Sources of Return Predictability

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Abstract

We develop an approach to determine whether a particular predictor represents a proxy for fundamental risk. We build on the assumption that risk-based predictors should be linked to new information about economic conditions. We show that most predictors forecast returns on *either* days with macroeconomic announcements *or* the remaining days, indicating that sources of return predictability differ across predictors: few are driven by fundamental risk; most have other origins. We show that Shiller's excess volatility is confined to non-announcement days, suggesting that the ability to forecast stock market's noise component underlies much of the predictability documented in the literature.

Keywords: Announcements; Returns' predictability; Risk

JEL Classification: G12, G14

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1 Introduction

Stock returns are predictable, as shown by a large and still-growing literature.[1] While there exists little dispute about this basic result, the interpretation of many of the best-known predictors is another matter, with proposed explanations ranging from behavioral theories to various frictions to risk-based theories.

In this paper, we develop an approach for identifying predictors which represent proxies for fundamental risk, which is based on an intuitive assumption that such predictors should be linked to new information about economic fundamentals. We hypothesize that days when important macroeconomic news is scheduled to be announced (announcement days) are more likely to coincide with releases of such information than other days (non-announcement days).[2] To support our assumption, we show that both excess volatility (with respect to the dividend discount model, (Shiller, 1981)) and residual volatility (with respect to the conditional CAPM) are concentrated on non-announcement days and virtually absent from announcement days. Building on the work of Andrei, Cujean, and Wilson (2023), we show that disagreement about the future fundamentals offers one potential explanation for our results. Consequently, predictors whose forecasting power is concentrated on announcement (non-announcement) days are more (less) likely to represent proxies for fundamental risk and less (more) likely to represent proxies for the excess volatility/noise component of stock market movements.

As in Savor and Wilson (2013), we define as announcement days (A-days) those trading days when news about inflation, unemployment, or Federal Open Market Committee (FOMC) interest rate decisions is scheduled to be released and all other trading days as non-announcement days (N-days). Using CRSP value-weighted returns aggregated

[1] See Cochrane (2007), Goyal and Welch (2007), Campbell and Thompson (2007), and Harvey, Liu, and Zhu (2015), among others.

[2] Previous literature finds that announcement days are indeed special, both in terms of time-series (Savor and Wilson, 2013) and cross-sectional (Savor and Wilson, 2014) return patterns.

separately for A- and N-days, we revisit the 1980s excess volatility puzzle which claims that the observed price movements cannot be justified by subsequent fundamentals. In particular, they cannot be explained by the stream of subsequent dividends since the realized prices move too much compared to the time-series of ex-post rational price (fundamental value) realization (Shiller, 1981). We show that the excess volatility puzzle defined in this way is very strong on N-days and limited on A-days. To this end, we use multivariate regressions ($Y_{t+1} = \beta_0 + \beta_1 r_t^A + \beta_2 r_t^N$) of future log changes in ex-post rational price (Y_{t+1}) on past returns accrued on both A-days (r_t^A) and N-days (r_t^N). Quarterly and annual returns accrued on A-days are positively related to future changes in fundamental value with $\beta_1 = 0.01$ ($t(\beta_1) = 1.81$) and $\beta_1 = 0.046$ ($t(\beta_1) = 1.7$) in regressions using quarterly and annual frequency data, respectively. This relation does not hold for their N-day counterparts with β_2 not significantly different from zero at any frequency. Hence, although it may be true that the price movements on N-days are too big to be justified by subsequent dividends, this is not the case for price movements experienced on A-days. Using the Campbell and Shiller (1988) decomposition, we further show that *both* the excess volatility (with respect to the dividend discount model) puzzle *and* the residual volatility (with respect to the conditional CAPM) puzzles are confined to non-announcement days and absent from announcement days. This further confirms our hypothesis that days when new information about *future* economic fundamentals is learned by the market are more likely to coincide with A-days than N-days. As a result, variables predicting A-day returns and those predicting N-day returns are crucially different with respect to the source of their ability to predict returns. While A-day predictors are driven by future fundamentals, N-day predictors seem to be predicting the "noise" component of stock market movements.

Building on the above, we find that many widely used stock market predictors forecast returns only on N-days. For example, log price/dividend ratio (pd_t, Campbell (1996), Litzenberger and Ramaswamy (1979)), long government yield (lty, Fama and

French (1989)), treasury bill yield (*tbl*, Campbell (1987)), investment-to-capital ratio (i/k, Cochrane (1991)), production output gap (*ogap*, Cooper and Priestley (2009)), cyclical consumption (*pce*, Atanasov, Moller, and Priestley (2020), consumption fluctuations (*skew*, Colacito, Ghysels, Meng, and Siwasarit (2016)), and year-end economic growth characteristics (*gpce*, *gip*, Møller and Rangvid (2015)) forecast future returns accrued on N-days with a negative sign, while term spread (*tms*, Fama and French (1989); Campbell (1987)), and long government return spread (*ltr*, Fama and French (1989)) forecast future N-day returns with a positive sign. These predictors do not exhibit comparable ability to predict A-day returns, and – most of the time – the point estimates for these predictors have opposite signs (none are statistically significant). By contrast, default yield spread (dfy, Fama and French (1989)), stock return variance (sum of squared daily returns on the S&P 500, *svar*, Guo (2006)), and oil price changes (*wtexas*, Driesprong, Jacobsen, and Maat (2008)) forecast stock returns accrued on A-days with a positive sign but do not work on N-days. Similarly, although nearness to 52-week Dow high (*dtoy*, Li and Yu (2012)) predicts next quarter's stock returns accrued on A-days with a negative sign, the variable lacks predictive power for N-day returns. Only nearness to all-time Dow high (*dtoat*, Li and Yu (2012)) and average correlation of stock returns (*avgcor*, Pollet and Wilson (2010)) predict returns on both types of days. Even then, the magnitude of this relationship and its statistical significance are much higher on N-days than on A-days.

The above evidence shows a clear dichotomy exists between A-days and N-days with respect to their return predictors. Strikingly, overwhelming majority of stock market predictors suggested in the literature forecast returns only on N-days (where excess and residual volatility are concentrated) but lack predictive power for A-days (which are more likely to be driven by new information about economic fundamentals). This allows us to group predictors into those that are linked to economic news and those that are not. The predictors that are based on direct measures of the amount of risk in the economy (like *svar*), which according to asset pricing theory should forecast returns (but fail to do so in reality), forecast quarterly returns accrued on A-days (but not on N-days). For the predictors historically documented to forecast future stock returns, we show that while they forecast N-day returns, they do not exhibit explanatory power for A-day returns. Overall, these findings are consistent with the hypothesis that sources of return predictability differ across predictors, with direct risk-based measures driven by economic fundamentals and most of the others having different origins. Since vast majority of predictors do not forecast A-day returns, we conclude that new information about future fundamentals is not at the heart of their ability to forecast returns.

We build on the work of Andrei et al. (2023) to show that disagreement about future fundamentals can present a potential explanation for our results. We construct a measure of disagreement about future stock market returns using IBES analysts' expectations of next year's prices as the cross-sectional variance of the difference between each analyst's expectation of the stock market return and the consensus expectation of the stock market return. We show that the predictive power of such-constructed disagreement measure is concentrated on N-days and missing from A-days for annual, 6-months, and quarterly returns. The methodology presented in this paper can be applied to yet-to-be-discovered stock market predictors in order to evaluate whether they forecast the economic fundamentals or excess volatility.

Related literature. This paper relates to a strain of literature documenting the differential behavior of asset returns on A-days and N-days and the potential explanations for these findings. Savor and Wilson (2014) show that stock returns on said A-days are significantly higher and their patterns easier to reconcile with known asset pricing theories than their N-day counterparts. In particular, they show that while the CAPM holds on A-days, it fails to hold on N-days. Similarly Brooks, Katz, and Lustig (2018) show that while the expectations hypothesis holds on A-days, it fails thereafter and this failure increases in the length of the window considered. Attempts have been made to reconcile these differences within standard asset pricing models (Savor and Wilson, 2014) and to find the drivers behind the phenomenon pointing to increases in the price of risk as opposed to the quantity of risk on A-days (Savor, Wilson, and Puhl, 2015). Meanwhile, other authors argued this differential behavior of A-day returns is only a by-product of high ex-post returns on those days rather than an evidence of them being in any way special (Ernst, Gilbert, and Hrdlicka, 2019). The results in our paper add three additional dimensions to the startling dichotomy between returns accrued on A-days and N-days. First, we show that excess (with respect to the dividend discount model) and residual (with respect to conditional CAPM) volatility is an N-day phenomenon and virtually missing from A-days. Second, we show that the widely-documented ability of various variables to predict stock market returns is confined to days when no new macroeconomic announcements are made. Finally, we show that disagreement about future fundamentals is a strong preditor of N-day but not A-day returns.

The paper also contributes to literature on stock market predictability. Goyal and Welch (2007) offer an extensive overview of variables found to predict stock market returns. Our work contributes to this strand of literature by showing that overwhelming majority of stock market return predictors reported in the literature lack forecasting power for the part of stock market returns earned on days when important information about macroeconomic fundamentals is revealed into financial markets. Instead, such predictors' ability to forecast stock market returns is confined to days which are unlikely to coincide with release of new information about future fundamentals. Since (as we show) excess volatility of the stock market is confined to these days, we conclude that it is the ability to forecast stock market's noise component that underlies much of stock market predictability documented in the literature.

2 Data and summary statistics

The macroeconomic announcements considered are in line with those used by Savor and Wilson (2013) and Savor and Wilson (2014). As in these papers, inflation and unemployment announcement dates come form the US Bureau of Labor Statistics (https://www.bls.gov/) with the available time series staring in 1958. We follow the authors in using consumer price index (CPI) announcements up to and including February 1972. Producer price index (PPI) announcements are used between March 1972 and January 2018 (inclusive). This is because in that time period PPI numbers are reported a few days prior to the CPI ones thus diminishing the informational content of the CPI numbers. Between February 2018 and December 2019, for some months CPI is again released before PPI. In our analysis we use the date of the earlier of these two announcements. FOMC interest rate announcement days come from the Federal Reserve website and are available from 1978 onward. Unscheduled FOMC meetings are excluded from the sample.

Data on stock market returns comes from Center for Research in Security Prices (CRSP). Data on risk-free interest rate comes from Professor Kenneth French's website. Our main stock market proxy is the CRSP NYSE, Amex, and Nasdaq value-weighted index of all listed shares. We collect daily values of this index between January 1953 and December 2022. We use those valuations and the daily risk free rate to construct log daily excess returns over this time period. These are then aggregated on a quarterly basis for all trading days in the given quarter ($r_t^{A\&N}$), all A-days in a given quarter (r_t^A), and all N-days in a given quarter (r_t^N).

Panel A of Table 1 presents the summary statistics for these returns. Since the predictor variables studied in this paper run between 1953Q1 and 2021Q4, we focus on that time period here. We see that the average quarterly return on N-days over this time period (1.2%) is almost twice as large as the average quarterly return on A-days (0.6%). Compared to N-day quarterly returns, A-day returns are less volatile (0.03 vs. 0.08), exhibit lower autocorrelation (-0.02 vs. 0.1), and are less negatively skewed (-0.64 vs. -0.75).

We test a wide range of variables historically documented to be predictors of stock returns. Table 2 provides a summary of those, their abbreviations used throughout the paper, references to papers that introduced them to the literature, and the frequency at which the variables are computed. With the exception of the price dividend ratio, the variables' time series are courtesy of Amit Goyal, Ivo Welch, and Athanasse Zafirov, who have kindly shared their data with us. Panels A trough D of Table 3 provide summary statistics of the predictor variables considered.

Data on analysts' one-year-ahead price expectations comes from IBES and covers the period between January 2000 and December 2022.

3 Excess and residual volatility – an N-day puzzle

Shiller (1981) shows that realized stock prices move too much to be justified by the subsequent changes in dividends. In this section we revisit the relationship between these price changes and the subsequent dividends for A-days and N-days, independently. We show that quarterly (annual) returns accrued on A-days forecast changes in next quarter (year) ex-post rational price. The same is not true for quarterly (annual) returns accrued on N-days. In regressions of fundamental value (understood as sum of discounted ex-post realized dividends) changes on lagged returns accrued on these two types of days, the coefficient for returns accrued on A-days is positive and significantly higher than that for returns accrued on N-days.

In what follows, we use the Campbell and Shiller (1988) decomposition to show that *both* the excess volatility puzzle (with respect to the dividend discount model) *and* the residual volatility (with respect to the conditional CAPM) are strictly N-day puzzles. This suggests that the price changes on the two types of days are driven by different processes and allows us to later on argue that the predictability of A-day returns must consequently have a different source to the predictability of N-day returns.

3.1 Shiller's excess volatility puzzle

We follow very closely Shiller (1981) methodology to calculate the real values of prices and dividends, and their de-trended counterparts. However, unlike the original paper we sample prices at the end of each period while the original paper records them for its beginning. Since this slightly alters the formulas and as we acknowledge the time that has passed since the original work, in what follows we briefly summarize the main idea behind the original excess volatility puzzle and the steps taken in the original work to arrive at it.

Revisiting Shiller (1981)'s approach. For the simple efficient markets model to be correct the real price P_t at the end of time period t should be equal to:

$$P_t = \sum_{k=1}^{\infty} \gamma^k E_t D_{t+k},^{3} \tag{1}$$

where the D_t is the real dividend paid at time t and γ is a constant real discount factor. As in the original work, we assume all dividends D_t occur at the end of the relevant time period t. The constant real interest rate r is defined such that $\gamma = 1/(1+r)$ and has the property that $r = E_t(H_t)$, where H_t is the holding period return $H_t \equiv (\Delta P_{t+1} + D_{t+1})/P_t$.[4]

It is possible to restate the relationship in Equation (1) using detrended prices and dividends. Such detrending is done by restating those time series as a proportion of the long-run growth factor: $p_t = P_t/\lambda^{t-T}$, $d_t = D_t/\lambda^{t-T}$,[5] where T is the last period for which we have observations (the base period) and λ^{t-T} is the growth factor. The growth factor is calibrated by estimating a long-run exponential growth path for the time series of real prices. To this end, we regress $ln\,(P_t)$ on a constant and time and set $\lambda = e^b$, where b is the coefficient on time in $ln\,(P_t) = a + b * t$. It can be shown

[3] $P_t = \sum_{k=0}^{\infty} \gamma^{k+1} E_t D_{t+k}$ in Shiller (1981).
[4] $H_t \equiv (\Delta P_{t+1} + D_t)/P_t$ in Shiller (1981).
[5] $d_t = D_t/\lambda^{t+1-T}$ in Shiller (1981).

that the following holds for such detrended time series:

$$p_t = \sum_{k=1}^{\infty} \overline{\gamma}^k E_t d_{t+k},\text{[6]} \tag{2}$$

where $\overline{\gamma} \equiv \lambda\gamma$ is the constant discount factor appropriate for the detrended time series of p_t and d_t. The corresponding discount rate $\overline{r}$, $\overline{\gamma} = 1/(1+\overline{r})$, can be shown to be equal to the mean detrended dividend divided by the mean detrended price:$\overline{r} = E(d)/E(p)$.[7]

The above relationship (2) can be re-written in terms of *ex-post* rational price series p_t^*. Such *ex-post* rational price is the present value of actual subsequent dividends:

$$p_t^* = \sum_{k=1}^{\infty} \overline{\gamma}^k d_{t+k}.\text{[8]} \tag{3}$$

As pointed out in the original paper, although the summation extends to infinity, with long enough time series we can observe a reasonably accurate approximation of p_t^*. Subject to the choice of terminal (base year) value of the *ex-post* rational price, p_T^*, the entire time series can be determined recursively by

$$p_t^* = \overline{\gamma}\left(p_{t+1}^* + d_{t+1}^*\right)\text{[9]}$$

working backwards from the base year.

Calibration. We follow the above process for the CRSP NYSE, Amex, Nasdaq value-weighted index of all common shares. Prices (p_t) are assumed to be the time series of CRSP index level excluding dividends. We calculate dividends (d_t) at monthly intervals between January 1950 and December 2019. Both prices and dividends are deflated using the CPI values provided by Professor Shiller on his website. We estimate the long-run exponential growth path using daily frequency data in line with $ln(P_t) = a+bt$ and set λ as e^b. $\overline{r}$ is estimated using monthly frequency data as the mean of the

[6] $p_t = \sum_{k=0}^{\infty} \overline{\gamma}^{k+1} E_t d_{t+k}$ in Shiller (1981).

[7] This follows from taking unconditional expectation of both sides of equation (2) and solving for $\overline{r}$. Compare: footnote 7, page 424 in (Shiller, 1981).

[8] $p_t^* = \sum_{k=0}^{\infty} \overline{\gamma}^{k+1} d_{t+k}$ in Shiller (1981).

[9] $p_t^* = \overline{\gamma}\left(p_{t+1}^* + d_t^*\right)$ in Shiller (1981).

detrended dividend divided by the mean of the detrended price. For the purpose of calculating p_t^*, the terminal value p_T^* is set as the average of the detrended real price over the sample. For the purpose of calculating P_t^*, the terminal value P_T^* is set to the terminal value of the real price process: P_T.

Excess volatility. Figure (1) shows the behaviour of detrended real prices (p_t) and detrended ex-post rational prices (p_t^*) of the CRSP NYSE, Amex, Nasdaq value-weighgted index between 1950 and 2022. This figure corresponds to Figures (1) and (2) in Shiller (1981). As in the original work, we observe that the realized prices seem too volatile for their movements to be driven by new information about the stream of subsequent dividends (i.e. for the efficient markets model as proposed by Equation (1) to accurately describe the price process).

3.2 Which price changes forecast future fundamental value changes?

Having computed the fundamental value (*ex-post* rational price) time series we are now in a position to test whether there is a difference in the informational content of changes in prices on A-days and N-days. In particular, we can now test which of them is better able to forecast future changes in fundamental value.

Let $\widetilde{P}_{t+1}^* = log(P_{t+1}^*) - log(P_t^*)$ and $\widetilde{p}_{t+1}^* = log(p_{t+1}^*) - log(p_t^*)$. These are the log change in the real ex-post rational price and the log change in the detrended real ex-post rational price, respectively. Setting Y_{t+1} to either $\widetilde{P}_{t+1}^*$ or $\widetilde{p}_{t+1}^*$, we can run the following regression to predict these changes at monthly, quarterly, and annual frequencies:

$$Y_{t+1} = \beta_0 + \beta_1 r_t^A + \beta_2 r_t^N, \tag{4}$$

where r_t^A and r_t^N are the part of the lagged return of the relevant frequency accrued on A-days and N-days, respectively. Since we are not only interested in the economic and statistical significance of β_1 and β_2, but also in formally testing whether $\beta_1 > \beta_2$, we turn to the following regression:

$$Y_{t+1} = \delta_0 + \delta_1(r_t^A + r_t^N) + \delta_2(r_t^A - r_t^N). \quad (5)$$

In the above, we observe that: $\beta_1 = \delta_1 + \delta_2$ and $\beta_2 = \delta_1 - \delta_2$. As a result, the following is true:

1. if $\beta_1 > \beta_2$, then $\delta_1 + \delta_2 > \delta_1 - \delta_2$, and so $\delta_2 > 0$
2. since $\delta_1 = 0.5(\beta_1 + \beta_2)$ and $\delta_2 = 0.5(\beta_1 + \beta_2)$, $\delta_2 > 0$ implies $\beta_1 > \beta_2$.

Hence, $\delta_2 > 0$ *if and only if* $\beta_1 > \beta_2$.

We estimate the relationships in Equation 4 and 5 at monthly, quarterly, and annual frequencies for two time periods: 1953 – 2022 and 1953 – 2010. This is to account for the fact that starting from January 2011 the terminal values of p_T^* and P_T^* become non-negligible share of p_t^* and P_t^*. Table 4 summarizes the results for $Y_{t+1} = \widetilde{P}_{t+1}^*$ i.e. the real ex-post rational price. Table 5 summarizes the results for $Y_{t+1} = \widetilde{p}_{t+1}^*$ i.e the *detrended* real ex-post rational price. In the below, unless separately specified, we summarize the regression estimates from the 1953 – 2010 time period.

At *monthly frequency*, we observe that although the relationship between the returns and the future fundamental value changes is positive for the share of monthly returns accrued on A-days ($\beta_1 = 0.003$ when $Y_{t+1} = p_t^*$; $\beta_1 = 0.004$ when $Y_{t+1} = P_t^*$) and negative for the share of monthly returns accrued on N-days ($\beta_2 = -0.002$ when $Y_{t+1} = p_t^*$; $\beta_2 = -0.003$ when $Y_{t+1} = P_t^*$), neither relationship is statistically significant. Similarly, although positive (0.003 across both specifications), δ_2 is not statistically significant ($t(\delta_2)$ equal to 1.3 and 1.28 for $Y_{t+1} = P_t^*$ and $Y_{t+1} = p_t^*$, respectively). There is no evidence that cumulative monthly A-day returns forecast future one-month-ahead changes of fundamental value better than their N-day counterparts. The same is, however, no longer true at quarterly and annual frequencies.

Quarterly frequency data shows that cumulative A-day returns forecast next quarter's log change of fundamental value with a positive sign. In the shorter time period (1953

– 2012) β_1 is equal to 0.010 and 0.014 when $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$, respectively. This means that a one percentage point increase in the cumulative A-day return in a given quarter leads to a 1.4 basis points (1 basis point) increase in the next quarter's log change in (de-trended) real ex-post rational price P_t^* (p_t^*). This relationship is statistically significant at 10% confidence level ($t(\beta_1) = 1.8$ when $Y_{t+1} = p_t^*$ and $t(\beta_1) = 1.81$ when $Y_{t+1} = P_t^*$). The relationship between N-day returns and future fundamental value changes is negative but not statistically significantly so ($t(\beta_2) = -0.001$ for both $Y_{t+1} = p_t^*$ and $Y_{t+1} = P_t^*$). Estimates of equation (5) indicate that $\beta_1 > \beta_2$ at quarterly frequency: $\delta_2 = 0.006$ for $Y_{t+1} = p_t^*$ and $\delta_2 = 0.008$ for $Y_{t+1} = P_t^*$ and statistically significant at 10% level ($t(\delta_2) = 1.78$ using p_t^*; $t(\delta_2) = 1.82$ using P_t^*). This means that, at quarterly frequency, A-day price changes are able to forecast next quarter's change in fundamental value better than N-day price changes.

We find similar results using *annual frequency* data. Cumulative A-day returns at this frequency forecast next year's changes in fundamental value with a positive sign: $\beta_1 = 0.035$ for $Y_{t+1} = p_t^*$ and $\beta_1 = 0.046$ for $Y_{t+1} = P_t^*$. Both estimates are significant at 10% confidence level. As such, a one percentage point increase in the cumulative A-day return in a given year leads to a 4.6 (3.5) basis points increase in next year's log change in (detrended) real ex-post rational price P_t^* (p_t^*). As in the quarterly returns case, the relationship between cumulative annual N-day returns and next year's fundamental value changes is negative but not statistically significantly so. Finally, estimates of equation (5) indicate that $\beta_1 > \beta_2$ at annual frequency: $\delta_2 = 0.022$ for $Y_{t+1} = p_t^*$ and $\delta_2 = 0.029$ for $Y_{t+1} = P_t^*$ and statistically significant at 5% level ($t(\delta_2) = 1.97$ using p_t^*; $t(\delta_2) = 1.99$ using P_t^*). Similarly to quarterly frequency, at annual frequency, A-day price changes are able to forecast next quarter's change in fundamental value better than N-day price changes.

These results shed more light on the excess volatility puzzle (Shiller, 1981). Although it is true that price movements in general are too big to be attributed to new information about actual subsequent fundamental value changes, a clear dichotomy exists in this respect for aggregate movements on A-days and N-days. We show that, although the aggregate price changes on N-days can not be justified by subsequent changes in fundamental value, the same is not true for aggregate price changes accrued on A-days. Quarterly returns accrued on A-days forecast future changes in ex-post rational price (detrended or not) with a positive sign. Furthermore, at both quarterly and annual frequency the ability to forecast such future changes in fundamental value is superior for A-day compared to N-day returns. This suggests that the movements in prices on A-days are not "too big relative to actual subsequent dividends" (Shiller, 1981).

3.3 Excess and residual volatility: an A/N-day decomposition

One well-known issue with Shiller (1981)'s fundamental value calculations is that they do not allow for time-varying discount rates. This may make the reader suspicious of the results derived above. Therefore, in what follows we use the Campbell and Shiller (1988) decomposition to further showcase that the excess volatility (relative to the Dividend Discount Model) and residual volatility (relative to the Conditional CAPM) phenomena are confined to N-days and (almost) absent from A-days.

Derivations. Let us define the following variables:

$$pd_t = \ln\left(\frac{P_t}{D_t}\right),$$

$$r_{t+1} = \ln(1 + R_{t+1}),$$

$$\Delta d_{t+1} = \ln\left(\frac{D_{t+1}}{D_t}\right),$$

$$\begin{aligned}
\sigma_R^2 &= Var[r_{t+1}] = Var[r_{t+1}^A + r_{t+1}^N], \\
\sigma_A^2 &= Var[r_{t+1}^A], \\
\sigma_N^2 &= Var[r_{t+1}^N],
\end{aligned}$$

$$\begin{aligned}
\overline{pd} &= E[pd_t], \\
\rho &= (1 + \exp(-\overline{pd}))^{-1}, \\
k &= -\ln\rho - (1-\rho)\ln(1/\rho - 1).
\end{aligned}$$

Then, Campbell-Shiller derive:

$$r_{t+1} \approx k + \Delta d_{t+1} + \rho pd_{t+1} - pd_t. \tag{6}$$

Rearranging (6) gives us

$$pd_t \approx k + \Delta d_{t+1} - r_{t+1} + \rho pd_{t+1},$$

which can be iterated forward to derive

$$pd_{t+1} \approx k + \Delta d_{t+2} - r_{t+2} + \rho pd_{t+2}.$$

Substituting this last expression into (6) gives

$$\begin{aligned} r_{t+1} &\approx k + \Delta d_{t+1} + \rho(k + \Delta d_{t+2} - r_{t+2} + \rho pd_{t+2}) - pd_t \\ &= (1+\rho)k + \Delta d_{t+1} + \rho \Delta d_{t+2} - \rho r_{t+2} + \rho^2 pd_{t+2} - pd_t \\ &= \frac{1-\rho^{1+1}}{1-\rho}k + \Sigma_{j=0}^{1} \rho^j \Delta d_{t+1+j} - \Sigma_{j=1}^{1} \rho^j r_{t+1+j} + \rho^{1+1} pd_{t+1+1} - pd_t. \end{aligned}$$

Repeating these iterations T times gives:

$$r_{t+1} \approx \frac{1-\rho^{T+1}}{1-\rho}k + \Sigma_{j=0}^{T} \rho^j \Delta d_{t+1+j} - \Sigma_{j=1}^{T} \rho^j r_{t+1+j} + (\rho^{T+1} pd_{t+T+1} - pd_t). \tag{7}$$

Since, by construction

$$r_{t+1} = r_{t+1}^A + r_{t+1}^N,$$

the following holds:

$$r_{t+1} = r_{t+1}^A + r_{t+1}^N \approx \frac{1-\rho^{T+1}}{1-\rho}k + \Sigma_{j=0}^{T} \rho^j \Delta d_{t+1+j} - \Sigma_{j=1}^{T} \rho^j r_{t+1+j} + (\rho^{T+1} pd_{t+T+1} - pd_t).$$

Since the variance of the LHS of (7) equals the covariance of the LHS with the RHS, and since dividing both sides by $Var[r_{t+1}]$ yields both sides to equal (approximately) one, it can be shown that the following holds true:

$$
\begin{aligned}
&\frac{Cov\left[r^A_{t+1}, \Sigma^T_{j=0}\rho^j \Delta d_{t+1+j}\right]}{Var[r^A_{t+1}]}\frac{Var[r^A_{t+1}]}{Var[r_{t+1}]} + \frac{Cov\left[r^N_{t+1}, \Sigma^T_{j=0}\rho^j \Delta d_{t+1+j}\right]}{Var[r^N_{t+1}]}\frac{Var[r^N_{t+1}]}{Var[r_{t+1}]} \\
&- \frac{Cov\left[r^A_{t+1}, \Sigma^T_{j=1}\rho^j r_{t+1+j}\right]}{Var[r^A_{t+1}]}\frac{Var[r^A_{t+1}]}{Var[r_{t+1}]} - \frac{Cov\left[r^N_{t+1}, \Sigma^T_{j=1}\rho^j r_{t+1+j}\right]}{Var[r^N_{t+1}]}\frac{Var[r^N_{t+1}]}{Var[r_{t+1}]} \\
&+ \frac{Cov\left[r^A_{t+1}, \rho^{T+1} pd_{t+T+1} - pd_t\right]}{Var[r^A_{t+1}]}\frac{Var[r^A_{t+1}]}{Var[r_{t+1}]} + \frac{Cov\left[r^N_{t+1}, \rho^{T+1} pd_{t+T+1} - pd_t\right]}{Var[r^N_{t+1}]}\frac{Var[r^N_{t+1}]}{Var[r_{t+1}]} \\
\approx\ & 1.
\end{aligned}
\tag{8}
$$

The expressions of the form

$$
\frac{Cov[r^k_{t+1}, y_{t+1}]}{Var[r^k_{t+1}]},\ k \in [A, N]
$$

are just the betas from a univariate regression of the following type

$$
y_{t+1} = \alpha_k + \beta_k r^k_{t+1} + \varepsilon^k_{t+1}
$$

or if $Cov[r^A_{t+1}, r^N_{t+1}] = 0$, they are also the betas from a bivariate regression of the following type

$$
y_{t+1} = \alpha + \beta_A r^A_{t+1} + \beta_N r^N_{t+1} + \varepsilon_{t+1}.
$$

The decomposition outlined by (8) allows us to measure the shares of A-day and N-day returns in total stock market volatility. It also allows us to measure how much each type of market return contributes to excess volatility. For a high value of T, the share of *excess* (relative to the DDM) volatility of returns under each regime are given by

$$
S^A_{EV} = \frac{Cov\left[r^A_{t+1}, \rho^{T+1} pd_{t+T+1} - pd_t\right]}{Var[r_{t+1}]} - \frac{Cov\left[r^A_{t+1}, \Sigma^T_{j=1}\rho^j r_{t+1+j}\right]}{Var[r_{t+1}]} \tag{9}
$$

and

$$
S^N_{EV} = \frac{Cov\left[r^N_{t+1}, \rho^{T+1} pd_{t+T+1} - pd_t\right]}{Var[r_{t+1}]} - \frac{Cov\left[r^N_{t+1}, \Sigma^T_{j=1}\rho^j r_{t+1+j}\right]}{Var[r_{t+1}]}. \tag{10}
$$

This is not the end of the story. A-day returns will account for a positive share of excess volatility under this measure. However, some of that share is likely due to changing measures of fundamental risk such as stock market return variance, which is somewhat persistent, but nowhere near as persistent as dividend-price ratios. If, following the Conditional CAPM, we believe that changing risk-free rates and changing measures of stock market variance are not *irrational* drivers of changes in returns, then we can further decompose these measures into shares due to risk-free rates, market return variances, and a residual. It's only the residual that requires explanation beyond the CCAPM. This is the definition of *residual* volatility (with respect to CCAPM).

We show that the above residual volatility is indeed almost entirely due to N-day returns. This is done by taking the CCAPM as a benchmark, and then allowing it to vary across regimes:

$$\begin{aligned} r^A_{t+1} &= r^A_{f,t+1} + \gamma^A Var_t[r_{t+1}] + \upsilon^A_{t+1} \\ r^N_{t+1} &= r^N_{f,t+1} + \gamma^N Var_t[r_{t+1}] + \upsilon^N_{t+1} \end{aligned} \tag{11}$$

where $Var_t[r_{t+1}]$ is the conditional expectation of the physical variance of market returns and υ_{t+1} is the residual.

As shown by Savor and Wilson (2013), γ^A is positive and significant while γ^N is not. Moreover, $r_{f,t+1}$ is slightly lower on A-days. Imposing (11) on (8) gives a rather lengthy expression which can be used to back out the *residual*, as opposed to *excess*, volatility of returns under each regime.

From the above,

$$\begin{aligned} r_{t+1} &= r^A_{t+1} + r^N_{t+1} \\ &= r^A_{f,t+1} + \gamma^A Var_t[r_{t+1}] + \upsilon^A_{t+1} + r^N_{f,t+1} + \gamma^N Var_t[r_{t+1}] + \upsilon^N_{t+1} \\ &= r^A_{f,t+1} + r^N_{f,t+1} + \gamma^A Var_t[r_{t+1}] + \gamma^N Var_t[r_{t+1}] + \upsilon^A_{t+1} + \upsilon^N_{t+1}. \end{aligned}$$

Then the middle two terms in (8) can each be replaced by:

$$\frac{Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j r_{t+1+j}\right]}{Var[r_{t+1}^{k=A,N}]}$$

$$= \frac{Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j r_{f,t+1+j}^{A}\right]}{Var[r_{t+1}^{k=A,N}]} + \frac{Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j r_{f,t+1+j}^{N}\right]}{Var[r_{t+1}^{k=A,N}]}$$
$$+\frac{\gamma^A Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j Var_{t+j}[r_{t+1+j}]\right]}{Var[r_{t+1}^{k=A,N}]} + \frac{\gamma^N Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j Var_{t+j}[r_{t+1+j}]\right]}{Var[r_{t+1}^{k=A,N}]}$$
$$+\frac{Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j \upsilon_{t+1+j}^{A}\right]}{Var[r_{t+1}^{k=A,N}]} + \frac{Cov\left[r_{t+1}^{k=A,N}, \Sigma_{j=1}^{T}\rho^j \upsilon_{t+1+j}^{N}\right]}{Var[r_{t+1}^{k=A,N}]}$$

The resulting variance decomposition contains sixteen terms, but many of them will be zero. For example we know from previous results that the covariance of r_A with future returns at any horizon is zero once variance-driven effects have been removed. According to this line of reasoning, residual volatility shares under each type of regime are then:

$$S_{RV}^{A} = \frac{Cov\left[r_{t+1}^{A}, \rho^{T+1}pd_{t+T+1} - pd_t\right]}{Var[r_{t+1}]} - \frac{Cov\left[r_{t+1}^{A}, \Sigma_{j=1}^{T}\rho^j \upsilon_{t+1+j}^{A}\right]}{Var[r_{t+1}]} \tag{12}$$

and

$$S_{RV}^{N} = \frac{Cov\left[r_{t+1}^{N}, \rho^{T+1}pd_{t+T+1} - pd_t\right]}{Var[r_{t+1}]} - \frac{Cov\left[r_{t+1}^{N}, \Sigma_{j=1}^{T}\rho^j \upsilon_{t+1+j}^{N}\right]}{Var[r_{t+1}]}. \tag{13}$$

In line with previous results and our reasoning, we would expect S_{RV}^{A} to be (almost) zero and S_{RV}^{N} to be (almost) one, for all T.

Evidence. Equipped with the above derivations and hypothesis we proceed to analyse the A-day and N-day components of excess and residual volatility using the wider CRSP universe index (spanning NYSE, Amex, and Nasdaq stocks) as a proxy.

Expected variance ($Var_t[r_{t+1}]$) – the estimate of aggregate risk according to conditional CAPM – is calculated in line with Savor and Wilson (2014) as the conditional expectation of one-quarter-ahead variance of daily market returns on the corresponding index.

This conditional forecast is computed as a function of contemporaneous (quarter t) excess returns accrued on A-days, excess returns accrued on N-days, realized variance (annualized average squared daily excess market return), and a constant. The corresponding coefficients are calibrated using constrained least squares (where the RV forecast is constrained to be non-negative) predictive regression of realized variance on the lagged variables mentioned before using quarterly data between 1964Q1 and 2022Q4.[10] Figure 2 compares the realized and expected variance between 1964 and 2022 computed for the wider CRSP universe index.

We then proceed to calculate the excess and residual volatility components given by equations 9, 10, 12, and 13 using quarterly data and wider CRSP universe index. Figure 3 shows the A-day and N-day components to excess volatility with respect to the dividend discount model. Figure 4 shows the A-day and N-day components to residual volatility with respect to conditional CAPM. The figures show that the contribution of A-day returns to *both* excess volatility with respect to dividend discount model and residual volatility with respect to the conditional CAPM is almost non-existent for high values of T (i.e. the number of quarters). In fact both the excess and residual volatility puzzles are almost entirely N-day phenomena.

The above results contribute to the literature showcasing differences in stock market behaviour between announcement and non-announcement days (Savor and Wilson (2013), Savor et al. (2015)). We show that while variance-in-mean relationship drives A-day returns, these accrued on N-days are primarily reversal-driven. This motivates the next section of our paper where we separate well-known stock market predictors into "variance-in-mean" and "reversal" ones depending on which returns are they capable of predicting.

[10]Savor and Wilson (2014) explain the model selection in greater detail.

4 Sources of return predictability

In this section we analyse the ability of various stock market predictors documented in the literature to forecast future aggregate quarterly stock market returns, their part accrued on A-days, and their part accured on N-days. Depending on whether a given variable forecasts the part of quarterly returns accured on A-days or N-days, we clasify it as a "variance-in-mean" or a "reversal" predictor, respectively.

Among the predictive variables summarized in Table 2, only *svar* constitutes a measure of the amount of physical risk on the market. As a result, it should be the only variable able to explain future stock returns since according to fundamental asset pricing theories the amount of physical risk should be the only driver behind stock market returns. Although the remaining variables are not such proxies for the physical amount of risk on the market, they have been historically found to predict returns.

Our analysis uses a univariate linear regression framework. We regress the relevant quarterly returns on the various predictors lagged by one quarter. The regression can be summarized as follows:

$$r^i_{t+1} = \alpha + \beta^i x_t, \quad i = (A\&N, A, N),$$

where $r^{A\&N}_{t+1}$, r^{A}_{t+1}, and r^{N}_{t+1} are the aggregate quarterly return, quarterly return accrued on A-days in a given quarter, and quarterly returns accrued on N-days in a given quarter, respectively. x_t is one of the predictors outlined in Table 2.

Panel A of Table 6 summarizes the regression results for variables which were found to be A-day but not N-day return predictors at quarterly frequency. We see that default yield spread (dfy) and oil price changes ($wtexas$) forecast returns accrued on A-days but lack predictive power for returns accrued over the whole quarter. A one percentage point increase in dfy ($wtextas$) leads to 79 (4) basis points *increase* in next quarter's A-day return. On the other hand, stock return variance ($svar$) and nearness to 52-week Dow high ($dtoy$) forecast returns accrued on A-days and over the entire quarter as a whole despite lacking the predictive power for returns accrued on N-days (which constitute the largest share of days in any given quarter). In fact a one percentage point *increase* in *svar* (*dtoy*) leads to 58 (6) basis points *increase* (*decrease*) in next quarter's A-day return and 90 (14) basis points *increase* (*decrease*) in next quarter's return accrued on both types of days.

Panel B of Table 6 shows that in-sample return predictability (if at all present for a given variable) is overwhelmingly an N-day phenomenon. Term spread (*tms*) and long government return spread (*ltr*) are positively correlated with future quarterly N-day returns. An *increase* of one percentage point in *tms* (*ltr*) leads to 52 (21) basis points *increase* in next quarter's N-day returns. The relationship between the remaining predictors and future quarterly N-day returns is negative. In particular, some well-established return predictors such as log price/dividend ratio ($logPD$), long government yield (*lty*), treasury bill rate (*tbl*), and investment to capital ratio (*ik*) are negatively correlated with future stock market returns. A percentage point *increase* in *lty* (*tbl*) leads to a 31 (36) basis points *decrease* in next quarter's N-day return. Similarly, a percentage point *increase* in *ik* and *logPD* lead to 548 and 2 bps *decrease* in next quarter's N-day return, respectively. More recently discovered return predictors such as production output gap (*ogap*), cyclical consumption (*pce*), consumption fluctuations (*skew*), and year-end economic growth characteristics (*gpce*, *gip*) also forecast future N-day returns with negative sign. Overwhelming majority of N-day return predictors also forecast quarterly returns accrued on both types of days. This is unsurprising since N-days constitute the vast majority of days in any given quarter.

Panel C shows that two of the predictors considered were statistically significant in predicting the quarterly returns accrued on *both* A-days and N-days between 1953 and 2021. These were nearness to all-time Dow high (*dtoat*) and average correlation of stock returns (*avgcor*). The magnitude of both relationships is higher for N-day returns than for A-day returns with $\beta^A = -0.03$, $\beta^N = -0.11$ for *dtoat* and $\beta^A = 0.05$ and $\beta^N = 0.13$ for *avcor*. Finally, *Panel D* shows that another fifteen variables historically found to predict stock market returns failed to do so in-sample between 1953 and 2021.

The results outlined above highlight a startling dichotomy between predictors of returns accrued on A-days and those accrued on N-days. We observe that the vast majority of variables historically documented to forecast stock market returns, if at all statistically significant in univariate regressions between 1953 and 2021, predict the part of quarterly returns accrued on N-days but lack predictive power for their part accrued on A-days. On the contrary, variables which have roots in fundamental asset pricing theories and are proxies for physical risk on the market, such as stock variance ($svar$) are both economically and statistically significant predictors of future returns accrued on A-days but not on N-days.

The above results allow us to determine the underlying sources of the widely documented in the literature stock market return predictability. Since the vast majority of well-known return predictors fails to forecast quarterly A-day returns, we can conclude that new information about market fundamentals is not at the heart of this predictability. Most predictor variables are not driven by the "variance-in-mean" relationship but have "reversal" behaviour of the stock market at their origin.

In the final section of this paper, we show that a basic model of disagreement about a signal in line with Andrei et al. (2023) can explain our results.

5 Disagreement

5.1 Heterogeneous signals and predictability

Andrei et al. (2023) show that the CAPM holds for heterogeneous investors with respect to their individual expectations even when it does not hold with respect to the consensus expectations (i.e. the empiricist discovers a flat security market line using variables' consensus aggregates). The authors also show that disagreement matters for the securities market line. On days when public information is revealed to the market (thus decreasing signal disagreement) the securities market line an empiricist can discover using consensus aggregates is stronger. In what follows we show that disagreement about a signal also explains the results presented in this paper.

Andrei et al. (2023) start with the following identity. Given a vector of excess returns $\widetilde{R}^e$, market weights M and market excess return $\widetilde{R}^e_M = M'\widetilde{R}^e$ the Law of Total Variance states that with respect to different investors with different information sets F_i:

$$Var[\widetilde{R}^e] = E[Var[\widetilde{R}^e|F_i]] + Var[E[\widetilde{R}^e|F_i]]$$

The assumptions made by the authors imply that everyone has the same posterior variance of returns conditional on their information, so

$$E[Var[\widetilde{R}^e|F_i]] = Var[\widetilde{R}^e|F_i] \equiv Var_i[\widetilde{R}^e].$$

Consensus expectations are defined as the (continuous analog of) the cross-sectional mean of individual expectations

$$\overline{E}[\widetilde{R}^e] = \frac{1}{N}\sum_{i=1}^{N} E[\widetilde{R}^e|F_i] = \frac{1}{N}\sum_{i=1}^{N} E_i[\widetilde{R}^e].$$

and finally further (very mild) assumptions are made which imply that there is zero covariance between consensus expectations and the cross-sectional dispersion in expectations (essentially Gaussian signals and a large number of investors). Then, the Law of Total Variance implies:

$$Var[\widetilde{R}^e] = Var_i[\widetilde{R}^e] + Var[\overline{E}[\widetilde{R}^e]] + Var[E_i[\widetilde{R}^e] - \overline{E}[\widetilde{R}^e]].$$

In this paper, we work with and are interested in the behaviour of the return on the aggregate stock market. Multiplying every variable before and after by the vector of market weights M and adding time subscripts (i.e. conditioning on an information set of investor i at date t):

$$Var_t[\widetilde{R}^e_{M,t+1}] = Var_{i,t}[\widetilde{R}^e_{M,t+1}] + Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] + Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]].$$

Rearranging gives

$$Var_{i,t}[\widetilde{R}^e_{M,t+1}] = Var_t[\widetilde{R}^e_{M,t+1}] - Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] - Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]].$$

The above expression shows that the variance of the market given any agent's information set $F_{i,t}$ equals the uncondtional date$-t$ variance minus the conditional variance of consensus returns (likely to be extremely small over short time intervals) *and* minus the cross sectional variance of expected market returns. The variance of consensus market returns is an entirely time series magnitude, while the last term is mainly cross-sectional (although it may also vary over time).

Finally suppose a conditional CAPM holds with respect to each agent's information set $F_{i,t}$. That is

$$E_i[\widetilde{R}^e_{M,t+1}] = \gamma Var_{i,t}[\widetilde{R}^e_{M,t+1}].$$

Then with respect to *consensus* beliefs

$$\overline{E}[\widetilde{R}^e] = \frac{1}{N}\sum_{i=1}^{N} E_i[\widetilde{R}^e] = \frac{\gamma}{N}\sum_{i=1}^{N} Var_{i,t}[\widetilde{R}^e_{M,t+1}] = \gamma Var_{i,t}[\widetilde{R}^e_{M,t+1}]$$

since all prior variances are the same by assumption. Then with respect to consensus beliefs, a condtional CAPM holds, but with respect to the conditional market variance of each agent given their information set. Plugging in from our Law of Total Variance for the market portfolio gives

$$\overline{E}[\widetilde{R}^e] = \gamma Var_t[\widetilde{R}^e_{M,t+1}] - \gamma Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] - \gamma Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]].$$

Standard tests for a variance-in-mean relation for market returns include only the first term on the RHS but not the second two. In small time intervals such as monthly or quarterly data, the second term is unlikely to be large, while the third term is likely to be large when there is dispersion of beliefs, and also somewhat variable over time. However, for our purposes, what is even more striking is that when agents observe dispersed signals $F_{i,t}$ which vary across agents, this last term is likely to be much larger than when they observe a common signal. Therefore the standard variance-in-mean regression of realized market returns on date-t market variance is likely to perform much better on announcement days than at other times, just as discovered by Savor and Wilson (2013). In general, to test for a Conditional CAPM, we should also include a measure of dispersion of beliefs $Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]$.

What about reversal? Over time infomation gets updated and disagreement disappears in a rational Bayesian framework. Since there is only disagreement on non-announcement days, all the reversal occurs on those days. According to this interpretation, things which predict A-day returns but not N-day returns are proxies for $Var_t[\widetilde{R}^e_{M,t+1}]$ while things that predict N-day returns but not A-day returns are proxies for $Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]$ (or conceivably $Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] + Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]$ or even $Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] + Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]] - 2Cov_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}], \overline{E}[\widetilde{R}^e_{M,t+1}]]$).

5.2 Disagreement

Following the derivations above, we know that conditional CAPM holds with respect to consensus beliefs, but with respect to the conditional market variance of each agent given their information set:

$$\overline{E}[\widetilde{R}^e_{M,t+1}] = \gamma Var_t[\widetilde{R}^e_{M,t+1}] - \gamma Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]] - \gamma Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]. \quad (14)$$

Consequently, for our empirical tests we would *ideally* require (in order of appearance): unconditional date-t variance, conditional variance of consensus returns, and the cross-sectional variance of expected market returns.

We calculate the *unconditional* date-t variance ($Var_t[\widetilde{R}^e_{M,t+1}]$) as in Savor and Wilson (2013) as the annualized average squared daily excess return for the last quarter (i.e. value for March 2000 uses all daily returns between January 1st 2000 and March 31st 2000).

Measures of *conditional* variance of *consensus* returns ($Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]]$) face a major challenge. Most, if not all of them, require time series of options' returns to extract consensus expectations of stock market returns. These are highly correlated with the returns on the stock market on which these options are written. This results in a high positive correlation between measures of $Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]]$ and measures of $Var_t[\widetilde{R}^e_{M,t+1}]$ mentioned before. Consequently, we skip $Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]]$ from our regressions.[11]

Dispersion of beliefs ($Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]$) is the time-$t$ variance of deviations of brokers' expected returns on the market from the consensus expectation of the market return. To construct this variable we use IBES analysts' price point forecasts. The forecast's length is 12 months and the lookback period is 6 months. This means that in June 2010 any forecasts of 12 month price for a given company made in the first half of the year are included in our calculations. Table 7 summarizes the IBES coverage we rely on in our calculations. We observe that no broker covers the whole market and that the coverage varies across the various brokers included in the sample. For example, at the end of December 2019 we have 198 brokers (*estimid*s). On average, they cover 93 individual stocks (*cusip*s). However, 25% of them do not cover more than 3 entities and 50% of them do not cover more than 18 entities.

We refer to the N stocks that the analyst covers as her *quasi*-market as opposed to the *true* market, which is the market index calculated in line with usual industry and academic practice. This quasi-market will differ across agents thus calling into question the interpretation of $Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]$ for low N. Therefore, we find it reasonable to trim our sample in such a way that each broker i included in the calculation in the dispersion of beliefs covers at least N = 100 stocks. *Please note:* even with such coverage threshold, low-N brokers' expectations still impact the consensus expectation on the true market as they are incorporated in the consensus expectation of the return on the individual stocks that these brokers do cover.

[11] In unreported analysis we use the residual from the regression of $Var_t[\overline{E}[\widetilde{R}^e_{M,t+1}]]$ on $Var_t[\widetilde{R}^e_{M,t+1}]$. Our conclusions do not change.

Figure 5 shows that the number or brokers considered for the calculation of the disagreement measure as a result of trimming our analysts' quasi market at N = 100 stocks will vary between 10 and 20 analysts during the time period considered. It also shows the potential coverage for other values of threshold N. Granted, 100 can be considered a high cut-off, but given the returns used in what follows are on the SP500 index, not an unreasonable one. The results are both quantitatively and qualitatively similar for $N \geq 70$.

5.3 Evidence

We take the simplified version of equation 14 to data using SP500 returns accrued at various frequencies on the two types of days analysed in this paper: announcement and non-announcement days:

$$r_{t+1}^{type} = \alpha + \beta_1 Var_t[\widetilde{R}^e_{M,t+1}] + \beta_2 Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]]. \tag{15}$$

Table 8 reports the results. Panel A shows that for annual and semiannual returns both the unconditional date-t variance and disagreement are statistically significant drivers of stock market returns. The relationship between the unconditional variance and returns is positive ($\beta_1 > 0$) while the relationship between disagreement and returns is negative ($\beta_2 < 0$). There is no statistically significant relationship for either variable and quarterly returns. Panel B shows that there is a statistically significant positive relationship between the unconditional stock market variance and stock market returns accrued on A-days for annual, semiannual, and quarterly frequency. At the same time, there is no statistically significant relationship between disagreement and A-day returns for any of these frequencies. As evidenced by Panel C, disagreement is a significant driver of returns accrued on N-days but not on A-days. This is in line with the hypothesis outlined above that disagreement plays far greater a role for stock market returns in the presence of dispersed signals (N-day) than it does in the presence of a common signal (A-days).

6 Conclusion

In this paper, we develop an approach to determine whether stock market predictors represent proxies for fundamental risk (i.e. are linked to new information about economic conditions) or excess volatility. Our methodology is based on the intuitive assumption that risk-based predictors should be linked to new information about economic conditions. As our proxy for such new information being released we use days when important macroeconomic announcements are made public to the markets. In support of this hypothesis we show, that both excess volatility (with respect to the dividend discount model) and residual volatility (with respect to the conditional CAPM) are phenomena limited to N-days and virtually absent from A-days. Furthermore, A-day returns are positively related to future changes in fundamental value (understood as a discounted sum of ex-post realized dividends in line with Shiller (1981)) while N-day returns are not. We use this multifaceted dichotomy to infer about the source of return predictability.

We study a wide range of well-known predictors and find that (with very few exceptions) they forecast returns accrued either on days with macroeconomic announcements (A-days) or on days when no such announcements are made (N-days). In the limited cases when the predictor forecasts returns on both types of days, both the magnitude and the statistical significance of this relationship are overwhelmingly concentrated on N-days. These results allow us to group predictors into those that are linked to economic fundamentals and those that are not. More specifically, predictors based on direct measures of the amount of risk in the economy, which according to asset pricing theory should forecast returns, forecast the share of quarterly returns accrued on A-days but not their share accrued on N-days. The opposite holds for predictors historically documented to forecast future stock market returns – they forecast only the part of returns accrued on N-days but lack predictive power for their share accrued on A-days.

Together, these results suggest that the sources of return predictability differ across predictors. While direct risk-based measures are backed by future economic fundamentals, the remaining ones have different origins. We argue our excess and residual volatility results suggest that the N-day returns predictors possess superior ability to explain the "noise" component of stock market returns. Building on the work of Andrei et al. (2023), we show that disagreement about the future fundamentals offers one potential explanation for our results.

The methodology presented can be further used to evaluate other predictors of asset returns in order to differentiate whether they forecast the economic fundamentals or the noise (i.e. volatility) component of the stock market.

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Figures

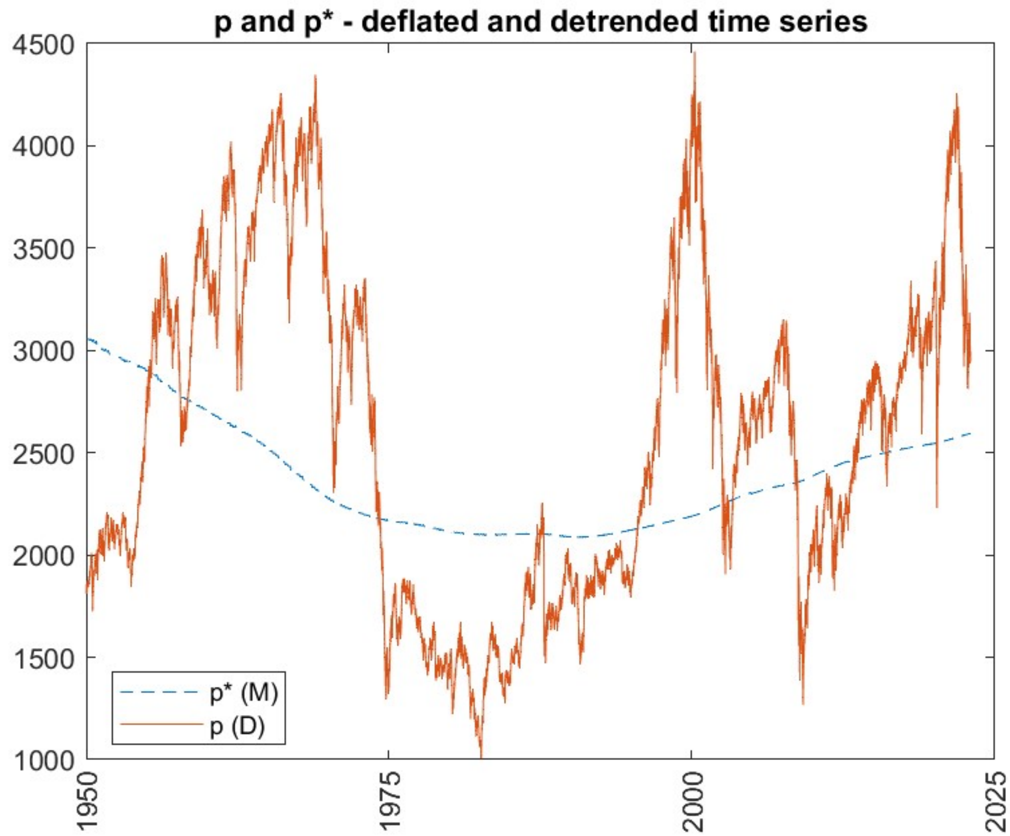

Figure 1: **Deflated and detrended market price (p) and fundamental value (p*)**

This figure shows the behaviour of detrended real prices (p_t) and corresponding ex-post rational prices (p_t^*) for the CRSP NYSE, Amex, Nasdaq value-weighted index between 1950 and 2022. It corresponds to figures (1) and (2) in Shiller (1981).

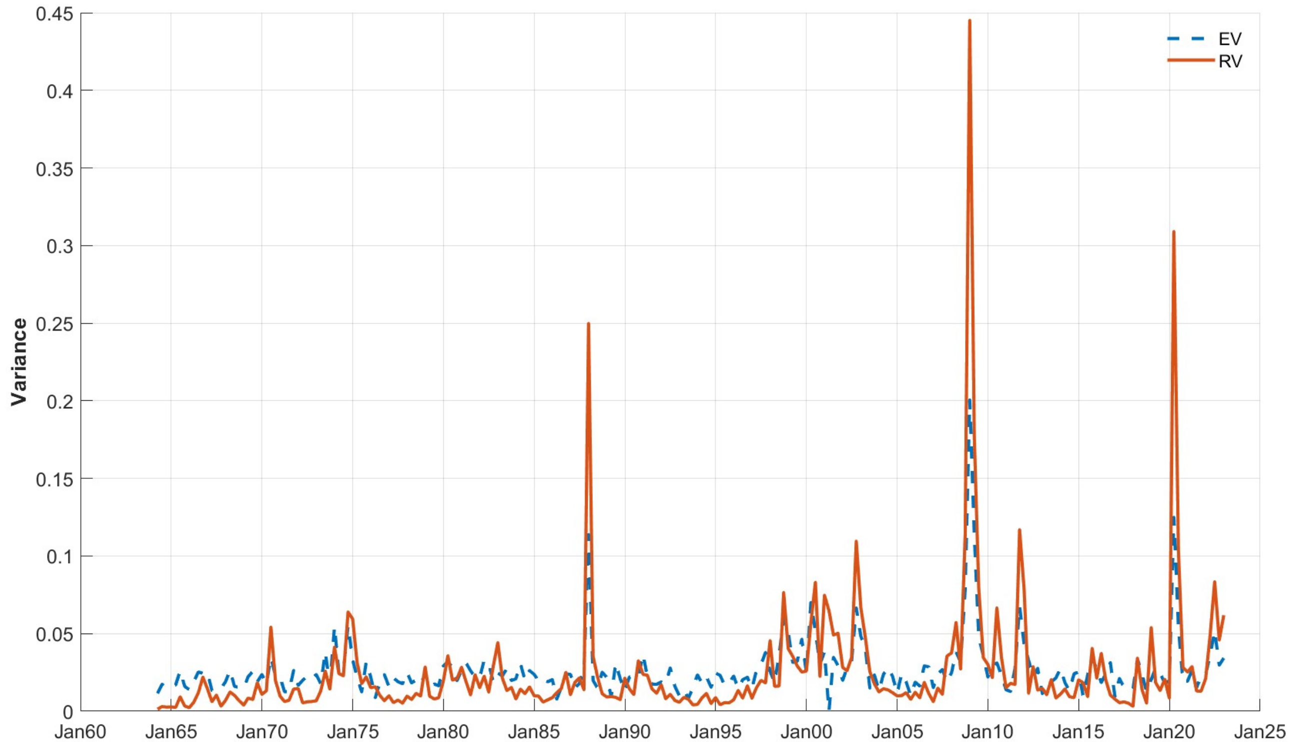

Figure 2: **Expected and Realized Variance computed using wider CRSP index**

The figure plots the realized variance of quarterly log excess market returns (RV) and its one-quarter-ahead forecast (EV) between 1964 and 2022. EV is a linear combination of RV, A-day, and N-day log excess returns.

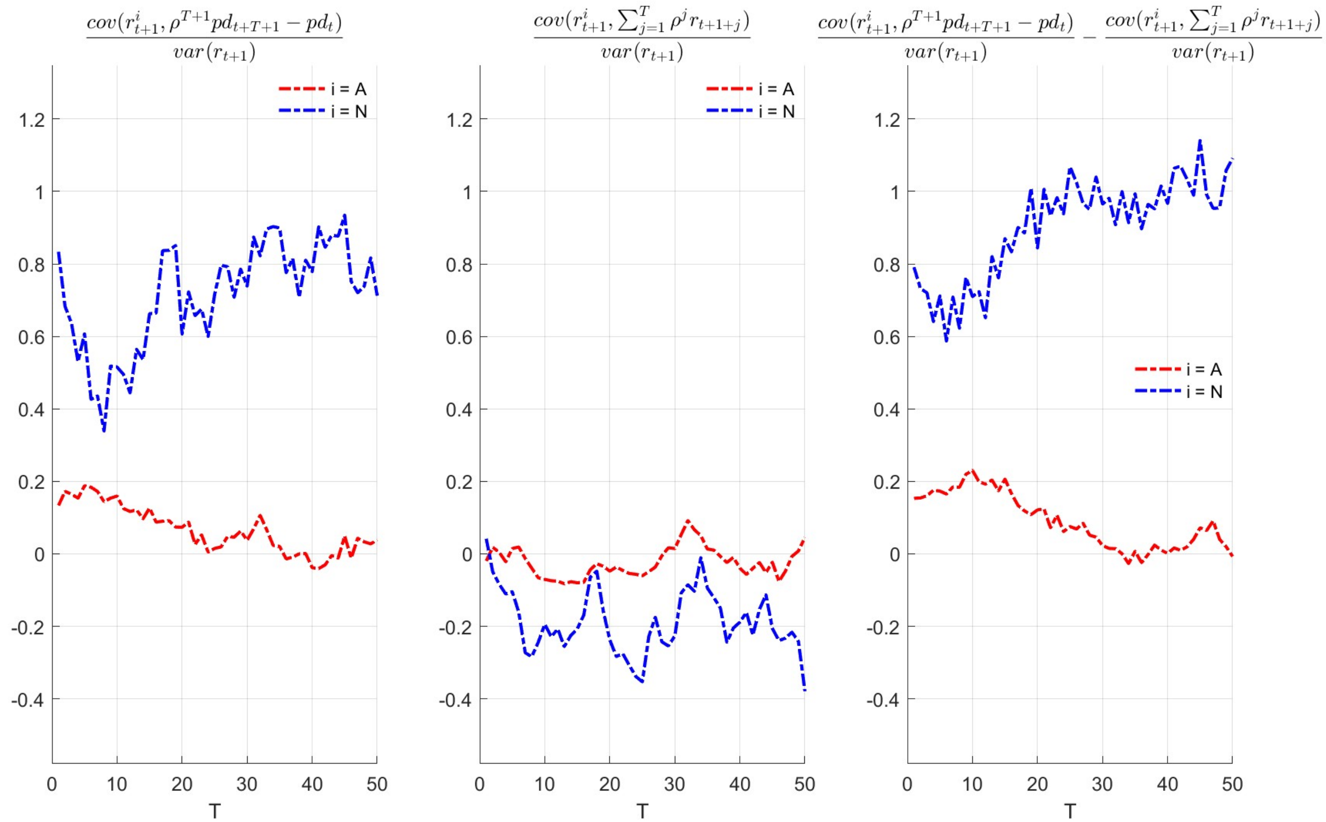

Figure 3: **Excess variance of the CRSP index – A- and N-day components**

The figure shows the contribution of quarterly A-day and N-day returns to the excess volatility of aggregate quarterly returns and its components as defined in equations 9 and 10 for various values of T. The returns and dividends correspond to the CRSP value-weighted index. Returns and dividends data cover the period between 1964 and 2022.

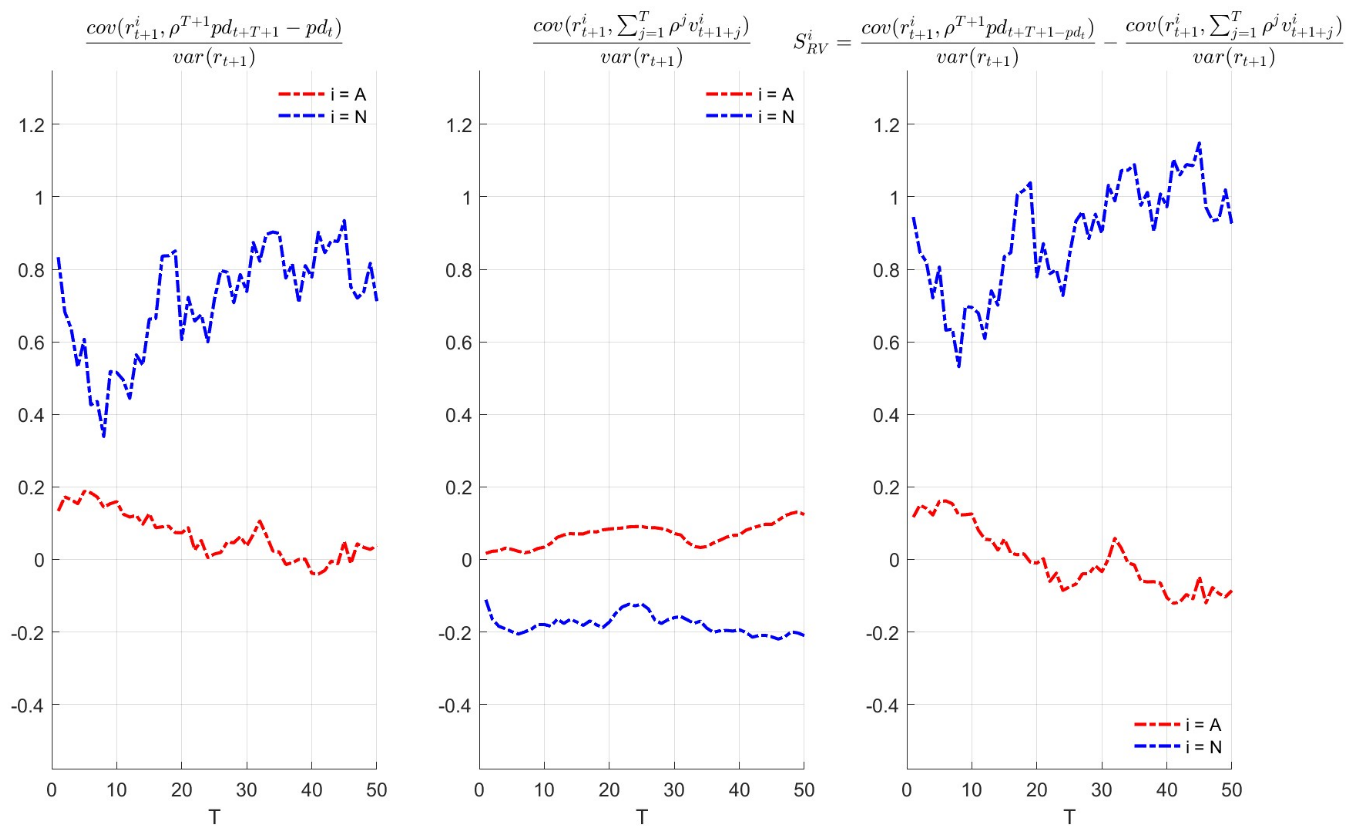

Figure 4: **Residual variance of the CRSP index – A-day and N-day components**

The figure shows the contribution of quarterly A-day and N-day returns to the residual volatility of aggregate quarterly returns and its components as defined in equations 12 and 13 for various values of T. The returns and dividends correspond to the CRSP value-weighted index. Returns and dividends data cover the period between 1964 and 2022.

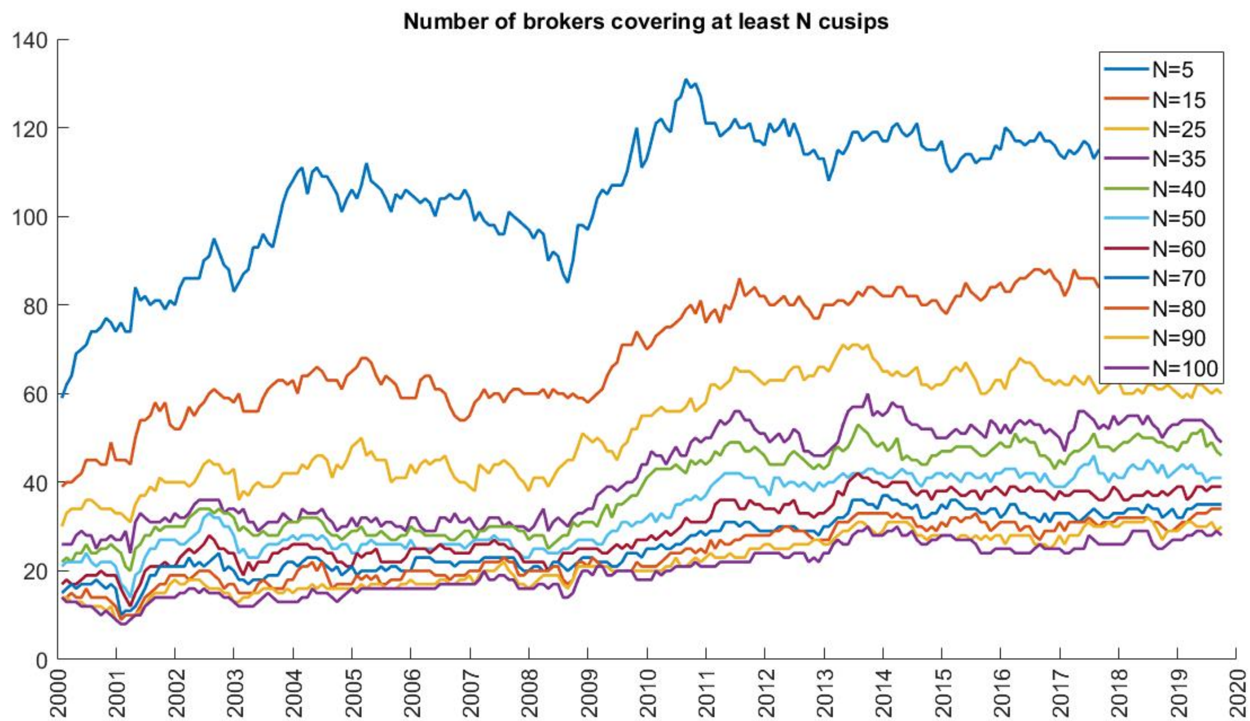

Figure 5: **IBES coverage – number of brokers covering at least N stocks**

This figure shows over time the number of brokers (*estimid*s) who cover at least N companies (*cusip*s) in a given month.

Tables

Table 1: Summary Statistics – quarterly returns – 1953 through 2021

The table reports summary statistics of quarterly returns, quarterly returns accrued on A-days, and quarterly returns accrued on N-days. Since predictor variables studied in this paper run between 1953Q1 and 2021Q4, we focus on this time period here. We report the summary statistics of the relevant time series: mean, standard deviation, minimum value, maximum value, first order autocorrelation, and skewness.

Variable	N	Start	End	Mean	SD	Min	Max	Autocorr	skew
Panel A: Returns									
r	276	19530331	20211231	0.02	0.08	−0.30	0.22	0.04	−0.77
rA	276	19530331	20211231	0.01	0.03	−0.18	0.13	−0.02	−0.64
rNA	276	19530331	20211231	0.01	0.07	−0.28	0.18	0.10	−0.75

Table 2: Variables definition

This table presents definitions of variables used to forecast stock market returns on A-days and N-days and the source of the data used. Most variables and content of this table are courtesy of Amit Goyal and co-authors.

OurName	**Descr**	**Authors**	**Freq**
GWZ_Q_pce	consumption/trend	Atanasov, Møller, Priestley	Quarterly
GWZ_M_vp	variance premium	Baekert, Hoerova	Monthly
GWZ_M_impvar	implied σ^2	Bakshi, Panayotov, Skoulakis	Monthly
GWZ_M_vrp	σ^2 risk premium	Bollerslev, Tauchen, Zhou	Monthly
GWZ_Q_govik	public sector investmt	Belo, Yu	Quarterly
GWZ_M_lzrt	9 illiq measures	Chen, Eaton, Paye	Monthly
GWZ_S_skew	skewness	Colacito, Ghysels, Meng, Siwasarit	Semiannual
GWZ_Q_crdstd	credit standards	Chava, Gallmeyer, Park	Quarterly
GWZ_M_ogap	prdctn-output gap	Cooper, Priestley	Monthly
GWZ_M_wtexas	oil price changes	Driesprong, Jacobsen, Maat	Monthly
GWZ_A_accrul	accruals	Hirshleifer, Hou, Teoh	Annual
GWZ_A_cfacc	accruals (CFO)	Hirshleifer, Hou, Teoh	Annual
GWZ_M_sntm	distilled sentiment	Huang, Jiang, Tu, Zhou	Monthly

Continued on next page

Table 2: – continued from previous page

OurName	Descr	Authors	Freq
GWZ_M_ndrbl	new order-ship durables	Jones, Tuzel	Monthly
GWZ_M_skvw	avg stock skewness	Jondeau, Zhang, Zhu	Monthly
GWZ_M_tail	x-sect tail risk	Kelly, Jiang	Monthly
GWZ_M_fbm	b/m x-sect factor	Kelly, Pruitt	Monthly
GWZ_M_dtoy	to Dow 52-week high	Li, Yu	Monthly
GWZ_M_dtoat	to Dow all-time high	Li, Yu	Monthly
GWZ_M_ygap	stock-bond yield gap	Maio	Monthly
GWZ_M_rdsp	stock return dispersion	Maio	Monthly
GWZ_M_svix	scaled risk-neutral vix	Martin	Monthly
GWZ_A_gpce	yearend econ growth	Møller, Rangvid	Annual
GWZ_A_gip	yearend econ growth	Møller, Rangvid	Annual
GWZ_M_tchi	14 technical indicators	Neely, Rapach, Tu, Zhou	Monthly
epbound_M3	low. bound on 3m exp. r. premium	Martin	Monthly
GWZ_A_house	housing/consumption	Piazzesi, Schneider, Tuzel	Annual
epbound_M6	low. bound on 6m exp. r. premium	Martin	Monthly
GWZ_M_avgcor	acvg corr stock returns	Pollett, Wilson	Monthly

Continued on next page

Table 2: – continued from previous page

OurName	Descr	Authors	Freq
epbound_M12	low. bound on 12m exp. r. premium	Martin	Monthly
GWZ_M_shtint	short interest	Rapach, Ringgenberg, Zhou	Monthly
GWZ_M_disag	analyst disagreement	Yu	Monthly
logPD	dividend price ratio	Campbell, Shiller	Monthly
logSP500e12p	earnings price ratio	Campbell, Shiller	Monthly
logSP500d12e12	dividend payout	Campbell, Shiller	Monthly
svar	σ^2	Guo	Monthly
bm	b/m	Kothari, Shanken	Monthly
ntis	net equity issuance	Boudoukh, Michaely, Richardson, Roberts	Monthly
BW_eqis	pct equity issuance	Baker, Wurgler	Annual
tbl	t-bill	Campbell	Monthly
lty	long govt yield	Fama, French	Monthly
ltr	long govt return	Fama, French	Monthly
tms	term spread	Fama, French	Monthly
dfy	default yield spread	Fama, French	Monthly
dfr	default return spread	Fama, French	Monthly

Continued on next page

Table 2: – continued from previous page

OurName	**Descr**	**Authors**	**Freq**
inflscsp	inflation	Fama, Schwert	Monthly
ik	invstmt/capital	Cochrane	Quarterly
cayGW	cnsm, wlth, incm	Lettau, Ludvigson	Quarterly

Table 3: Summary Statistics – 1953 through 2021

The table reports summary statistics of stock market predictors analysed. Panel A (B) reports summary statistics of variables that have been found to be A-day (N-day) returns' predictors in univariate linear regressions using quarterly data. Panel C (D) reports summary statistics of variables which have been found to predict returns accrued on both (neither) A-days and (nor) N-days. For each of the variables we report the length of its time series and the first and last month for which the data is available. We then report the summary statistics of the relevant time series: mean, standard deviation, minimum value, maximum value, first order autocorrelation, and skewness.

Variable	N	Start	End	Mean	SD	Min	Max	Autocorr	skew
Panel A: A-day return predictors									
dfy	276	19530331	20211231	0.01	0.00	0.00	0.03	0.87	1.87
svar	276	19530331	20211231	0.01	0.01	0.00	0.11	0.38	6.74
GWZ_M_wtexas	276	19530331	20211231	0.01	0.08	−0.54	0.45	0.03	−0.41
GWZ_M_dtoy	276	19530331	20211231	0.93	0.08	0.58	1.00	0.64	−1.75
Panel B: N-day return predictors									
logPD	275	19530630	20211231	4.96	0.39	4.09	5.95	0.94	0.24
lty	276	19530331	20211231	0.06	0.03	0.01	0.15	0.98	0.74
tbl	276	19530331	20211231	0.04	0.03	0.00	0.15	0.95	0.88
tms	276	19530331	20211231	0.02	0.01	−0.04	0.05	0.84	−0.15

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Table 3: – continued from previous page

Variable	N	Start	End	Mean	SD	Min	Max	Autocorr	skew
ltr	276	19530331	20211231	0.02	0.05	−0.15	0.24	−0.05	0.89
ik	276	19530331	20211231	0.04	0.00	0.03	0.04	0.97	0.44
GWZ_M_ogap	276	19530331	20211231	0.00	0.07	−0.16	0.14	0.95	0.08
GWZ_Q_pce	273	19531231	20211231	0.00	0.04	−0.11	0.08	0.94	−0.20
GWZ_S_skew	275	19530630	20211231	−0.21	0.61	−1.29	1.28	0.50	0.43
GWZ_A_gpce	273	19531231	20211231	0.00	0.00	−0.01	0.02	0.78	0.03
GWZ_A_gip	273	19531231	20211231	0.01	0.02	−0.05	0.05	0.70	−0.90
Panel C: Predictors of returns on both types of days									
GWZ_M_dtoat	276	19530331	20211231	0.90	0.10	0.54	1.00	0.79	−1.15
GWZ_M_avgcor	276	19530331	20211231	0.27	0.11	0.03	0.71	0.53	1.00
Panel D: Variables which do not predict returns									
cayGW	276	19530331	20211231	0.00	0.04	−0.28	0.05	0.86	−3.33
ntis	276	19530331	20211231	0.01	0.02	−0.05	0.05	0.94	−0.76
dfr	276	19530331	20211231	0.00	0.03	−0.15	0.16	−0.13	−0.52

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Table 3: – continued from previous page

Variable	N	Start	End	Mean	SD	Min	Max	Autocorr	skew
bm	276	19530331	20211231	0.50	0.25	0.13	1.20	0.98	0.75
logSP500d12e12	276	19530331	20211231	−0.74	0.30	−1.24	1.38	0.89	2.81
logSP500e12p	276	19530331	20211231	−2.84	0.42	−4.81	−1.90	0.94	−0.72
GWZ_M_lzrt	276	19530331	20211231	−1.76	0.35	−4.69	−1.20	0.71	−4.40
GWZ_M_skvw	276	19530331	20211231	0.03	0.05	−0.38	0.16	−0.01	−2.56
GWZ_M_tail	276	19530331	20211231	0.42	0.05	0.30	0.53	0.90	−0.66
GWZ_M_fbm	276	19530331	20211231	0.17	0.11	−0.10	0.62	0.85	1.10
GWZ_M_ygap	275	19530630	20211231	−2.90	0.41	−4.84	−2.02	0.93	−0.83
GWZ_M_rdsp	276	19530331	20211231	0.03	0.01	0.01	0.12	0.66	3.60
GWZ_M_tchi	276	19530331	20211231	−0.02	1.45	−2.68	1.06	0.60	−0.94
GWZ_Q_govik	276	19530331	20211231	0.03	0.01	0.03	0.06	0.97	1.09
GWZ_A_house	273	19531231	20211231	−0.25	0.01	−0.26	−0.22	0.95	0.37

Table 4: **Forecasting changes in fundamental value using real ex-post rational price P^*_{t+1} as its proxy**

This table reports the results of regressing the change in real ex-post rational price $\widetilde{P}^*_{t+1}$ on lagged returns accrued on A-days and N-days at various frequencies. The left-hand side of the table presents results of estimating equation (4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$. The right-hand side of the table presents results of estimating equation (5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$. In both cases $Y_{t+1} = \widetilde{P}^*_{t+1}$. For each of the equations two time periods are considered: 1953 – 2022 and 1953 – 2010. This is to account for the fact that starting from January 2011 the terminal value of P^*_T is becoming non-negligible share of P^*_t. t-statistics are reported in the second row below each coefficient value. Since Y_{t+1} are constructed using non-overlapping windows, standard unadjusted t-statistics are reported.

Eq.(4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$					Eq.(5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$				
β_0	β_1	β_2	$Adj.R^2$	N	δ_0	δ_1	δ_2	$Adj.R^2$	N
Panel A: Monthly data 1953 – 2022					Panel A: Monthly data 1953 – 2022				
0.003	0.002	-0.002	0.00%	839	**0.003**	0.000	0.002	0.00%	839
[39.96]	[0.60]	[-1.31]			**[39.96]**	[0.03]	[1.05]		
Panel B: Monthly data 1953 – 2010					Panel B: Monthly data 1953 – 2010				
0.003	0.004	-0.003	0.08%	695	**0.003**	0.001	0.003	0.08%	695
[31.49]	[0.85]	[-1.37]			**[31.49]**	[0.26]	[1.30]		
Panel C: Quarterly data 1953 – 2022					Panel C: Quarterly data 1953 – 2022				
0.008	0.007	0.000	-0.32%	279	**0.008**	0.003	0.004	-0.32%	279
[40.62]	[1.05]	[-0.13]			**[40.62]**	[0.98]	[0.98]		
Panel D: Quarterly data 1953 – 2010					Panel D: Quarterly data 1953 – 2010				
0.008	**0.014**	-0.001	0.61%	231	**0.008**	0.006	**0.008**	0.61%	231
[34.61]	**[1.81]**	[-0.53]			**[34.61]**	[1.56]	**[1.82]**		
Panel E: Annual data 1953 – 2022					Panel E: Annual data 1953 – 2022				
0.033	0.032	-0.005	-0.67%	69	**0.033**	0.013	0.018	-0.67%	69
[18.34]	[1.17]	[-0.46]			**[18.34]**	[0.93]	[1.24]		
Panel F: Annual data 1953 – 2010					Panel F: Annual data 1953 – 2010				
0.030	**0.046**	-0.012	3.72%	57	**0.030**	0.017	**0.029**	3.72%	57
[16.02]	**[1.70]**	[-1.16]			**[16.02]**	[1.19]	**[1.99]**		

Table 5: **Forecasting changes in fundamental value using *detrended* real ex-post rational price p^*_{t+1} as its proxy**

This table reports the results of regressing the change in *detrended* real ex-post rational price $\widetilde{p}^*_{t+1}$ on lagged returns on A-days and N-days at various frequencies. The left-hand side of the table presents results of estimating equation (4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$. The right-hand side of the table presents results of estimating equation (5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$. In both cases $Y_{t+1} = \widetilde{p}^*_{t+1}$. For each equation two time periods are considered: 1953 – 2022 and 1953 – 2010. This is to account for the fact that starting from January 2011 the terminal value of p^*_T is becoming non-negligible share of p^*_t. t-statistics are reported in the second row below each coefficient value. Since Y_{t+1} are calculated using non-rolling windows, standard unadjusted t-statistics are reported.

Eq.(4): $Y_{t+1} = \beta_0 + \beta_1 r^A_t + \beta_2 r^N_t$					Eq.(5): $Y_{t+1} = \delta_0 + \delta_1(r^A_t + r^N_t) + \delta_2(r^A_t - r^N_t)$				
β_0	β_1	β_2	$Adj.R^2$	N	δ_0	δ_1	δ_2	$Adj.R^2$	N
Panel A: Monthly data 1953 – 2022					Panel A: Monthly data 1953 – 2022				
0.000	0.002	-0.002	0.05%	839	**0.000**	0.000	0.002	0.05%	839
[-2.66]	[0.66]	[-1.46]			**[-2.66]**	[0.03]	[1.16]		
Panel B: Monthly data 1953 – 2010					Panel B: Monthly data 1953 – 2010				
0.000	0.003	-0.002	0.07%	695	**0.000**	0.001	0.003	0.07%	695
[-4.34]	[0.83]	[-1.36]			**[-4.34]**	[0.24]	[1.28]		
Panel C: Quarterly data 1953 – 2022					Panel C: Quarterly data 1953 – 2022				
0.000	0.006	0.000	-0.21%	279	**0.000**	0.003	0.003	-0.21%	279
[-3.25]	[1.19]	[-0.15]			**[-3.25]**	[1.11]	[1.11]		
Panel D: Quarterly data 1953 – 2010					Panel D: Quarterly data 1953 – 2010				
-0.001	**0.010**	-0.001	0.56%	231	**-0.001**	0.005	**0.006**	0.56%	231
[-5.47]	**[1.80]**	[-0.46]			**[-5.47]**	[1.57]	**[1.78]**		
Panel E: Annual data 1953 – 2022					Panel E: Annual data 1953 – 2022				
-0.002	0.025	-0.005	0.11%	69	**-0.002**	0.010	0.015	0.11%	69
[-1.66]	[1.29]	[-0.67]			**[-1.66]**	[0.98]	[1.43]		
Panel F: Annual data 1953 – 2010					Panel F: Annual data 1953 – 2010				
-0.004	**0.035**	-0.009	3.69%	57	**-0.004**	0.013	**0.022**	3.69%	57
[-2.81]	**[1.67]**	[-1.20]			**[-2.81]**	[1.14]	**[1.97]**		

Table 6: Univariate regressions - predicting quarterly returns

This table reports the results of univariate regressions of quarterly returns on predictor variables. All regressions are of the following type:

$$r_{t+1}^{i} = \alpha + \beta x_t, \quad i = (A\&N, A, N),$$

where r_{t+1}^{i} is the quarterly return (columns (2) through (4)), quarterly return accrued on A-days (columns (5) through (7)), or quarterly return accrued on N-days (columns (8) through (10)). In the interest of readability we only report the values of the β coefficient, it's t-statistics, and the R^2 for each of the regressions. Panel A (B) reports regression results for variables that have been found to be A-day (N-day) returns' predictors. Panel C (D) reports regression results for variables which have been found to predict returns accrued on both (neither) A-days and (nor) N-days. Variables are summarized in Table 2. Period covered: 1953 – 2021.

	Quarterly returns			A-day quarterly returns			N-day quarterly returns		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
Panel A: Announcement day return predictors									
dfy	1.36	[1.18]	0.1%	**0.79**	**[1.90]**	0.9%	0.57	[0.55]	−0.3 %
svar	**0.90**	**[1.94]**	1.0%	**0.58**	**[3.54]**	4.0%	0.32	[0.76]	−0.2 %
GWZ_M_wtexas	0.02	[0.33]	−0.3 %	**0.04**	**[1.77]**	0.8%	−0.02	[−0.35]	−0.3 %
GWZ_M_dtoy	**-0.14**	**[-2.05]**	1.2%	**-0.06**	**[-2.42]**	1.7%	−0.08	[−1.32]	0.3%
Panel B: Non-announcement day return predictors									

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Table 6: – continued from previous page

Variable	Quarterly returns β	Quarterly returns $t(\beta)$	Quarterly returns R^2	A-day quarterly returns β	A-day quarterly returns $t(\beta)$	A-day quarterly returns R^2	N-day quarterly returns β	N-day quarterly returns $t(\beta)$	N-day quarterly returns R^2
logPD	−0.02	[−1.42]	0.4%	0.00	[0.45]	−0.3 %	**-0.02**	**[-1.78]**	0.8%
lty	**-0.30**	**[-1.74]**	0.7%	0.01	[0.19]	−0.4 %	**-0.31**	**[-2.03]**	1.1%
tbl	**-0.38**	**[-2.39]**	1.7%	−0.01	[−0.22]	−0.3 %	**-0.36**	**[-2.59]**	2.0%
tms	**0.63**	**[1.78]**	0.8%	0.11	[0.87]	−0.1 %	**0.52**	**[1.64]**	0.6%
ltr	**0.22**	**[2.40]**	1.7%	0.01	[0.30]	−0.3 %	**0.21**	**[2.57]**	2.0%
ik	**-5.31**	**[-3.34]**	3.6%	0.17	[0.29]	−0.3 %	**-5.48**	**[-3.89]**	4.9%
GWZ_M_ogap	**-0.31**	**[-4.25]**	5.9%	0.00	[−0.17]	−0.4 %	**-0.30**	**[-4.73]**	7.2%
GWZ_Q_pce	**-0.47**	**[-3.49]**	4.0%	−0.06	[−1.11]	0.1%	**-0.41**	**[-3.45]**	3.9%
GWZ_S_skew	−0.01	[−1.39]	0.3%	0.00	[0.70]	−0.2 %	**-0.01**	**[-1.84]**	0.9%
GWZ_A_gpce	**-3.62**	**[-3.57]**	4.2%	−0.28	[−0.76]	−0.2 %	**-3.34**	**[-3.70]**	4.5%
GWZ_A_gip	**-0.91**	**[-3.49]**	4.0%	−0.03	[−0.32]	−0.3 %	**-0.88**	**[-3.80]**	4.7%
Panel C: Announcement and non-announcement day return predictors									
GWZ_M_dtoat	**-0.15**	**[-2.87]**	2.6%	**-0.03**	**[-1.77]**	0.8%	**-0.11**	**[-2.49]**	1.9%
GWZ_M_avgcor	**0.18**	**[4.17]**	5.6%	**0.05**	**[3.00]**	2.8%	**0.13**	**[3.41]**	3.7%

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Table 6: – continued from previous page

Variable	Quarterly returns β	Quarterly returns $t(\beta)$	Quarterly returns R^2	A-day quarterly returns β	A-day quarterly returns $t(\beta)$	A-day quarterly returns R^2	N-day quarterly returns β	N-day quarterly returns $t(\beta)$	N-day quarterly returns R^2
Panel D: Variables not predicting either announcement or non-announcement returns									
cayGW	−0.03	[−0.23]	−0.35 %	0.04	[0.92]	−0.06 %	−0.08	[−0.63]	−0.22 %
ntis	−0.25	[−0.99]	−0.01 %	−0.04	[−0.39]	−0.31 %	−0.22	[−0.95]	−0.04 %
dfr	0.08	[0.40]	−0.31 %	−0.04	[−0.54]	−0.26 %	0.12	[0.67]	−0.20 %
bm	0.01	[0.26]	−0.34 %	0.00	[−0.59]	−0.24 %	0.01	[0.53]	−0.26 %
logSP500d12e12	0.02	[1.25]	0.20%	0.01	[1.62]	0.59%	0.01	[0.74]	−0.16 %
logSP500e12p	0.00	[0.26]	−0.34 %	−0.01	[−1.34]	0.29%	0.01	[0.83]	−0.11 %
GWZ_M_lzrt	−0.01	[−0.51]	−0.27 %	−0.01	[−0.91]	−0.06 %	0.00	[−0.20]	−0.35 %
GWZ_M_skvw	−0.06	[−0.61]	−0.23 %	−0.01	[−0.14]	−0.36 %	−0.06	[−0.62]	−0.22 %
GWZ_M_tail	0.13	[1.41]	0.36%	0.00	[0.12]	−0.36 %	0.13	[1.53]	0.49%
GWZ_M_fbm	0.02	[0.38]	−0.31 %	0.02	[1.06]	0.04%	0.00	[−0.01]	−0.37 %
GWZ_M_ygap	0.01	[0.44]	−0.30 %	−0.01	[−1.37]	0.32%	0.01	[1.05]	0.04%
GWZ_M_rdsp	−0.06	[−0.15]	−0.36 %	0.18	[1.21]	0.17%	−0.24	[−0.66]	−0.20 %
GWZ_M_tchi	0.00	[0.46]	−0.29 %	0.00	[−0.67]	−0.20 %	0.00	[0.79]	−0.14 %
GWZ_Q_govik	0.24	[0.33]	−0.33 %	−0.16	[−0.59]	−0.24 %	0.40	[0.61]	−0.23 %

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Table 6: – continued from previous page

Variable	Quarterly returns			A-day quarterly returns			N-day quarterly returns		
	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2	β	$t(\beta)$	R^2
GWZ_A_house	0.60	[1.12]	0.10%	−0.11	[−0.56]	−0.25 %	0.71	[1.49]	0.45%

Table 7: **IBES coverage**

This table reports the IBES coverage over time for our chosen 12-months-ahead price forecast with a 6 months' lookback period. For each December, we report the number of analysts (*estimid*s) in our sample and the summary statistics for the number of companies (*cusip*s) that they cover.

		*cusip*s covered						
date	*estimid*s	mean	std	min	25%	50%	75%	max
12/29/2000	166	47.2	85.3	1	3	11	46	535
12/31/2001	122	77.6	105.7	1	8	33	91	526
12/31/2002	156	61.8	105.1	1	4	19	73	706
12/31/2003	199	52.9	93.7	1	4	15	54	640
12/31/2004	224	49.8	93.7	1	4	15	52	627
12/30/2005	215	54.7	100.2	1	4	15	53	639
12/29/2006	219	54.6	105.4	1	4	16	45	664
12/31/2007	213	56.4	112.1	1	3	13	48	687
12/31/2008	217	62.4	118.9	1	4	13	52	654
12/31/2009	232	60.9	117.6	1	4	12	54	703
12/31/2010	254	59.5	115.5	1	2	10	62	719
12/30/2011	232	69.2	127.4	1	2	14	69	718
12/31/2012	217	70.4	129.1	1	2	14	77	737
12/31/2013	215	81.7	148.7	1	2	14	82	750
12/31/2014	198	85.8	149.0	1	4	20	89	720
12/31/2015	202	87.4	155.5	1	3	19	92	748
12/30/2016	199	86.9	154.4	1	3	21	83	722
12/29/2017	193	92.6	163.1	1	3	22	90	736
12/31/2018	187	95.9	165.2	1	4	22	95	762
12/31/2019	198	93.3	168.6	1	3	18	91	885
12/31/2020	208	94.3	182.0	1	2	14	79	934
12/31/2021	216	94.8	186.5	1	3	16	73	1051
12/30/2022	207	106.4	205.6	1	3	14	94	1036

Table 8: **Disagreement and stock market returns**

This table reports the results of univariate regressions of annual, 6-months, and quarterly SP500 returns on unconditional date-t variance and dispersion of beliefs for various types of days:

$$r_{t+1}^{type} = \alpha + \beta_1 Var_t[\widetilde{R}^e_{M,t+1}] + \beta_2 Var_t[E_i[\widetilde{R}^e_{M,t+1}] - \overline{E}[\widetilde{R}^e_{M,t+1}]].$$

Panel A reports results for returns accrued on all days in the given period, while Panel B (C) reports the results for returns accrued on days when important information is (not) released onto the market i.e. A-days (N-days). Unadjusted standard errors are reported since observations do not overlap.

Panel A: Returns accrued on all days

	Annual			Semiannual			Quarterly		
α	-0.01	**0.16**	**0.18**	0.01	**0.07**	**0.08**	0.01	0.03	0.03
	-0.11	**1.80**	**2.49**	0.36	**2.21**	**2.45**	0.92	1.43	1.41
β_1	17.43		**58.64**	1.24		**11.30**	-2.57		-1.31
	0.92		**3.10**	0.21		**1.77**	-0.96		-0.45
β_2		-121.24	**-271.91**		**-58.80**	**-89.32**		-22.30	-19.05
		-1.62	**-3.49**		**-2.19**	**-2.85**		-1.38	-1.07
N	19	19	19	38	38	38	76	76	76
$R^2(\%)$	-0.91	8.31	39.08	-2.65	9.27	14.32	-0.09	1.18	0.10

Panel B: Returns accrued on A-days

	Annual			Semiannual			Quarterly		
α	-0.01	0.00	0.00	-0.01	0.00	0.01	-0.01	0.00	0.00
	-0.62	-0.08	0.08	-0.78	0.18	0.47	-1.05	-0.40	-0.33
β_1	11.88		**15.70**	**5.62**		**7.72**	**3.17**		**3.35**
	1.64		**1.67**	**2.22**		**2.56**	**2.76**		**2.65**
β_2		15.14	-25.21		2.22	-18.63		5.55	-2.73
		0.48	-0.65		0.17	-1.26		0.75	-0.35
N	19	19	19	38	38	38	76	76	76
$R^2(\%)$	8.63	-4.49	5.42	9.56	-2.70	11.02	8.09	-0.58	6.98

Panel C: Returns accrued on N-days

	Annual			Semiannual			Quarterly		
α	0.01	**0.16**	**0.18**	0.02	**0.07**	**0.07**	0.02	0.03	0.03
	0.13	**2.15**	**2.67**	0.75	**2.28**	**2.31**	1.61	1.85	1.82
β_1	5.55		**42.94**	-4.38		3.58	**-5.74**		**-4.67**
	0.32		**2.46**	-0.80		0.58	**-2.53**		**-1.89**
β_2		**-136.37**	**-246.70**		**-61.02**	**-70.69**		**-27.85**	-16.32
		-2.13	**-3.44**		**-2.44**	**-2.33**		**-1.97**	-1.07
N	19	19	19	38	38	38	76	76	76
$R^2(\%)$	-5.26	16.49	35.66	-0.98	11.77	10.11	6.72	3.70	6.92