytime) when the market is closed (open) for trading; and the result barely changes for betas estimated using a 12-month rolling regression on daily returns, or for realized betas estimated using high-frequency (intraday) returns. Furthermore, our result is not driven by strategically early or delayed news releases by LEAD announcers, and it is robust to different testing procedures. On days other than LEADs, the market beta-return relation is mostly flat.

The linear upward-sloping security market line reported for LEADs implies a higher market risk premium on LEADs than on other days. We confirm this proposition, and we also show that one-third of the cumulative log excess market return is earned on LEADs alone, even though LEADs account for only 5% of all trading days in our sample. We also propose a hybrid trading strategy that bets on beta on LEADs, and bets against beta on other days. The strategy generates a Sharpe ratio equal to 0.306 when annualized, an estimate that is three times the Sharpe ratio earned from the familiar strategy that continuously bets against beta over the full sample period. Finally, we show that the average realized beta of firms announcing on LEADs increases significantly relative to non-announcing days, and that this beta increase on LEADs is also higher than the rise in average realized beta of firms announcing on other days.

In summary, our findings suggest that earnings announcements reported on LEADs have “macro” implications for firm-level (micro) equity prices.

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