Asset Pricing: A Tale of Two Days*

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Abstract

We show that asset prices behave very differently on days when important macroeconomic news is scheduled for announcement relative to other trading days. In addition to significantly higher average returns for risky assets on announcement days, return patterns are also much easier to reconcile with standard asset pricing theories, both cross-sectionally and across 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, in contrast to market or aggregated non-announcement day returns where there is no evidence of predictability. We explore the implications of our findings in the context of various asset pricing models.

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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 documented. In this paper, we show that for an important subset of days stock market beta actually 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 (hereinafter, 'announcement days' or 'a-days'), stock market beta is economically and statistically significantly related to returns on individual stocks. This relation also holds for portfolios containing stocks sorted by their estimated beta, for the 25 Fama-French size and book-to-market portfolios, for industry portfolios, and even for assets other than equities, such as government bonds or currency carry-trade portfolios. The relation between beta and expected returns is still significant controlling for firm size and book-to-market ratio, and also 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 very low or not significantly different from zero, 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 Figure 1. We estimate stock market betas for all stocks using rolling windows of 12 months of daily returns from 1964 to 2011. We then

[1] Seminal early studies include Black, Jensen, and Scholes (1973), Black (1972), Fama and French (1992), and Black (1993). Polk, Thomson, and Vuolteenaho (2005) is a more recent paper.

sort stocks into one of ten beta-decile value-weighted portfolios. Figure 1 plots average realized excess returns for each portfolio against average portfolio betas separately for non-announcement days (blue points and line) and announcement days (red points and line).[2] 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 return of about 1.5 basis points (bps), with a t-statistic for the slope coefficient estimate above three.

[FIGURE 1 ABOUT HERE]

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 return of 10.3 bps. The relation is also very statistically significant, with a t-statistic of over 13. Furthermore, the $\mathrm{R}^2 s$ 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 market beta.

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) (SW) find that in the 1958-2009 period the average excess daily return on a broad index of U.S. stocks is 11.4 bps on announcement days versus 1.1 bps on all other days. The non-announcement day average excess return is actually 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.[3] SW further show that the volatility of announcement day returns is

[2]Note that in Figure 1 the betas for each portfolio are the same on both kinds of days; only the average realized excess returns are different.

[3]Lucca and Moench (2011) confirm these results in the post-1994 period for pre-scheduled FOMC announcements, with the estimated share of the announcement day cumulative return increasing to over 80%

only slightly higher, so that the Sharpe ratio of announcement day returns is an order of magnitude higher.[4] 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 documented on such days is actually 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 much 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.[5] 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 VAR specifications, when we use weighted least squares, and also when we divide our sample into two halves. By contrast, on other days there is no evidence of such predictability, with a coefficient on expected variance that is actually negative and not statistically significant.

Combined with our previous findings on 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

in this more recent period. In the 1964-2011 sample period considered in this paper, the corresponding share is over 70%.

[4]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.

[5]We thank John Campbell, Stefano Giglio, Christopher Polk, and Robert Turley for providing us with their data.

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 there is no such risk-return trade-off on other days.

Our results have an analogue in the research that established potentially puzzling relationships between average returns and stock characteristics.[6] Instead of examining how expected returns vary with stock characteristics, we investigate how stock returns vary with types of information events.[7] 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 public.[8] The challenge for future research is to reconcile the two sets of relationships. 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, there exists a clear link 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 I describes our results on the relation

[6] As early examples of this literature, see Basu (1983), Chan, Chen, and Hsieh (1985), Chan and Chen (1991), and Fama and French (1996).

[7] 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.

[8] 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.

between betas and returns on announcement and non-announcement days; Section II shows evidence on the risk-return trade-off on each type of day; Section III explains why our results are hard to reconcile with several prominent models and discusses avenues for future research that could potentially explain the differences between announcement and non-announcement days; and Section IV 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.

I. Betas on Announcement and Non-announcement Days

I.A. Data and Methodology

We obtain stock and Treasury bond return data from CRSP. Our main stock market proxy is the CRSP NYSE/AMEX/NASDAQ value-weighted index of all listed shares. We obtain returns for the 25 size- and book-to-market-sorted portfolios and the 10 industry portfolios from Kenneth French's website. We estimate a test asset's stock market beta (and other factor betas) over rolling one-year windows using daily returns.[9] 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 SW. Inflation and unemployment announcement dates come from the Bureau of Labor Statistics' website, where they become available starting in 1958. We use Consumer Price Index (CPI) announcements before February 1972 and Producer Price Index (PPI) thereafter (as in SW), since 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's website 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

[9] All our findings remain the same if we instead estimate betas over 5-year periods using monthly returns. They also do not change if we use Scholes-Williams betas.

we employ for stock portfolios sorted on market beta, industry, size, and book-to-market, 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:

$$R^N_{j,t+1} - R^N_{f,t+1} = \gamma^N_0 + \gamma^N_1 \widehat{\beta}_{j,t} \tag{1}$$

and

$$R^A_{j,t+1} - R^A_{f,t+1} = \gamma^A_0 + \gamma^A_1 \widehat{\beta}_{j,t}, \tag{2}$$

where $\widehat{\beta}_{j,t}$ is test asset j's stock market beta for period t (estimated over the previous year using daily returns) from the first-stage regression, $R^N_{j,t+1} - R^N_{f,t+1}$ is the excess return on the test asset on n-days, and $R^A_{j,t+1} - R^A_{f,t+1}$ 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.[10] 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 run separately for announcement and non-announcement days, we also 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:

$$R_{j,t+1} - R_{f,t+1} = \gamma_0 + \gamma_1 \widehat{\beta}_{j,t} + \gamma_2 A_{t+1} + \gamma_3 \widehat{\beta}_{j,t} A_{t+1}, \tag{3}$$

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-

[10] This approach provides standard errors that reflect cross-sectional correlation of the residuals across stocks. We do not correct the standard errors for potential autocorrelations of the cross-sectional estimates, because our analysis indicates those are not significant enough to have a material impact.

sectional correlation of the residuals.

I.B. 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 Panel A, we estimate equations (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 -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%.

[TABLE 1 ABOUT HERE]

The picture is very different on announcement days. The intercept is 1.3 bps and is not significantly different from zero. 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^2s. 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.

The results are similar for equal-weighted portfolios: 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).

In Panel B, we apply a pooling methodology to estimate the difference in the intercept and slope coefficients in a single regression using all days, and obtain the same results as those in Panel A. The regression specification is given by equation (3), and t-statistics are computed using clustered standard errors. For value-weighted portfolios, 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) on n-days, 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, since 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, 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.

Figure 1 plots average realized excess returns for ten beta-sorted portfolios against average portfolio betas separately for non-announcement days and announcement days (discussed in the Introduction).[11] As a robustness check, Figure 2 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 with a t-statistic of 11.7), while the beta coefficient is negative and significant (-1.4 with a t-statistic of -6.5). In contrast, on announcement days the intercept is not significantly different from zero (-0.8 with a t-statistic of -1.5), and the beta coefficient is positive and significant (10.4 with a t-statistic of 18.5), and almost the same as the average

[11] Note that for ease of exposition the x-axis does not always intersect the y-axis at zero in the figures we show.

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.

[FIGURE 2 ABOUT HERE]

One potential worry is that our results are biased by using betas that are not conditioned on the type 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 below, 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, it is the differences in average realized excess returns that drive our findings.

I.C. Book-to-Market and Size, Industry, Bond, and Carry Portfolios

Figure 3 presents analogous results to those in Figures 1 and 2 for the 25 size- and book-to-market-sorted portfolios. For non-announcement day returns, the blue points replicate the standard finding that betas are unable to price these portfolios. In particular, stocks with higher betas have lower average returns. The blue line is the fitted value of equation (1), in which stock market beta is found to command a negative risk premium (-5.2 bps, with a t-statistic of 3.9).

[FIGURE 3 ABOUT HERE]

The red 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 (red) estimate of the announcement-day securities market line has an intercept of 0.4 (t-statistic=0.3) and a slope of 10.7 (t-statistic=8.5), which is very close to the estimated announcement-day stock market risk premium of 10.5 bps. The R^2 equals 75.9%, indicating that most of the variation in average excess returns of the 25 Fama-French portfolios on announcement days is accounted for by their stock market betas.[12]

[12] Market betas do not help explain the cross-section of momentum portfolio returns on either announce-

We further show below 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.

Figure 4 shows the same chart for ten industry portfolios. Once again, the blue points lie around a flat or mildly downward-sloping line with a positive intercept, and we are unable to reject a zero or negative relationship between the stock market beta and average returns, with a slope of -1.3 (t-statistic = -1.6). In contrast, the red points lie closely around an announcement-day SML, whose slope is estimated to equal 7.2 (t-statistic=2.5).

[FIGURE 4 ABOUT HERE]

We next repeat the same analysis for all of our equity portfolios together (ten beta-sorted, 25 Fama-French, and ten industry portfolios). Since the various constituent portfolios are formed according to very different characteristics, this is a very stringent and important test confirming the robustness of our results. Figure 5 provides the beta / average return chart for the 45 test portfolios, while Table 2 reports coefficient estimates for Fama-MacBeth (Panel A) and pooled regressions (Panel B) for these test assets combined.

Figure 5 looks about the same as our previous charts. On n-days, the intercept is positive and significant (3.3 bps with a t-statistic of 5.4), the slope coefficient is negative and significant (-1.7 bps with a t-statistic of -2.9), and the R^2 is 16.2%. On the other hand, on a-days the intercept is not significantly different from zero (-0.4 with a t-statistic of -0.5), the slope coefficient is positive and significant (10.9 bps with a t-statistic of 12.6), and extremely close to the sample average a-day market return, and the R^2 is 78.7%. As before, market betas explain most of the cross-sectional return variation on announcement days, while on non-announcement days they actually predict lower returns for higher-beta assets.

[FIGURE 5 ABOUT HERE]

In Panel A of Table 2, on a-days the implied risk premium is estimated to be 8.7 bps

ment or non-announcement days.

(t-statistic = 2.7), while the n-day slope is negative and insignificant (-1.4 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 Panel B, where the slope on n-days is slightly negative (-1.4, which is 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 quite 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).

[**TABLE 2 ABOUT HERE**]

Figure 6 plots estimates of average excess returns against beta for government bonds with maturities of 1, 5, 7, 10, 20, and 30 years. The blue line shows a completely flat SML indicating a zero relation between beta and average excess returns. In contrast, the red points lie closely around an announcement-day SML, whose slope is estimated to equal 6.2 (t-statistic=4.4) for bonds.[13]

[**FIGURE 6 ABOUT HERE**]

Finally, market betas are positively related to returns even for currency carry-trade portfolios. In Figure 7, we plot the average daily returns to the currency-only component of five carry-trade portfolios (P1 through P5) from November 1983 to December 2011, 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 and 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 covers 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 (2012).[14] 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

[13] The implied risk premium for bonds is biased upward, since SW show that market betas of bonds (unlike our findings for stocks) are significantly higher on announcement days relative to non-announcement days.

[14] We thank Pasquale della Corte for providing us with their data on daily portfolio exchange-rate return components.

returns to the currency carry trade are on average positive.

As shown in Figure 7, while on non-announcement days the standard pattern, where 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 thus negative on n-days but positive on a-days. The difference between a-day and n-day returns is 5.0 bps per day and is statistically significant (t-statistic = 2.2).

Figure 7 plots the average exchange-rate component of returns for the five carry-trade portfolios on the y-axis and their market betas on the x-axis. As before, we find virtually no difference between portfolio betas across different types of day. 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 relationship reverses, and becomes strongly positive, with an economically and statistically significant slope across the five portfolios. Thus, the pattern we previously document in the paper 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 betas earn lower average returns, also consistent with their betas.

[FIGURE 7 ABOUT HERE]

I.D. 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 3, 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 as controls firm size, book-to-market ratio (the two characteristics identified by Fama and French (1992) as helping explain the cross-section of average stock returns), and past one-year return; and in Panels C and D 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 A, we see that 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 Tables 1 and 2, most likely because individual stock betas are estimated with more measurement error than those for portfolios. The size coefficient on a-days remains economically and statistically strongly significant, while the book-to-market one 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: 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 between the dummy and market betas, and are presented in Panel B.

[TABLE 3 ABOUT HERE]

In Panels C and D, we add factor betas as controls instead of firm characteristics. With the Fama-MacBeth approach (Panel C), 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 D).

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

I.E. Large Absolute Returns or Announcement Day Returns?

One possible explanation for our findings is that announcement days may be 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, it may be the case that market betas are 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 returns in the top decile) for the 25 Fama-French portfolios. We find that the relationship between beta and average returns on such days is actually strongly negative, with an implied risk premium of -39.1 bps (t-statistic = -7.5). This implied risk premium is much lower than the average return on large-move days, which equals -10.4 bps. We can thus reject this alternative explanation. Furthermore, SW show that the volatility of market returns is not much greater in magnitude on announcement days. Instead, it is the market Sharpe ratio that is much higher on such days.

[FIGURE 8 ABOUT HERE]

I.F. 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 higher. 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,[15] and that our findings reflect this relation rather than 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 the average, and explore the relation between betas and returns during such periods. Based on prior work, we suggest two candidate periods: the month of January and the turn of the month.[16] Starting with Rozeff and Kinney (1976), a large body of work documents 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. Figures 9 and 10 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. Of course, it could be the case that these phenomena simply represent anomalies or artifacts of the data rather than genuinely higher risk premia, but we ignore this issue for the purposes of our tests.

[**FIGURES 9 AND 10 ABOUT HERE**]

In Figure 11, we show that for the 25 Fama-French portfolios market betas are only very weakly related to average returns during the turn-of-the-month period. The implied risk premium is positive, but it is quite low (1.9 bps relative to the average turn-of-the-month 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 Figure 12, is substantially higher (9.6 bps), but it is not statistically significant (t-statistic = 1.1). Moreover, market betas explain only a very small

[15] As an extreme example, if the risk premium is zero, market betas should obviously not forecast returns.

[16] We thank Ralph Koijen for suggesting the turn-of-the-month effect.

fraction of cross-sectional return variation during that month, with an R^2 of 5.2%.

To sum up, 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.

[**FIGURES 11 AND 12 ABOUT HERE**]

I.G. Average Returns and Cumulative Return Shares

In this section, we compare the average realized excess returns on announcement and non-announcement days. Table 4 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 obvious 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.

[**TABLE 4 ABOUT HERE**]

The second point is that for many test assets the 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 actually outperform the high book-to-market portfolios. The pattern is pretty nearly monotonic except for the extreme value stocks. The factor HML 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 when the market risk premium and Sharpe ratio are much higher.

Furthermore, small firm stocks do not outperform big firm 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 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 part 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 actually 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.

In summary, Table 4 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 SW shows that long-term bonds also earn most of their annual excess returns on announcement days (and 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.

In order to further demonstrate the importance of announcement days for performance of various test assets, in Table 5 we provide the implied shares of cumulative excess returns that are earned on these days. Specifically, we define the share as having a numerator equal to the log mean excess return on a-days times the number of a-days. The denominator is the sum of the log mean excess return on a-days times the number of a-days and the log mean excess return on n-days times the number of n-days. Campbell and Viceira (2002) (chapter 2) note that a buy-and-hold investor maximizing expected CRRA utility of terminal wealth and allocating wealth between a riskless asset and a risky asset should set his share in the risky asset proportional to the log average, and therefore this (rather than the mean excess return) seems the more appropriate measure for such an investor. Our results are quite similar using just mean excess returns.[17]

The first panel of Table 5 shows the shares for the 25 Fama-French size- and book-to-market-sorted portfolios. Small growth has a negative average excess return on n-days and a negative overall excess return (meaning that it underperformed the risk-free asset over the sample period), but a positive (and high) average excess return on a-days. In consequence, the a-day cumulative return is minus 355% of the total cumulative return. Obviously, in cases of negative total excess returns, the magnitude of our measure is not overly meaningful, but the general point is that small growth stocks were a very bad investment, except, crucially, on a-days. The next two small-cap growth portfolios also have negative n-day average excess returns but overall positive excess returns, so the a-day cumulative returns are respectively 187% and 156% of the total return. A-day returns account for the majority of cumulative returns for all portfolios in the lowest two book-to-market quintiles and also for the smallest and largest of the median book-to-market portfolios. The implied share monotonically declines with book-to-market so that value portfolios earn a smaller share of total returns on a-days than growth portfolios, but even small and large value earn 37% and 50% respectively of their cumulative returns on a-days, which account for only 11.3% of trading days.

For beta-sorted portfolios, the share is not monotonic in beta but U-shaped. For the lowest-beta portfolio, the a-day share is 61%, declining to 25% for the third-lowest beta portfolio. It then almost monotonically increases to 49% for the 6th beta portfolio, 48% for the 7th beta portfolio, 87% for the 8th beta portfolio, 155% for the 9th (which has a negative n-day average excess return but positive overall excess return), and an enormous -575% for the highest beta portfolio (which has a negative n-day and overall excess return).

[TABLE 5 ABOUT HERE]

[17] The share of compounded excess returns that is actually earned on a-days is difficult to interpret. For example, an investor borrowing $1 at the risk-free rate to finance a $1 long position in the market at the beginning of 1964, and rolling over every day, would have $143.38 by the end of 2011. If he had done so only on a-days, he would have $5.67, and if only on n-days, $25.30. Both the compounded a-day return and the compounded n-day return are significantly less than the total compounded return, so that the sum of the shares of the total return earned on a- and n-days is much less than one.

The table also reports shares for industry-sorted portfolios, which range from 31% for non-durables to 101% for high-technology firms and 106% for durables. The share of market returns earned on a-days implied by our estimates is 74%.

Taken together the numbers show that for all test assets a significant fraction of their total return is earned on a-days, which constitute just 11.3% of the sample. The lowest fraction is 25% for the third-lowest beta decile portfolio, followed by 31% for non-durables. For all other portfolios, at least one third of their total returns are earned on a-days. For about half of the test assets, the majority of returns are earned on a-days, and for the market, growth stocks, high-beta stocks, and stocks in cyclical industries an overwhelming majority is earned on a-days.

I.H. 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 may be biased by this approach, where betas are not conditioned on the type of day. For example, different a-day and n-day betas could potentially help explain the differences in average returns that we document. In order to examine this hypothesis, we now compute betas separately for announcement and non-announcement days.

Table 6 presents the difference between betas estimated separately for a-days and n-days (together with the n-day betas, as a 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 Fama-French 25 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, where it is 0.074 higher 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 of the betas over the types of day, given the difference in risk premia, constitutes an important part of the puzzle.

[TABLE 6 ABOUT HERE]

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. Thus, our findings are not affected by using the same betas for both types of day.

II. 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 relate it to 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 7 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 U.S. 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).[18] T-statistics are based on Newey-West standard errors with four lags.

[TABLE 7 ABOUT HERE]

[18] See Campbell et al. (2012) for a discussion of these variables and the properties of their variance forecast.

The first two rows show results when the market return is not split up 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 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). Since the forecasting power of the regression appears to be not much affected by the inclusion of some variables (even though they are significant), 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 re-estimating the regression each period using only data up to date t to forecast RV_{t+1}.[19] The adjusted R^2 of our chosen specification is 21.9%.

Figure 13 plots the predicted variable EV_t implied by the last specification in Table 7 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.

[FIGURE 13 ABOUT HERE]

[19] These results are available upon request.

Using this estimate of EV_t, we next examine the relation between risk and expected returns. Panel A of Table 8 shows our findings for a standard test of the risk-return trade-off, in which log aggregate 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 (2011)) 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 0.48. The adjusted R^2, equaling -0.5%, is also not consistent with an economically important role for market variance in explaining variation in realized market returns.

[**TABLE 8 ABOUT HERE**]

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 there exists clear evidence 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 since the forecasting variable is EV_t.[20] By contrast, non-announcement day returns are not related to EV_t, with a coefficient that is negative -0.055 (t-statistic = -0.1) and an adjusted R^2 of -0.05%.

Panel C present estimates of a VAR using RV_t instead of EV_t, partly as a robustness check and partly because the dynamics are simpler. Again, we find strong evidence of a risk-return

[20] In unreported results, we find that controlling for EV_t substantially reduces the observed (positive) autocorrelation for aggregate quarterly a-day returns, suggesting that part of a-day return autocorrelation is due to autocorrelation in EV_t. In other words, because expected a-day returns depend positively on EV_t, and EV_t is positively autocorrelated, expected a-day returns are also positively autocorrelated, and consequently realized a-day returns are mildly positively autocorrelated. Consistent with this reasoning, conditioning on EV_t substantially reduces the estimated autocorrelation in a-day returns.

trade-off on announcement days and none on other days.[21]

As an additional robustness check, we re-estimated the VARs in Table 8 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 there is a robustly positive statistical relation 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).[22]

III. 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 in a-day and n-day stock market betas for any of our test assets. Indeed, to the extent that growth stock betas are different on a-days, they are actually lower than n-day betas.

These findings are difficult to explain with standard models of the cross-section of asset returns. Indeed, we now present arguments that there is no simple modification of standard models that can explain our results.

[21] The forecasts of RV_t implied by the estimated coefficients in Panels A, B, and C are all positive. Our results are robust to using weighted least squares.

[22] These results are available on request.

III.A. Potential Explanations That Cannot Fit the Data

III.A.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 (A or N), given that the betas do not vary across regimes, we have

$$rp^g_{j,t} = \ln E_t \left[\frac{1 + R^g_{j,t+1}}{1 + R^g_{f,t+1}} \right] = \beta_j rp^g_{MKT,t}. \tag{4}$$

Here $rp_{j,t}$ is shorthand for the log mean excess return on asset j. Note that in the n-day regime we allow it to be zero or negative.

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

$$\begin{aligned} rp_{j,t,T} &= \Sigma_{s=0}^{T-1} rp^g_{j,t+s} = \Sigma_{s=0}^{T-1} \beta_j rp^g_{MKT,t+s} \\ &= \beta_j \Sigma_{s=0}^{T-1} rp^g_{MKT,t+s} = \beta_j rp_{MKT,t,T}. \end{aligned} \tag{5}$$

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 very 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, since a time-aggregated CAPM is rejected by the data.

III.A.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 SW, 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 SW 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-French (1992) two-factor model, in which size and book-to-market are characteristics which 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:

$$r_{j,t+1}-r_{f,t+1}+0.5Var_t[r_{j,t+1}] = p_1Cov_t[r_{j,t+1}, v_{1,t+1}]+p_2Cov_t[r_{j,t+1}, v_{2,t+1}]+\delta_{j,1}v_{1,t+1}+\delta_{j,2}v_{2,t+1}+\eta_{j,t+1}. \tag{6}$$

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

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

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, and in the SW 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 $\delta_{j,1}\sigma_{1,g}^2+\delta_2\sigma_{1,2,g}$, 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-events type models, in which some event with a very low probability commands a high risk price. Although possible, such models may be problematic because they are very difficult to test. We note that the 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 then show that for all the remaining cases any test asset whose market betas are invariant to regime must have identical factor exposures. That is:

$$\beta_{j,A} = \beta_{j,N} \equiv \beta_j \Rightarrow \delta_{j,1} = \delta_{j,2} = \beta_j \tag{7}$$

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

$$rp_j^g = \beta_j rp_{MKT}^g. \tag{8}$$

And these assets should then obey 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. Figure 14 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, while 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.

[FIGURE 14 ABOUT HERE]

We also show more formally that the positive relation between beta and returns holds exclusively on announcement days. First, for average returns (shown in Figure 14) 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 8.65 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.

III.A.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. Since 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).[23]

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 (2012) propose such a model, as do Campbell et al. (2012). These models imply a high risk premium for assets whose returns co-move 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 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. Furthermore, in unreported results we adapt the method of Campbell et al. (2012) to estimate variance news betas for our test assets separately for a-days and n-days, and find the same pattern on both types of day: all portfolios have positive variance news betas and growth stocks have higher

[23] Conditional two-factor models with time-varying factor loadings can be rewritten as unconditional three or four-factor models with constant loadings.

such betas than value. 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.[24]

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 very difficult to provide a fundamental economic argument as to why betas do not change.

III.B. 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: i.e., a common factor to asset returns that is not priced and does not relate to fundamentals (see, e.g., De Long, Shleifer, Summers, and Waldmann (1990)).

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, whereas the news on other days is mostly about current earnings and consumption (plus noise). Then many of our stylized facts may follow. Growth stocks should display high market betas on both days, and value stocks will 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, while their betas can actually 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.

[24] These results are available on request.

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 it may forecast only future a-day returns because n-day returns are noisy. Of course, these claims need a model to evaluate them, and this is a direction for future research.

Consistent with this general idea, SW 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 document 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. Figure 15 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 $N = 1$ to 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 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 (since the conditional variance itself is positively serially correlated).

[FIGURE 15 ABOUT HERE]

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 dashed lines in Figure 15. However, the actual variance ratios for a-day returns still all lie above the upper confidence interval, confirming that a-day returns are indeed 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 8. Figure 16 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.)

[FIGURE 16 ABOUT HERE]

In this case, the variance ratio for a-day returns rises from 1 to only 1.17 after 4 quarters and then gradually declines back to 1. For n-day returns, there is no positive autocorrelation 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 1/2-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 twenty, and 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, they may also explain why previous tests failed to establish strong evidence of return reversal at longer horizons.[25] First, the definite reversal on n-days is mingled with a lack of reversal on a-days. Second, there exists a strong positive autocorrelation of a-day returns due to the serial correlation of expected returns 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 actually a good proxy for aggregate wealth, and that there is a non-systematic component to stock market returns.[26] However, the news that emerges on a-days affects all risky assets, including non-stock market assets, so there is likely no such non-systematic 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, will generally be higher on average when the signal is more precise, and that the effect on the risk-return trade-off is ambiguous.[27] It seems plausible that these models could be used to generate noise in n-day returns, using 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.[28]

[25] See Lo and MacKinlay (1989) or Campbell, Lo, and MacKinlay, chapter 2 (1996). For a more recent discussion, see Pastor and Stambaugh (2012).

[26] Pollet and Wilson (2011) use this idea to show that average correlation, not market variance, should be a good predictor of future market returns, without considering the distinction between a-days and n-days.

[27] Brevik and d'Addona (2009) incorporate Epstein-Zin preferences into the same setup and show that the result on the risk premium also becomes ambiguous.

[28] 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 (2012) 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); and Frazzini and Lamont (2007)).

Finally, the nature of n-day versus a-day information may 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. Insomuch as disagreement induces overvaluation, then 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 Figures 15 and 16.

There are surely other possible explanations 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 risky assets, including the aggregate stock market and government bonds, a-day returns account for a very 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.

IV. 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 non-equity 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 indeed 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 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: 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 towards a contradiction 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. We recall equation (6) in Section III:

$$r_{j,t+1}-r_{f,t+1}+0.5Var_t[r_{j,t+1}] = p_1 Cov_t[r_{j,t+1}, v_{1,t+1}]+p_2 Cov_t[r_{j,t+1}, v_{2,t+1}]+\delta_{j,1}v_{1,t+1}+\delta_{j,2}v_{2,t+1}+\eta_{j,t+1}.$$

The variance of factor 1's innovation in the a-day regime is given by $\sigma^2_{1,A}$ and by $\sigma^2_{1,N}$ in the n-day regime. Generically we write this as $\sigma^2_{1,t}$. The variance of factor 2's innovation is then $\sigma^2_{2,t}$ and their covariance $\sigma_{12,t}$. The other parameters are defined in Section III. Our claim is that equation (7) follows, in which case we can derive the counterfactual predictions discussed in Section III.

The test assets' market betas in each regime are derived from equation (6):

$$\begin{aligned} \beta_{j,t} &= \frac{Cov_t[r_{j,t+1}, r_{M,t+1}]}{Var_t[r_{M,t+1}]} = \frac{Cov_t[\delta_{j,1}v_{1,t+1}+\delta_{j,2}v_{2,t+1}, v_{1,t+1}+v_{2,t+1}]}{Var_t[v_{1,t+1}+v_{2,t+1}]} \\ &= \frac{\delta_{j,1}(\sigma^2_{1,t}+\sigma_{12,t})+\delta_{j,2}(\sigma^2_{2,t}+\sigma_{12,t})}{(\sigma^2_{1,t}+\sigma_{12,t})+(\sigma^2_{2,t}+\sigma_{12,t})}, \end{aligned} \tag{9}$$

and market variance in each regime is given by

$$\sigma^2_{M,t} = (\sigma^2_{1,t}+\sigma_{12,t})+(\sigma^2_{2,t}+\sigma_{12,t}). \tag{10}$$

Risk premia in each regime equal

$$\begin{aligned} rp_{j,t} &= p_1 Cov_t[r_{j,t+1}, v_{1,t+1}] + p_2 Cov_t[r_{j,t+1}, v_{2,t+1}] \\ &= p_1 Cov_t[\delta_{j,1} v_{1,t+1} + \delta_{j,2} v_{2,t+1}, v_{1,t+1}] + p_2 Cov_t[\delta_{j,1} v_{1,t+1} + \delta_{j,2} v_{2,t+1}, v_{2,t+1}] \\ &= p_1(\delta_{j,1}\sigma_{1,t}^2 + \delta_{j,2}\sigma_{12,t}) + p_2(\delta_{j,2}\sigma_{2,t}^2 + \delta_{j,1}\sigma_{12,t}) \end{aligned} \tag{11}$$

so that in particular the market risk premium is given by

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

Note that 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. Note also that it cannot be the case that $p_1 = p_2$, since that would imply $rp_{M,t} = p_1\sigma_{M,t}^2$, which is contrary to what the data suggests (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, $p_1 \neq p_2$.

Second, for what follows, we need to establish that

$$(\sigma_{1,A}^2 + \sigma_{12,A})(\sigma_{2,N}^2 + \sigma_{12,N}) \neq (\sigma_{1,N}^2 + \sigma_{12,N})(\sigma_{2,A}^2 + \sigma_{12,A}). \tag{13}$$

We assume towards a contradiction that this inequality does not hold. Plugging our expressions for market variance from equation (10) into the resulting equality gives

$$(\sigma_{M,A}^2 - (\sigma_{2,A}^2 + \sigma_{12,A}))(\sigma_{2,N}^2 + \sigma_{12,N}) = (\sigma_{M,N}^2 - (\sigma_{2,N}^2 + \sigma_{12,N}))(\sigma_{2,A}^2 + \sigma_{12,A}).$$

Rearranging gives

$$(\sigma_{2,A}^2 + \sigma_{12,A}) = \frac{\sigma_{M,A}^2}{\sigma_{M,N}^2}(\sigma_{2,N}^2 + \sigma_{12,N}). \tag{14}$$

Now plugging equation (14) into the expression for the market risk premium, equation (12) gives

$$rp_{M,A} = p_1(\sigma^2_{M,A} - \frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}(\sigma^2_{2,N} + \sigma_{12,N})) + p_2\frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}(\sigma^2_{2,N} + \sigma_{12,N}) \tag{15}$$

and

$$rp_{M,N} = p_1(\sigma^2_{M,N} - (\sigma^2_{2,N} + \sigma_{12,N})) + p_2(\sigma^2_{2,N} + \sigma_{12,N}). \tag{16}$$

Equation (16), for the n-day market risk premium, then implies that (recall that $p_1 \neq p_2$)

$$(\sigma^2_{2,N} + \sigma_{12,N}) = \frac{rp_{M,N} - p_1\sigma^2_{M,N}}{p_2 - p_1} \tag{17}$$

and plugging (17) into equation (12) for the a-day market risk premium, implies

$$\begin{aligned} rp_{M,A} &= p_1(\sigma^2_{M,A} - \frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}\left(\frac{rp_{M,N} - p_1\sigma^2_{M,N}}{p_2 - p_1}\right)) + p_2\frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}\left(\frac{rp_{M,N} - p_1\sigma^2_{M,N}}{p_2 - p_1}\right) \qquad (18) \\ &= p_1\sigma^2_{M,A} + (p_2 - p_1)\frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}\left(\frac{rp_{M,N} - p_1\sigma^2_{M,N}}{p_2 - p_1}\right) \\ &= p_1\sigma^2_{M,A} + \frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}rp_{M,N} - p_1\frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}\sigma^2_{M,N} \\ &= \frac{\sigma^2_{M,A}}{\sigma^2_{M,N}}rp_{M,N}. \end{aligned}$$

Thus, for the inequality (13) 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: a-day market variance is only marginally higher than n-day variance, while the risk premium is ten times higher. Therefore, the inequality (13) 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, since 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

$$\beta_{j,A} = \frac{\delta_{j,1}(\sigma^2_{1,A} + \sigma_{12,A}) + \delta_{j,2}(\sigma^2_{2,A} + \sigma_{12,A})}{(\sigma^2_{1,A} + \sigma_{12,A}) + (\sigma^2_{2,A} + \sigma_{12,A})} = \frac{\delta_{j,1}(\sigma^2_{1,N} + \sigma_{12,N}) + \delta_{j,2}(\sigma^2_{2,N} + \sigma_{12,N})}{(\sigma^2_{1,N} + \sigma_{12,N}) + (\sigma^2_{2,N} + \sigma_{12,N})} = \beta_{j,N}. \tag{19}$$

Proof: Rearranging the middle two expressions of equation (19) gives:

$$\begin{aligned}
& \left(\delta_{j,1}(\sigma^2_{1,A} + \sigma_{12,A}) + \delta_{j,2}(\sigma^2_{2,A} + \sigma_{12,A})\right)\left((\sigma^2_{1,N} + \sigma_{12,N}) + (\sigma^2_{2,N} + \sigma_{12,N})\right) \\
= \; & \left(\delta_{j,1}(\sigma^2_{1,N} + \sigma_{12,N}) + \delta_{j,2}(\sigma^2_{2,N} + \sigma_{12,N})\right)\left((\sigma^2_{1,A} + \sigma_{12,A}) + (\sigma^2_{2,A} + \sigma_{12,A})\right) \\
\Leftrightarrow \; & \delta_{j,1}((\sigma^2_{1,A} + \sigma_{12,A})(\sigma^2_{2,N} + \sigma_{12,N}) - (\sigma^2_{1,N} + \sigma_{12,N})(\sigma^2_{2,A} + \sigma_{12,A})) \\
= \; & \delta_{j,2}((\sigma^2_{1,A} + \sigma_{12,A})(\sigma^2_{2,N} + \sigma_{12,N}) - (\sigma^2_{1,N} + \sigma_{12,N})(\sigma^2_{2,A} + \sigma_{12,A})).
\end{aligned}$$

Therefore, given inequality (13), (which we proved above), we have for such assets

$$\delta_{j,1} = \delta_{j,2} = \beta_j \tag{20}$$

and so any such asset must have identical factor exposures, as claimed, and equation (7) 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 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

$$\begin{aligned}
rp_{j,t} &= p_1(\delta_{j,1}\sigma^2_{1,t} + \delta_{j,1}\sigma_{12,t}) + p_2(\delta_{j,1}\sigma^2_{2,t} + \delta_{j,1}\sigma_{12,t}) \qquad (21) \\
&= \delta_{j,1} rp_{M,t} = \beta_j rp_{M,t}
\end{aligned}$$

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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Figure 1: Average Excess Returns for 10 Beta-Sorted Portfolios

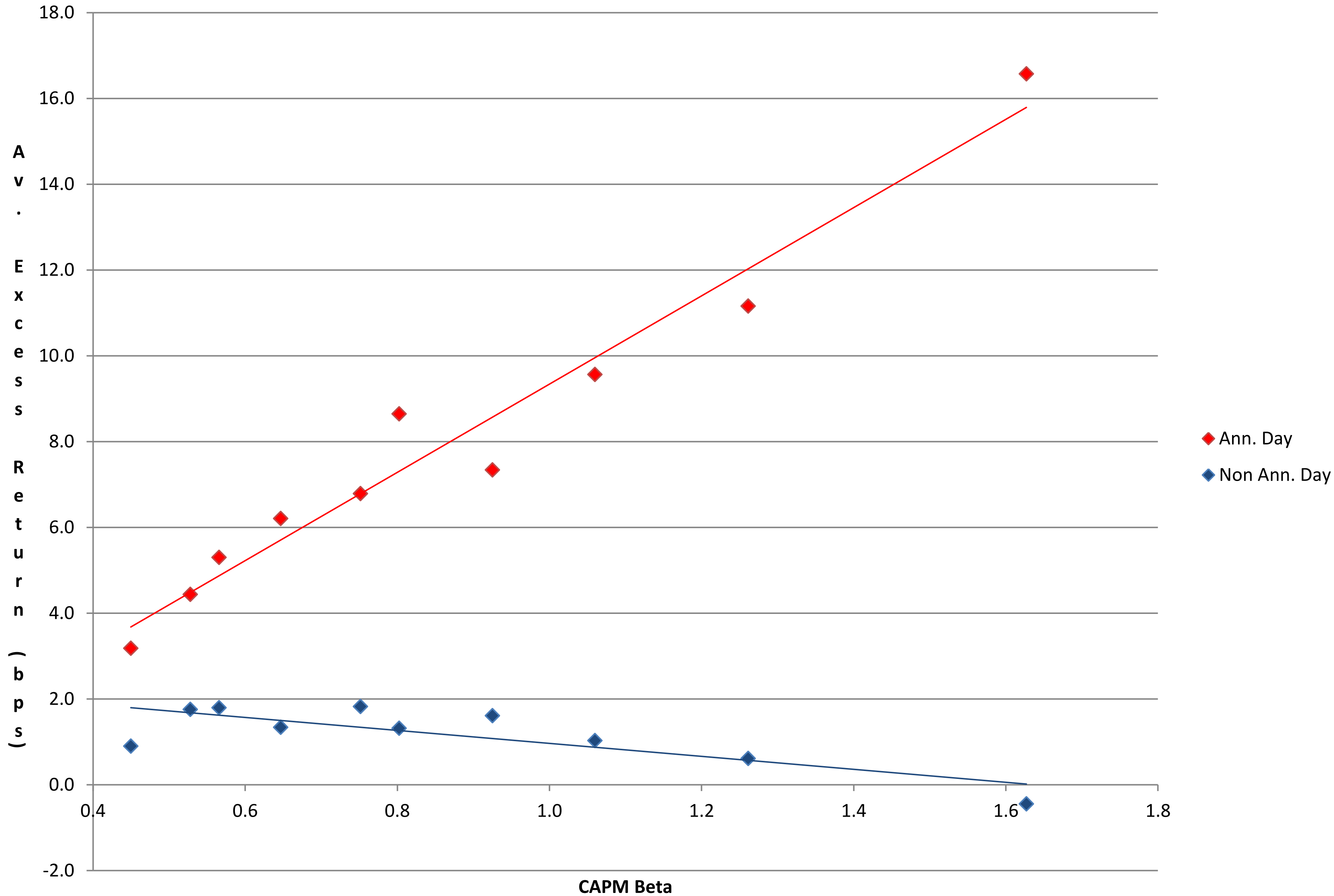

Figure 2: Average Excess Returns for 50 Beta-Sorted Portfolios

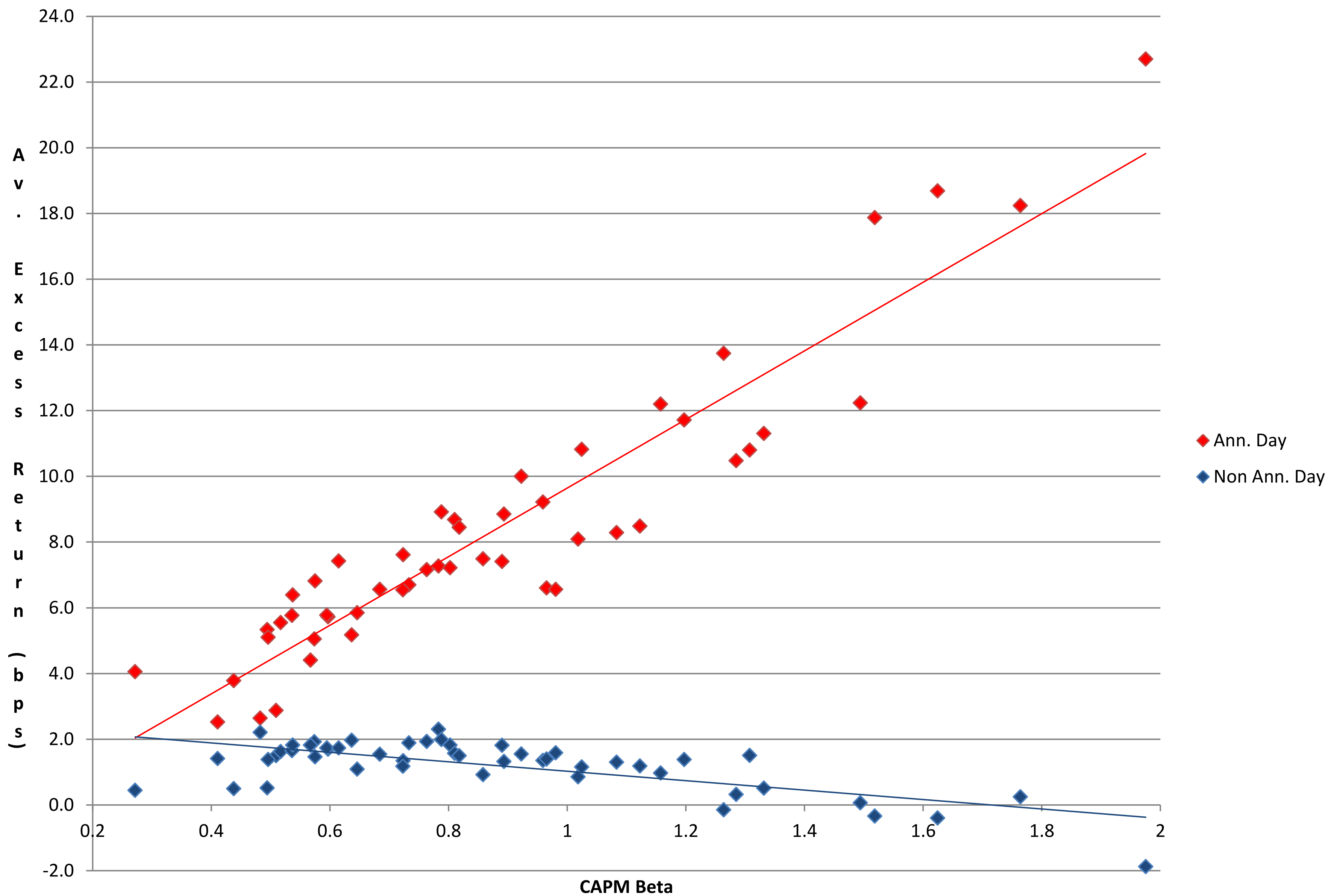

Figure 3: Average Excess Returns for 25 Fama-French Portfolios

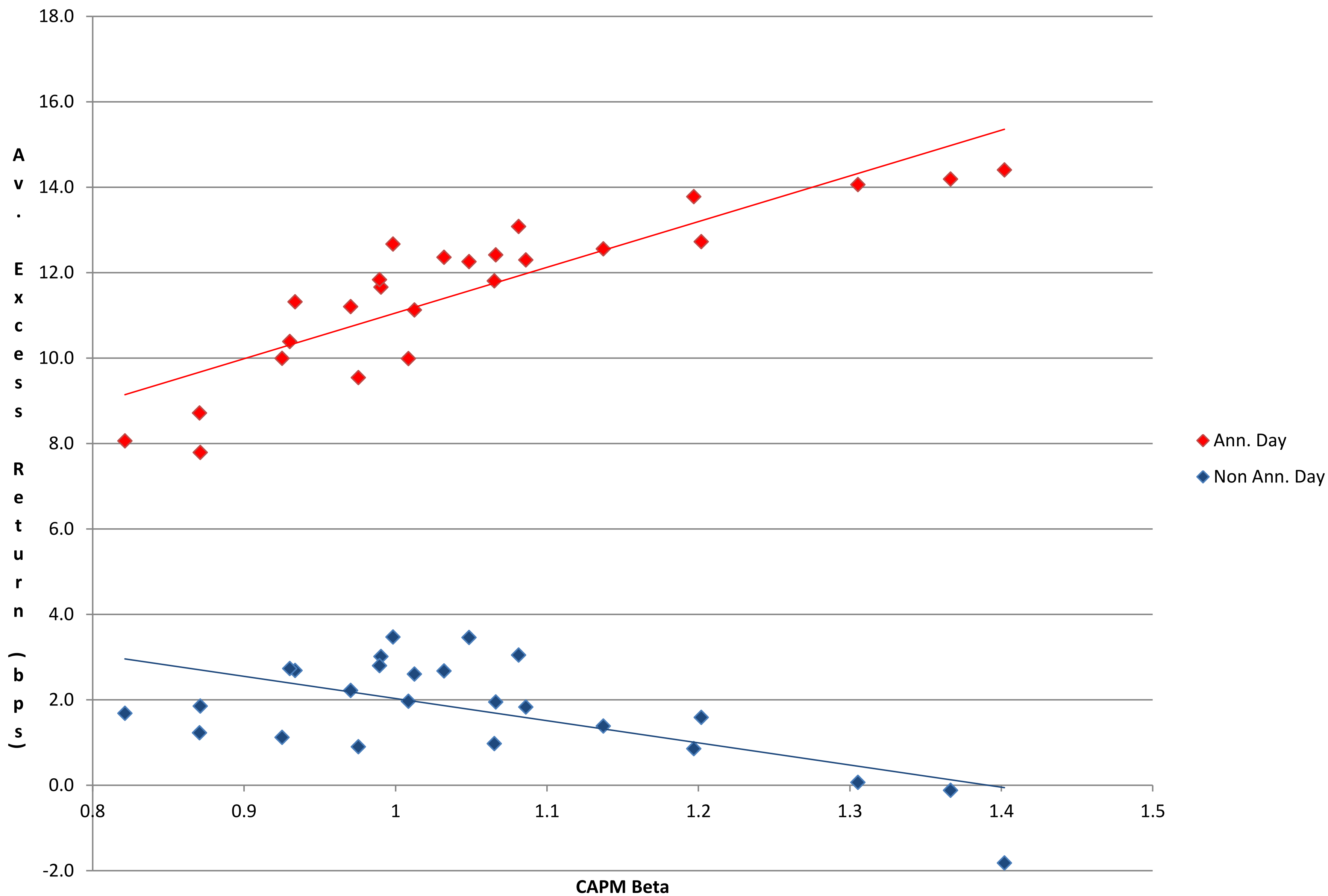

Figure 4: Average Excess Returns for 10 Industry Portfolios

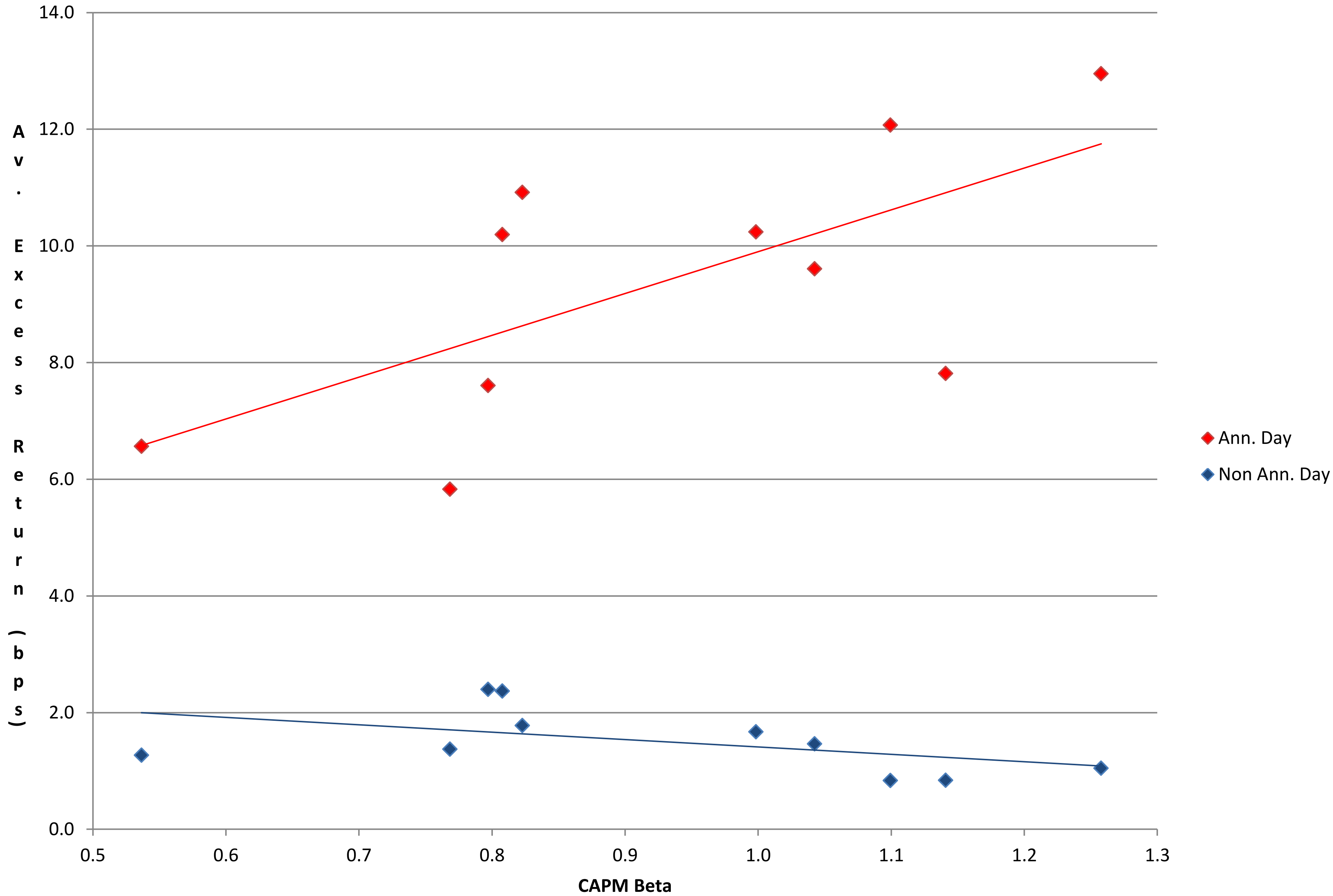

Figure 5: Average Excess Returns for Beta-sorted, FF 25, and Industry Portfolios

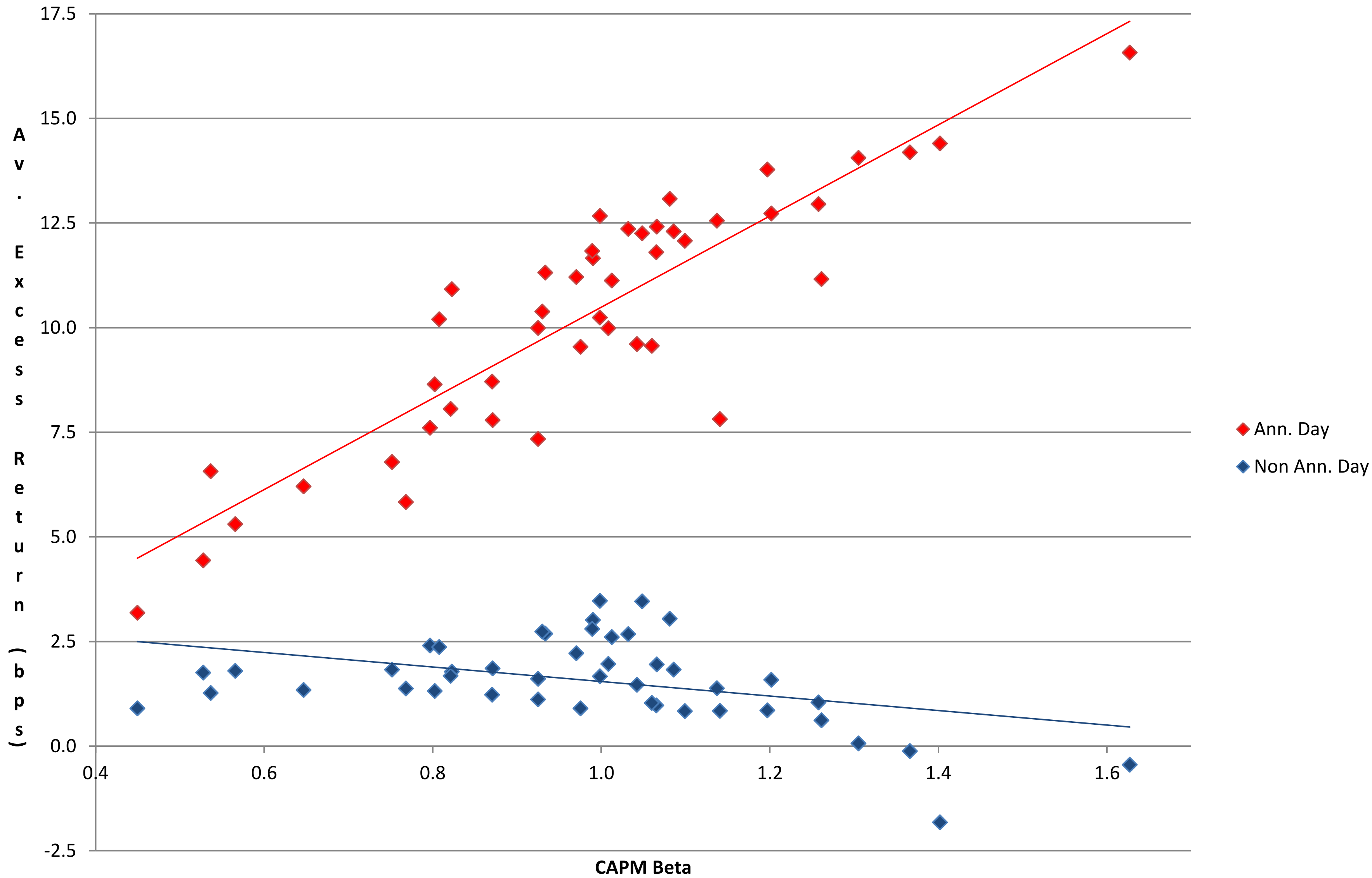

Figure 6: Average Excess Returns for Treasury Bonds of Different Maturities

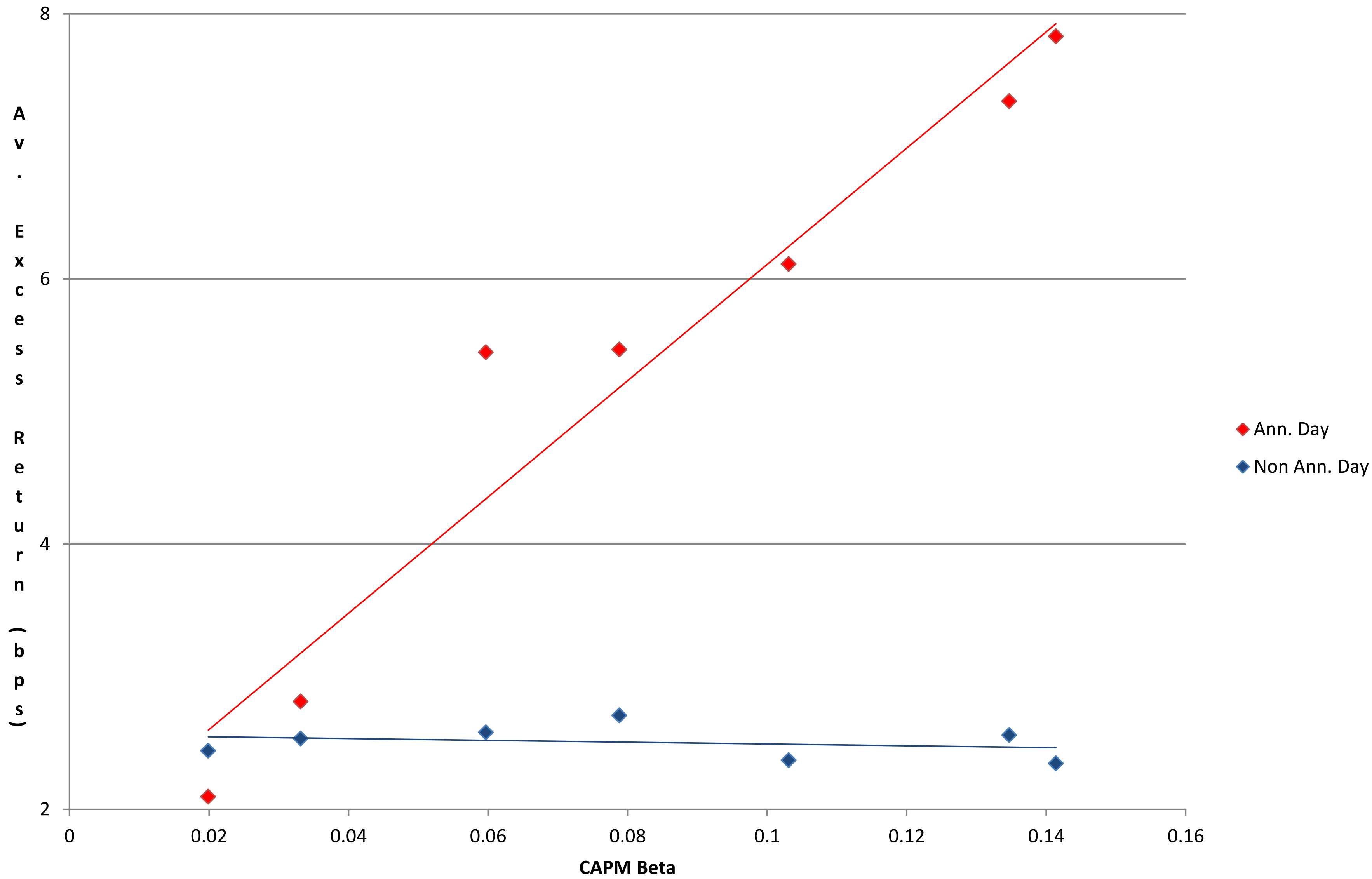

Figure 7: Average Excess Returns for Carry-Trade Portfolios

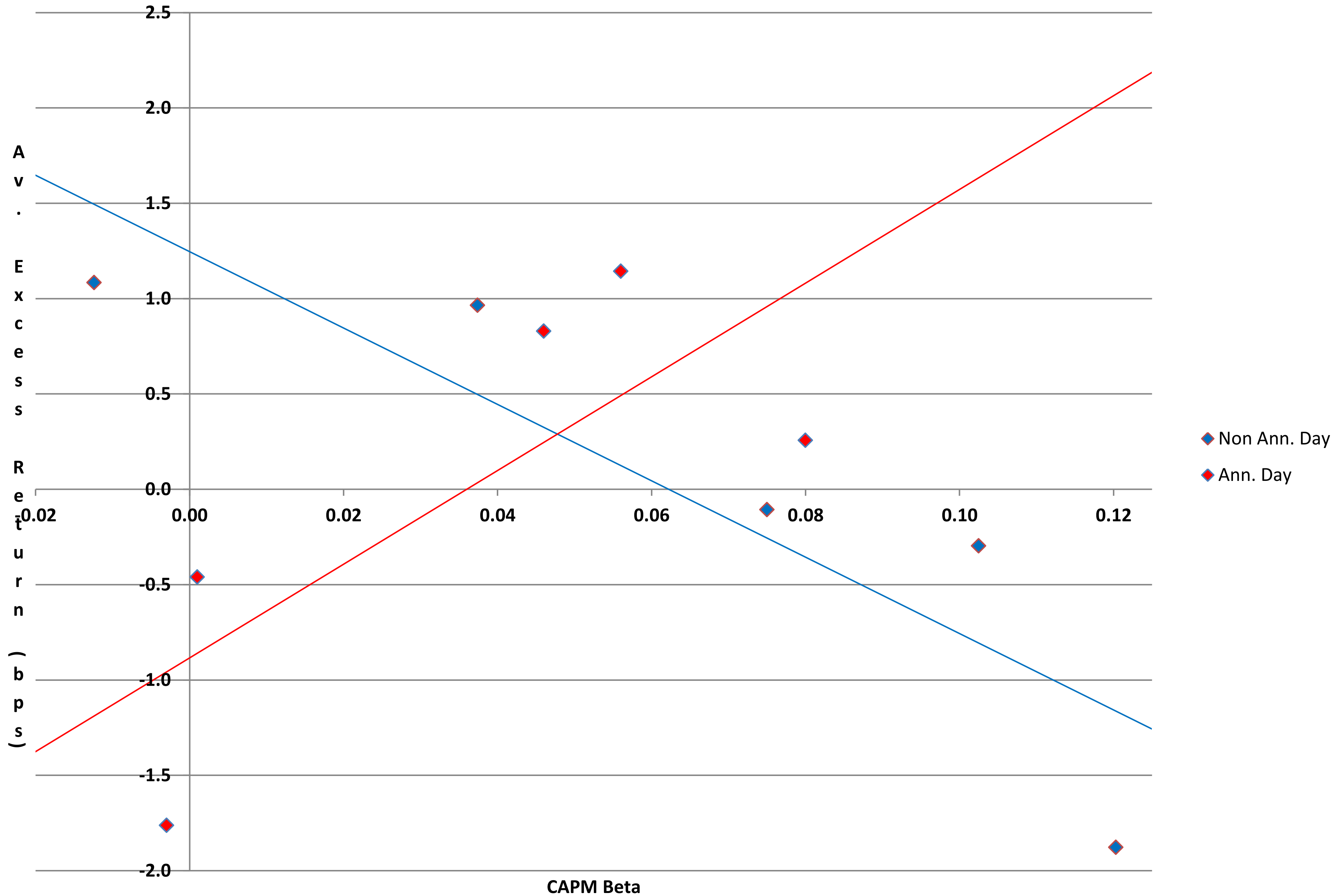

Figure 8: Average Excess Returns for 25 Fama-French Portfolios

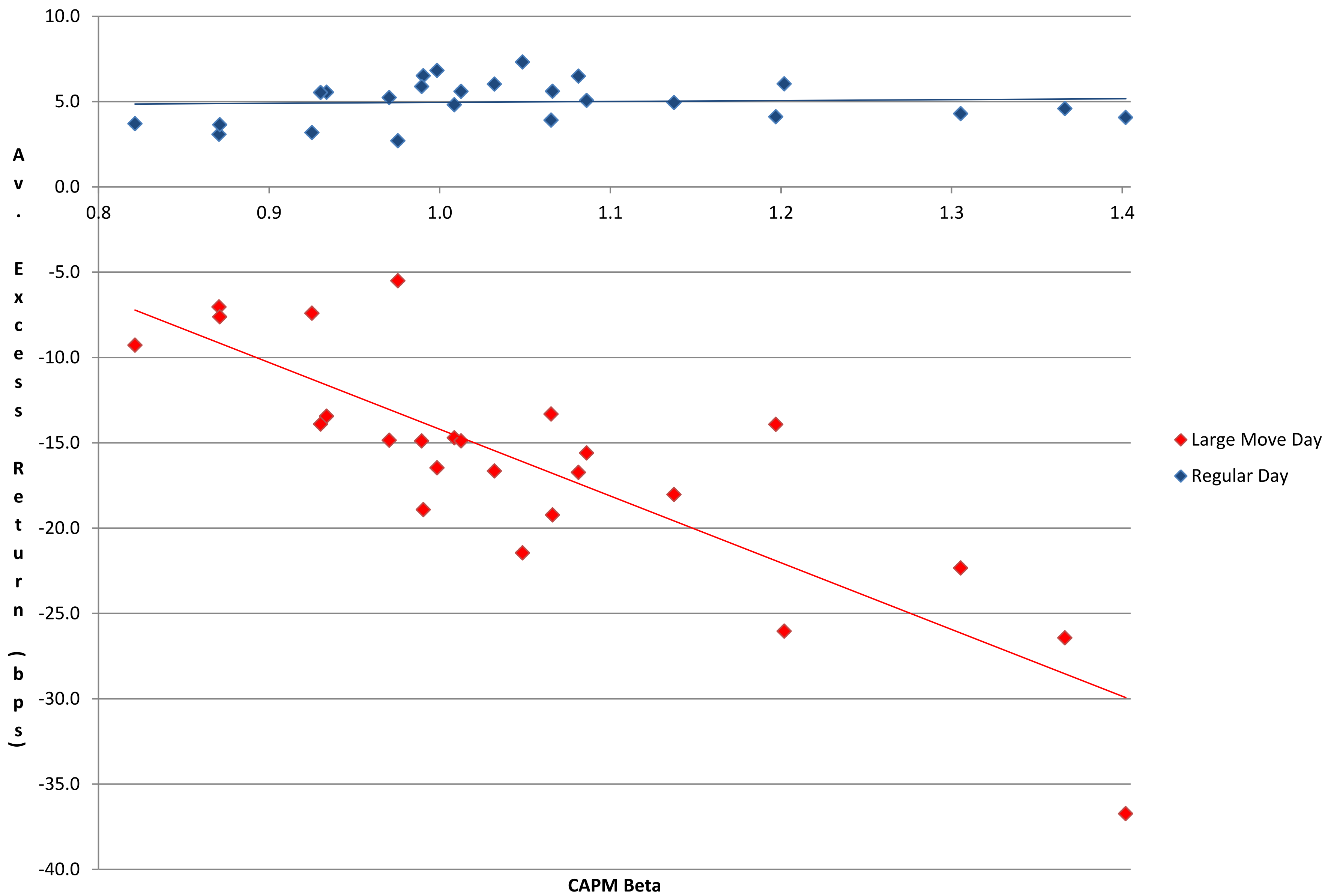

Figure 9: Average Excess Market Return Across Different Periods

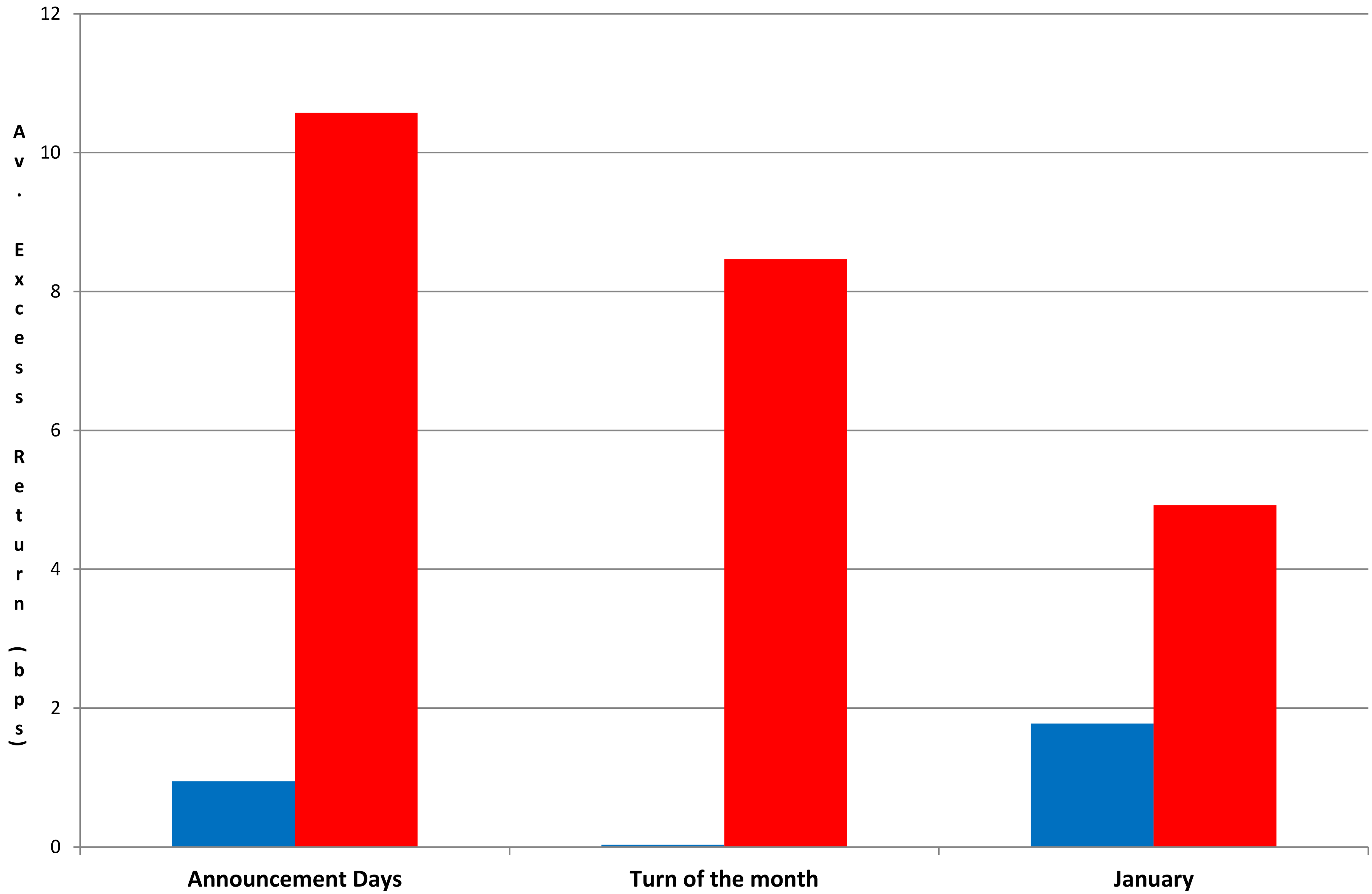

Figure 10: Annualized Market Sharpe Ratio Across Different Periods

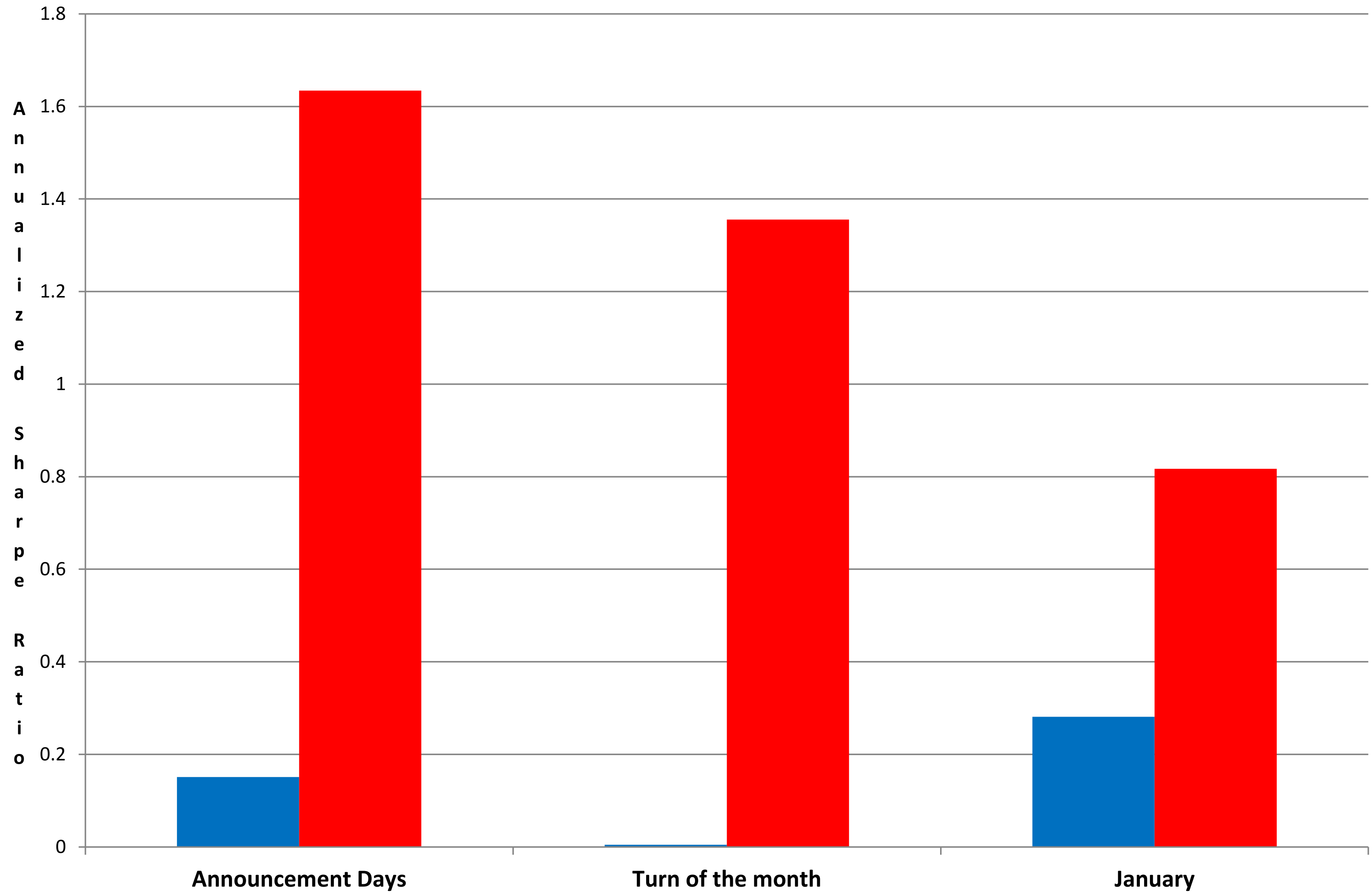

Figure 11: Average Excess Returns for 25 Fama-French Portfolios

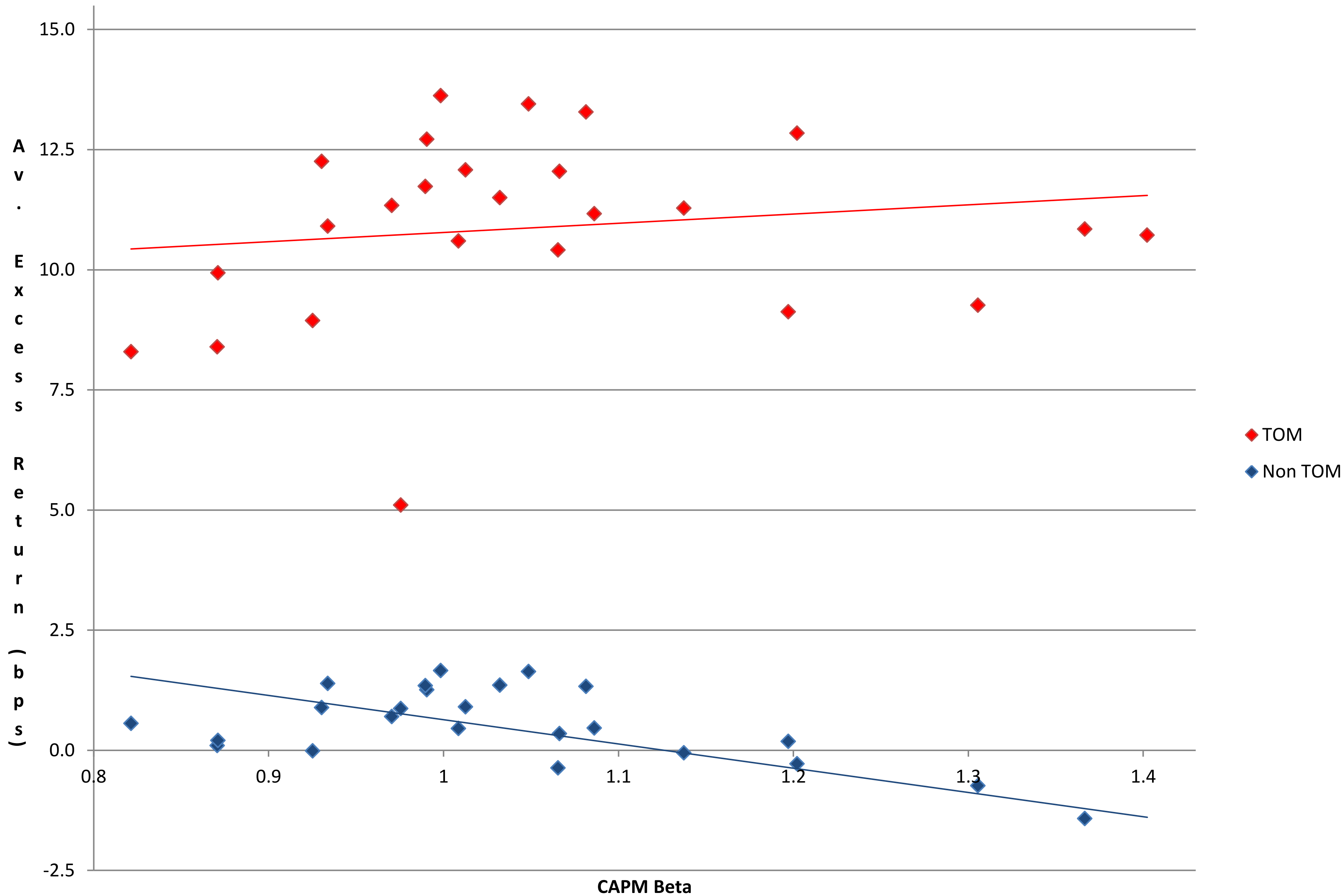

Figure 12: Average Excess Returns for 25 Fama-French Portfolios

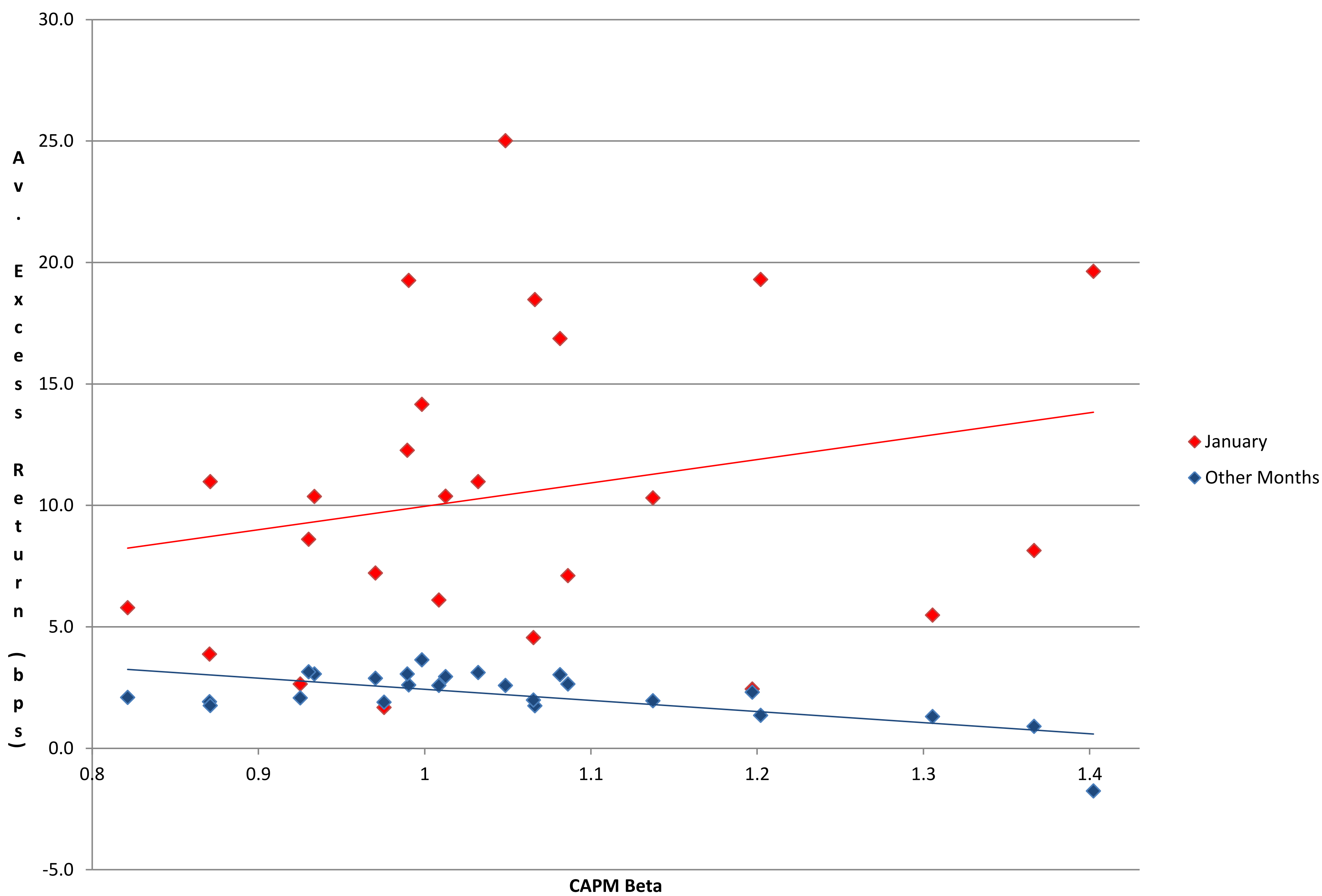

Figure 13: Realized vs. Expected Variance

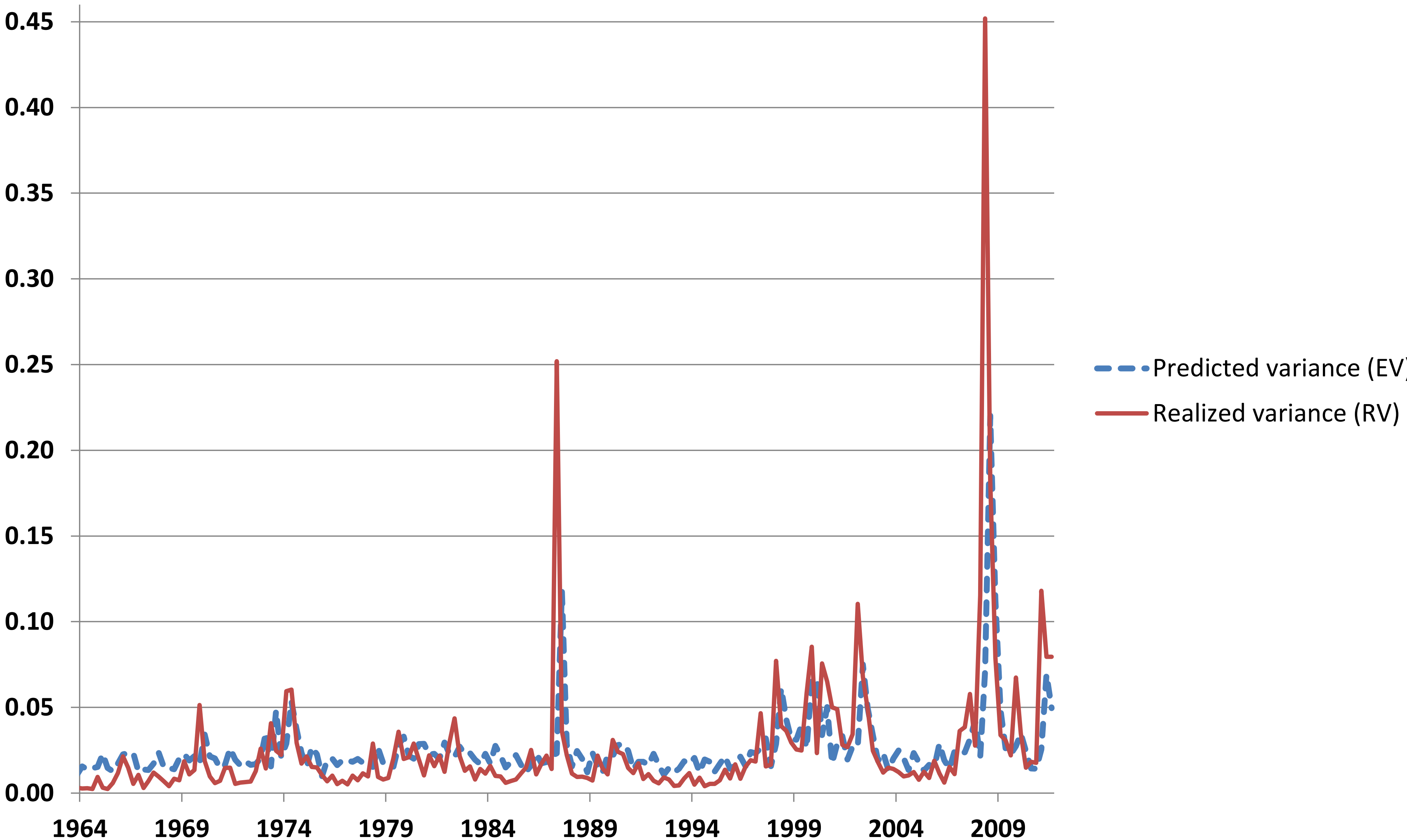

Figure 14: Average Excess Returns for 45 Constant-Beta Portfolios

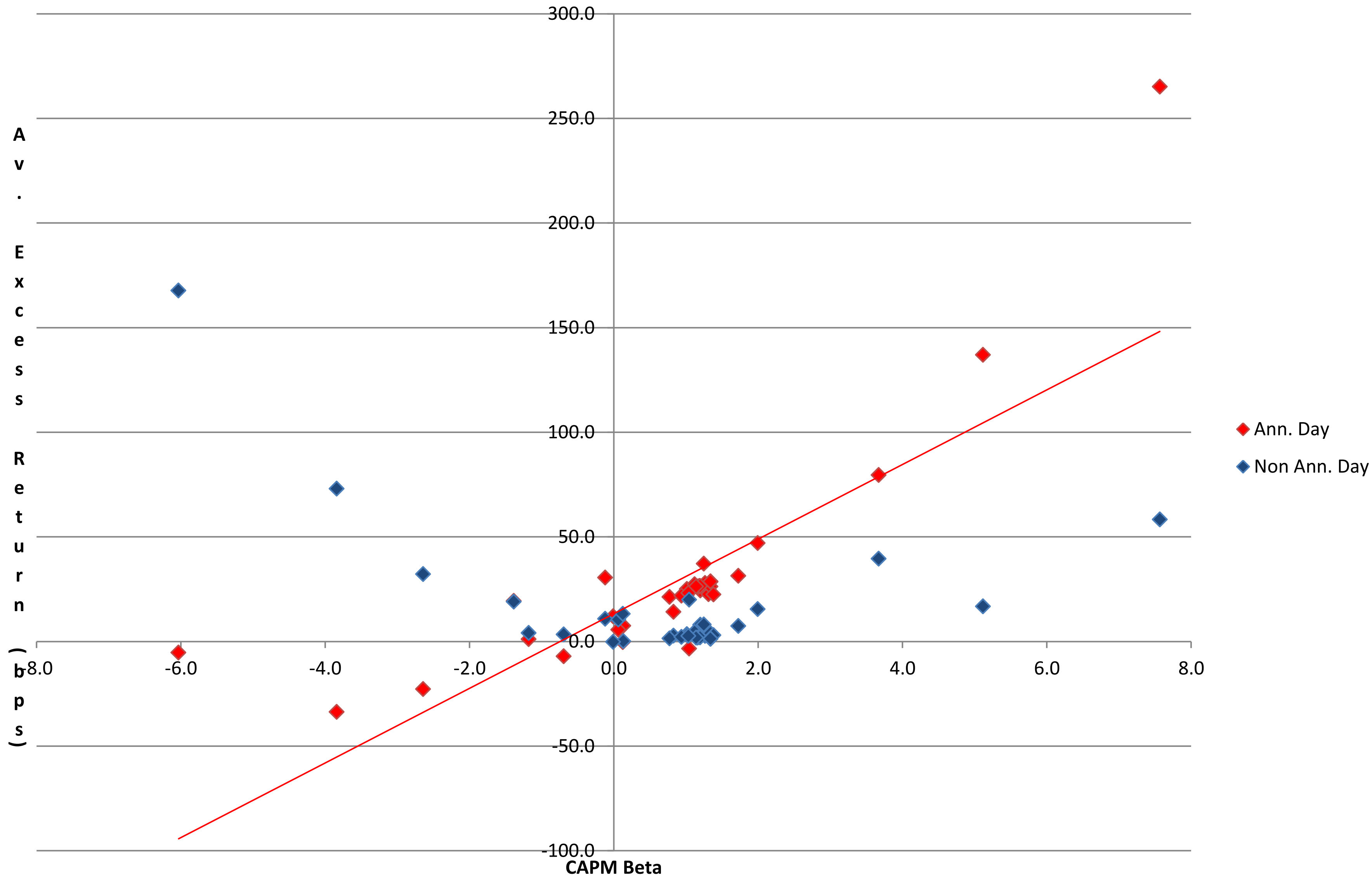

Figure 15: Variance Ratios of Quarterly Returns

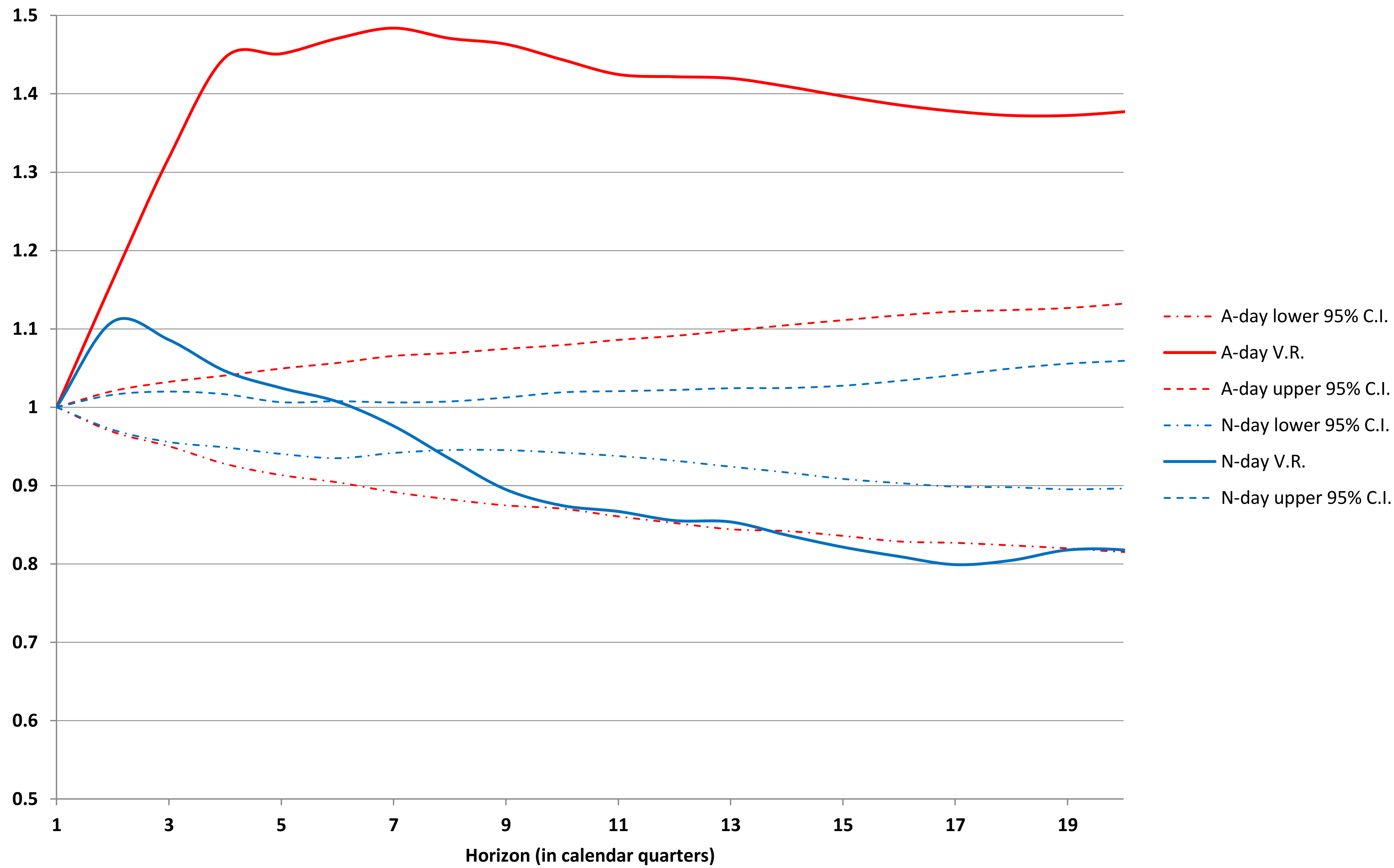

Figure 16: Variance Ratios of Quarterly Return Residuals

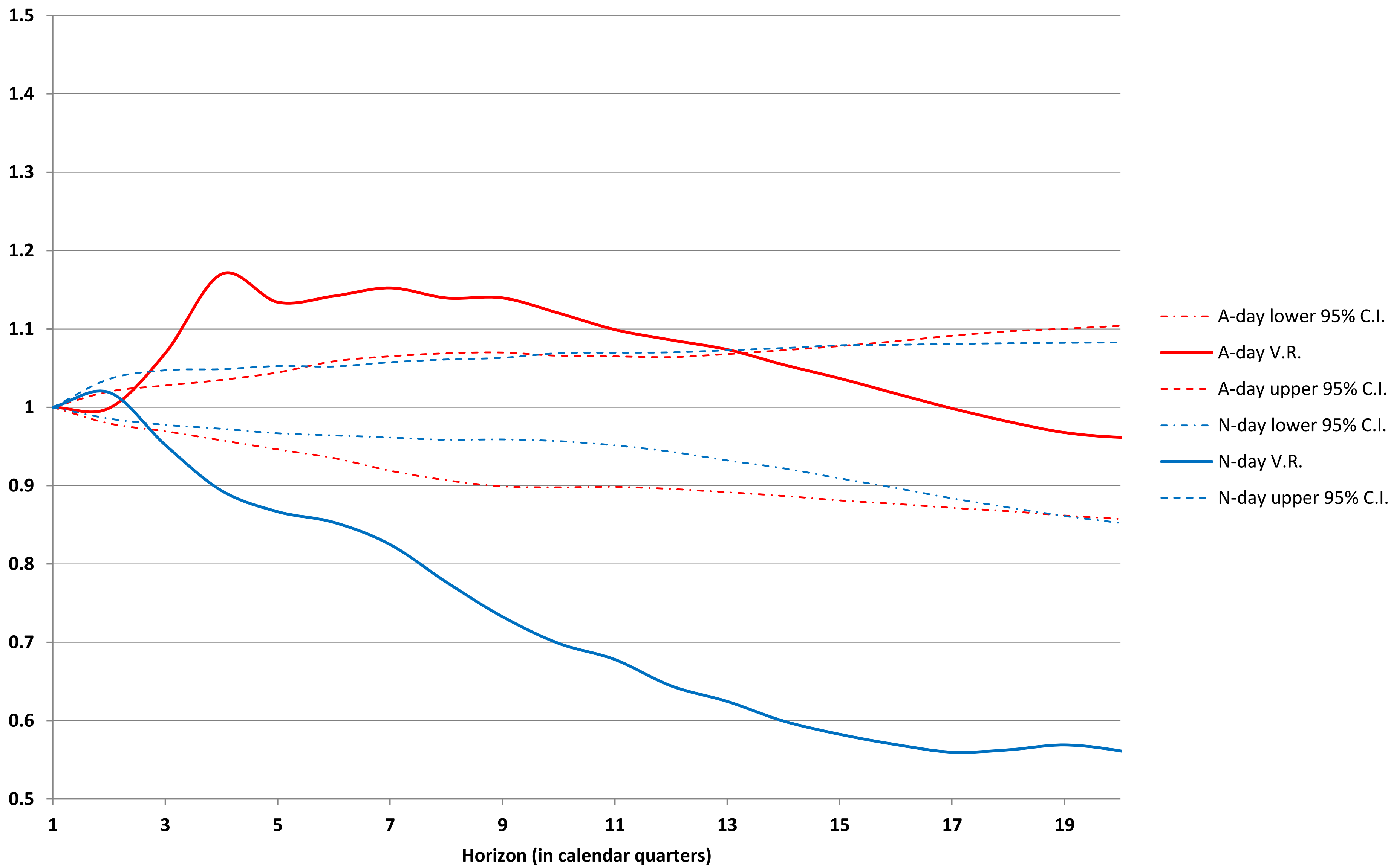

Table 1: Daily Excess Returns for 10 Beta-sorted Portfolios

Panel A: Fama-MacBeth regressions

	Value-weighted		Av. R^2	Equal-weighted		Av. R^2
	Intercept	Beta		Intercept	Beta	
A-Day	0.00013	0.00092	0.514	0.00089	0.00094	0.574
	[0.90]	[2.81]		[8.59]	[2.96]	
N-Day	0.00020	-0.00010	0.492	0.00069	-0.00031	0.564
	[3.64]	[-0.89]		[16.60]	[-2.80]	
A-Day - N-day	-0.00007	**0.00103**		0.00020	**0.00126**	
	[-0.44]	**[2.89]**		[1.99]	**[3.57]**	

Panel B: Pooled regression

Value-weighted					Equal-weighted				
Intercept	Beta	Ann.	Ann. * Beta	R^2	Intercept	Beta	Ann.	Ann. * Beta	R^2
0.00024	-0.00015	0.00016	**0.00084**	0.001	0.00079	-0.00039	0.00061	**0.00119**	0.001
[3.26]	[-1.18]	[0.81]	**[2.74]**		[10.55]	[-2.85]	[3.01]	**[3.62]**	

Panel A reports estimates from Fama-MacBeth regressions of daily excess returns on betas for ten portfolios sorted by stock market beta and rebalanced monthly. Estimates are computed separately for days with scheduled inflation, unemployment, and FOMC interest rate decisions (A-days) and other days (N-days). The difference is reported in the last row. Panel B reports estimates for the same ten portfolios of a single pooled regression, where we add an A-day dummy (Ann.) and an interaction term between this dummy and market beta (Ann.*Beta).

Beta is the same for both types of days, and is estimated using one year of daily returns. Stocks are then sorted into deciles based on their beta, returns of the resulting portfolios are computed (using equal or value weights), and beta is estimated again for each portfolio. The sample covers the 1964-2011 period. T-statistics are reported in parentheses. In Panel A, they are calculated using the standard deviation of the time-series of coefficient estimates. In Panel B, they are calculated using clustered standard errors (by trading day).

Table 2: Daily Excess Returns for 10 Beta-sorted, 25 Fama-French, and 10 Industry Portfolios

Panel A: Fama-MacBeth regressions

	Intercept	Beta	Av. R^2
A-Day	0.00033	0.00087	0.303
	[2.18]	[2.74]	
N-Day	0.00027	-0.00014	0.284
	[4.62]	[-1.27]	
A-Day - N-day	0.00006	**0.00101**	
	[0.39]	**[3.01]**	

Panel B: Pooled regression

Intercept	Beta	Ann.	Ann. * Beta	R^2
0.00028	-0.00014	0.00052	**0.00045**	0.001
[3.02]	[-1.16]	[2.04]	**[4.10]**	

Panel A reports estimates from Fama-MacBeth regressions of daily excess returns on betas for ten beta-sorted portfolios, 25 Fama-French portfolios, and ten industry portfolios. Estimates are computed separately for days with scheduled inflation, unemployment, and FOMC interest rate decisions (A-days) and other days (N-days). Panel B reports estimates for the same 45 portfolios of a single pooled regression, where we add an A-day dummy (Ann.) and an interaction term between this dummy and market beta (Ann.*Beta).

The sample covers the 1964-2011 period. T-statistics are reported in parentheses. In Panel A, they are calculated using the standard deviation of the time-series of coefficient estimates. In Panel B, they are calculated using clustered standard errors (by trading day).

Table 3: Daily Excess Returns for Individual Stocks

Panel A: Firm Characteristics (Fama-MacBeth)

	Beta	Size	B/M	Past 1-year			Av. R^2
A-Day	0.00072	-0.00030	0.00003	-0.00024			1.92%
	[3.33]	[-9.27]	[1.01]	[-2.50]			
N-Day	-0.00009	-0.00021	0.00008	-0.00008			2.01%
	[-1.18]	[-17.94]	[7.08]	[-1.96]			
A-Day - N-day	**0.00081**	-0.00009	-0.00005	-0.00017			
	[3.54]	[-2.59]	[-1.70]	[-1.58]			

Panel B: Firm Characteristics (Pooled Regression)

	Beta	Size	B/M	Past 1-year	Ann.	Ann. * Beta	R^2
	-0.00018	-0.00026	0.00001	-0.00009	0.00079	**0.00048**	0.02%
	[-2.05]	[-11.39]	[1.36]	[-1.30]	[4.72]	**[3.55]**	

Panel C: Factor Betas (Fama-MacBeth)

	Beta	SMB beta	HML beta	UMD beta			Av. R^2
A-Day	0.00042	0.00018	0.00004	-0.00013			1.94%
	[2.03]	[2.25]	[0.49]	[-2.83]			
N-Day	-0.00025	0.00008	0.00012	-0.00014			1.95%
	[-3.47]	[2.73]	[3.94]	[-1.12]			
A-Day - N-day	**0.00066**	0.00011	-0.00008	-0.00001			
	[3.06]	[1.23]	[-0.83]	[-0.11]			

Panel D: Factor Betas (Pooled Regression)

	Beta	SMB beta	HML beta	UMD beta	Ann.	Ann. * Beta	R^2
	-0.000003	0.000001	0.000001	-0.000001	0.001100	**0.000023**	0.01%
	[-2.47]	[2.13]	[2.38]	[-1.55]	[4.44]	**[2.95]**	

The table reports estimates from Fama-MacBeth and pooled regressions of daily excess returns for individual stocks on their stock market betas (*Beta*), log market capitalization (*Size*), book-to-market ratios (*B/M*), and past one-year return (*Past 1-year*) in Panels A and B; and on stock market betas, size (*SMB*) factor betas, value (*HML*) factor betas, and momentum (*UMD*) factor betas in Panels C and D. The announcement-day indicator variable (*Ann.*) equals one on days with scheduled inflation, unemployment, and FOMC interest rate announcements and is zero otherwise. Betas are the same for both types of days, and are estimated using one year of daily returns and re-estimated each month.

The sample covers the 1964-2011 period. T-statistics are reported in parentheses. In Panel A, they are calculated using the standard deviation of the time-series of coefficient estimates. In Panel B, they are calculated using clustered standard errors (by trading day).

Table 4: Average Returns by Type of Day

Panel A: 25 Fama-French Portfolios

		Growth	**2**	**3**	**4**	**Value**
Small	N-day	-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]
2	N-day	-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]
3	N-day	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]
4	N-day	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]
Large	N-day	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-French Factors

	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]

Continued from the previous page.

Panel C: 10 Beta-sorted Portfolios

	Low	2	3	4	5
N-day	0.7	1.8	1.9	1.3	2.0
	[0.85]	[3.10]	[3.29]	[2.00]	[2.73]
A-day	4.4	6.4	4.7	5.9	7.4
	[2.04]	[4.29]	[2.96]	[3.26]	[3.53]
	6	**7**	**8**	**9**	**High**
N-day	1.4	1.5	0.9	0.5	-0.4
	[1.63]	[1.54]	[0.76]	[0.39]	[-0.23]
A-day	8.0	7.8	10.0	11.5	16.7
	[3.30]	[2.80]	[3.12]	[2.92]	[3.22]

Panel D: 10 Industry Portfolios

	NoDur	Durbl	Manuf	Enrgy	HiTec
N-day	2.4	0.8	1.4	2.4	1.0
	[2.83]	[0.65]	[1.42]	[1.88]	[0.74]
A-day	7.6	7.8	9.6	10.2	13.0
	[3.10]	[2.19]	[3.33]	[2.94]	[3.25]
	Telcm	**Shops**	**Hlth**	**Utils**	**Other**
N-day	1.4	1.7	1.8	1.3	0.8
	[1.27]	[1.61]	[1.70]	[1.56]	[0.75]
A-day	5.6	10.2	10.9	6.6	12.1
	[1.84]	[3.33]	[3.69]	[2.92]	[3.70]

This table reports average daily excess returns for the 25 Fama-French size and book-to-market sorted portfolios in Panel A. Panel B presents average returns for the market, SMB, HML, and UMD factors. Panels C and D shows 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.

Table 5: Cumulative Return Shares on Announcement Days

Panel A: 25 Fama-French Portfolios

	Growth	2	3	4	Value
Small	-354.7	64.3	54.7	39.7	37.1
2	187.3	69.0	45.2	42.5	43.6
3	156.1	57.3	48.1	42.6	38.4
4	92.0	78.1	50.1	40.4	44.9
Large	83.0	71.5	65.6	51.9	49.8

Panel B: 10 Beta-Sorted Portfolios

Low	2	3	4	5
60.9	33.0	24.9	40.0	34.1
6	**7**	**8**	**9**	**High**
49.0	48.2	86.9	155.3	-574.7

Panel C: 10 Industry Portfolios

NoDur	Durbl	Manuf	Enrgy	HiTec
31.4	105.5	56.5	44.1	101.2
Telcm	**Shops**	**Hlth**	**Utils**	**Other**
45.9	52.9	52.5	46.5	89.5

Market
73.9

The table reports percentage shares of cumulative log excess returns earned on announcement days for different portfolios for the 1964-2011 period. Shares are computed as having a numerator that equals the log mean excess return on a-days times the number of a-days, and the denominator that equals the sum of the log mean excess return on a-days times the number of a-days and the log mean excess return on n-days times the number of n-days. Announcement days account for 11.34% of all trading days in this period.

Panel A covers the 25 Fama-French size- and book-to-market-sorted portfolios, Panel B the ten beta-sorted portfolios (going from low to high beta), and Panel C the ten industry portfolios. All numbers are given in percent.

Table 6: Market Betas by Type of Day

Panel A: 10 Beta-Sorted Portfolios

	Low	2	3	4	5
β_{non}	0.233	0.351	0.442	0.559	0.677
β_{ann} - β_{non}	-0.021	-0.044	-0.035	-0.025	-0.026
	[-0.58]	[-1.76]	[-1.47]	[-0.92]	[-1.07]

	6	7	8	9	High
β_{non}	0.806	0.959	1.107	1.341	1.726
β_{ann} - β_{non}	-0.017	-0.016	-0.005	0.005	-0.025
	[-0.63]	[-0.71]	[-0.29]	[0.19]	[-0.48]

Panel B: Fama-French 25 Portfolios

		Growth	2	3	4	Value
Small	β_{non}	1.007	0.877	0.784	0.739	0.745
	β_{ann} - β_{non}	-0.067	-0.071	-0.062	-0.050	-0.074
		[-2.12]	[-2.43]	[-2.21]	[-1.69]	[-2.44]
2	β_{non}	1.100	0.931	0.871	0.831	0.940
	β_{ann} - β_{non}	-0.058	-0.031	-0.022	-0.015	-0.052
		[-2.24]	[-1.36]	[-0.84]	[-0.51]	[-1.54]
3	β_{non}	1.111	0.911	0.840	0.840	0.840
	β_{ann} - β_{non}	-0.023	-0.025	-0.033	-0.029	-0.028
		[-1.04]	[-1.45]	[-1.53]	[-1.24]	[-1.06]
4	β_{non}	1.083	0.928	0.912	0.869	0.963
	β_{ann} - β_{non}	0.016	0.008	-0.025	-0.035	-0.071
		[0.79]	[0.45]	[-1.10]	[-1.50]	[-2.43]
Large	β_{non}	1.053	0.971	0.961	0.928	0.975
	β_{ann} - β_{non}	0.008	0.019	0.009	0.009	-0.016
		[0.40]	[1.03]	[0.49]	[0.36]	[-0.58]

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-French size and book-to-market sorted portfolios in Panel B. T-statistics for the difference are computed using robust standard errors and are reported in brackets.

Table 7: Forecasting Quarterly Market Return Variance

	Constant	rA_t-rN_t	rA_t	rN_t	$rMKT_t$	RV_t	PE_t	TY_t	DEF_t	VS_t	Adj. R^2
RV_{t+1}	-0.086				-0.045	0.317	0.015	0.002	0.015	0.028	24.3%
	[-1.65]				[-1.21]	[3.08]	[1.73]	[0.70]	[1.46]	[1.25]	
RV_{t+1}	-0.083				-0.049	0.309	0.026		0.022		24.2%
	[-1.90]				[-1.41]	[3.12]	[2.24]		[1.81]		
RV_{t+1}	-0.074		0.082	-0.071		0.294	0.024		0.021		24.7%
	[-1.78]		[1.16]	[-1.88]		[3.07]	[2.12]		[1.76]		
RV_{t+1}	0.015	0.060				0.407					21.8%
	[4.69]	[2.40]				[4.30]					
RV_{t+1}	0.014	0.103			0.055	0.417					21.9%
	[4.85]	[2.15]			[1.22]	[4.89]					
RV_{t+1}*	0.014		0.158	-0.048		0.417					21.9%
	[4.85]		[1.76]	[-1.92]		[4.89]					

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 Campbell, Giglio, Polk, and Turley's (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.

*Indicates the specification used to forecast RV in the next table.

Table 8: Market Returns and Expected Variance

	Intercept	$rMKT_t$		EV_t	Adj. R^2/F-stat
Panel A: Quarterly Market Return					
$rMKT_{t+1}$	0.004	0.084		0.193	-0.5%
	[0.362]	[1.141]		[0.482]	0.50
EV_{t+1}	0.013	0.002		0.498	23.5%
	[7.139]	[0.142]		[6.117]	30.25

	Intercept	rA_t	rN_t	EV_t	Adj. R^2/F-stat
Panel B: Quarterly Ann. and Non-Ann. Day Market Returns					
rA_{t+1}	-0.003	0.101	0.011	0.372	7.1%
	[-1.493]	[1.017]	[0.395]	[4.765]	5.86
rN_{t+1}	0.005	-0.151	0.106	-0.055	0.0%
	[0.362]	[-0.560]	[1.333]	[-0.102]	0.98
EV_{t+1}	0.013	0.023	-0.003	0.479	23.2%
	[5.964]	[0.414]	[-0.254]	[4.636]	20.15

	Intercept	rA_t	rN_t	RV_t	Adj. R^2/F-stat
Panel C: Quarterly Ann. and Non-Ann. Day Market Returns (Realized Variance)					
rA_{t+1}	0.002	0.159	-0.007	0.155	7.1%
	[1.380]	[1.613]	[-0.240]	[4.765]	5.86
rN_{t+1}	0.004	-0.160	0.109	-0.023	0.0%
	[0.567]	[-0.668]	[1.637]	[-0.102]	0.98
RV_{t+1}	0.014	0.158	-0.048	0.417	21.9%
	[4.855]	[1.762]	[-1.915]	[4.885]	18.75

The table reports OLS estimates of a VAR(1) using quarterly data from 1964 to 2011. Variables included are: quarterly log market excess returns (rMKT), quarterly aggregate announcement-day log market excess returns (rA), quarterly aggregate non-announcement-day log market excess returns (rN), the expected variance of the market return (EV, computed using the specification given in the last row of Table 7), 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 VAR.