

Asset pricing: A tale of two days[☆]Pavel Savor^{a,*}, Mungo Wilson^b^a Fox School of Business, Temple University, United States^b Said Business School and Oxford-Man Institute, Oxford University, United Kingdom

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ABSTRACT

We show that asset prices behave very differently on days when important macroeconomic news is scheduled for announcement. In addition to significantly higher average returns for risky assets on announcement days, return patterns are much easier to reconcile with standard asset pricing theories, both cross-sectionally and over time. On such days, stock market beta is strongly related to average returns. This positive relation holds for individual stocks, for various test portfolios, and even for bonds and currencies, suggesting that beta is after all an important measure of systematic risk. Furthermore, a robust risk–return trade-off exists on announcement days. Expected variance is positively related to future aggregated quarterly announcement day returns, but not to aggregated non-announcement day returns. We explore the implications of our findings in the context of various asset pricing models.

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1. Introduction

Stock market betas should be important determinants of risk premia. However, most studies find no direct relation between beta and average excess returns across stocks.¹ Over time, expected returns should depend positively on market risk, most often proxied for by some measure of expected market volatility, but such a relation has not yet been conclusively found. In this paper, we show that for an important subset of trading days stock market beta is strongly related to returns, and a robustly positive risk–return trade-off also exists on these same days.

Specifically, on days when news about inflation, unemployment, or Federal Open Markets Committee (FOMC) interest rate decisions is scheduled to be announced (announcement days or a-days), stock market beta is economically and statistically significantly related to returns on

¹ Seminal early studies include Black, Jensen, and Scholes (1972), Black (1972, 1993), and Fama and French (1992). Polk, Thomson, and Vuolteenaho (2006) is a more recent paper.

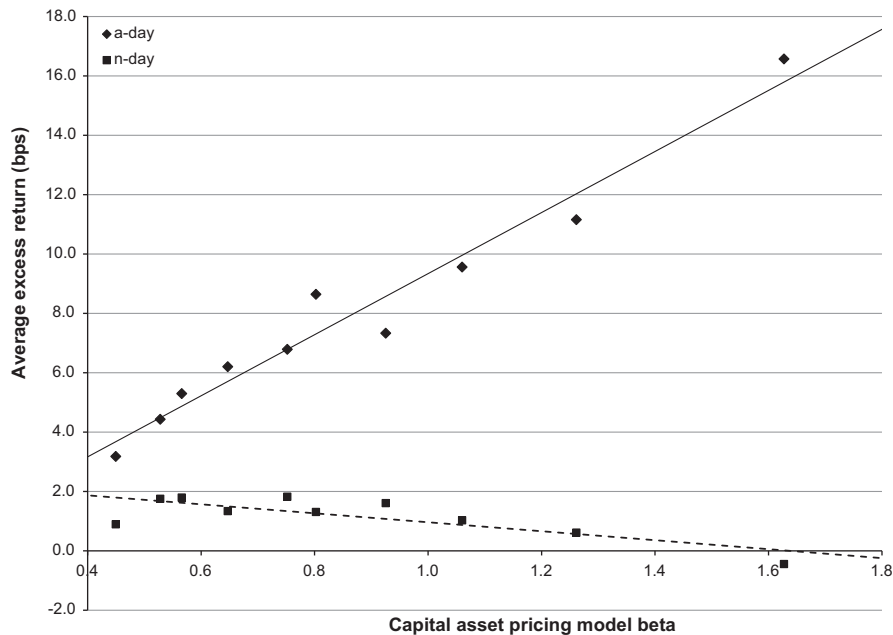


Fig. 1. Average excess returns for ten beta-sorted portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for ten beta-sorted portfolios of all NYSE, Amex, and Nasdaq stocks separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

individual stocks. This relation also holds for portfolios containing stocks sorted by their estimated beta, for the 25 Fama and French size and book-to-market portfolios, for industry portfolios, for portfolios sorted on idiosyncratic risk and downside beta, and even for assets other than equities, such as government bonds and currency carry-trade portfolios. The relation between beta and expected returns is still significant controlling for firm size and book-to-market ratio, as well as controlling for betas with the size, value, and momentum factors. The asset pricing restrictions implied by the mean-variance efficiency of the market portfolio (see, e.g., [Cochrane, 2001](#), Chapter 1.4) appear to be satisfied on announcement days: the intercept of the announcement-day securities market line (SML) for average excess returns is either not significantly different from zero or very low, and its slope is not significantly different from the average announcement-day stock market excess return. By contrast, beta is unrelated to average returns on other days (non-announcement days or n-days), with the implied market risk premium typically being negative.

Our main finding is summarized in [Fig. 1](#). We estimate stock market betas for all stocks using rolling windows of 12 months of daily returns from 1964 to 2011. We then sort stocks into one of ten beta-decile value-weighted portfolios. [Fig. 1](#) plots average realized excess returns for each portfolio against full-sample portfolio betas separately for non-announcement days (square-shaped points and a dotted line) and announcement days (diamond-shaped points and a solid line). The non-announcement-day points show a negative relation between average returns and beta. An increase in beta of one is associated with a reduction in average daily

excess returns of about 1.5 basis points (bps), with a *t*-statistic for the slope coefficient estimate above three.

In contrast, on announcement days the relation between average returns and beta is strongly positive. An increase in beta of one is associated with an increase in average excess returns of 10.3 bps. The relation is also very statistically significant, with a *t*-statistic over 13. Furthermore, the R^2 s of each line are, respectively, 63.1% for non-announcement days and 95.9% for announcement days. For the beta-sorted portfolios, almost all variation in announcement-day average excess returns is explained just by variation in their market betas.

These results suggest that beta is after all an important measure of systematic risk. At times when investors expect to learn important information about the economy, they demand higher returns to hold higher-beta assets. Moreover, earlier research establishes that these announcement days represent periods of much higher average excess returns and Sharpe ratios for the stock market and long-term Treasury bonds. [Savor and Wilson \(2013\)](#) find that in the 1958–2009 period the average excess daily return on a broad index of US stocks is 11.4 bps on announcement days versus 1.1 bps on all other days. The non-announcement-day average excess return is not significantly different from zero, while the announcement-day premium is highly statistically significant and robust. These estimates imply that over 60% of the equity risk premium is earned on announcement days, which constitute just 13% of the sample period.² [Savor and Wilson](#)

² [Lucca and Moench \(2013\)](#) confirm these results in the post-1994 period for pre-scheduled FOMC announcements, with the estimated

further show that the volatility of announcement-day returns is only slightly higher, so that the Sharpe ratio of announcement-day returns is an order of magnitude higher.³ Therefore, investors are compensated for bearing beta risk exactly when risk premia are high.

One potential alternative explanation for our results is that there is nothing special about announcement days per se, but rather that the strong positive relation between betas and returns on such days is driven by some particular feature of announcement days that is also shared by other days. However, we do not find evidence supporting this alternative hypothesis. We show that no similar relation exists on days when the stock market experiences large moves or on those days when average market returns are predictably higher than the sample mean (more specifically, during the month of January or during the turn of the month).

We next show that expected variance forecasts quarterly aggregated announcement-day returns (with a large positive coefficient and a *t*-statistic above four), which is consistent with a time series trade-off between risk and expected returns. Expected variance, which should represent a good proxy for market risk, is by far the most important factor for predicting returns on announcement days. This result is very robust, holding in a variety of vector autoregression (VAR) specifications, when we use weighted least squares and also when we divide our sample into halves. By contrast, on other days no evidence exists of such predictability, with a coefficient on expected variance that is negative and not statistically significant.

Combined with our previous findings on the relation between returns and market betas, this result highlights an important puzzle. Two major predictions of standard asset pricing theories hold on those days when certain important macroeconomic information is scheduled for release, which are also characterized by very high risk premia. On days without announcements, however, there is no support for either hypothesis (if anything, for market betas the relation with returns is the opposite of what theory predicts). Any complete theory thus would have to explain both why market betas determine expected returns on announcement days and why they do not on other days. Deepening the puzzle, we find little difference between market betas across different types of days. We show formally that, to the extent that the capital asset pricing model (CAPM) does not hold on non-announcement days for assets with identical betas on both types of days, no unconditional two-factor model can be consistent with our results. Moreover, a successful theory would also have to argue why higher expected risk results in higher expected return on announcement days when no such risk–return trade-off exists on other days. We also consider the possibility that an unconditional one- or two-factor model explains the cross section of asset

returns but that we fail to detect this because of estimation uncertainty and conclude that this is not a likely explanation for our findings.

Our results have an analogue in the research that established potentially puzzling relations between average returns and stock characteristics⁴. Instead of examining how expected returns vary with stock characteristics, we investigate how stock returns vary with types of information events. Our main finding is that cross-sectional patterns and the nature of the aggregate risk–return trade-off are completely different depending on whether there is a pre-scheduled release of important macroeconomic information to the public⁵. (We are agnostic about the exact nature of the news coming out on announcement days, merely assuming that it is reflected in returns and that market betas are, therefore, possibly the relevant measure of systematic risk on such days). The challenge for future research is to reconcile the two sets of relations. Announcement days matter because for many risky assets, including the aggregate stock market and long-term government bonds, returns on those days account for a very large portion of their cumulative returns. Furthermore, a clear link exists between macroeconomic risk and asset returns on those days. Finally, non-announcement days constitute the great majority of trading days in a given year and, consequently, also cannot be ignored. A good theory should explain both where the majority of cumulative returns come from and what happens most of the time.

The rest of the paper is organized as follows. [Section 2](#) describes our results on the relation between betas and returns on announcement and non-announcement days. [Section 3](#) shows evidence on the risk–return trade-off on each type of day. [Section 4](#) explains why our results are hard to reconcile with several prominent models and discusses avenues for future research that could explain the differences between announcement and non-announcement days. [Section 5](#) concludes. In the Appendix, we present a formal argument illustrating how no unconditional two-factor model can explain the cross section of expected returns on both types of days.

2. Betas on announcement and non-announcement days

2.1. Data and methodology

We obtain stock and Treasury bond return data from the Center for Research in Security Prices (CRSP). Our main stock market proxy is the CRSP NYSE, Amex, and Nasdaq value-weighted index of all listed shares. We obtain returns for the 25 size- and book-to-market-sorted portfolios and the ten industry portfolios from Kenneth French's website (<http://mba.tuck.dartmouth.edu/pages/faculty/ken.french>). We estimate a test asset's stock market beta (and other factor betas) in two different ways. First, in the figures, we simply compute a single

(footnote continued)

share of the announcement-day cumulative return increasing to over 80% in this more recent period. In the 1964–2011 sample period considered in this paper, the corresponding share is over 70%.

³ They rationalize such a difference with an equilibrium model in which agents learn about the expected future growth rate of aggregate consumption mainly through economic announcements.

⁴ For early examples in this literature, see [Basu \(1983\)](#), [Chan, Chen, and Hsieh \(1985\)](#), [Chan and Chen \(1991\)](#), and [Fama and French \(1996\)](#).

⁵ [Balduzzi and Moneta \(2012\)](#) use intra-day data to measure bond risk premia around macroeconomic announcements and are similarly unable to reject a single-factor model at high frequency.

Table 1

Daily excess returns on announcement and non-announcement days.

The table reports estimates from Fama-MacBeth regressions of daily excess returns on betas for various test portfolios. Estimates are computed separately for days with scheduled inflation, unemployment, and Federal Open Market Committee interest rate decisions (announcement days or a-days) and other days (non-announcement days or n-days). The difference is reported in the last row. The table also reports estimates for the same portfolios of a single pooled regression, when we add an a-day dummy (*Ann.*) and an interaction term between this dummy and market beta (*Ann.*Beta*).

Panels A and B show results for ten portfolios sorted by stock market beta and rebalanced monthly, value-weighted and equal-weighted, respectively. Panel C shows results for ten value-weighted beta portfolios, 25 Fama and French portfolios, and ten industry portfolios all together. The sample covers the 1964–2011 period. *t*-statistics are reported in parentheses. For Fama-MacBeth regressions, they are calculated using the standard deviation of the time series of coefficient estimates. For pooled regressions, they are calculated using clustered standard errors (by trading day).

| Type of day | Fama-MacBeth regression | | | Pooled regression | | | | |
|---|-------------------------|--------------------------|------------|--------------------|---------------------|-------------------|--------------------------|-------|
| | Intercept | Beta | Avg. R^2 | Intercept | Beta | <i>Ann.</i> | <i>Ann.*Beta</i> | R^2 |
| <i>Panel A: Ten beta-sorted portfolios (value-weighted)</i> | | | | | | | | |
| a-day | 0.00013 [0.90] | 0.00092 [2.81] | 0.514 | 0.00024 [3.26] | −0.00015 [−1.18] | 0.00016 [0.81] | 0.00084 [2.74] | 0.001 |
| n-day | 0.00020 [3.64] | −0.00010 [−0.89] | 0.492 | | | | | |
| a-day − n-day | −0.00007 [−0.44] | 0.00103 [2.89] | | | | | | |
| <i>Panel B: Ten beta-sorted portfolios (equal-weighted)</i> | | | | | | | | |
| a-day | 0.00089 [8.59] | 0.00094 [2.96] | 0.574 | 0.00079 [10.55] | −0.00039 [−2.85] | 0.00061 [3.01] | 0.00119 [3.62] | 0.001 |
| n-day | 0.00069 [16.60] | −0.00031 [−2.80] | 0.564 | | | | | |
| a-day − n-day | 0.00020 [1.99] | 0.00126 [3.57] | | | | | | |
| <i>Panel C: Ten beta-sorted (value-weighted), 25 Fama and French, and ten industry portfolios</i> | | | | | | | | |
| a-day | 0.00033 [2.18] | 0.00087 [2.74] | 0.303 | 0.00028 [3.02] | −0.00014 [−1.16] | 0.00052 [2.04] | 0.00045 [4.10] | 0.001 |
| n-day | 0.00027 [4.62] | −0.00014 [−1.27] | 0.284 | | | | | |
| a-day − n-day | 0.00006 [0.39] | 0.00101 [3.01] | | | | | | |

unconditional full-sample beta for each test asset. Second, in the tables, we compute time-varying betas over rolling one-year windows using daily returns. (All of our findings remain the same if we instead estimate betas over five-year periods using monthly returns. They also do not change if we use Scholes-Williams betas.) We measure a stock's log market capitalization (ME) and book-to-market (BM) as in Fama and French (1996). The sample covers the 1964–2011 period.

Our macroeconomic announcement dates are the same as in Savor and Wilson (2013). Inflation and unemployment announcement dates come from the US Bureau of Labor Statistics website (<http://www.bls.gov>), where they are available starting in 1958. We use consumer price index (CPI) announcements before February 1972 and producer price index (PPI) thereafter (as in Savor and Wilson), because PPI numbers are always released a few days earlier, which diminishes the news content of CPI numbers. The dates for the FOMC scheduled interest rate announcement dates are available from the Federal

Reserve website (<http://www.federalreserve.gov>) from 1978. Unscheduled FOMC meetings are not included in the sample.

We first present results using the classic two-step testing procedure for the CAPM, which we employ for stock portfolios sorted on market beta, industry, size and book-to-market, idiosyncratic risk, and downside beta; for individual stocks; and for Treasury bonds and currency carry-trade portfolios.

For the second-stage regressions, we adopt the Fama-MacBeth procedure and compute coefficients separately for announcement and non-announcement days. More specifically, for each period we estimate the following cross-sectional regressions:

$$R_{j,t+1}^N - R_{f,t+1}^N = \gamma_0^N + \gamma_1^N \hat{\beta}_{j,t} \quad (1)$$

and

$$R_{j,t+1}^A - R_{f,t+1}^A = \gamma_0^A + \gamma_1^A \hat{\beta}_{j,t}, \quad (2)$$

where $\hat{\beta}_{j,t}$ is test asset j 's stock market beta for period t (estimated over the previous year using daily returns) from the first-stage regression, $R_{j,t+1}^N - R_{f,t+1}^N$ is the excess return on the test asset on n -days, and $R_{j,t+1}^A - R_{f,t+1}^A$ is the excess return on the test asset on a -days. We then calculate the sample coefficient estimate as the average across time of the cross-sectional estimates, and the standard error equals the time series standard deviation of the cross-sectional estimates divided by the square root of the respective sample lengths. Using this method, we can test whether the difference in coefficient estimates is statistically significant by applying a simple t -test for a difference in means.

In addition to Fama-MacBeth regressions run separately for announcement and non-announcement days, we estimate a single regression and directly test whether beta coefficients (implied risk premia) are different on a -days and n -days. Specifically, we estimate the following panel regression:

$$R_{j,t+1} - R_{f,t+1} = \gamma_0 + \gamma_1 \hat{\beta}_{j,t} + \gamma_2 A_{t+1} + \gamma_3 \hat{\beta}_{j,t} A_{t+1}, \quad (3)$$

where A_{t+1} is a deterministic indicator variable that equals one if day $t+1$ is an announcement day and zero otherwise. Standard errors are then clustered by time to adjust for the cross-sectional correlation of the residuals.

We use rolling betas in all the tables. The figures and all related discussions rely on full-sample betas.

2.2. Beta-sorted portfolios

Table 1 reports results for portfolios sorted on stock market beta, which are rebalanced each month. We estimate betas for each individual stock using one year of daily returns, sort stocks into deciles according to this beta, and then estimate each portfolio's beta using one year of daily returns. We report results for both value-weighted and equal-weighted portfolios.

In the left-hand side of Panel A, we estimate Eqs. (1) and (2) using the Fama-MacBeth approach and show that for value-weighted returns on non-announcement days the intercept γ_0^N equals 2.0 bps (t -statistic=3.6) and the slope of the SML γ_1^N equals -1.0 bps (t -statistic= -0.9), implying a negative equity risk premium. The average R^2 for the cross-sectional regressions is 49.2%.

The picture is very different on announcement days. The intercept is 1.3 bps and is not significantly different from zero (t -statistic=0.9). The slope of the SML is 9.2 bps (t -statistic=2.8), and it is not significantly different from the average announcement-day market excess return of 10.5 bps (the t -statistic for the difference is 0.5). And the average R^2 is now 51.4%. The fact that the intercept is not statistically different from zero and that the implied risk premium is very close to the observed risk premium addresses the critique by [Lewellen, Nagel, and Shanken \(2010\)](#), who suggest that asset pricing tests focus on the implied risk premium and intercepts in cross-sectional regressions and not just on R^2 's. A test for differences across regimes, which is a simple t -test comparing means between the announcement-day and non-announcement-day samples, implies that the slope coefficient is 10.3 bps

higher on a -days, with a t -statistic of 2.9. The intercepts are not significantly different. We also use a bootstrap to estimate standard errors for R^2 on non-announcement days and find that the announcement-day R^2 is outside the 95% confidence interval for the non-announcement-day R^2 .

The results are similar for equal-weighted portfolios (Panel B, left-hand side). The slope is significantly negative on non-announcement days (-3.1 bps, with a t -statistic of -2.8) and significantly positive (and not statistically distinguishable from the average announcement-day market excess return) on announcement days (9.4 bps, with a t -statistic of 3.0). Both intercepts are now positive and significant. The slope coefficient is significantly higher on announcement days, with a difference of 12.6 bps (t -statistic=3.6).

On the right-hand side of Panels A and B, we apply a pooling methodology to estimate the difference in the intercept and slope coefficients in a single regression using all days, and we obtain the same results as those from the Fama-MacBeth regressions. The regression specification is given by Eq. (3), and t -statistics are computed using clustered standard errors. For value-weighted portfolios (Panel A), the n -day intercept equals 2.4 bps (t -statistic=3.3) and is 1.6 bps higher (but not significantly so) on a -days. The n -day slope coefficient equals -1.5 bps (t -statistic= -1.2) and is significantly higher on a -days, with a difference of 8.4 bps (t -statistic=2.7). The non-significance of the announcement-day indicator on its own is also noteworthy, because in the absence of the interaction term it is highly positive and significant. Thus, all of the outperformance of different beta-sorted portfolios on a -days is explained by their betas.

For equal-weighted portfolios (Panel B), we get similar results. The n -day intercept is 7.9 bps (t -statistic=10.6), which is 6.1 bps lower than the intercept on a -days (t -statistic=3.0). The n -day slope coefficient is -3.9 bps (t -statistic= -2.9), and the a -day slope coefficient is 11.9 bps higher, with a t -statistic for the difference of 3.6.

Fig. 1 plots average realized excess returns for ten beta-sorted portfolios against full-sample portfolio betas separately for non-announcement days and announcement days. (For ease of exposition, the x -axis does not always intersect the y -axis at zero in the figures we show.) As a robustness check, Fig. A1 in the Appendix charts the same variables for 50 beta-sorted portfolios, with very similar findings. On non-announcement days, the intercept is positive and significant (2.5 bps, with a t -statistic of 11.7), while the beta coefficient is negative and significant (-1.4 bps, with a t -statistic of -6.5). In contrast, on announcement days the intercept is not significantly different from zero (-0.8 bps, with a t -statistic of -1.5), and the beta coefficient is positive and significant (10.4 bps, with a t -statistic of 18.5) and almost the same as the average announcement-day market excess return. Very intriguingly, the highest-beta portfolio has the lowest n -day return (-1.9 bps) and also the highest a -day return (22.7 bps), so that the very same portfolio exhibits very different performance on different types of days.

One potential worry is that our results are biased by using betas that are not conditioned on the type of day.

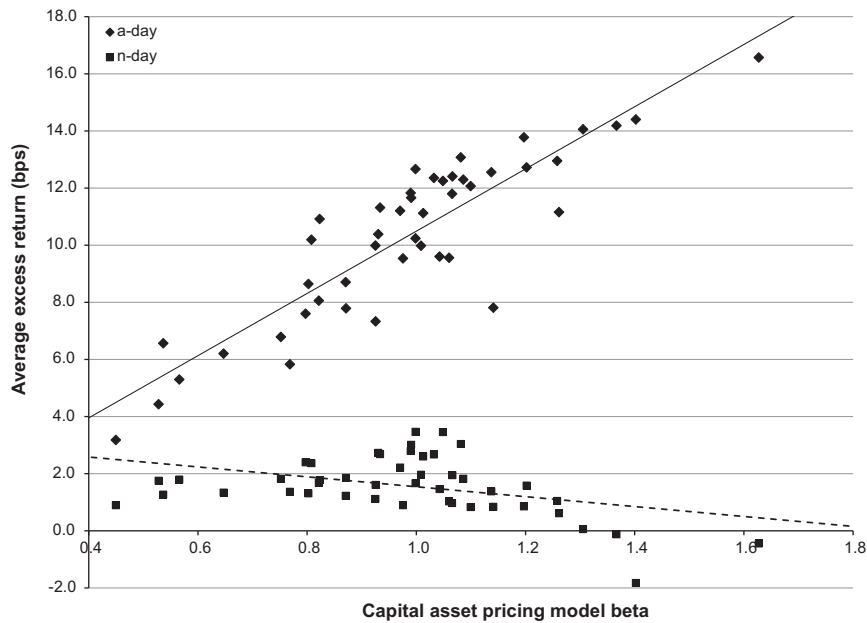


Fig. 2. Average excess returns for ten beta-sorted, 25 Fama and French, and ten industry portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for ten beta-sorted portfolios, 25 Fama and French size- and book-to-market-sorted portfolios, and ten industry portfolios separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

However, when we estimate betas separately for announcement and non-announcement days, we find very small differences between the two betas for all of our test portfolios. We present these results in Section 2.10, which strongly suggest that differences in market betas for individual stocks and various test portfolios on announcement and non-announcement days do not account for our results. Instead, the differences in average excess returns drive our findings.

2.3. Book-to-market, size, and industry portfolios

We next add the 25 size- and book-to-market-sorted portfolios and ten industry portfolios to the ten beta-sorted ones, and we repeat our analysis for all these different equity portfolios together. Because the various constituent portfolios are formed according to very different characteristics, this is a stringent and important test confirming the robustness of our findings.

Fig. 2 presents analogous results to those in Fig. 1 for the 45 test portfolios. (Figs. A2 and A3 in the Appendix show the same beta and average return chart separately for the 25 Fama and French and ten industry portfolios.) For non-announcement-day returns, the square-shaped points replicate the standard finding that betas are unable to price these portfolios. In particular, stocks with higher betas have lower average returns. The dotted line is the fitted value of Eq. (1), in which stock market beta is found to command a mildly negative risk premium (-1.7 bps, with a t -statistic of -2.9). Furthermore, the intercept is positive and significant (3.3 bps, with a t -statistic of 5.4), and the R^2 is only 16.2% .

The diamond-shaped points give the average announcement-day excess returns for the same portfolios, plotted against the same betas. Now again the predictions of the CAPM hold almost perfectly. The estimate of the (solid) announcement-day securities market line has an intercept of -0.4 (t -statistic = -0.5) and a slope of 10.9 (t -statistic = 12.6), which is extremely close to the estimated announcement-day stock market risk premium of 10.5 bps. The R^2 equals 78.7% , indicating that most of the variation in average excess returns of these 45 equity portfolios on announcement days is accounted for by their stock market betas.

As before, market betas explain most of the cross-sectional return variation on announcement days (including the hard-to-price small growth portfolio), while on non-announcement days they predict lower returns for higher-beta assets. We further show that almost all cumulative returns of growth stocks, small stocks, and the market itself are earned on announcement days. By contrast, although all portfolios earn higher returns on announcement days, value stocks earn a substantial amount of their total returns on non-announcement days. In unreported results, we find that for momentum portfolios market betas are not significantly positively related to average returns on either announcement or non-announcement days.

Panel C of Table 1 then reports coefficient estimates for Fama-MacBeth (left-hand side) and pooled regressions (right-hand side) for the 45 test assets combined. Using the Fama-MacBeth approach, on a-days the implied risk premium is estimated to be 8.7 bps (t -statistic = 2.7), and the n-day slope is negative and insignificant (-1.4 bps,

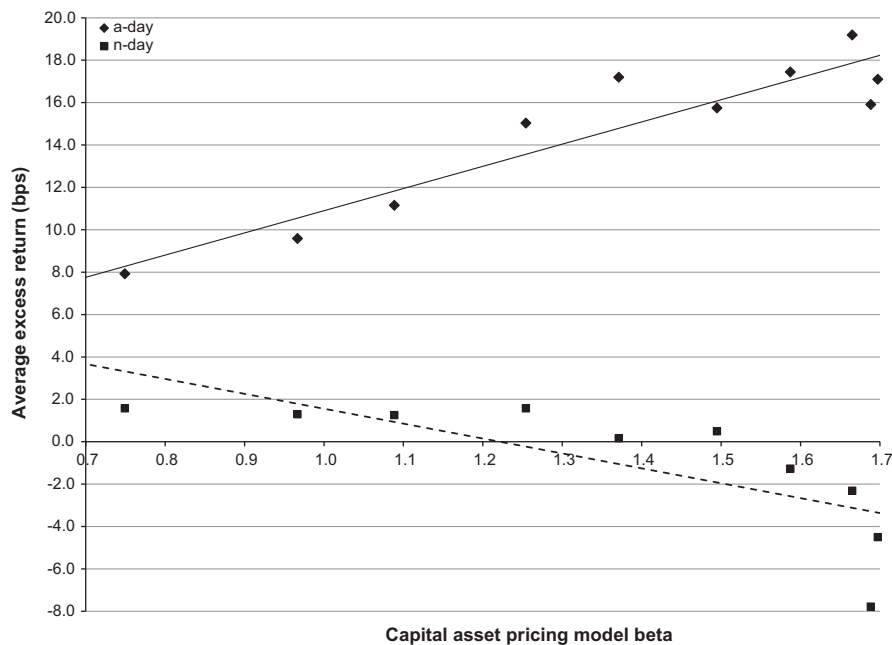


Fig. 3. Average excess returns for ten idiosyncratic volatility-sorted portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for portfolios sorted on idiosyncratic return volatility separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

with a t -statistic of -1.3). The difference in the slope coefficients is 10.1 bps (t -statistic=3.0), indicating that beta is much more positively related to average returns on a-days. This result is confirmed by the pooled regression, in which the slope on n-days is slightly negative (-1.4 bps, the same as in the Fama-MacBeth regression) but is 4.5 bps higher on a-days (t -statistic=4.1). In this regression, a-day beta does not drive out the a-day indicator effect, which indicates that, even controlling for beta, a-day returns are 5.2 bps higher (t -statistic=2.0).

Lucca and Moench (2013) focus on FOMC announcements and replicate the finding in Savor and Wilson (2013) of a significantly higher market risk premium (puzzlingly, in their sample a significant fraction of this premium seems to occur before the release of the FOMC decision).

To ensure our results do not hold just for FOMC announcements, we repeat our analysis for each type of announcement (FOMC, inflation, and unemployment) separately. Our test assets include the ten beta-sorted, 25 Fama and French, and ten industry portfolios. For only FOMC a-days, the a-day market risk premium is 23.5 bps (versus 2.0 for other days), the slope of the a-day SML is 21.6 bps (t -statistic=7.5), which is not statistically different from the actual risk premium, and the SML intercept is 0.9 bps (t -statistic=0.3). On non-FOMC days (which now include other types of announcements), the slope of the SML is negative at -1.4 bps (t -statistic= -2.6), and its intercept is significant and positive at 3.8 bps (t -statistic=6.9).

For inflation a-days only, the market risk premium is 8.2 bps (versus 1.8 for other days), the slope of the a-day SML is 10.6 bps (t -statistic=7.3), which is again not statistically different from the realized risk premium, and the

SML intercept is -1.5 bps (t -statistic= -1.0). On noninflation days, the slope of the SML is -1.1 bps (t -statistic= -1.8), and its intercept is 3.3 bps (t -statistic=5.4). Finally, on unemployment a-days, the market risk premium is 5.6 bps (versus 1.9 for other days), the slope of the a-day SML is 4.9 bps (t -statistic=3.0), again not statistically different from the actual risk premium, and the SML intercept is 0.9 bps (t -statistic=0.5). On all other days, the slope of the SML is -0.8 bps (t -statistic= -1.2), and its intercept is 3.2 bps (t -statistic=5.0). In the Appendix, Figs. A4, A5, and A6 plot average excess returns and betas separately for FOMC, inflation, and unemployment announcements, respectively.

We conclude that our principal results hold separately for each of our announcement types. The predictions of the CAPM regarding the slope and the intercept of the SML are confirmed on a-days and are rejected on n-days.

2.4. Idiosyncratic risk and downside beta portfolios

As a further test of our findings, in Figs. 3 and 4 we explore the relation between market beta and average returns for portfolios sorted on idiosyncratic risk (defined as the standard deviation of return residuals relative to the market model) and downside beta, defined as in Lettau, Maggiori, and Weber (2013).

For idiosyncratic risk-sorted portfolios, market betas increase monotonically from low-risk to high-risk portfolios. On announcement days, the implied risk premium (the beta coefficient) is 10.5 bps (t -statistic=7.1), while the intercept is not significant (0.4 bps, with a t -statistic of 0.2). The R^2 on announcement days is 86.2%. The high

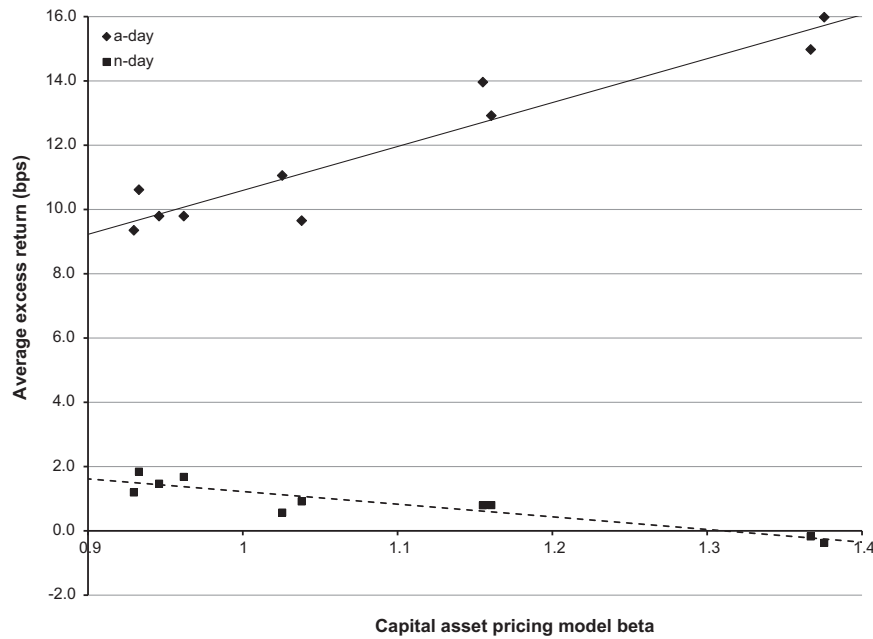


Fig. 4. Average excess returns for ten downside beta-sorted portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for portfolios sorted on downside beta separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

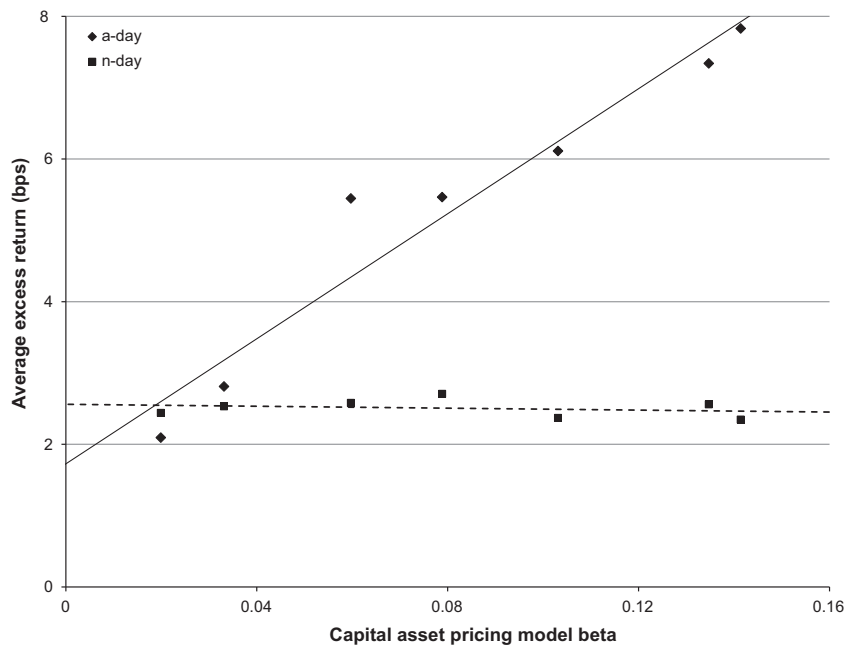


Fig. 5. Average excess returns for Treasury bonds of different maturities. This figure plots average daily excess returns in basis points (bps) against market betas for US Treasury bonds of different maturities separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each bond, the same estimate of its full-sample beta is used for both types of day.

a-day returns for the highest idiosyncratic risk portfolios are particularly remarkable, given the earlier findings in the literature. In contrast, on non-announcement days the

implied risk premium is negative (–7.0 bps, with a t -statistic of –3.2), which is consistent with the finding in [Ang, Hodrick, Xing, and Zhang \(2006\)](#) that high idiosyncratic risk

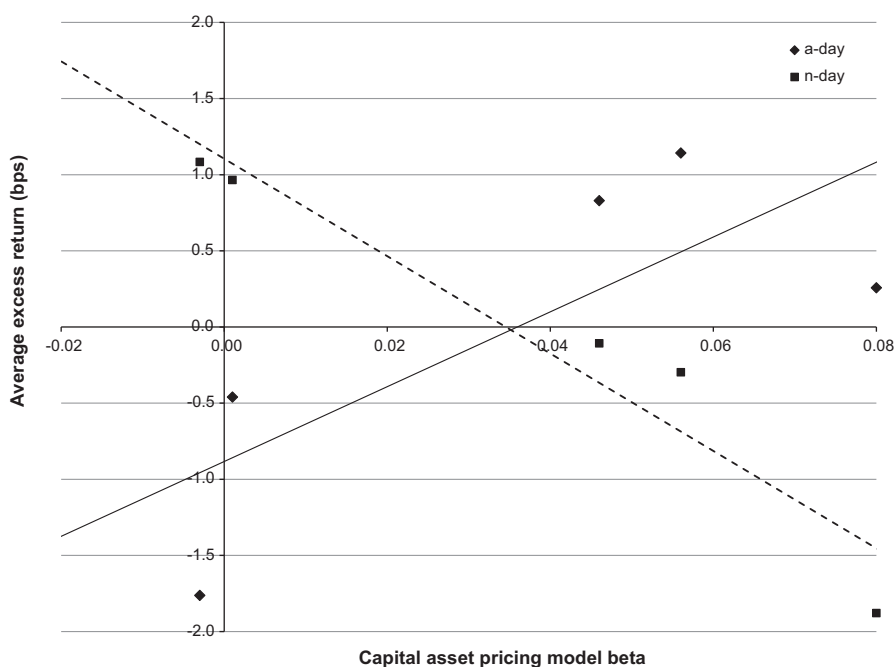


Fig. 6. Average excess returns for currency carry-trade portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for five currency portfolios sorted on interest rate differentials (as described in Della Corte, Riddiough, and Sarno, 2013) separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1983–2011 period. For each currency portfolio, the same estimate of its full-sample beta is used for both types of day.

portfolios have anomalously low average returns, and the intercept is positive and significant (8.6 bps, with a t -statistic of 2.8).

For downside beta-sorted portfolios, the pattern of market betas is non-monotonic: low and high downside risk portfolios have higher betas than medium downside risk portfolios. The a-day implied risk premium is 13.7 bps (t -statistic=8.6), the intercept is -3.1 bps (t -statistic= -1.8), and the R^2 is 90.3%. As before, on n-days everything looks very different. The implied risk premium is -3.9 bps (t -statistic= -6.6), and the intercept is 5.2 bps (t -statistic=7.9).

To summarize, our finding on the different relation between beta and returns on a-days and n-days extends to portfolios formed on idiosyncratic risk and downside beta. On a-days strong evidence exists in favor of the CAPM pricing both sets of portfolios, with positive and high implied risk premia and insignificant intercepts. On n-days both sets of portfolios show a strong negative relation between excess returns and market betas (with positive and significant intercepts).

2.5. Bond and currency portfolios

Fig. 5 plots estimates of average excess returns against market beta for government bonds with maturities of one, two, five, seven, ten, 20, and 30 years. The dotted line shows a completely flat SML for n-days, indicating no relation between beta and average excess returns. In contrast, the diamond points lie closely around an announcement-day SML, whose slope is estimated to equal 41.6 bps (t -statistic=8.3). This implied risk premium

for bonds is biased upward, as Savor and Wilson (2013) show that market betas of bonds (unlike our findings for stocks) are significantly higher on announcement days relative to non-announcement days.

Finally, market betas are positively related to returns even for currency carry-trade portfolios. In Fig. 6, we plot the average daily returns to the currency-only component of five carry-trade portfolios (from November 1983 to December 2011) on the y-axis and their market betas on the x-axis, and we do so separately for a-days and n-days. The portfolios are formed as follows. Every day we allocate currencies to five foreign exchange portfolios using their one-month forward premia (P1 contains lowest-yielding currencies; P5, highest-yielding currencies), and then the next day, within each basket, we take a simple average of the log exchange-rate returns only. Data cover the 20 most liquid developed and emerging market currencies (25 before the introduction of the euro). Our approach is the same as in Della Corte, Riddiough, and Sarno (2013). The high-yielding currencies in P5 usually depreciate relative to the low-yielding currencies in P1 but, as is well known, not by enough on average to offset the difference in yields, so that the returns to the currency carry trade are on average positive.

While on non-announcement days the standard pattern, in which low-yield currencies tend to appreciate and high-yield currencies tend to depreciate, holds, on announcement days the reverse is true: low-yield currencies depreciate and high-yield currencies appreciate. The average exchange-rate component of the return on P5 minus P1 is consequently negative on n-days but

positive on a-days. The difference between average a-day and n-day returns is 5.0 bps and is statistically significant (t -statistic=2.2).

As shown in Fig. 6, on n-days the relation between average exchange-rate returns and market betas is negative and both economically and statistically significant. On a-days the relation reverses and becomes strongly positive, with an economically and statistically significant slope across the five portfolios. Thus, the pattern we previously show for various stock portfolios and for government bonds also appears to hold for foreign exchange rates. High-yield currencies earn higher returns on a-days, consistent with their market betas, while low-yield currencies earn lower average returns on the same days, also consistent with their betas. As before, we find virtually no difference between portfolio betas across different types of day.

2.6. Individual stocks

Our results so far show that on announcement days market betas are strongly positively related to returns for a variety of test assets, including various stock portfolios, government bonds of different maturities, and carry-trade currency portfolios. We next evaluate the ability of beta to explain returns on announcement days for individual stocks. In Table 2, we run Fama-MacBeth (as before, separately for a- and n-days) and pooled regressions of realized excess returns on a firm's stock market beta. In Panels A and B, we include only beta as an explanatory variable with no controls. In Panels C and D, we add as controls firm size and book-to-market ratio, the two characteristics identified by Fama and French (1992) as helping explain the cross section of average stock returns, as well as past one-year return. In Panels E and F, our controls are a firm's betas with the Fama-French small-minus-big (SML), high-minus-low (HML), and the Carhart up-minus-down (UMD) factors. The sample covers all CRSP stocks for which we have the necessary data.

In Panel C, non-announcement days are consistent with the standard results. Size is strongly negatively related to average returns, book-to-market is strongly positively related, and beta is not significantly related. (Past one-year return is negatively related to non-announcement day returns but is barely significant.) By contrast, on announcement days market beta is strongly related to returns. The coefficient estimate is 7.2 bps, with a t -statistic of 3.3. The difference between a- and n-day beta coefficients is 8.1 and is statistically significant (t -statistic=3.5). Both the implied a-day market risk premium and the difference between a- and n-day risk premia are somewhat lower than those in Table 1, most likely because individual stock betas are estimated with more uncertainty than those for portfolios. The size coefficient on a-days remains economically and statistically strongly significant, while the book-to-market coefficient becomes less important, no longer statistically significant and with its magnitude dropping by more than 50%.

Beta appears to be identifying variation in expected returns independent of variation explained by other characteristics. As Panels A and B show, the beta coefficient is similar when only beta is included in the regression, while the coefficients on firm characteristics are similar when only characteristics are included. These results suggest that on announcement days beta identifies sources of expected returns unrelated to size, book-to-market, and past returns. The findings continue to hold for a pooled regression with an a-day dummy and the interaction term between the dummy and market betas, and they are presented in Panel D.

In Panels E and F, we add factor betas as controls instead of firm characteristics. With the Fama-MacBeth approach (Panel E), on n-days stock returns are negatively related to market beta, with a coefficient of -2.5 bps and a t -statistic of -3.5 , and positively related to SMB and HML betas, as is standard. On a-days, individual stock returns are positively related to market betas, with a coefficient of 4.2 bps (t -statistic=2.0), and the 6.6 bps difference relative to n-days is strongly significant (t -statistic=3.1). Stock returns are still positively related to SMB betas on a-days but are no longer significantly related to HML betas. Interestingly, although returns are negatively related to UMD betas on both types of day, the coefficient is significant only on a-days. As before, these results do not change when we use a single pooled regression (Panel F).

We conclude that the strong positive relation between market beta and returns on a-days holds even for individual stocks, despite the fact that estimation error in individual stock betas probably makes it much harder to detect such a relation.

2.7. Large absolute returns or announcement-day returns?

One possible explanation for our findings is that announcement days are times of large market moves and that stocks with higher betas co-move more with the market on these large-move (instead of announcement) days, generating a purely mechanical success for stock market beta. In other words, market betas could be related to returns on announcement days solely because these days are more likely to be periods of extreme market movements and not because announcement days are fundamentally different in any other way. To address this possibility, we estimate securities market lines for days of large market returns (defined as absolute excess returns in the top decile) for the 25 Fama and French portfolios and show the results in Fig. 7. We find that the relation between beta and average returns on such days is strongly negative, with an implied risk premium of -39.1 bps (t -statistic= -7.5). This implied risk premium is much lower and statistically different than the average return on large-move days, which equals -10.4 bps. We can thus reject this alternative explanation. Furthermore, Savor and Wilson (2013) show that the volatility of market returns is not much greater in magnitude on announcement days (the skewness and kurtosis are also similar). Instead, it is the market Sharpe ratio that is much higher on such days.

Table 2

Daily excess returns for individual stocks.

The table reports estimates from Fama-MacBeth and pooled regressions of daily excess returns for individual stocks on just their stock market betas (Beta) in Panels A and B; on stock market betas, log market capitalization (Size), book-to-market ratios (BM), and past one-year return (Past one-year) in Panels C and D; and on stock market betas, size (small-minus-big, SMB) factor betas, value (high-minus-low, HML) factor betas, and momentum (up-minus-down, UMD) factor betas in Panels E and F. The announcement-day indicator variable (*Ann.*) equals one on days with scheduled inflation, unemployment, and Federal Open Market Committee interest rate announcements and is zero otherwise.

t-statistics, reported in parentheses, are calculated using the standard deviation of the time series of coefficient estimates in Panels A, C, and E and using clustered standard errors (by trading day) in Panels B, D, and F.

| Panel A: Beta only (Fama-MacBeth) | | | | | Avg. R^2 | |
|---|--------------------------|----------------------|---------------------|----------------------|--------------------------|---------------------------|
| Type of day | Beta | | | | | |
| a-day | 0.00054 [2.46] | | | | | 1.42% |
| n-day | −0.00024 [−3.12] | | | | | 1.43% |
| a-day - n-day | 0.00079 [3.36] | | | | | |
| Panel B: Beta only (pooled regression) | | | | | R^2 | |
| | Beta | | | <i>Ann.</i> | <i>Ann.*Beta</i> | |
| | −0.00035 [−3.85] | | | 0.00071 [4.82] | 0.00056 [2.11] | 0.01% |
| Panel C: Firm characteristics as controls (Fama-MacBeth) | | | | | Avg. R^2 | |
| Type of day | Beta | Size | BM | Past one-year | | |
| a-day | 0.00072 [3.33] | −0.00030 [−9.27] | 0.00003 [1.01] | −0.00024 [−2.50] | | 1.92% |
| n-day | −0.00009 [−1.18] | −0.00021 [−17.94] | 0.00008 [7.08] | −0.00008 [−1.96] | | 2.01% |
| a-day - n-day | 0.00081 [3.54] | −0.00009 [−2.59] | −0.00005 [−1.70] | −0.00017 [−1.58] | | |
| Panel D: Firm characteristics as controls (pooled regression) | | | | | R^2 | |
| | Beta | Size | BM | Past one-year | <i>Ann.</i> | <i>Ann.*Beta</i> |
| | −0.00018 [−2.05] | −0.00026 [−11.39] | 0.00001 [1.36] | −0.00009 [−1.30] | 0.00079 [4.72] | 0.00048 [3.55] |
| Panel E: Factor betas as controls (Fama-MacBeth) | | | | | Avg. R^2 | |
| Type of day | Beta | SMB beta | HML beta | UMD beta | | |
| a-day | 0.00042 [2.03] | 0.00018 [2.25] | 0.00004 [0.49] | −0.00013 [−2.83] | | 1.94% |
| n-day | −0.00025 [−3.47] | 0.00008 [2.73] | 0.00012 [3.94] | −0.00014 [−1.12] | | 1.95% |
| a-day - n-day | 0.00066 [3.06] | 0.00011 [1.23] | −0.00008 [−0.83] | −0.00001 [−0.11] | | |
| Panel F: Factor betas as controls (pooled regression) | | | | | R^2 | |
| | Beta | SMB beta | HML beta | UMD beta | <i>Ann.</i> | <i>Ann.*Beta</i> |
| | −0.000003 [−2.47] | 0.000001 [2.13] | 0.000001 [2.38] | −0.000001 [−1.55] | 0.001100 [4.44] | 0.000023 [2.95] |

2.8. High average returns or announcement-day returns?

Another potential explanation is that our results are not driven by announcement days but rather more generally by periods when risk premia are high. In other words, it could be the case that market betas help explain the cross section of returns much better during those periods when the equity risk premium is high (as an extreme example, if

the risk premium is zero, market betas should not forecast returns) and that our findings reflect this relation instead of something that is specific to announcement days.

One way to address this alternative is to identify other recurring and predictable periods when the market risk premium is significantly higher than average and to explore the relation between betas and returns during such periods. Based on prior work, we suggest two candidate periods: the

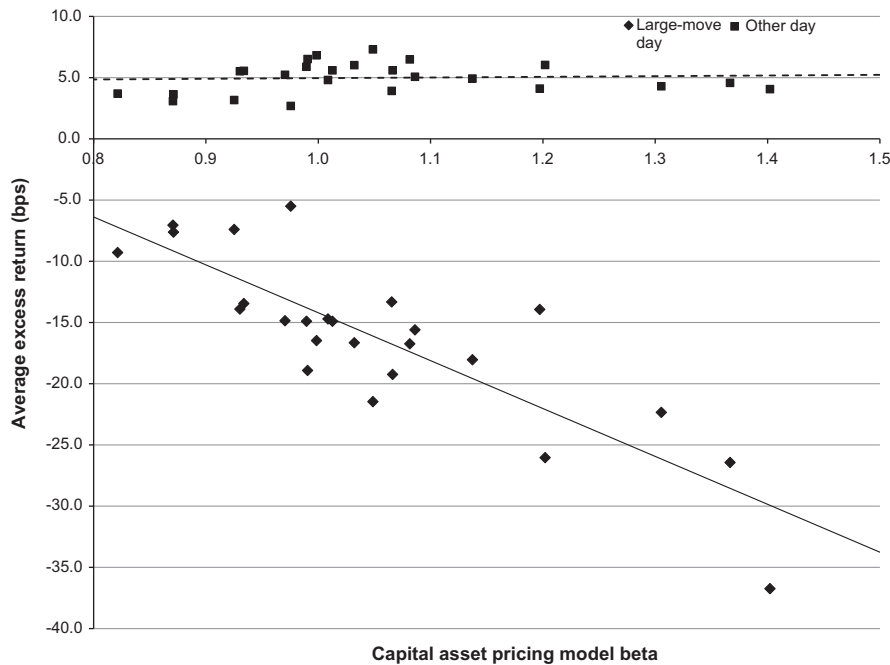


Fig. 7. Average excess returns for 25 Fama and French portfolios on large-move days. This figure plots average daily excess returns in basis points (bps) against market betas for the 25 Fama and French size- and book-to-market-sorted portfolios separately for large-move days (days on which the market return is in the top 10% by absolute return over the 1964–2011 period) and all other days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

month of January and the turn of the month. Starting with [Rozeff and Kinney \(1976\)](#), a large body of work finds high stock returns in January. [Ariel \(1987\)](#) and [Lakonishok and Smidt \(1988\)](#) show that stock returns are on average especially high during the turn of the month, typically defined as the last trading day of a month plus the first four trading days of the following month. [Figs. 8 and 9](#) show that the January and the turn-of-the-month effects are roughly comparable to announcement days, both in terms of average excess returns and Sharpe ratios. It could be the case that these phenomena simply represent anomalies or artifacts of the data, not genuinely higher risk premia, but we ignore this issue for the purposes of our tests.

In [Fig. 10](#), we show that for the 25 Fama and French portfolios market betas are only weakly related to average returns during the turn-of-the-month period. The implied risk premium is positive, but it is low (1.9 bps relative to the average turn-of-the-month excess return of 8.5 bps) and not statistically significant (t -statistic=0.7). Furthermore, the R^2 for the regression of average excess returns on market betas is only 2.2%. The implied risk premium during January, shown in [Fig. 11](#), is substantially higher (9.6 bps), but it is not statistically significant (t -statistic=1.1). Moreover, market betas explain only a small fraction of cross-sectional return variation during that month, with an R^2 of 5.2%.

To summarize, in contrast to announcement days, the beta-return relation is not strongly positive during these other periods of high average market returns, and thus we conclude that our results are specific to announcement days rather than generally holding for any high-return period.

2.9. Average returns and cumulative return shares

In this subsection, we compare the average realized excess returns on announcement and non-announcement days. [Table 3](#) reports these average returns for the 25 size- and book-to-market-sorted portfolios in Panel A; for the market, SMB, HML, and UMD factors in Panel B; for the ten beta-sorted portfolios in Panel C; and for the ten industry portfolios in Panel D. The first notable feature of the table is that all portfolio returns are much higher on announcement days. If these average excess returns correspond to risk premia, then this fact indicates that all portfolios are exposed to announcement-day risk.

The second point is that for many test assets the usual patterns of average excess returns are reversed on announcement days. Panel A shows that on non-announcement days the value portfolios outperform the growth portfolios for each size quintile (the well-known value premium). On announcement days, however, the low book-to-market portfolios outperform the high book-to-market portfolios. The pattern is nearly monotonic, except for the extreme value stocks. The HML factor return is positive and statistically significant on non-announcement days, but negative and insignificant on announcement days (Panel B). Thus, the standard value-beats-growth pattern is reversed on announcement days, the same periods when the market risk premium and Sharpe ratio are much higher.

Furthermore, small stocks do not outperform large stocks on non-announcement days. All of the well-known outperformance of small stocks occurs on announcement days. The return on the SMB factor is

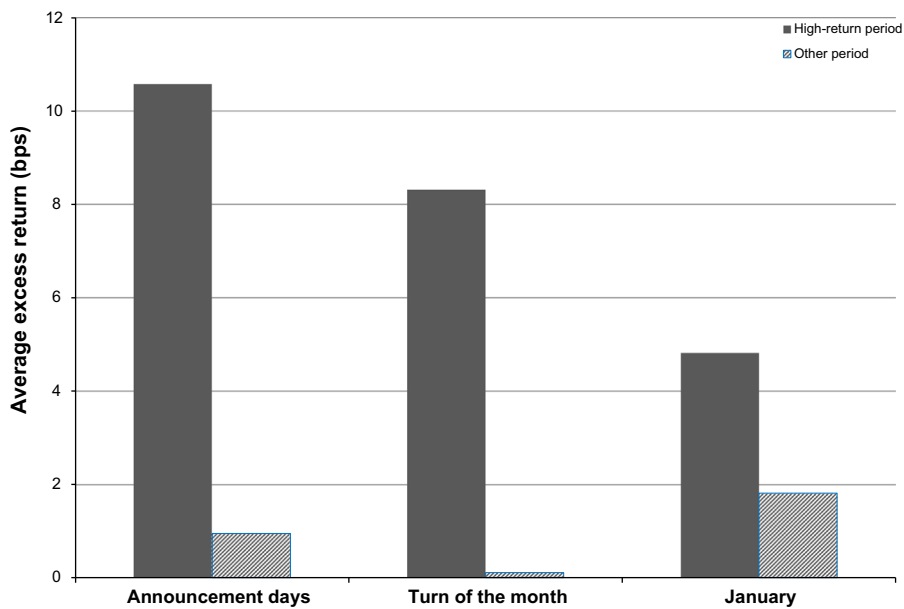


Fig. 8. Average excess market return across different periods. This figure plots the average daily excess return in basis points (bps) for the value weighted index of all NYSE, Amex, and Nasdaq stocks separately for announcement days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) versus all other days; the turn of the month (the last trading day of a month and the first four trading days of the following month) versus all other days; and January versus other months.

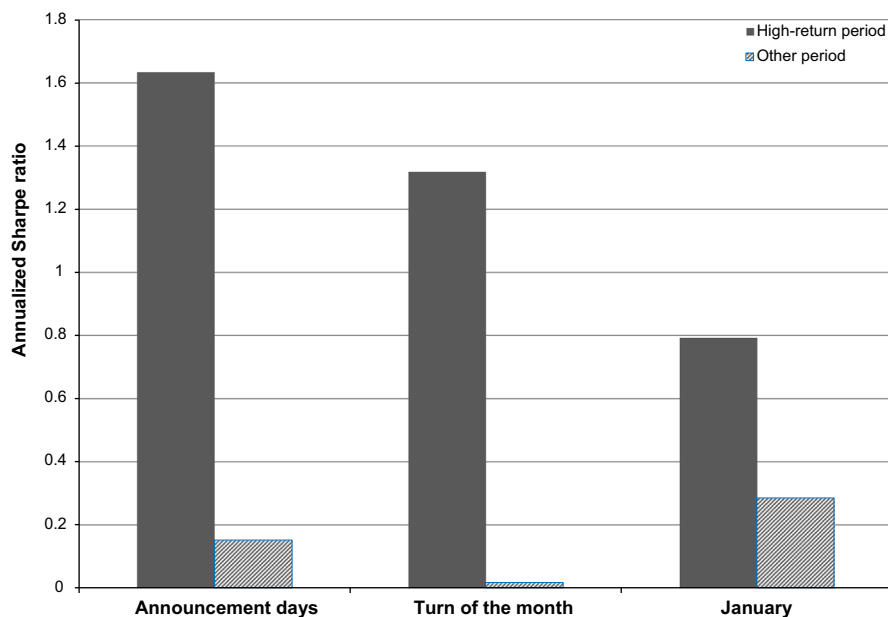


Fig. 9. Annualized market Sharpe ratio across different periods. This figure plots the annualized Sharpe ratio for the value-weighted index of all NYSE, Amex, and Nasdaq stocks separately for announcement days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) versus all other days; the turn of the month (the last trading day of a month and the first four trading days of the following month) versus all other days; and January versus other months.

basically zero on non-announcement days (as it is for the extreme growth portfolios) and very high on announcement days. Interestingly, momentum also outperforms by a factor of nearly two on announcement days (although the returns to UMD are still strongly significant on non-announcement days), suggesting that some fraction of momentum is explained by the same phenomenon.

In Panel C, we can see the return pattern is also reversed for beta-sorted portfolios. For example, the highest-beta decile suffers the lowest n-day excess return (which is negative) of all ten portfolios but enjoys by far the highest a-day return (16.7 bps). Similarly, as Panel D shows, high-tech stocks have the lowest n-day excess return (1.0 bps) and the highest a-day return (13.0 bps) of all industry portfolios.

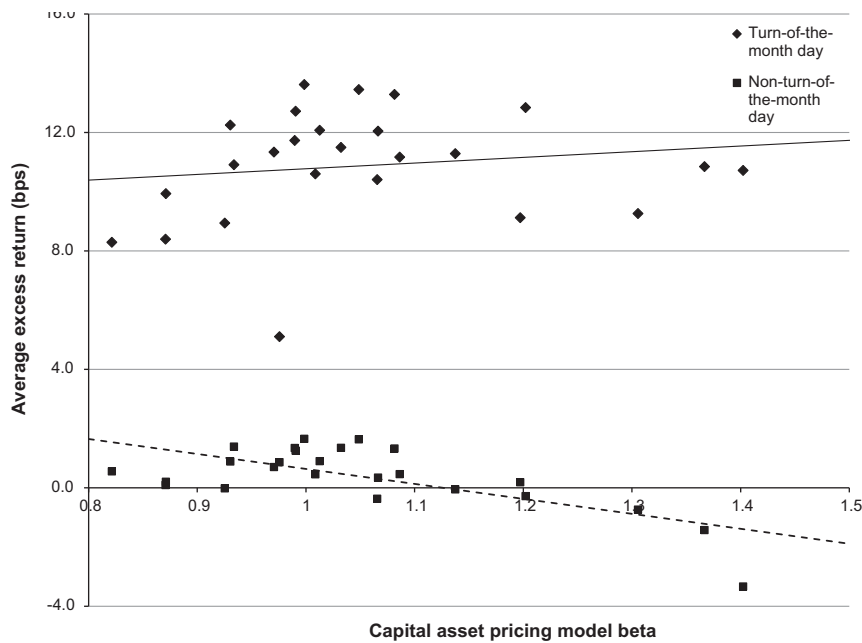


Fig. 10. Average excess returns for 25 Fama and French portfolios on turn-of-the-month days. This figure plots average daily excess returns in basis points (bps) against market betas for the 25 Fama and French size- and book-to-market-sorted portfolios separately for the turn of the month (the last trading day of a month and the first four trading days of the following month) and all other days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

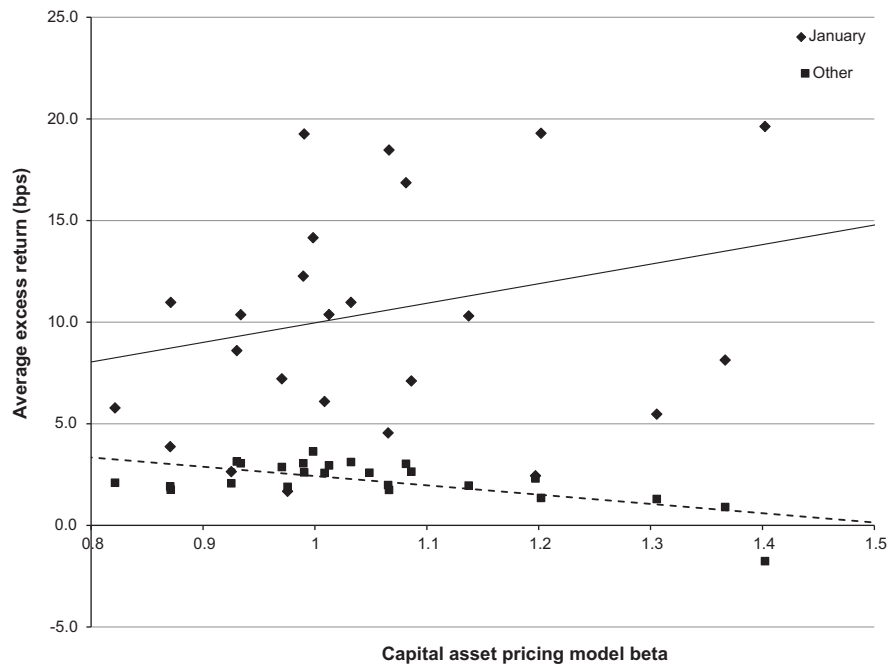


Fig. 11. Average excess returns for 25 Fama and French portfolios in January. This figure plots average daily excess returns in basis points (bps) against market betas for the 25 Fama and French size- and book-to-market-sorted portfolios separately for trading days in January and trading days in all other months. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

In summary, Table 3 shows that the following assets do well on announcement days and otherwise earn very low average excess returns: the market, small stocks, growth

stocks, and high-beta stocks. Previous work by Savor and Wilson (2013) shows that long-term bonds also earn most of their annual excess returns on announcement days (and

Table 3

Average excess returns by type of day.

This table reports average daily excess returns for the 25 Fama and French size and book-to-market-sorted portfolios in Panel A. Panel B presents average returns for the market (Mktrf), small-minus-big (SMB), high-minus-low (HML), and up-minus-down (UMD) factors. Panels C and D show the average excess returns for the ten beta-sorted and ten industry portfolios, respectively. The sample covers the 1964–2011 period. Averages are reported separately for announcement and non-announcement days (a-days and n-days). Numbers are expressed in basis points, and *t*-statistics are reported in brackets.

| Panel A: 25 Fama and French portfolios | | | | | | | | | | | |
|--|-------|-------------|----------|--------------------|--------|-----------|-------------------------|--------|-------------|-----------|-----------|
| Type of Day | | Growth | 2 | 3 | 4 | Value | | | | | |
| n-day | Small | − 1.8 | 1.6 | 1.9 | 3.0 | 3.5 | | | | | |
| | | [− 1.54] | [1.53] | [2.09] | [3.38] | [3.83] | | | | | |
| a-day | | 14.4 | 12.7 | 12.4 | 11.7 | 12.3 | | | | | |
| | | [4.54] | [4.64] | [4.95] | [4.82] | [5.17] | | | | | |
| n-day | 2 | − 0.1 | 1.4 | 2.7 | 2.8 | 3.0 | | | | | |
| | | [− 0.10] | [1.34] | [2.72] | [2.94] | [2.78] | | | | | |
| a-day | | 14.2 | 12.5 | 12.4 | 11.8 | 13.1 | | | | | |
| | | [4.31] | [4.38] | [4.48] | [4.37] | [4.36] | | | | | |
| n-day | 3 | 0.8 | 1.0 | 2.0 | 2.7 | 2.6 | | | | | |
| | | [0.05] | [1.88] | [2.43] | [2.92] | [3.38] | | | | | |
| a-day | | 14.1 | 12.3 | 11.2 | 11.3 | 12.7 | | | | | |
| | | [4.21] | [4.52] | [4.41] | [4.42] | [4.45] | | | | | |
| n-day | 4 | 0.9 | 1.1 | 1.2 | 1.7 | 1.9 | | | | | |
| | | [0.75] | [1.01] | [2.05] | [2.91] | [2.41] | | | | | |
| a-day | | 13.8 | 11.8 | 9.9 | 10.4 | 11.1 | | | | | |
| | | [4.22] | [4.27] | [3.73] | [3.99] | [3.86] | | | | | |
| n-day | Large | 0.9 | 1.1 | 1.2 | 1.7 | 1.9 | | | | | |
| | | [0.84] | [1.12] | [1.22] | [1.67] | [1.66] | | | | | |
| a-day | | 9.5 | 9.9 | 8.7 | 8.1 | 7.8 | | | | | |
| | | [3.10] | [3.44] | [3.00] | [2.79] | [2.52] | | | | | |
| | | | | | | | | | | | |
| Panel B: Fama and French factors | | | | | | | | | | | |
| Type of Day | | Mktrf | SMB | HML | UMD | | | | | | |
| n-day | | 1.0 | 0.5 | 2.2 | 3.0 | | | | | | |
| | | [0.99] | [0.90] | [4.66] | [4.32] | | | | | | |
| a-day | | 10.6 | 3.3 | − 1.4 | 5.7 | | | | | | |
| | | [3.82] | [2.38] | [− 1.08] | [3.20] | | | | | | |
| | | | | | | | | | | | |
| Panel C: Ten beta-sorted portfolios | | | | | | | | | | | |
| Type of Day | | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High |
| n-day | | 0.7 | 1.8 | 1.9 | 1.3 | 2.0 | 1.4 | 1.5 | 0.9 | 0.5 | − 0.4 |
| | | [0.85] | [3.10] | [3.29] | [2.00] | [2.73] | [1.63] | [1.54] | [0.76] | [0.39] | [− 0.23] |
| a-day | | 4.4 | 6.4 | 4.7 | 5.9 | 7.4 | 8.0 | 7.8 | 10.0 | 11.5 | 16.7 |
| | | [2.04] | [4.29] | [2.96] | [3.26] | [3.53] | [3.30] | [2.80] | [3.12] | [2.92] | [3.22] |
| | | | | | | | | | | | |
| Panel D: Ten industry portfolios | | | | | | | | | | | |
| Type of Day | | Nondurables | Durables | Manu- facturing | Energy | High-tech | Telecom- munications | Shops | Health care | Utilities | Other |
| n-day | | 2.4 | 0.8 | 1.4 | 2.4 | 1.0 | 1.4 | 1.7 | 1.8 | 1.3 | 0.8 |
| | | [2.83] | [0.65] | [1.42] | [1.88] | [0.74] | [1.27] | [1.61] | [1.70] | [1.56] | [0.75] |
| a-day | | 7.6 | 7.8 | 9.6 | 10.2 | 13.0 | 5.6 | 10.2 | 10.9 | 6.6 | 12.1 |
| | | [3.10] | [2.19] | [3.33] | [2.94] | [3.25] | [1.84] | [3.33] | [3.69] | [2.92] | [3.70] |

this relation is increasing with bond maturity). All other portfolios also earn significantly higher returns on announcement days, but their relative returns (with respect to other days) are less remarkable.

To further demonstrate the importance of announcement days for performance of various test assets, in Table 4 we provide separately the cumulative log excess returns that are earned on each type of day. These sum to the total

log cumulative excess return earned over the entire sample period.

These numbers could require some explanation. The bottom panel of the table shows that over the 1964–2011 period log excess returns for the market on a-days sum to 1.381 and on n-days to 0.487. Together these sum to 1.868. An investment in the risk-free asset from 1964 to 2011 returned a 12.042-fold gross return, and an investment in

Table 4

Cumulative log excess returns by type of day.

The table reports cumulative log excess returns earned on announcement days and non-announcement days for different portfolios for the 1964–2011 period. Announcement days account for 11.3% of all trading days in this period. Panel A covers the ten beta-sorted portfolios (going from low to high beta); Panel B, the 25 Fama and French size- and book-to-market-sorted portfolios; Panel C, the ten industry portfolios; and Panel D, the market portfolio.

| <i>Panel A: Ten beta-sorted portfolios</i> | | | | | | | | | | |
|--|-------------------|--|--|--|--|-----------------------|--|--|--|--|
| Portfolio | Announcement days | | | | | Non-announcement days | | | | |
| Low | 0.556 | | | | | 0.357 | | | | |
| 2 | 0.851 | | | | | 1.728 | | | | |
| 3 | 0.618 | | | | | 1.869 | | | | |
| 4 | 0.777 | | | | | 1.167 | | | | |
| 5 | 0.970 | | | | | 1.872 | | | | |
| 6 | 1.037 | | | | | 1.081 | | | | |
| 7 | 1.000 | | | | | 1.073 | | | | |
| 8 | 1.271 | | | | | 0.192 | | | | |
| 9 | 1.426 | | | | | −0.507 | | | | |
| High | 2.031 | | | | | −2.385 | | | | |

| <i>Panel B: 25 Fama and French portfolios</i> | | | | | | | | | | |
|---|-------------------|-------|-------|-------|-------|-----------------------|-------|-------|-------|-------|
| Portfolio | Announcement days | | | | | Non-announcement days | | | | |
| | Growth | 2 | 3 | 4 | Value | Growth | 2 | 3 | 4 | Value |
| Small | 1.878 | 1.672 | 1.641 | 1.542 | 1.626 | −2.766 | 1.082 | 1.588 | 2.767 | 3.230 |
| 2 | 1.841 | 1.642 | 1.621 | 1.552 | 1.707 | −0.988 | 0.863 | 2.307 | 2.473 | 2.570 |
| 3 | 1.820 | 1.615 | 1.474 | 1.488 | 1.659 | −0.755 | 1.412 | 1.896 | 2.387 | 3.106 |
| 4 | 1.787 | 1.545 | 1.300 | 1.358 | 1.445 | 0.180 | 0.511 | 1.573 | 2.417 | 2.113 |
| Large | 1.218 | 1.289 | 1.114 | 1.026 | 0.977 | 0.308 | 0.626 | 0.730 | 1.212 | 1.265 |

| <i>Panel C: Ten industry portfolios</i> | | | | | | | | | | |
|---|-------------------|--|--|--|--|-----------------------|--|--|--|--|
| Industry | Announcement days | | | | | Non-announcement days | | | | |
| Nondurables | 0.984 | | | | | 2.154 | | | | |
| Durables | 0.951 | | | | | −0.050 | | | | |
| Manufacturing | 1.236 | | | | | 0.953 | | | | |
| Energy | 1.280 | | | | | 1.621 | | | | |
| High-tech | 1.627 | | | | | −0.019 | | | | |
| Telecommunications | 0.683 | | | | | 0.804 | | | | |
| Shops | 1.311 | | | | | 1.168 | | | | |
| Health care | 1.411 | | | | | 1.278 | | | | |
| Utilities | 0.852 | | | | | 0.980 | | | | |
| Other | 1.553 | | | | | 0.182 | | | | |

| <i>Panel D: Market</i> | | | | | | | | | | |
|------------------------|-------------------|--|--|--|--|-----------------------|--|--|--|--|
| Portfolio | Announcement days | | | | | Non-announcement days | | | | |
| Market | 1.381 | | | | | 0.487 | | | | |

the market returned a 77.996-fold return. Thus, the market outperformed the risk-free asset by a factor of $6.477 = \exp(1.868)$. Of this log sum of 1.868, 1.381 was earned on a-days, so that the a-day share of total log excess returns was $1.381/1.868 = 73.9\%$. All other numbers in the table should be interpreted in the same way.

Panel A of Table 4 shows cumulative log excess returns for beta-sorted portfolios. For the low-beta portfolios, the cumulative return is sometimes higher on n-days (meaning that the majority of the cumulative excess return is earned on n-days), but not by much: 0.556 on a-days versus 0.357 on n-days for the lowest-beta portfolio (higher on a-days), and between 0.618 and 0.970 on a-days versus 1.167 to 1.872 on n-days for Portfolios 2 through 5. For Portfolios 6 and 7, the cumulative returns

are about the same on both types of day. And for the three highest-beta portfolios, the cumulative excess returns on a-days are much higher (1.271, 1.426, and 2.031 on a-days versus 0.192, −0.507, and −2.385 on n-days). Thus, the share of the cumulative log excess return over the entire period that is earned on a-days is always much greater than 11.3% (the share of a-days in the sample) and for high-beta portfolios equals or significantly exceeds 50%.

Panel B provides the same information for the 25 Fama and French portfolios. Extreme growth stocks suffer either negative or extremely low total log excess returns on n-days. Going from the smallest to the largest size quintile, the numbers are −2.766, −0.988, −0.755, 0.180, and 0.308. By contrast, on a-days the corresponding numbers are 1.878, 1.841, 1.820, 1.787, and 1.218. As a result, for

Table 5

Market betas by type of day.

This table reports the difference in estimated market betas across announcement and non-announcement days for the ten beta-sorted portfolios in Panel A and the 25 Fama and French size- and book-to-market-sorted portfolios in Panel B. β_{ann} and β_{non} are market betas estimated only on announcement and non-announcement days, respectively. *t*-statistics for the difference are computed using robust standard errors and are reported in brackets.

| Panel A: Ten beta-sorted portfolios | | | | | | | | | | |
|---|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-----------------|-------------------|
| Beta | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High |
| β_{non} | 0.233 | 0.351 | 0.442 | 0.559 | 0.677 | 0.806 | 0.959 | 1.107 | 1.341 | 1.726 |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | −0.021 [−0.58] | −0.044 [−1.76] | −0.035 [−1.47] | −0.025 [−0.92] | −0.026 [−1.07] | −0.017 [−0.63] | −0.016 [−0.71] | −0.005 [−0.29] | 0.005 [0.19] | −0.025 [−0.48] |
| Panel B: 25 Fama and French portfolios | | | | | | | | | | |
| Beta | Growth | 2 | 3 | 4 | Value | | | | | |
| β_{non} | Small | 1.007 | 0.877 | 0.784 | 0.739 | 0.745 | | | | |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | | −0.067 [−2.12] | −0.071 [−2.43] | −0.062 [−2.21] | −0.050 [−1.69] | −0.074 [−2.44] | | | | |
| β_{non} | 2 | 1.100 | 0.931 | 0.871 | 0.831 | 0.940 | | | | |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | | −0.058 [−2.24] | −0.031 [−1.36] | −0.022 [−0.84] | −0.015 [−0.51] | −0.052 [−1.54] | | | | |
| β_{non} | 3 | 1.111 | 0.911 | 0.840 | 0.840 | 0.840 | | | | |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | | −0.023 [−1.04] | −0.025 [−1.45] | −0.033 [−1.53] | −0.029 [−1.24] | −0.028 [−1.06] | | | | |
| β_{non} | 4 | 1.083 | 0.928 | 0.912 | 0.869 | 0.963 | | | | |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | | 0.016 [0.79] | 0.008 [0.45] | −0.025 [−1.10] | −0.035 [−1.50] | −0.071 [−2.43] | | | | |
| β_{non} | Large | 1.053 | 0.971 | 0.961 | 0.928 | 0.975 | | | | |
| $\beta_{\text{ann}} - \beta_{\text{non}}$ | | 0.008 [0.40] | 0.019 [1.03] | 0.009 [0.49] | 0.009 [0.36] | −0.016 [−0.58] | | | | |

extreme growth stocks the overwhelming proportion of their cumulative log excess returns is earned on a-days. The negative total excess returns, which we find for the extreme growth and beta portfolios, are hard to rationalize. For the second-lowest book-to-market quintile, the findings are similar, though less extreme. The majority of cumulative log excess returns are again earned on a-days. For high book-to-market stocks, the relative performance on n-days is better, with the n-day numbers higher than the a-day numbers across all size quintiles. The best relative n-day performance is for small value, which returned 1.626 on a-days versus 3.230 on n-days, implying an a-day share of total log excess returns (as defined above) of about 33%.

The key take-away from Panels A and B is that, while all test portfolios earn a significant and disproportionate fraction of their total excess returns on a-days, the fraction is overwhelming for high-beta and growth portfolios (n-day cumulative excess returns are often negative for those portfolios).

Panel C reports the results for industry-sorted portfolios. All industries earn a substantial fraction of their cumulative log excess returns on a-days, but, similarly to beta, size, and book-to-market portfolios, the fraction varies significantly across industries. For example, nondurables return 0.984 on a-days versus 2.154 on n-days. Durables, by contrast, earn 0.951 on a-days and about zero on n-days, meaning that all of their cumulative log excess returns come from a-days. Generally, cyclical industries such as durables, manufacturing, and financials (included in Other) earn a dominant share of their total excess returns on a-days (as does high-tech), suggesting an

important role for exposure to the business cycle in determining this share. Consistent with this, nondurables, which are less exposed, earn the lowest proportion of their excess returns on a-days, and energy and health care also have a more even distribution between the two types of day.

Taken together, these results show that for all test assets a significant fraction of their total excess return is earned on a-days, which constitute just 11.3% of the sample. All portfolios earn at least more than twice that share on a-days. For about half of the test assets, the majority of their total excess returns comes from a-days, and for the market, growth stocks, high-beta stocks, and stocks in cyclical industries an overwhelming majority is earned on a-days.

2.10. Announcement-day versus non-announcement-day betas

Our analysis above uses the same betas for each test asset on both announcement and non-announcement days (i.e., we estimate betas using all days, without distinguishing between a- and n-days). One potential worry is that our results are biased by this approach, in which betas are not conditioned on the type of day. For example, different a-day and n-day betas could help explain the differences in average returns that we show. To examine this hypothesis, we now compute betas separately for announcement and non-announcement days.

Table 5 presents the difference between betas estimated separately for a-days and n-days over the entire 1964–2011 sample (together with the n-day betas, as a

Table 6

Forecasting quarterly market return variance.

This table reports coefficient estimates of a predictive regression for RV (annualized average squared daily excess market return) using quarterly data from 1964 Q1 to 2011 Q4. The regression is estimated using constrained least squares, where the RV forecast is constrained to be non-negative. In addition to lagged RV , our predictive variables include the quarterly log market excess return ($rMKT$), the quarterly announcement-day log market excess return (rA), the quarterly non-announcement-day log market excess return (rN), together with the [Campbell, Giglio, Polk, and Turley \(2012\)](#) variables: log aggregate price-earnings ratio (PE), the term spread (TY), the default spread (DEF), and the value spread (VS). Newey-West t -statistics with four lags are reported in brackets beneath the relevant coefficient estimates. The final column reports the adjusted R^2 .

The specification in the last row is used to forecast RV in [Table 7](#).

| Constant | $rA_t - rN_t$ | rA_t | rN_t | $rMKT_t$ | RV_t | PE_t | TY_t | DEF_t | VS_t | Adj. R^2 |
|-------------------|-----------------|-----------------|-------------------|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|------------|
| –0.086 [–1.65] | | | | –0.045 [–1.21] | 0.317 [3.08] | 0.015 [1.73] | 0.002 [0.70] | 0.015 [1.46] | 0.028 [1.25] | 24.3% |
| –0.083 [–1.90] | | | | –0.049 [–1.41] | 0.309 [3.12] | 0.026 [2.24] | | 0.022 [1.81] | | 24.2% |
| –0.074 [–1.78] | | 0.082 [1.16] | –0.071 [–1.88] | | 0.294 [3.07] | 0.024 [2.12] | | 0.021 [1.76] | | 24.7% |
| 0.015 [4.69] | 0.060 [2.40] | | | | 0.407 [4.30] | | | | | 21.8% |
| 0.014 [4.85] | 0.103 [2.15] | | | 0.055 [1.22] | 0.417 [4.89] | | | | | 21.9% |
| 0.014 [4.85] | | 0.158 [1.76] | –0.048 [–1.92] | | 0.417 [4.89] | | | | | 21.9% |

reference point). For the ten beta-sorted portfolios (Panel A), the difference is not statistically significant for any of the portfolios, with the largest difference equaling -0.044 . For the 25 Fama and French portfolios (Panel B), the difference is significant for only six (mostly small-cap) portfolios, and the magnitude is never too large. The largest difference is for the small value portfolio, when it equals 0.074 on n -days, which is a 10% relative difference. These magnitudes are too small to be a significant factor in explaining the very large differences in average return patterns between a -days and n -days. In fact, as we argue below, the similarity in betas over the types of day, given the differences in risk premia, constitutes an important part of the puzzle.

When we estimate different (announcement and non-announcement day) betas for each stock before sorting into portfolios, we find very little difference in our results. We conclude that using the same betas for both types of day does not affect our findings.

3. The risk–return trade-off on announcement days

We now present evidence on the risk–return trade-off for the two types of days. Our main estimate of aggregate risk is a conditional forecast of one-quarter-ahead variance of daily market returns, EV_t . As pointed out by [French, Schwert, and Stambaugh \(1987\)](#), realized variance is an ex post measure of conditional market risk and so equals the sum of an ex ante measure and an innovation. Theories, such as the CAPM, that relate expected returns to variance do so for the ex ante measure, not the innovation, and therefore we use the conditional forecast in our main tests. To check that our results are robust to our forecasting specification, we also use the average squared daily excess market return over a given quarter, RV_t , as our simple forecast of next quarter's variance.

[Table 6](#) presents results on one-quarter-ahead forecasts of RV using various predictive variables. We use constrained least squares to ensure all the forecasts are non-

negative. Our predictive variables include aggregate quarterly log announcement-day excess returns ($r_{A,t}$) and non-announcement-day excess returns ($r_{N,t}$), which together add up to the log market excess return over the quarter ($r_{MKT,t}$). We also use quarter t 's realized variance RV_t , the market price–earnings ratio (PE_t), the US Treasury yield spread (TY_t), the default spread (DEF_t), and the value spread (VS_t), all as in [Campbell, Giglio, Polk, and Turley \(2012\)](#).⁶ t -statistics are based on Newey–West standard errors with four lags.

The first two rows show results when the market return is not divided between announcement and non-announcement days. Realized variance is statistically significantly forecast by its own lag and marginally by the market price–earnings ratio and the default spread. The adjusted R^2 for this specification is 24.3%. The quarterly market return, the yield spread, and the value spread are not significant predictors of future realized variance. When we drop the term and value spreads from the forecasting regression, the statistical significance of the remaining variables increases, as shown in the second row.

In the third row, we split market returns into announcement-day and non-announcement-day returns. We find that lagged RV , PE , and DEF are still significant, with coefficients of similar magnitude as before. The coefficient on announcement-day returns is positive but not significant, while the coefficient on non-announcement-day returns is negative and marginally significant. When we use the difference between a - and n -day returns as a predictive variable, the coefficient is positive and statistically significant (and continues to be so if we control for the overall market return, as shown in the fourth and fifth specifications). Because the inclusion of some variables (even though they are significant) does not appear to affect very much the forecasting power of the

⁶ See [Campbell, Giglio, Polk, and Turley \(2012\)](#) for a discussion of these variables and the properties of their variance forecast.

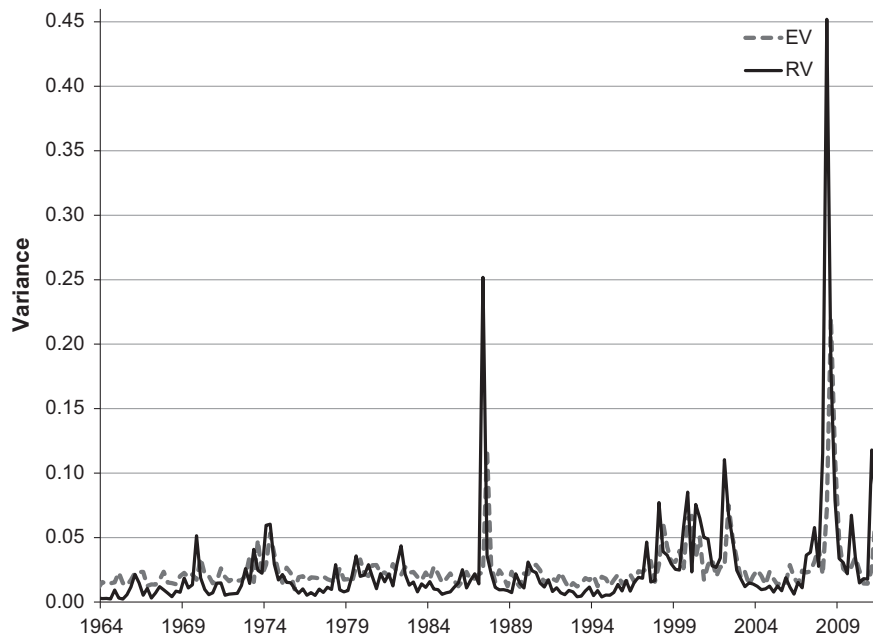


Fig. 12. Realized versus expected variance. This figure plots the realized variance of quarterly log excess market returns (RV) and its one-quarter-ahead forecast (EV) over the 1964–2011 period. EV is a linear combination of RV, a-day, and n-day log returns, as given in the bottom specification in Table 6.

Table 7

Market returns and expected variance.

The table reports ordinary least squares estimates of a VAR(1) using quarterly data from 1964 to 2011. Variables are quarterly log market excess returns ($rMKT_t$), quarterly aggregate announcement-day log market excess returns (rA_t), quarterly aggregate non-announcement-day log market excess returns (rN_t), the expected variance of the market return (EV, computed using the specification given in the last row of Table 6), and the realized variance of the market return (RV), obtained from Campbell, Giglio, Polk, and Turley (2012). Newey-West t -statistics with four lags are reported in brackets beneath the relevant coefficient estimates. The final column reports adjusted R^2 and F-statistics for each equation of the vector autoregression.

Panel A: Quarterly market return

| Dependent variable | Intercept | $rMKT_t$ | EV_t | Adj. R^2 /F-statistic |
|--------------------|------------------|------------------|------------------|-------------------------|
| $rMKT_{t+1}$ | 0.004 [0.362] | 0.084 [1.141] | 0.193 [0.482] | –0.5% 0.50 |
| EV_{t+1} | 0.013 [7.139] | 0.002 [0.142] | 0.498 [6.117] | 23.5% 30.25 |

Panel B: Quarterly announcement-day and non-announcement-day market returns

| Dependent variable | Intercept | rA_t | rN_t | EV_t | Adj. R^2 /F-statistic |
|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------------|
| rA_{t+1} | –0.003 [–1.493] | 0.101 [1.017] | 0.011 [0.395] | 0.372 [4.765] | 7.1% 5.86 |
| rN_{t+1} | 0.005 [0.362] | –0.151 [–0.560] | 0.106 [1.333] | –0.055 [–0.102] | 0.0% 0.98 |
| EV_{t+1} | 0.013 [5.964] | 0.023 [0.414] | –0.003 [–0.254] | 0.479 [4.636] | 23.2% 20.15 |

Panel C: Quarterly announcement-day and non-announcement-day market returns

| Dependent variable | Intercept | rA_t | rN_t | EV_t | Adj. R^2 /F-statistic |
|--------------------|------------------|--------------------|--------------------|--------------------|-------------------------|
| rA_{t+1} | 0.002 [1.380] | 0.159 [1.613] | –0.007 [–0.240] | 0.155 [4.765] | 7.1% 5.86 |
| rN_{t+1} | 0.004 [0.567] | –0.160 [–0.668] | 0.109 [1.637] | –0.023 [–0.102] | 0.0% 0.98 |
| RV_{t+1} | 0.014 [4.855] | 0.158 [1.762] | –0.048 [–1.915] | 0.417 [4.885] | 21.9% 18.75 |

regression, we opt for a simple specification given in the last row, which uses a-day and n-day quarterly returns, together with RV_t . We employ this regression to construct a linear prediction of RV_{t+1} (EV_t). Our results are robust to reestimating the regression each period using only data up to date t to forecast RV_{t+1} . The adjusted R^2 of our chosen specification is 21.9%.

Fig. 12 plots the predicted variable EV_t implied by the last specification in Table 6 against realized variance RV_{t+1} . The overall fit is relatively good, with EV_t capturing both lower-frequency changes and higher-frequency spikes in realized market variance. We conclude that it represents a good estimate of conditional (ex ante) variance of market excess returns.

Using this estimate of EV_t , we next examine the relation between risk and expected returns. Panel A of Table 7 shows our findings for a standard test of the risk–return trade-off, in which aggregate log market excess returns over quarter t to $t+1$ are regressed on our estimate of conditional variance at the end of quarter t , EV_t . We also include lagged log market returns, although the coefficient is not significant and does not affect any of our results. The familiar result (see, e.g., French, Schwert, and Stambaugh, 1987, or Pollet and Wilson, 2010) is that EV_t is not a statistically significant predictor of future market returns. The coefficient is positive at 0.193, but not significant, with a t -statistic of just 0.48. The adjusted R^2 , equaling -0.5% , is also not consistent with an economically important role for market variance in forecasting variation in realized market returns.

In Panel B, we separately estimate the ability of EV_t to predict announcement-day and non-announcement-day log excess returns over the following quarter. (We also include an equation estimating the dynamics of EV_t in each panel.) The most notable observation about the first equation is that clear evidence exists of predictability and of a risk–return trade-off for announcement-day returns. EV_t is a statistically and economically significant predictor of returns on these days, with a coefficient of 0.37 (t -statistic=4.8) and an adjusted R^2 of 7.1%. Given that announcement-day returns consist of the sum of only eight or nine individual daily returns over a quarter, this R^2 is remarkably high, especially because the forecasting variable is EV_t . By contrast, non-announcement-day returns are not related to EV_t , with a coefficient that is negative -0.06 (t -statistic= -0.1) and an adjusted R^2 of 0.0%.

Panel C presents estimates of a VAR using RV_t instead of EV_t as the measure of risk, partly as a robustness check and partly because the dynamics are simpler. Again, we find strong evidence of a risk–return trade-off on announcement days and none on other days.

As an additional robustness check, we reestimate the VARs in Table 7 for each half of our sample period. In the first half, conditional market variance is positively related to future market returns, with a highly significant coefficient. This same relation is observed separately for both announcement- and non-announcement-day returns. In the second half, however, conditional variance remains a statistically significant predictor only for announcement-day returns. Thus, we conclude that a robustly positive

statistical relation exists between conditional market variance and future announcement-day returns in the 1964–2011 period. There is no comparable result for either non-announcement-day or total market returns, because the relation is unstable and disappeared in the more recent 24-year period.

We also extend our analysis to include more conditioning variables in the VAR, with very similar results concerning the significance of the risk–return trade-off for each type of return (for the full sample and each half of the sample). Our results are likewise robust to using weighted least squares.

4. Discussion

Our results show that two predictions of the conditional CAPM are satisfied on announcement days: asset risk premia equal stock market risk premia times asset market beta; and the conditional variance of market returns strongly positively forecasts future market excess returns, consistent with a positive risk–return trade-off. By contrast, neither of these predictions is satisfied on non-announcement days. Furthermore, we find very little difference between a-day and n-day stock market betas for any of our test assets. To the extent that growth stock betas are different on a-days, they are lower than n-day betas.

4.1. Potential explanations that cannot fit the data

These findings are difficult to explain with standard models of the cross section of asset returns. In this subsection, we argue that no simple modification of standard models is consistent with our results.

4.1.1. The CAPM holds all the time, but n-day market risk premium is zero or negative

This straightforward rationalization of our results can be ruled out easily. Suppose the CAPM holds on both types of day, then in regime g (which can be A or N , corresponding to announcement and non-announcement days), given that the betas do not vary across regimes, we have

$$rp_{j,t}^g = \ln E_t \left[\frac{1 + R_{j,t+1}^g}{1 + R_{f,t+1}^g} \right] = \beta_j rp_{MKT,t}^g. \quad (4)$$

The term $rp_{j,t}$ is shorthand for the log mean excess return on asset j . In the n-day regime, we allow it to be zero or negative. Our claim here is given for the CAPM expressed in log mean returns, but it is equally valid (only with more algebra) for just raw excess returns. Our results on the potential impact of estimation uncertainty below are also identical if we use log instead of raw excess returns.

Aggregating over all days in a period of T days, we get

$$\begin{aligned} rp_{j,t,T} &= \sum_{s=0}^{T-1} rp_{j,t+s}^g = \sum_{s=0}^{T-1} \beta_j rp_{MKT,t+s}^g \\ &= \beta_j \sum_{s=0}^{T-1} rp_{MKT,t+s}^g = \beta_j rp_{MKT,t,T}^g. \end{aligned} \quad (5)$$

Thus, a time-aggregated CAPM then has to hold at, say, monthly or quarterly frequencies, which we know is not true from prior work. Although simple, this case illustrates the important point that, to the extent that the CAPM holds on a-days, it cannot also hold on n-days, because a time-aggregated CAPM is rejected by the data.

Our rejection of a time-aggregated CAPM could be due to estimation uncertainty, and not because a time-aggregated CAPM does not hold. We consequently carry out simulations to address this possibility, assuming that the CAPM prices the cross section of beta-sorted portfolios in each regime, but with a zero market risk premium in the n-day regime. We aggregate our simulated returns to a monthly frequency and evaluate the results.

In the data, we estimate a slope coefficient of -14.4 bps for this monthly CAPM, which is marginally significantly negative (t -statistic $= -1.85$) and strongly significantly below the realized market risk premium (t -statistic $= 7.37$). In our simulations, such a negative slope coefficient occurs only 3.4% of the time, so we conclude that this estimate is unlikely to be consistent with a time-aggregated CAPM in the presence of estimation uncertainty.⁷ In any case, the actual estimated n-day premium is not zero but is positive, and if we adjust for this in our simulations, we estimate a negative SML slope only 1.5% of the time, and we never estimate a slope of -14.4 bps or lower.

4.1.2. Unconditional linear two-factor models

More plausible is the idea that there are two priced risk factors whose covariance matrix varies between types of day. Such models nest, for example, the model of Savor and Wilson (2013), which they propose as the explanation for the difference in market and bond risk premia observed across types of day; the Case I model of Bansal and Yaron (2004) (on which the Savor and Wilson model is based); the model of Campbell and Vuolteenaho (2004), as implemented empirically in that paper; the model of Brennan, Wang, and Xia (2004); and the Fama and French (1992) two-factor model, in which size and book-to-market are characteristics that proxy for the unknown true factors that explain the cross section of expected returns.

All such models are of the following general form, with log excess returns on the left-hand side:

$$r_{j,t+1} - r_{f,t+1} + 0.5 \text{Var}_t[r_{j,t+1}] = p_1 \text{Cov}_t[r_{j,t+1}, v_{1,t+1}] + p_2 \text{Cov}_t[r_{j,t+1}, v_{2,t+1}] + \delta_{j,1} v_{1,t+1} + \delta_{j,2} v_{2,t+1} + \eta_{j,t+1}. \quad (6)$$

Here, p_1 and p_2 are (possibly negative) constant risk prices. $v_{1,t+1}$ and $v_{2,t+1}$ are mean-zero priced market risk factors, assumed to be lognormally distributed with

regime-dependent covariance matrices Σ_A and Σ_N , where

$$\Sigma_A = \begin{bmatrix} \sigma_{1,A}^2 & \sigma_{12,A} \\ \sigma_{12,A} & \sigma_{2,A}^2 \end{bmatrix}, \quad (7)$$

and so on. $\delta_{j,1}$ and $\delta_{j,2}$ are factor loadings that are independent of the regime, and $\eta_{j,t+1}$ is an asset-specific shock orthogonal to the factors. For example, in the Campbell and Vuolteenaho (2004) model, the two factors correspond to cash flow and discount rate news; in the Savor and Wilson (2013) model, to news about current and expected future log aggregate dividend growth. The assumption that the factor loadings are constant still allows for changing factor betas. For example, in regime g , asset j 's covariance with the first factor is $\delta_{j,1} \sigma_{1,g}^2 + \delta_{j,2} \sigma_{12,g}$, which varies with Σ_g . Finally, we are implicitly assuming that we can identify the two regimes by equating them with our a-day and n-day subsamples.

The maintained hypothesis is that the firm-specific shocks aggregate out at the level of the market return to zero. The assumption of lognormal factor innovations also rules out rare event-type models, in which some event with a very low probability commands a high risk price. Although possible, such models are problematic because they are very difficult to test. Furthermore, the average a-day market return during the recent financial crisis was robustly positive.

We present most of our formal argument in the Appendix and provide only a summary here. First, we can rule out two uninteresting special cases because they each have counterfactual implications. Second, we show that for all the remaining cases any test assets whose market beta is invariant to regime must have identical factor exposures. That is,

$$\beta_{j,A} = \beta_{j,N} \equiv \beta_j \Rightarrow \delta_{j,1} = \delta_{j,2} = \beta_j. \quad (8)$$

Such an asset must then obey the CAPM in each regime:

$$r p_j^g = \beta_j r p_{MKT}^g. \quad (9)$$

So this asset should follow a time-aggregated CAPM, as argued above, and we know this is not the case.

Not only do some of our test assets have nearly identical betas in each regime (and do not obey this restriction, as we show), but we can also construct linear combinations of all pairs of test assets such that these linear combinations have identical betas in each regime. All such combinations of test assets should then satisfy the CAPM in each regime, for any two-factor model of the kind we assume. Fig. 13 plots realized average excess returns against betas for such identical-beta pairs for the 45 combinations of our ten beta-sorted portfolios. (Some of these combinations involve extreme long-short positions in the underlying beta-sorted portfolios, so the resulting average returns are also somewhat extreme.) The a-day portfolios all lie close to a strongly upward-sloping line, consistent with the CAPM, and the n-day risk premia lie on a U-shaped curve that is high for low (negative) beta combinations, much lower for medium-beta combinations, and high again for the high-beta combinations.

⁷ We also show that the average SML intercept and slope coefficients are correct (the average intercept estimate is zero and the average slope estimate equals the market risk premium) and that estimates are as likely to be too high as too low, both of which help validate our simulation.

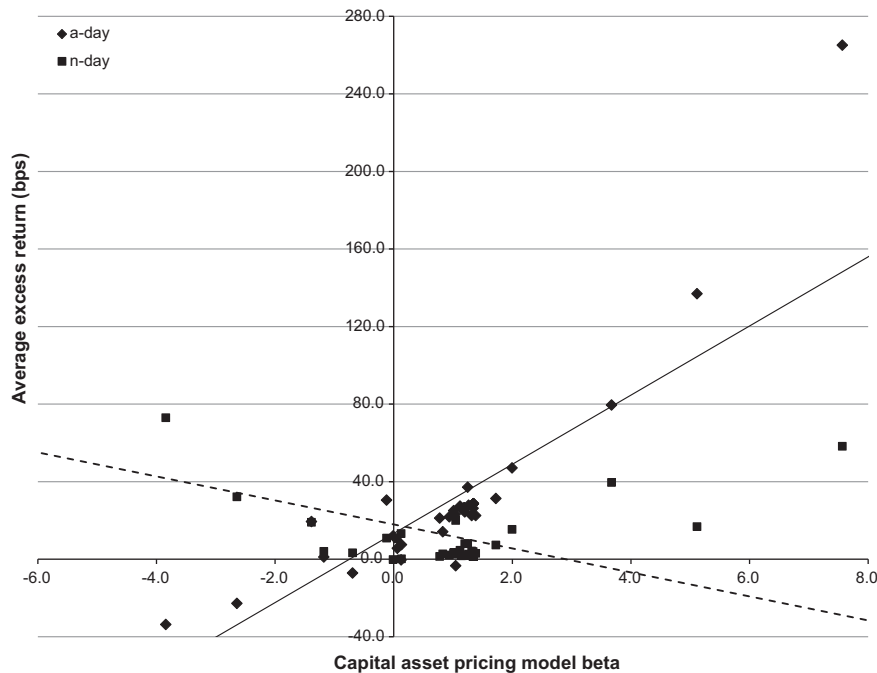


Fig. 13. Average excess returns for 45 constant-beta portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for all 45 pairwise combinations of the ten beta-sorted portfolios separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. For each of the ten beta-sorted portfolios, we estimate a separate a-day and n-day market beta over the full sample of 1964–2011, and then construct all 45 pairwise linear combinations of the ten having the same implied market beta on both types of day. This implied beta is the beta reported on the x-axis.

We also show more formally that the positive relation between beta and returns holds exclusively on announcement days. First, for average returns (shown in Fig. 13) we estimate a slope coefficient of 17.8 bps (t -statistic=9.1) on a-days, versus a negative slope coefficient on n-days of -6.2 bps (t -statistic= -3.2). We also run Fama-MacBeth regressions and compute a slope coefficient of 8.6 bps (t -statistic=2.1) on a-days, versus a slope of -1.9 bps (t -statistic= -1.25) on n-days. These patterns are clearly inconsistent with the CAPM on n-days even for these identical beta combinations. Consequently, given the reasoning above and the formal arguments in the Appendix, we can rule out all such two-factor models.

As in our previous discussion of the CAPM, we consider the possibility that the failure of a two-factor model could be due to estimation uncertainty. We again run simulations to address this issue, although the parameter choices are somewhat less obvious given that no unconditional two-factor model can match our estimates of both market betas and test asset risk premia across types of day. Specifically, we evaluate how often the best fit of a two-factor model, chosen to match market risk premia and variances across regimes, could imply betas that vary little across regimes and, at the same time, estimate a strongly positive slope coefficient on a-days but a mildly negative slope coefficient on n-days.

We find that models chosen to match observed betas across both types of day always imply parameter values that would result in the CAPM holding on n-days (contrary to our results). Because we estimate risk premia with

uncertainty, and our simulations help us evaluate that uncertainty, we find that in our simulated data we can still falsely reject the CAPM on n-days, while correctly failing to reject it on a-days up to 12.8% of the time. However, in the same simulations, our pseudo-estimates of the SML slopes for such models are both negative on n-days and positive on a-days at most 7.9% of the time. (Models chosen to match other moments can sometimes achieve these twin implications more often, but then imply very different betas across regimes or levels of beta that are completely at odds with the data.) In these cases, the models propose the presence of a hard-to-detect a-day factor with a very high risk price and low variance. We conclude that it is therefore possible, but not likely, that our results are consistent with a two-factor model in the presence of estimation uncertainty.

4.1.3. Three- (and more) factor models

Another possibility is that a third priced factor is present on a-days and largely absent on n-days and that this factor can explain the different cross sections of average returns. Without further moment restrictions, we cannot fit such models using only a-day and n-day average returns and market betas. Because only one factor appears to matter on a-days, we cannot allocate average returns between the remaining two factors on n-days. (As argued above, we can already reject all models with fewer than three factors.) We also cannot fit conditional two-factor models with time-varying factor loadings, as

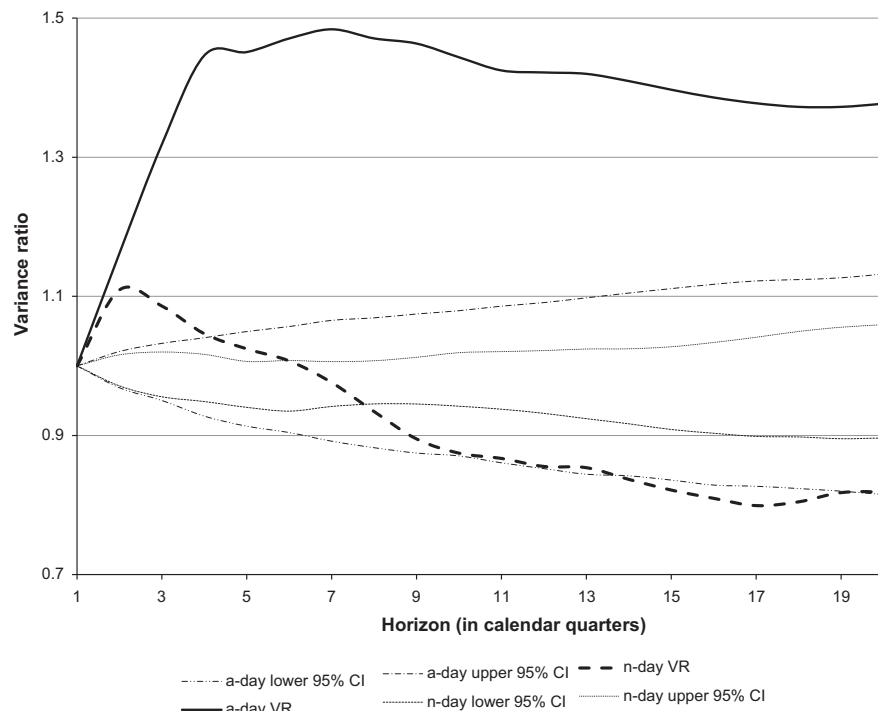


Fig. 14. Variance ratio (VR) of market returns. This figure plots n -quarter variance ratios of daily log excess market returns separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and nonannouncement days or n-days (all other days), for a horizon of 1–20 quarters. The n -quarter variance ratio is the variance of daily returns over n -quarters divided by n times the one-quarter variance. Bootstrapped 95% upper and lower confidence intervals (CIs) for independent and identically distributed returns (ratios of one for all n) are reported as dotted lines. The sample covers the 1964–2011 period.

one can rewrite such models as unconditional three- or four-factor models with constant loadings.

A strong potential candidate for a third factor is news about future market variance, which would not affect market betas (holding the nature of discount rate news constant) across each type of day. [Bansal, Kiku, Shaliastovich, and Yaron \(2013\)](#) propose such a model, as do [Campbell, Giglio, Polk, and Turley \(2012\)](#). These models imply a high risk premium for assets whose returns comove negatively with news about future aggregate risk. If a-days are the main periods during which investors learn about future aggregate risk, then in principle such a factor could explain both the higher announcement-day risk premia across assets, the single factor structure of such returns on a-days, and the similarity of betas across each type of day.

However, such models generally imply a higher relative risk premium for value stocks, as these stocks are found to have a higher exposure to variance news (a more negative or less positive sensitivity to variance innovations), which is contrary to our results on a-day performance of value and growth stocks. Furthermore, in unreported results we adapt the method of [Campbell, Giglio, Polk, and Turley \(2012\)](#) to estimate variance news betas for our test assets separately for a-days and n-days, and we find the same pattern on both types of day: all portfolios have positive variance news betas, and growth stocks have higher such betas than value stocks. This greater positive co-skewness for growth stocks makes them less risky than value stocks

on a-days as well as n-days and, therefore, cannot explain their relative outperformance on a-days.

Although we cannot rule out all three-factor models as we can two-factor models, our results still pose a strong challenge to such models. Any multifactor model has to explain why risk premia change while betas do not. For two-factor models, we argue that this is impossible, but even for models with more than two factors, we conjecture that it will be difficult to provide a fundamental economic argument as to why betas do not change, while return patterns look very different.

4.2. Explanations

In the remainder of this section, we briefly discuss some possible avenues for future research that could shed further light on this “tale of two days” puzzle. We begin by considering the possibility that returns on n-days contain a common noise factor: a common factor to asset returns that is not priced and is not related to fundamentals (see, e.g., [De Long, Shleifer, Summers, and Waldmann, 1990](#)). We use the term “noise” here in the sense of mispricing. In other words, in the absence of limits to arbitrage, we consider the possibility that certain securities exhibit predictably positive or negative abnormal (risk-adjusted) returns. In the previous subsection, we were interested only in arbitrage-free prices driven by factor models. Thus, given a stochastic discount factor M_{t+1} , in [Section 4.1](#) we consider models in which expected excess returns (or their

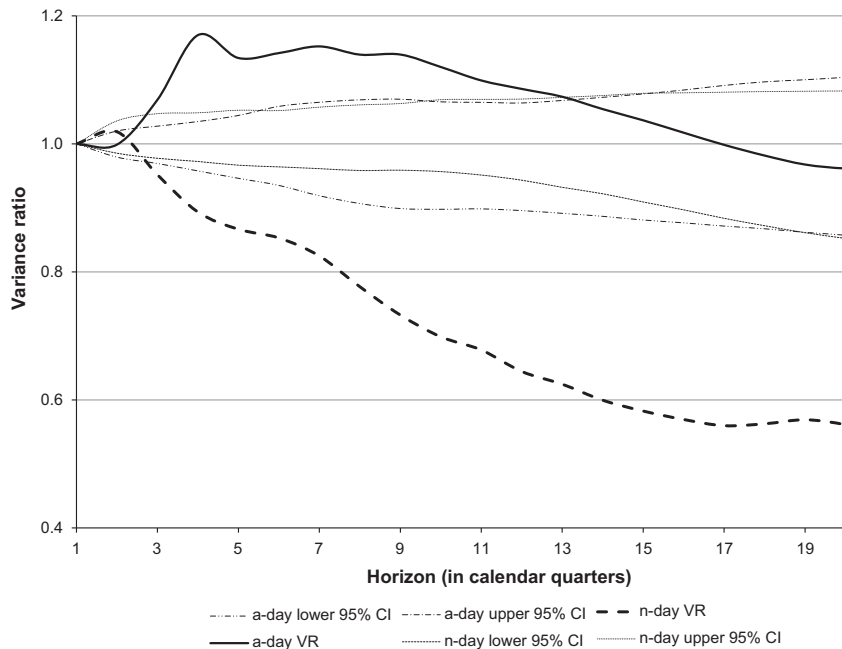


Fig. 15. Variance ratio (VR) of market return residuals. This figure plots n -quarter variance ratios of daily log excess market return residuals (from the vector autoregression reported in Table 7, Panel B) separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days), for a horizon of 1–20 quarters. The n -quarter variance ratio is the variance of daily return residuals over n -quarters divided by n times the one-quarter variance. Bootstrapped 95% upper and lower confidence intervals (CIs) for independent and identically distributed return residuals (ratios of one for all n) are reported as dotted lines. The sample covers the 1964–2011 period.

logs) satisfy

$$E_t[R_{j,t+1} - R_{f,t+1}] = -\text{Cov}_t[R_{j,t+1}, M_{t+1}], \quad (10)$$

whereas in this subsection we discuss theories in which this equality does not necessarily always hold, at least on n-days.

Assume that such a noise factor is present mainly on n-days (and largely absent on a-days) and that the market and growth stocks are more highly exposed to it than value stocks. Assume also that on a-days investors learn about important state variables, to which long-term bonds, the market, and growth stocks are highly exposed, and the news on other days is mostly about current earnings and consumption (plus noise). Then many of our stylized facts can follow. Growth stocks should display high market betas on both days, and value stocks would display low market betas on both days (because of their relative exposures to the noise factor). Growth stocks should earn low risk premia on n-days (if most of their market risk is unpriced noise risk) and much higher risk premia on a-days, and their betas can be somewhat lower on a-days because of the absence of the noise factor. All stocks should earn higher risk premia on a-days than on n-days, but in the cross section those most highly exposed to state variable news should outperform other stocks on a-days. Finally, market variance (as a proxy for risk) on a-days could be much more informative about fundamental risk than market variance on n-days, but forecast only future a-day returns because n-day returns are noisy. These claims need a model to evaluate them, and this is a direction for future research.

Consistent with this general idea, Savor and Wilson (2013) find that a-day market returns, at least since the early 1980s, exhibit significant ability to forecast future consumption growth, whereas n-day returns have no such predictive power. We also show that n-day market returns exhibit long-run reversal in a manner that seems consistent with noisy n-day returns. A-day returns exhibit no detectable reversal at horizons of up to five years.

Fig. 14 plots the variance ratios of a-day and n-day returns separately for horizons up to 20 quarters. Specifically, for returns on each type of day, we calculate the quarterly variance of daily returns over the full sample. This forms the denominator of the variance ratio. Then we calculate the N -quarter variance of daily returns for $N = 1$ –20 quarters, and these estimates, divided by N , form the numerators of the two variance ratios. We plot the implied variance ratios from horizons of one (when the ratios by construction equal one) to 20. If returns are independently and identically distributed (i.i.d.), each series should plot as a horizontal flat line. In fact, the a-day variance ratio rises at first, up to horizons of about four quarters, and at longer horizons remains roughly around its peak. This behavior implies positive serial correlation in a-day returns, perhaps due to the strong risk–return trade-off for a-day returns shown in the previous section (because the conditional variance itself is positively serially correlated).

The figure also plots 95% confidence intervals for each type of variance ratio calculated using simulations, under the null that each series is i.i.d. with its actual mean and variance. Because a-day returns are slightly more volatile,

the confidence interval for a-day returns variance ratios is somewhat wider, as shown by the upper and lower dotted lines in Fig. 14. However, the actual variance ratios for a-day returns still all lie above the upper confidence interval, confirming that a-day returns are positively autocorrelated.

By contrast, the variance ratios for n-day returns decline over the horizon, to around 0.8 at 20 quarters, and lie below the lower 95% confidence interval for i.i.d. returns at horizons beyond eight quarters. These findings imply long-term reversal of n-day returns. Combined with the finding of no reversal for a-day returns, the results are consistent with noise in n-day returns and its absence on a-days.

The positive autocorrelation in returns evidenced at shorter horizons is substantially reduced if we carry out the same variance ratio exercise for the residuals from our VAR in Table 7. Fig. 15 charts the variance ratios for these residuals, together with the bootstrapped 95% confidence intervals for a-day and n-day variance ratio functions separately, using the null that the residuals are i.i.d. (The bootstrap methodology accounts for the many fewer a-days in the sample period.)

The variance ratio for a-day returns rises from 1 to only 1.17 after four quarters and then gradually declines back to 1. For n-day returns, no positive autocorrelation exists even at short horizons, and the reversal begins immediately and continues all the way to 20 quarters. The a-day variance ratio function lies inside the 95% confidence interval for i.i.d. returns after the first 13 quarters. Thus, we are unable to reject the hypothesis that the variance of 3.5-year or longer-term a-day unexpected returns is just the variance of the quarterly unexpected return times the period length. By contrast, we can reject such a claim for n-day returns for any window longer than three quarters. There exists a definite reversal in n-day returns, which increases with the horizon up to at least five years. The variance of five-year unexpected returns is little more than half the variance of quarterly unexpected n-day returns times 20, and it is both economically and statistically very different from the variance ratio implied by i.i.d. n-day returns. Therefore, for both returns and even more for unexpected returns, the evidence suggests that a-day returns are i.i.d. in the longer run (and positively autocorrelated at shorter horizons), while n-day returns display strong reversals, consistent with a hypothesis of much higher degree of noise in n-day returns.

Not only do these results indicate further important differences between the two types of returns, but they could also explain why previous tests failed to establish strong evidence of return reversal at longer horizons.⁸ First, the definite reversal on n-days is mingled with a lack of reversal on a-days. Second, a strong positive autocorrelation of a-day returns exists due to the serial correlation of expected variance and the very strong risk–return

trade-off on a-days. Both these effects mask the high level of reversal in n-day return residuals.

Why would n-day market returns contain an unpriced noise factor? One possibility is that the stock market is not a good proxy for aggregate wealth and that there exists a nonsystematic component to stock market returns.⁹ However, the news that emerges on a-days affects all risky assets, including non-stock market assets, so there is likely no such nonsystematic component on a-days (or its relative importance is lower).

The existence of such a noise factor need not necessarily be evidence of investor irrationality. For example, Veronesi (1999) considers an economy in which investors are uncertain about the value of the conditional mean growth rate of consumption and update using a noisy independent signal. Veronesi (1999) shows that the volatility of market returns can be either increasing or decreasing in the noise of the signal, that it will generally be higher on average when the signal is more precise, and that the effect on the risk–return trade-off is ambiguous. Brevik and d'Addona (2010) incorporate Epstein–Zin preferences into the same setup and show that the result on the risk premium also becomes ambiguous. It seems plausible that these models could be used to generate noise in n-day returns, employing the idea that an announcement represents a more precise independent signal (and thus be consistent with our findings). To our knowledge, however, these ideas have not been extended to multiple risky assets.¹⁰

Finally, the nature of n-day versus a-day information could be such that disagreement about growth in aggregate variables (earnings, consumption, etc.) is lower on a-days. As hypothesized, for example, by Hong and Sraer (2012), in the presence of limits to arbitrage and disagreement about aggregate growth, higher-beta assets are more likely to be overvalued, which is consistent with our n-day results. On a-days, the CAPM should then work to the extent that disagreement is absent on these days. By construction, betas are the same on both types of day. Inasmuch as disagreement induces overvaluation, in a dynamic model it also ought to induce reversal, and so an additional implication of this model is that reversal should be much stronger for the systematic component of n-day returns than for a-day returns, consistent with what we show in Figs. 14 and 15.

Other possible explanations surely exist for our results, but the standard for future asset pricing theories should require them to match the cross section of average returns and market betas across both announcement and non-announcement days. First, a-days matter because for many

⁹ Pollet and Wilson (2010), without considering the distinction between a-days and n-days, use this idea to show that average correlation, not market variance, should be a good predictor of future market returns.

¹⁰ Pastor and Veronesi (2006) use a related idea of learning about productivity to explain the high valuations attributed to technology stocks during the technology boom of the 1990s. Savor and Wilson (2014) show that imprecise signals of aggregate earnings growth can rationalize the otherwise puzzling earnings announcement premium (Beaver, 1968; Chari, Jagannathan and Ofer, 1988; Ball and Kothari, 1991; Cohen, Dey, Lys, and Sunder, 2007; Frazzini and Lamont, 2007).

⁸ See Lo and MacKinlay (1989) or Campbell, Lo, and MacKinlay (1996, Chapter 2). For a more recent discussion, see Pastor and Stambaugh (2012).

risky assets, including the aggregate stock market and government bonds, a-day returns account for a large fraction of cumulative returns. Second, a-days matter because a clear link between macroeconomic risk and asset returns exists on those days. Third, n-days matter because they constitute the great majority of trading days in a given year. A good theory should explain both what happens most of the time and where the majority of cumulative returns come from.

5. Conclusion

We find strong evidence that stock market beta is positively related to average returns on days when employment, inflation, and interest rate news is scheduled to be announced. By contrast, beta is unrelated or even negatively related to average returns on non-announcement days. The announcement-day relation between beta and expected returns holds for individual stocks, various test portfolios, and even nonequity assets such as bonds and currency portfolios. Small stocks, growth stocks, high-beta stocks, the stock market itself, and long-term bonds earn almost all of their annual excess return on announcement days. These results suggest that beta represents an important measure of systematic risk. At times when investors expect to learn important information about the economy, they demand higher returns to hold higher-beta assets.

We also show that a stable and robust market risk–return trade-off exists but is confined to announcement-day

returns. It remains to supply the fundamental economic explanation as to why our findings hold. Such an explanation must be consistent with the relatively high average non-announcement-day returns of value stocks over growth stocks and the similarity in market betas of most test assets for each type of day. We intend to address these issues in future work. One potential explanation is that announcement-day returns provide a much clearer signal of aggregate risk and expected future market returns, perhaps as a result of reduced noise or disagreement on announcement days.

Appendix A. Implications for two-factor models

We claim that our results rule out all unconditional two-factor models that satisfy two requirements: First, both factors are conditionally lognormally distributed (at least approximately), with the distribution depending only on whether the day is an a-day or an n-day; and second, the two factors add up to the market return shock. Our argument proceeds by assuming that such a model is true and then deriving an implication of all such models that we can demonstrate to be false in the data. Recall Eq. (6) in Section 4:

$$r_{j,t+1} - r_{f,t+1} + 0.5 \text{Var}_t[r_{j,t+1}] = p_1 \text{Cov}_t[r_{j,t+1}, v_{1,t+1}] + p_2 \text{Cov}_t[r_{j,t+1}, v_{2,t+1}] + \delta_{j,1} v_{1,t+1} + \delta_{j,2} v_{2,t+1} + \eta_{j,t+1}.$$

The variance of factor 1's innovation is given by $\sigma_{1,A}^2$ in the a-day regime and by $\sigma_{1,N}^2$ in the n-day regime. Generically we write this as $\sigma_{1,t}^2$. The variance of factor

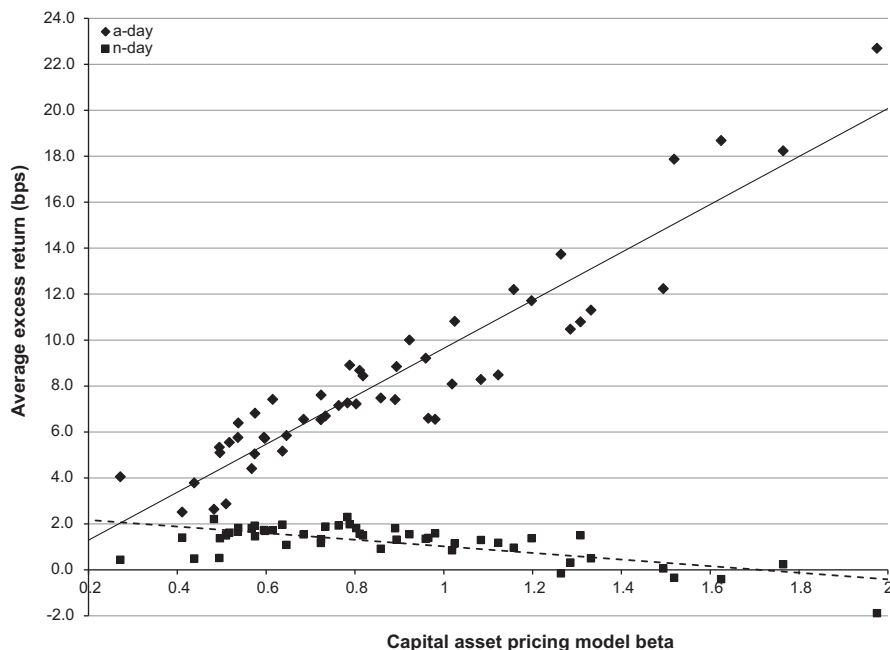


Fig. A1. Average excess returns for 50 beta-sorted portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for 50 beta-sorted portfolios of all NYSE, Amex, and Nasdaq stocks separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample market beta is also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

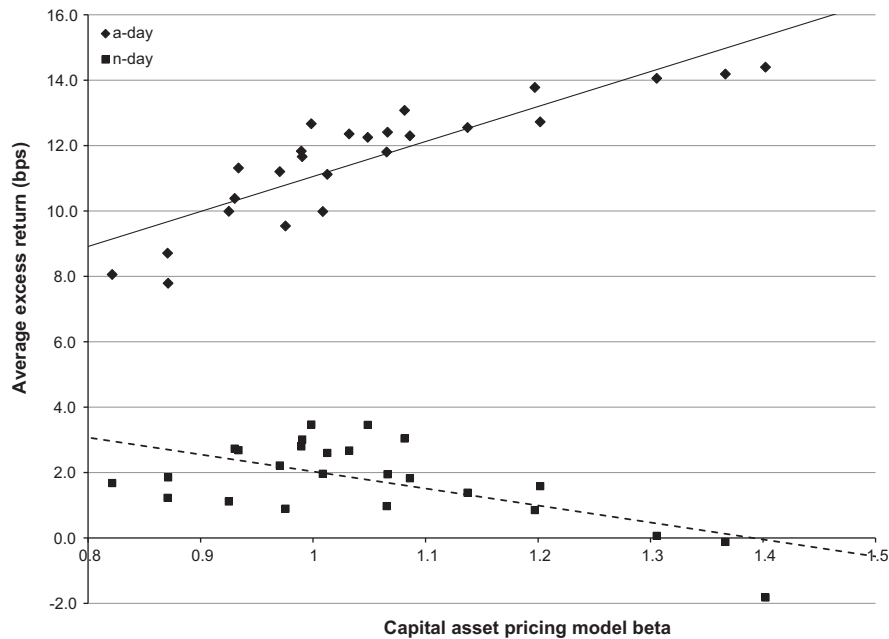


Fig. A2. Average excess returns for 25 Fama and French portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for the 25 Fama and French size- and book-to-market-sorted portfolios separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

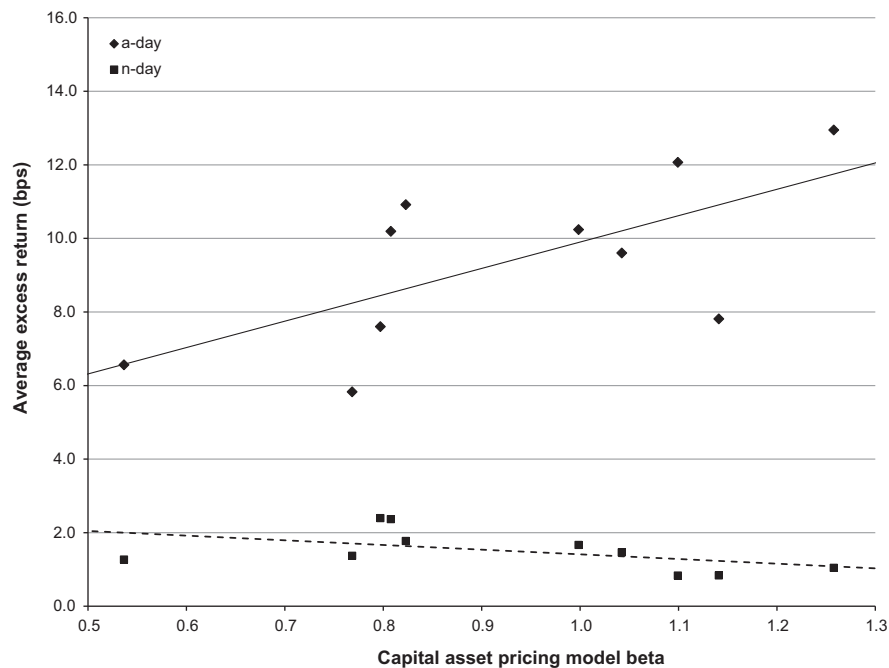


Fig. A3. Average excess returns for ten industry portfolios. This figure plots average daily excess returns in basis points (bps) against market betas for ten industry portfolios separately for announcement days or a-days (days on which inflation, employment, or Federal Open Market Committee interest rate decisions are scheduled to be announced) and non-announcement days or n-days (all other days). The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

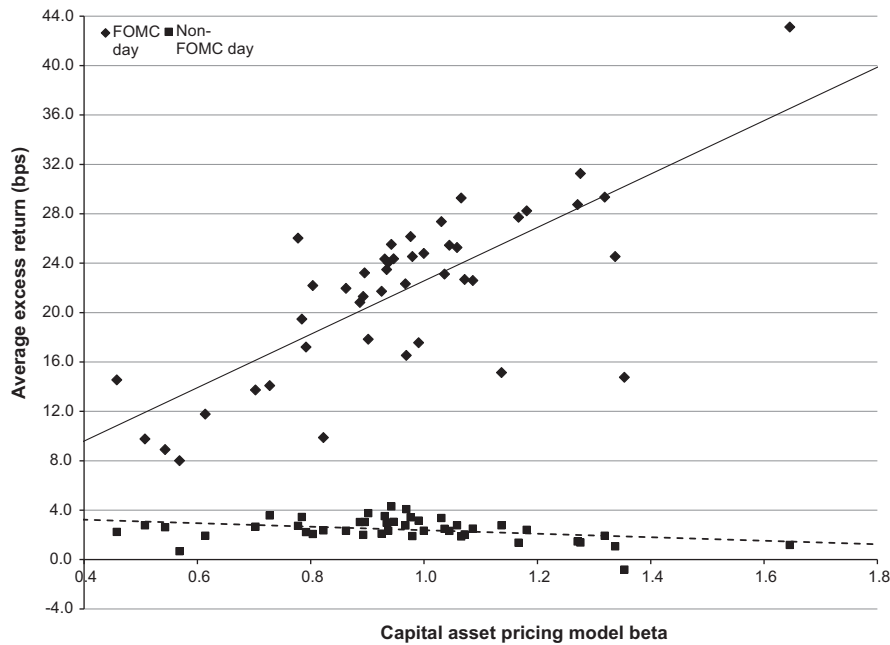


Fig. A4. Average excess returns for ten beta-sorted, 25 Fama and French, and ten industry portfolios on Federal Open Market Committee (FOMC) days. This figure plots average daily excess returns in basis points (bps) against market betas for ten beta-sorted portfolios, 25 Fama and French size and book-to-market-sorted portfolios, and ten industry portfolios separately for FOMC days (days on which FOMC interest rate decisions are scheduled to be announced) and all other days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1978–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

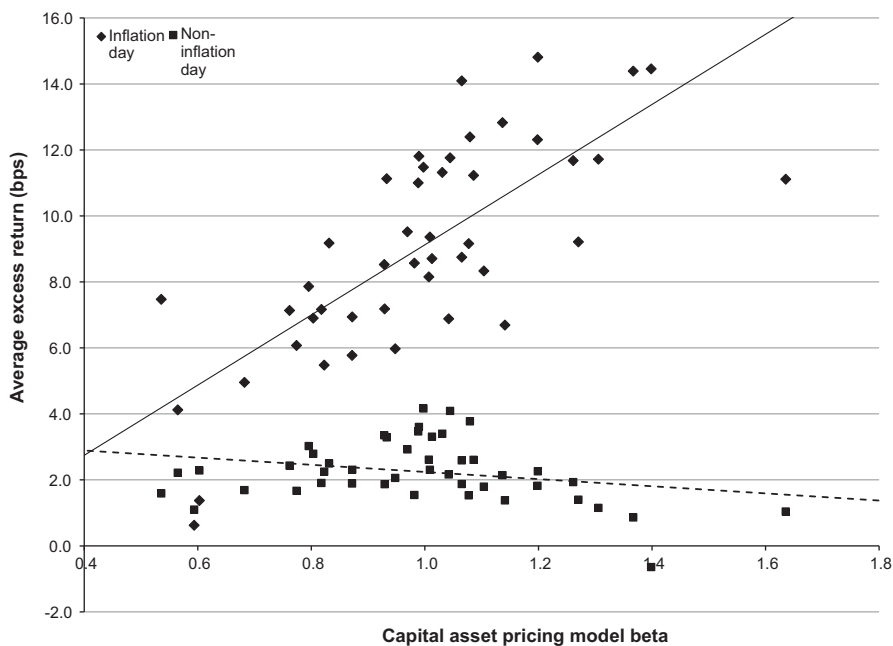


Fig. A5. Average excess returns for ten beta-sorted, 25 Fama and French, and ten industry portfolios on inflation days. This figure plots average daily excess returns in basis points (bps) against market betas for ten beta-sorted portfolios, 25 Fama and French size- and book-to-market-sorted portfolios, and ten industry portfolios separately for inflation days (days on which inflation numbers are scheduled to be announced) and all other days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

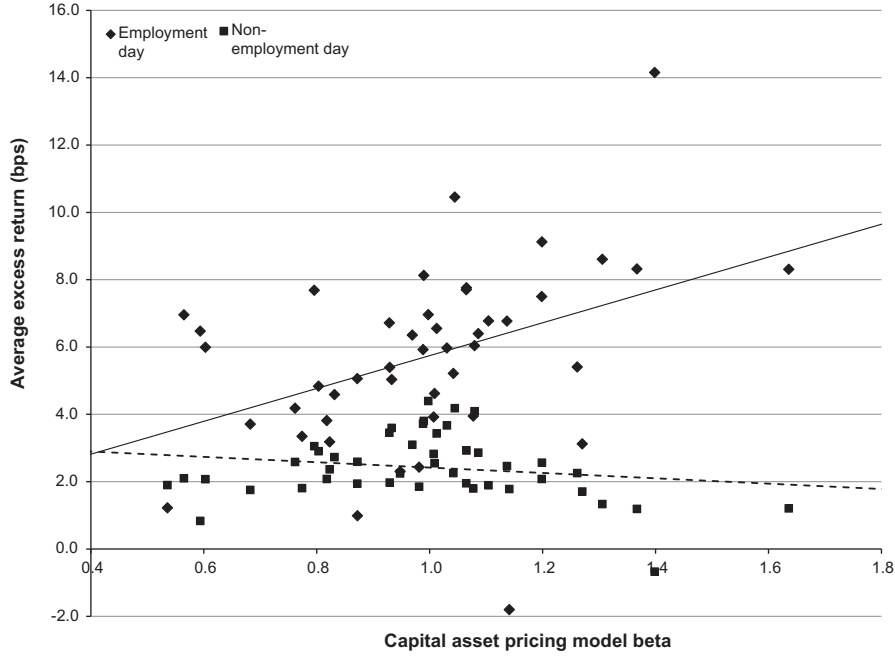


Fig. A6. Average excess returns for ten beta-sorted, 25 Fama and French, and ten industry portfolios on employment days. This figure plots average daily excess returns in basis points (bps) against market betas for ten beta-sorted portfolios, 25 Fama and French size- and book-to-market-sorted portfolios, and ten industry portfolios separately for employment days (days on which employment numbers are scheduled to be announced) and all other days. The implied ordinary least squares estimates of the securities market line for each type of day are also plotted. The sample covers the 1964–2011 period. For each test portfolio, the same estimate of its full-sample beta is used for both types of day.

2's innovation is then $\sigma_{2,t}^2$ and its covariance is $\sigma_{12,t}$. The other parameters are defined in Section 4. Our claim is that Eq. (8) follows, in which case we can derive the counterfactual predictions discussed in Section 4.

The test assets' market betas in each regime are derived from Eq. (6)

$$\begin{aligned}\beta_{j,t} &= \frac{\text{Cov}_t[r_{j,t+1}, r_{M,t+1}]}{\text{Var}_t[r_{M,t+1}]} = \frac{\text{Cov}_t[\delta_{j,1}v_{1,t+1} + \delta_{j,2}v_{2,t+1}, v_{1,t+1} + v_{2,t+1}]}{\text{Var}_t[v_{1,t+1} + v_{2,t+1}]} \\ &= \frac{\delta_{j,1}(\sigma_{1,t}^2 + \sigma_{12,t}) + \delta_{j,2}(\sigma_{2,t}^2 + \sigma_{12,t})}{(\sigma_{1,t}^2 + \sigma_{12,t}) + (\sigma_{2,t}^2 + \sigma_{12,t})},\end{aligned}\quad (11)$$

and market variance in each regime is given by

$$\sigma_{M,t}^2 = (\sigma_{1,t}^2 + \sigma_{12,t}) + (\sigma_{2,t}^2 + \sigma_{12,t}). \quad (12)$$

Risk premia in each regime equal

$$\begin{aligned}rp_{j,t} &= p_1 \text{Cov}_t[r_{j,t+1}, v_{1,t+1}] + p_2 \text{Cov}_t[r_{j,t+1}, v_{2,t+1}] \\ &= p_1 \text{Cov}_t[\delta_{j,1}v_{1,t+1} + \delta_{j,2}v_{2,t+1}, v_{1,t+1}] + p_2 \text{Cov}_t[\delta_{j,1}v_{1,t+1} \\ &\quad + \delta_{j,2}v_{2,t+1}, v_{2,t+1}] \\ &= p_1(\delta_{j,1}\sigma_{1,t}^2 + \delta_{j,2}\sigma_{12,t}) + p_2(\delta_{j,2}\sigma_{2,t}^2 + \delta_{j,1}\sigma_{12,t})\end{aligned}\quad (13)$$

so that in particular the market risk premium is given by

$$rp_{M,t} = p_1(\sigma_{1,t}^2 + \sigma_{12,t}) + p_2(\sigma_{2,t}^2 + \sigma_{12,t}). \quad (14)$$

Our model nests the special case of a one-factor model with regime-dependent market betas. It does not nest models with two factors and regime-dependent factor exposures, as these can be rewritten as three- or four-factor models with constant exposures. Also, it cannot be the case that $p_1 = p_2$, because that would imply $rp_{M,t} = p_1\sigma_{M,t}^2$, which

is contrary to what the data suggest. Savor and Wilson (2013) show that the ratio of the a-day risk premium to a-day market variance is an order of magnitude greater than the corresponding n-day ratio. Consequently, $p_1 \neq p_2$.

For what follows, we need to establish that

$$(\sigma_{1,A}^2 + \sigma_{12,A})(\sigma_{2,N}^2 + \sigma_{12,N}) \neq (\sigma_{1,N}^2 + \sigma_{12,N})(\sigma_{2,A}^2 + \sigma_{12,A}). \quad (15)$$

We assume that this inequality does not hold and then show that this assumption implies a contradiction. Plugging our expressions for market variance from Eq. (12) into the resulting equality gives

$$\begin{aligned}(\sigma_{MA}^2 - (\sigma_{2,A}^2 + \sigma_{12,A}))(\sigma_{2,N}^2 + \sigma_{12,N}) \\ = (\sigma_{MN}^2 - (\sigma_{2,N}^2 + \sigma_{12,N}))(\sigma_{2,A}^2 + \sigma_{12,A}).\end{aligned}\quad (16)$$

Rearranging gives

$$(\sigma_{2,A}^2 + \sigma_{12,A}) = \frac{\sigma_{MA}^2}{\sigma_{MN}^2}(\sigma_{2,N}^2 + \sigma_{12,N}). \quad (17)$$

Now plugging Eq. (17) into the expression for the market risk premium, Eq. (14) gives

$$rp_{MA} = p_1 \left(\sigma_{MA}^2 - \frac{\sigma_{MA}^2}{\sigma_{MN}^2}(\sigma_{2,N}^2 + \sigma_{12,N}) \right) + p_2 \frac{\sigma_{MA}^2}{\sigma_{MN}^2}(\sigma_{2,N}^2 + \sigma_{12,N}) \quad (18)$$

and

$$rp_{MN} = p_1(\sigma_{MN}^2 - (\sigma_{2,N}^2 + \sigma_{12,N})) + p_2(\sigma_{2,N}^2 + \sigma_{12,N}). \quad (19)$$

Eq. (19), for the n-day market risk premium, then implies that (recall that $p_1 \neq p_2$)

$$(\sigma_{2,N}^2 + \sigma_{12,N}) = \frac{rp_{M,N} - p_1 \sigma_{M,N}^2}{p_2 - p_1} \quad (20)$$

and plugging Eq. (20) into Eq. (14) for the a-day market risk premium implies

$$\begin{aligned} rp_{M,A} &= p_1 \left(\sigma_{M,A}^2 - \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} \left(\frac{rp_{M,N} - p_1 \sigma_{M,N}^2}{p_2 - p_1} \right) \right) + p_2 \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} \left(\frac{rp_{M,N} - p_1 \sigma_{M,N}^2}{p_2 - p_1} \right) \\ &= p_1 \sigma_{M,A}^2 + (p_2 - p_1) \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} \left(\frac{rp_{M,N} - p_1 \sigma_{M,N}^2}{p_2 - p_1} \right) \\ &= p_1 \sigma_{M,A}^2 + \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} rp_{M,N} - p_1 \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} \sigma_{M,N}^2 \\ &= \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2} rp_{M,N}. \end{aligned} \quad (21)$$

Thus, for the inequality in Eq. (15) not to hold, the a-day market risk premium must equal the ratio of the a-day market variance to the n-day market variance times the n-day market risk premium. But Savor and Wilson (2013) show that this is definitely not the case: the a-day market variance is only marginally higher than the n-day variance, while the risk premium is ten times higher. Therefore, the inequality in Eq. (15) must hold. Intuitively, the factor covariance matrices must vary across days in a way that is not simply equivalent to an increase in market variance, because we do not observe any such increase.

But if factor variances and covariances must vary across regimes in this way, then, given the above expressions for market betas, we have the implication that for any two-factor model of this kind any asset with identical a-day and n-day betas must have

$$\begin{aligned} \beta_{j,A} &= \frac{\delta_{j,1}(\sigma_{1,A}^2 + \sigma_{12,A}) + \delta_{j,2}(\sigma_{2,A}^2 + \sigma_{12,A})}{(\sigma_{1,A}^2 + \sigma_{12,A}) + (\sigma_{2,A}^2 + \sigma_{12,A})} \\ &= \frac{\delta_{j,1}(\sigma_{1,N}^2 + \sigma_{12,N}) + \delta_{j,2}(\sigma_{2,N}^2 + \sigma_{12,N})}{(\sigma_{1,N}^2 + \sigma_{12,N}) + (\sigma_{2,N}^2 + \sigma_{12,N})} = \beta_{j,N}. \end{aligned} \quad (22)$$

Proof. Rearranging the middle two expressions of Eq. (22) gives

$$\begin{aligned} &(\delta_{j,1}(\sigma_{1,A}^2 + \sigma_{12,A}) + \delta_{j,2}(\sigma_{2,A}^2 + \sigma_{12,A}))((\sigma_{1,N}^2 + \sigma_{12,N}) + (\sigma_{2,N}^2 + \sigma_{12,N})) \\ &= (\delta_{j,1}(\sigma_{1,N}^2 + \sigma_{12,N}) + \delta_{j,2}(\sigma_{2,N}^2 + \sigma_{12,N}))((\sigma_{1,A}^2 + \sigma_{12,A}) + (\sigma_{2,A}^2 + \sigma_{12,A})) \\ &\Leftrightarrow \delta_{j,1}((\sigma_{1,A}^2 + \sigma_{12,A})(\sigma_{2,N}^2 + \sigma_{12,N}) - (\sigma_{1,N}^2 + \sigma_{12,N})(\sigma_{2,A}^2 + \sigma_{12,A})) \\ &= \delta_{j,2}((\sigma_{1,A}^2 + \sigma_{12,A})(\sigma_{2,N}^2 + \sigma_{12,N}) - (\sigma_{1,N}^2 + \sigma_{12,N})(\sigma_{2,A}^2 + \sigma_{12,A})). \quad \square \end{aligned} \quad (23)$$

Therefore, given the inequality in Eq. (15) (which we proved above), we have for such assets

$$\delta_{j,1} = \delta_{j,2} = \beta_j \quad (24)$$

and so any such asset must have identical factor exposures, as claimed, and Eq. (8) follows.

Intuitively, if factor covariance matrices vary in a way that is not simply equivalent to a change in market variance, any asset that has identical betas across regimes

must have identical exposures to both factors. For example, if cash flow news prevails on n-days, but discount-rate news prevails on a-days, assets with identical market betas on both days must have identical cash flow and discount-rate betas.

But then such an asset has a risk premium given by

$$\begin{aligned} rp_{j,t} &= p_1(\delta_{j,1}\sigma_{1,t}^2 + \delta_{j,1}\sigma_{12,t}) + p_2(\delta_{j,1}\sigma_{2,t}^2 + \delta_{j,1}\sigma_{12,t}) \\ &= \delta_{j,1}rp_{M,t} = \beta_jrp_{M,t}, \end{aligned} \quad (25)$$

and thus its risk premium should satisfy a CAPM in each regime. Furthermore, aggregating daily returns over longer-time periods (for example a month or a quarter) implies that for such assets the CAPM should hold unconditionally at lower frequencies, a hypothesis we can easily reject.

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