The Day Destroys the Night, Night Extends the Day:

A Clientele Perspective on Equity Premium Variation

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This version: November 2022

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Abstract

We decompose market returns into their overnight and intraday components, which dramatically improves equity premium forecasts. Past smoothed overnight market returns strongly negatively forecast subsequent close-to-close returns (quarterly R^2 of over 14%), primarily through intraday mean reversion. In contrast, past smoothed intraday market returns strongly positively forecast subsequent overnight returns; this partially-offsetting effect explains PE's relatively poor forecasting ability (R^2 only 3%). Our decomposition also resurrects the conditional CAPM: If we allow market betas to vary with past smoothed overnight returns, the four Fama-French factors' alphas decrease on average by 84%. We interpret these return patterns through a clientele perspective. First, individual investor expectations and consumption growth strongly positively forecast overnight market returns, while intermediary risk tolerance strongly negatively forecasts intraday market returns. Second, aggregate cash-flow news occurs primarily intraday and is positively (negatively) correlated with revisions in expected future overnight (intraday) returns. Finally, while the Tech boom, Covid crash/rebound, and patterns in meme stocks were primarily driven by overnight returns, the Global Financial Crisis was mostly an intraday phenomenon.

JEL classification: G02, G12, G23, N22

1 Introduction

Our understanding of financial markets has evolved in the last few decades to recognize the potential importance of investor heterogeneity, whether it might be modeling conservative vs. aggressive investors (Wang (1996)), noise traders vs. smart money (De Long, Shleifer, Summers, and Waldmann (1990)), or individuals vs. institutions (Gabaix and Koijen (2022)). Though such heterogeneity is likely important for asset prices, researchers are hamstrung by the fact that the return data we typically study reflect just the net effect of the clienteles in play. This paper exploits the fact that different types of investors likely prefer to trade or hold stocks at different points in times, which allows us to empirically characterize investor heterogeneity. For example, some investors may prefer to trade at or near the morning open, while others may prefer to trade near the close.

Of course, these two periods differ along several key dimensions, including information flow, market liquidity, and borrowing costs. It seems likely that many aspects of investor heterogeneity that might be relevant for asset pricing also manifest as a tendency to trade in one of these periods rather than the other. In this light, the presence of "overnight" and "intraday" clienteles seems a reasonable and perhaps even natural view of markets.

We use this clientele perspective along with the distinction between overnight vs. intraday returns to shed new light on time variation in the equity premium. In particular, we argue that the overnight and intraday components of market returns reflect, at least in part, the demand of the clientele that is dominant in trading around the open and close respectively, and thus can be used to reveal characteristics of each clientele.

We first decompose variation in PE based on past intraday and overnight price movements by smoothing these components of past returns.[1] Our main analysis then uses these smoothed variables to forecast subsequent close-to-close returns, revealing much stronger mean reversion in the equity premium. In our sample, PE's relation to subsequent close-to-

[1] We confirm that smoothed past overnight returns and smoothed past intraday returns explain a significant portion (77%) of the variation in PE. Adding past smoothed earnings growth increases that to 88%. However, the earnings growth component of variation in PE has no ability to predict subsequent returns.

close returns is weak at best (R^2 of just 3%). However, isolating the variation in PE due to smoothed past overnight returns provides nearly five times the forecasting ability (R^2 over 14%).

We then decompose the dependent variable in these forecasting regressions to better understand the drivers of the variation in close-to-close equity premium. We first find that mean reversion in the equity premium linked to the smoothed price-earnings ratio (PE) occurs entirely intraday and is, in fact, a much stronger phenomenon in the intraday period, as there is economically and statistically significant mean *aversion* linked to PE that occurs overnight and partially offsets the intraday mean reversion. These initial results suggest (which we support with a bevy of additional subsequent tests) that the overnight clientele is more responsible for the mean aversion (extrapolation) component that pushes prices away from fundamentals (because of changes in risk tolerance / sentiment) while the intraday clientele is more responsible for the mean reversion component.

When we forecast these two market return components with the overnight and intraday components of our PE decomposition, we find striking results. Mean reversion in the stock market is primarily intraday reversion to past overnight returns; in other words, a "day destroys the night" phenomenon. In a regression of intraday returns on past smoothed overnight and intraday returns, the coefficient on the former is negative with a t-statistic of -5.67 and an R^2 of roughly 13%.

In contrast, PE positively forecasts overnight returns because there is strong continuation of past smoothed intraday returns that happens overnight (thus, a "night extends the day" phenomenon). In a regression of overnight returns on past smoothed overnight and intraday returns, the coefficient on the latter is positive with a t-statistic of 3.96 and an R^2 over 22%.

We then use our striking predictability results to reexamine the conditional CAPM. We document that a large portion of the CAPM alpha of the four Fama-French factors (SMB, HML, RMW, and CMW) is explained by conditional CAPM beta. Over our sample, the unconditional CAPM alpha on an equal-weight portfolio of those four factors is 3.35%/year.

Allowing the CAPM beta of that portfolio to vary with the past smoothed overnight market return reduces the unconditional abnormal return to 0.55%/year, a percentage drop of more than 84%.[2] This result arises because a one-standard-deviation decline in the past smoothed overnight market return (which we show forecasts an increase in the equity premium of more than five percentage points) also forecasts an increase in CAPM beta of 0.2. Thus, the conditional CAPM *does* explain the unconditional returns of the Fama-French asset-pricing anomalies over these two decades, in contrast to the conclusion of Lewellen and Nagel (2006) and a testament to the importance of our overnight / intraday decomposition of PE.

Nevertheless, though the unconditional alpha is close to zero after allowing CAPM betas to vary with the past smoothed overnight market return, once we allow the conditional alpha of this portfolio to move with the past smoothed overnight market return as well, we find that a one-standard-deviation increase in our overnight variable forecasts an increase in the conditional CAPM alpha of the composite Fama-French non-market factor portfolio of 2.9%/year. Thus, our novel decomposition ultimately reveals rich conditional mispricing relative to a conditional CAPM that may facilitate a better understanding of the underlying economics driving the Fama-French five-factor model.

Momentum still breaks the conditional CAPM. Interestingly, we do find strong movement in momentum's market beta linked to past intraday returns; however, since this component does not predict the equity premium, momentum's conditional CAPM alpha does not materially change. Furthermore, once we allow the conditional alpha of the momentum portfolio to vary with past smoothed intraday returns as well, we find that a one-standard-deviation increase in our intraday variable forecasts an increase in the conditional CAPM alpha of the momentum portfolio of roughly 7%/year.

Our ability to forecast the market is not only statistically and economically significant

[2] As we estimate conditional time-series factor regressions, our findings are not subject to the critique of Lewellan and Nagel (2006) that previous conditional cross-sectional CAPM tests (like Jagannathan and Wang, 1996 and Lettau and Ludvigson, 2001) ignore important restrictions on their tests' cross-sectional slopes.

but also is robust to an out-of-sample analysis.[3] A simple strategy that times the market based on the smoothed overnight return produces a CAPM alpha of 2.1% per quarter with an associated t-statistic of 2.75. Including the five non-market factors of Fama and French (2015) and Carhart (1997) results in an alpha of 1.4% per quarter with a t-statistic of 3.16. This strategy continues to earn an economically and statistically significant six-factor alpha of 1% per quarter (t-statistic of 2.43) on an out-of-sample basis (where the parameters are estimated using an expanding window).

Interpreting this predictability from a clientele perspective naturally leads to the question of how overnight and intraday clienteles differ. We characterize these clienteles in four ways: First, we analyze the relation of each return component with investor expectations from survey data. Second, we analyze the relation of each return component with standard macro-finance variables. Third, we examine the Tech boom/bust, the Global Financial Crisis (GFC), and the Covid crash/rebound through our clientele lens. Finally, we split aggregate close-to-close discount rate news into two components reflecting revisions in future overnight and intraday expected returns and then measure the way those two components move with aggregate close-to-close cash-flow news.

Our analysis of Greenwood and Shleifer's (2014) investor expectations reveals novel facts. In particular, we find that their main observation that individual investors extrapolate past returns reflects extrapolation of smoothed intraday returns, as smoothed overnight returns have very little explanatory power, either alone or in tandem. Further consistent with our extrapolation story, we find that individual investor expectations *positively* forecast subsequent overnight market returns but have no information about future intraday returns. As our predictability results imply that intraday returns are primarily driven by cash-flow news (as our modified Campbell (1991) return decomposition confirms), these findings are consistent with investors overreacting to news about fundamentals, rather than realized

[3] All our empirical findings are also robust to controls for a host of well-known forecasting variables, including, for example, realized volatility; the term, default, and value premia; and the consumption-wealth ratio of Lettau and Ludvigson (2001).

returns. Thus, our results help flesh out why Greenwood and Shleifer (2014) find that individual investor expectations are strongly negatively correlated with statistical-model-based expected close-to-close returns. Our results also address the on-going debate in the behavioral finance literature as to whether investors extrapolate fundamentals or returns when forming their biased beliefs.[4]

Our macro-finance analysis also yields interesting results. A generation of financial economists has tried to link consumption growth to close-to-close market returns, but with little empirical success. However, our novel decomposition reveals a strong link between consumption growth and overnight returns. Past consumption growth forecasts subsequent overnight returns with a t-statistic of 4.88. In contrast, consumption growth has a negative and insignificant relation to subsequent intraday returns.[5] We also find that our Intermediary Risk Tolerance measure that accumulates the shocks of Adrian et al. (2014) strongly negatively forecasts intraday market returns.

In sum, the return predictability results based on individual investor expectations, as well as those results based on our macro-finance variables, all support the notion that mean aversion primarily occurs overnight (both individual investor expectations and consumption growth positively predict overnight market returns), while mean reversion primarily occurs intraday (intermediary risk tolerance negatively forecasts intraday market returns). As such, our findings point to different clienteles operating in the overnight and intraday periods, with the former having characteristics typically associated with households and the latter having characteristics typically associated with institutions.

We then zoom in on three bubble/crisis episodes in the last three decades. We show that

[4]Some researchers model the formulation of beliefs as the extrapolation of fundamentals (Barberis, Shleifer, and Vishny (1998); Rabin and Vayanos (2010); Fuster, Hebert, and Laibson (2012); and Bordalo, Gennaioli, and Shleifer (2018)), while others model belief formulation as price/return extrapolation (De Long, Shleifer, Summers, and Waldmann (1990); Hong and Stein (1999); Barberis, Greenwood, Jin, and Shleifer (2018); Farhi and Werning (2020); and Bastianello and Fontanier (2022a,b)). Fontanier (2022) argues that distinguishing between these two different ways in which investor beliefs may be biased matters for determining the appropriate policy response.

[5]Indeed, we show that consumption growth not only predicts but also is contemporaneously correlated with overnight returns. These links are evident at leads/lags of up to 2 quarters.

the Tech boom of the late 1990s and the Covid crash and rebound of 2020 were primarily an overnight phenomenon, consistent with the view that individual investors were largely responsible for these events. In a similar fashion, we show that the large price spikes in meme stocks were primarily an overnight phenomenon. In contrast, the Global Financial Crisis of 2008 was primarily an intraday phenomenon, consistent with the important role intermediaries played during that market dislocation. Our findings for the Tech and GFC episodes are consistent with the analysis of Campbell, Giglio, and Polk (2013) who argue that the former was a boom/bust primarily driven by discount rates while the latter was primarily a cash-flow-news event.

Finally, we summarize our findings using a VAR and a modified version of the return decomposition of Campbell (1991). Specifically, we decompose aggregate close-to-close discount-rate news into news about future expected intraday and overnight components of market returns. Consistent with our clientele interpretation, news about future expected overnight (intraday) returns is positively (negatively) correlated with cash-flow news. In other words, when good news about fundamentals arrives, the overnight clientele continues to push prices in the direction of that cash-flow news, resulting in a positive correlation with fundamentals. The intraday clientele then pulls prices back, hence the negative correlation. Moreover, and also in line with our interpretation, we find that intraday returns are driven primarily by cash-flow news while overnight returns are driven mostly by discount-rate news.

In summary, all four approaches we take to characterize those two clienteles point in the same direction: The overnight clientele displays risk tolerance variation and behavioral characteristics typically associated with households, and the intraday clientele displays the type of risk tolerance variation associated with institutions. This set of observations dovetails with evidence presented in Lou, Polk, and Skouras (LPS 2019), in the context of the cross-section of average firm-level overnight and intraday stock returns; households are key members of the overnight clientele and institutions trade more aggressively during the day.

The organization of our paper is as follows. Section 2 briefly summarizes existing literature. Section 3 describes the data and empirical methodology. Section 4 presents our main results on time-series variation in the equity premium. Section 5 provides our key pricing results, including results from a conditional CAPM that prices the unconditional returns of the four Fama-French non-market factors. Section 6 presents evidence supporting our interpretation of the findings. Section 7 concludes.

2 Related Literature

LPS are the first to link investor heterogeneity to the persistence of the overnight and intraday components of firm-level returns. Their work documents strong *firm-level* return continuation across both the overnight and intraday return components, i.e. an own-component continuation effect, along with an offsetting cross-component reversal effect. Consistent with the interpretation that these effects represent important and persistent investor clienteles, LPS show that the return predictability they find lasts for years. In contrast to LPS, at the aggregate level, we find no own-component continuation, if anything there is some evidence of own-component reversal. Moreover, the aggregate cross component lead-lag effect is asymmetric: Smoothed past overnight returns forecast intraday return reversals, while smoothed past intraday returns forecast overnight return continuation. Therefore, the equity premium predictability studied here is distinct from the cross-sectional patterns documented in earlier research.

The idea that institutions and individuals represent important heterogeneity in asset markets goes back to at least Gompers and Metrick (2001). Early work by Cohen (2003) uses flow of funds data to show that the equity allocations of individuals are cyclical while institutions keep a roughly constant allocation to equities over time. More recently, Greenwood and Shleifer (2014) show that investor expectations are strongly negatively correlated with model-based expected returns while Ben-Rephael, Kandel, and Wohl (2012) show that net exchanges by households between bond and equity retail mutual funds within the same fund family negatively forecast future market excess returns. Cohen, Gompers, and Vuolteenaho (2002) document that institutions buy shares from (sell shares to) individuals in response to positive (negative) cash-flow news. Conversely, individuals buy shares from (sell shares to) institutions in response to negative (positive) discount-rate news.

Our paper also relates to the literature studying fund flows and market dynamics. Warther (1995) and Edelen and Warner (2001) find a positive relationship between aggregate mutual fund flows and concurrent monthly, weekly, or daily market returns. Vayanos and Woolley (2013) and Gabaix and Koijen (2022) study asset pricing consequences of flows when there are financial frictions. Similarly, Lou and Polk (2022) argue that the actions of momentum traders can be destabilizing, pushing prices away from fundamental value.

3 Data and Methodology

Our core US sample spans the period 1993 to 2019, constrained by the availability of TAQ data.

3.1 Measuring Overnight and Intraday Components

To decompose the close-to-close return into its overnight and intraday components, we use the volume-weighted average price (VWAP) in the first half hour of trading (9:30 am - 10:00 am) for the SPDR S&P 500 Trust ETF, as reported in TAQ.[6] We rely on VWAP to ensure that our open prices are robust.

We define the intraday return, $r^{MKT}_{intraday,s}$, as the price appreciation between market open and close of the same day s, and impute the overnight return, $r^{MKT}_{overnight,s}$, based on this

[6]We have also verified that our results are robust to using open prices from other sources: a) open prices as reported by the Center for Research in Security Prices (CRSP) which also starts in 1993 (since their data are sourced from TAQ), b) the first trade price from TAQ, and c) the midpoint of the quoted bid-ask spread at the open from TAQ. We have also confirmed that our main predictability results are robust to using the open prices on a broad bottom-up market proxy rather than the SP 500 ETF. When doing so, to safeguard against the possibility that our VWAP may be driven by very small orders, we exclude observations where there are fewer than 1000 shares traded in the first half hour (we have also checked that our results are not sensitive to this restriction).

intraday return and the standard daily close-to-close return, $r^{MKT}_{close-to-close,s}$,

$$\begin{aligned} r^{MKT}_{intraday,s} &= \frac{P^{MKT}_{close,s}}{P^{MKT}_{open,s}} - 1, \\ r^{MKT}_{overnight,s} &= \frac{1 + r^{MKT}_{close-to-close,s}}{1 + r^{MKT}_{intraday,s}} - 1. \end{aligned}$$

In other words, we assume that dividend adjustments, share splits, and other corporate events that could mechanically move prices take place overnight. We then accumulate these overnight and intraday returns across days in each month t.

$$\begin{aligned} r^{MKT}_{intraday,t} &= \prod_{s \in t} (1 + r^{MKT}_{intraday,s}) - 1, \\ r^{MKT}_{overnight,t} &= \prod_{s \in t} (1 + r^{MKT}_{overnight,s}) - 1, \\ (1 + r^{MKT}_{intraday,t})(1 + r^{MKT}_{overnight,t}) &= (1 + r^{MKT}_{t}). \end{aligned}$$

3.2 Measuring the Drivers of PE

We hypothesize that there are different investor clienteles. For example, at a particular point in time, one clientele may be bullish on the market, while another clientele may be bearish and thus trade in the opposite direction, To the extent that these different clienteles have varying degrees of trading intensities during the day versus overnight (i.e. at the market open), variation in the relative magnitudes of overnight and intraday returns provides useful insights into their collective behavior and subsequent market performance.

To take this prediction to the data, we define smoothed returns using monthly returns as follows:

$$\begin{aligned} EWMA_{Overnight,t} &= \lambda r^{MKT}_{Overnight,t} + (1 - \lambda) EWMA_{Overnight,t-1}, \\ EWMA_{Intraday,t} &= \lambda r^{MKT}_{Intraday,t} + (1 - \lambda) EWMA_{Intraday,t-1}, \end{aligned}$$

Our results are robust to a reasonable range of smoothing parameters; we set λ equal to $\frac{1}{120+1}$ for our analysis which implies a center of mass of ten years and a half-life for the resulting weights of approximately 7 years.

3.3 Other Data

We measure quarterly consumption growth using the change in log per-capita consumption expenditures, on a seasonally-adjusted basis, measured in 1992 dollars. We take PE from Shiller's website but ensure that we remove any interpolation so that the resulting variable does not use ex post information. To create Intermediary Risk Tolerance (*Intermediary RT*), we take the intermediary factor from Adrian et al. (2014) and accumulate the resulting factor shock to create a level variable. We take individual investor expectations (*Indiv. Inv. Exp.*) for the American Association of Individual Investors from the online appendix of Greenwood and Shleifer (2014). We choose this specific variable among many other measures of investor expectations because it has the longest history.

3.4 Summary Statistics

Table I reports summary statistics of our variables, with two key takeaways. First, the average quarterly overnight return is 1.8% while the average quarterly intraday return is 0. This finding is consistent with a literature that finds that much of the equity premium is earned overnight.[7]

Another key takeaway is that the two smoothed past return components – smoothed overnight and intraday returns – are only weakly correlated (0.05) with each other. This fact suggests a role for each of these two components to capture different aspects of time variation in the equity premium.

[7] Work by Kelly and Clark (2011) suggests that aggregate stock returns on average are higher overnight than intraday. See related work by Branch and Ma (2008), Cliff, Cooper, and Gulen (2008), Tao and Qiu (2008), Berkman et al. (2009), Branch and Ma (2012), and Akbas et al. (2019). Lou, Polk, and Skouras (2019) note that this effect is concentrated in large stocks.

Table I Panel A also confirms that the intraday components of returns are more volatile than their overnight counterparts. This finding echos the fact that researchers since at least Fama (1965) have shown that volatility is higher during trading hours than non-trading hours.[8] Figure 1 plots our two smoothed return components against PE.

4 Main Empirical Results

A well-accepted view in finance is that household risk tolerance / sentiment drives variation in the equity premium. Typically, researchers have identified this mean reversion using scaled price ratios, like Shiller's CAPE variable (PE), which measure low-frequency movements away from fundamentals. Of course, variation in PE is due to either variation in cumulative overnight returns, cumulative intraday returns, or cumulative earnings growth. Indeed, in Table II column one, we confirm that these three variables explain 99% of the variation in PE. However, though reasonable arguments can be made that PE is stationary, these three components are not. As a consequence, we use in our analysis smoothed versions of these three components of PE to guarantee stationarity. The rest of the table shows that these three smoothed variables explain as much as 88% of the variation in PE. We will show that these three smoothed variables differentially forecast subsequent market return components.

Table III presents several key findings of the paper across three related analyses. In Panel A, we forecast close-to-close excess returns; in Panel B, we forecast intraday excess returns; and in Panel C, we forecast overnight excess returns. The intraday and overnight excess returns are constructed by subtracting 6.5/24 and 17.5/24 respectively of the risk-free rate from the corresponding return component. Though we simply allocate the T-bill return based on the relative portion of the 24-hour day, that methodological choice does not affect our findings to any significant extent, and our results are robust to other ways of allocating the risk-free return.

[8] See also French (1980) and French and Roll (1986).

4.1 Strong predictability of the close-to-close equity premium

Table III Panel A column (1) documents that PE has a tenuous relation with subsequent close-to-close returns, at least in our sample, with a t-statistic of only -1.77 and an R^2 of just 3%. Despite this lack of overall return predictability, the rest of the table shows that examining PE's components reveals fascinating insights about the drivers of time-series variation in the equity premium. Column (2) in the table shows that past smoothed intraday returns have an insignificant relation to subsequent close-to-close quarterly returns. However, the information in is surprisingly strong, both statistically and economically, which is the first key finding of the paper.[9] Statistically, the t-statistic is over 5.5, more than three times the t-statistic on PE. The R^2, at 14.1%, is more than four times as large.

In all of these regressions, the right-hand side variables are normalized for the ease of interpretation. Therefore, a one-standard-deviation move in smoothed overnight returns forecasts a change in the quarterly equity premium of 3.2%. The third column in the table shows the results when we lag the right-hand-side variables by an additional quarter. The ability of past smoothed overnight returns to forecast subsequent returns remains strong.

If we include smoothed earnings growth, there is virtually no change in the point estimate of interest. The final column adds several well-known return forecasting variables to the regression, the *cay* of Lettau and Ludvigson (2001), the value spread of Campbell and Vuolteenaho (2004), and realized volatility, with our effect subsuming all other variables.[10]

[9] Our decomposition not only reveals striking differences in equity premium dynamics across these two parts of the day, it reduces concerns about classic econometric issues associated with forecasting market returns. In many time-series tests of return predictability, the forecasting variable is persistent with shocks that are correlated with return shocks. In this case, the small-sample p-values obtained from the usual student-t test can be misleading (Stambaugh, 1999; Hodrick, 1992, and others). Indeed, Nelson and Kim (1993); Ang and Bekaert (2007); Lewellen (2004); Torous et al. (2005); Campbell and Yogo (2006); and Polk, Thompson, and Vuolteenaho (2006) all propose sophisticated procedures to deal with the Stambaugh (1999) problem. For example, PE in our sample has an AR(1) coefficient of 0.94, and the PE shock has a correlation of 0.93 with the corresponding return shock. However, since our decomposition finds that past smoothed overnight returns negatively predict intraday returns and since the correlation between overnight and intraday returns is close to zero, the Stambaugh size distortions are no longer a concern, alleviating worries related to this long-standing econometric issue. Similar considerations apply in all regressions of Table III, and we have confirmed that p-values do not change significantly if we apply the correction of Polk, Thompson and Vuolteenaho (2006).

[10] In untabulated results, we have also confirmed that our findings are robust to controlling for the term

4.2 Mean reversion intraday and mean aversion overnight

In the remaining two panels, we decompose the market return on the left-hand side of the regression as well. In Panel B of Table III, we forecast intraday excess returns. As can be seen in the first column, PE has a strong negative relation with subsequent intraday returns. This result suggests that intraday clienteles – institutions, for example – help facilitate the well-known mean reversion in aggregate returns.

Since past smoothed overnight returns track the mean reversion in close-to-close returns, we expect that $EWMA_{Overnight}$ also captures the intraday mean reversion weakly identified by PE in column (1) of this panel, and column (2) confirms that view. The result that the mean reversion linked to past overnight returns primarily occurs intraday is the second key finding of the paper. As in Panel A, Column (3) of Panel B shows that these results are robust to lagging by an additional quarter, and column (4) shows that adding smoothed earnings growth does not change the result qualitatively. Column (5) confirms that the result is robust to the inclusion of other return forecasting variables from prior literature.

Panel C of Table III forecasts overnight returns and presents the third major finding of the paper – strong return continuation that happens overnight. Column (1) shows that we can measure that overnight return continuation, at least to some degree, with PE. The coefficient on PE is positive and significant at the 10% level. Thus, part of the reason that PE does a poor job predicting mean reversion in close-to-close market returns is the partially offsetting mean *aversion* that occurs overnight. Our decomposition of PE refines this result considerably, as once we decompose PE, it is clear that smoothed intraday returns are what drive the overnight continuation. Taken at face value, this finding seems reasonable. Since there is more volatility in intraday returns and intraday moves are arguably more salient, one might expect intraday returns to drive future household expectations and trading decisions. More importantly, our predictability results imply that past smoothed returns primarily reflect aggregate cash-flow news, as this variable has little information about subsequent

spread, the default spread, and the SVIX of Martin (2017).

close-to-close returns. The notion that investor expectations may be (excessively) driven by fundamentals has a long history in behavioral economics. We explore this idea more fully in Section 6.

5 Pricing Tests

5.1 A Conditional CAPM

Our next analysis examines the extent to which our powerful conditioning variables (past smoothed overnight and intraday market returns) also track variation in CAPM betas. Since we have already established that these variables forecast the equity premium, if conditional betas comove with the conditional equity premium, alphas in a conditional CAPM analysis will change, perhaps significantly so.

As a baseline, in Table IV Panel A, we show the unconditional CAPM alphas of the Fama French size, value, investment, profitability factors as well as an equal-weight average of these four factors. We also include a momentum factor and a betting-against-beta strategy. All factors are from Ken French's website.

In Panel B, we interact the market return with our two lagged conditioning variables. These variables are demeaned and standardized to aid in interpretation. The unconditional alpha of the composite strategy drops by roughly 84% in magnitude from a significant 84 bps/quarter to an insignificant 14 bps/quarter once we allow its market beta to vary with our conditioning variables. The ability to track the conditional CAPM beta is due to the past smoothed overnight market return, with a loading of -0.213 and an associated t-statistic of -6.79. In other words, for a one-standard-deviation increase in smoothed overnight market returns, the market beta of the composite strategy decreases by 0.213. In contrast to the evidence in Lewellen and Nagel (2006), the conditional CAPM *does* explain the unconditional returns of the Fama-French factors, at least over our 22-year sample period.

Though we also find that momentum's CAPM beta varies through time, that variation is linked to the past smoothed intraday return which we know does not forecast variation in the equity premium. As a consequence, there is little reduction in the unconditional alpha of the momentum factor within our conditional beta model.

In Panel C, we also allow the conditional CAPM alphas to vary with our conditioning variables. We find that the conditional CAPM alpha of the equal-weight Fama-French four-factor portfolio varies positively with lagged smoothed overnight market returns. In contrast, the conditional CAPM alpha of momentum varies positively with lagged smoothed intraday market returns. Thus, our conditioning variables also reveal striking time-variation in conditional CAPM alphas over this time period.

5.2 Out-of-sample Market Timing

In Table V, we examine the economic magnitude of our equity-premium predictability by forming a managed portfolio based on $EWMA_{Overnight}$. We then estimate the alphas of this portfolio with respect to the CAPM, the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, and the Fama-French-Carhart six-factor model (i.e., Fama and French's five-factor model augmented with a momentum factor as in Carhart (1997)).

Column (1) of Panel A shows that a strategy that times the market based on $EWMA_{Overnight}$ produces a CAPM alpha of 2.1% per quarter with an associated t-statistic of 2.75. Estimating this alpha out-of-sample (Panel B) reduces the alpha only slightly: the estimate remains an economically large 1.6% per quarter with a t-statistic of 2.68. These results are robust to controlling for other risk factors. For example, column (4) in Panel A of Table V shows that the in-sample six-factor alpha is 1.4% (t-statistic = 3.16) per quarter. The six-factor alpha for the out-of-sample strategy remains 1% per quarter with a t-statistic of 2.43.

6 A Clientele-Based Interpretation

One interpretation of our findings is that there are different investor clienteles that trade at different points in time; some prefer to trade at market open and others at market close. In this section, we conduct additional analyses to shed more light on investor heterogeneity across the intraday and overnight periods. In particular, we offer four broad pieces of evidence. We first turn to individual investor expectations to study how these beliefs vary with past overnight and intraday market returns. We confirm Greenwood and Shleifer's (2014) key conclusion that investors extrapolate past returns when forming expectations; we then refine this message with the observation that investors more specifically extrapolate past intraday returns. We also show that these expectations positively forecast future overnight returns but not future intraday returns.

Second, we examine two key macro-finance variables that are the focus of many prior studies and are also interesting in our context. Specifically, we study the relation between intraday/overnight market returns and consumption growth, a classic asset-pricing variable that is only weakly linked to close-to-close market returns. We then examine whether a measure of intermediary risk tolerance is related to mean reversion in equity returns, and in particular, the mean reversion that primarily occurs intraday.

Third, we estimate a VAR-based return decomposition, following Campbell (1991). This technique allows us to decompose discount-rate news into components reflecting revisions in expectations of future overnight and intraday returns and to link those components to cash-flow news implied by the VAR (i.e., the residual term).

Fourth, we examine three bubble/crash episodes in the last three decades: the late 1990s Tech boom and subsequent bust, the Global Financial Crisis (GFC), and the Covid crash and rebound of 2020, all through our clientele prism. The last event is particularly relevant as it occurred after the publication of LPS. Anecdotal evidence suggests that the Covid lockdown and subsequent aggressive government policies resulted in many households being relatively flush with cash and making aggressive investments in the equity market. The

Covid sub-period thus provides a unique opportunity to confirm when households are more likely to trade – overnight or intraday.

6.1 Individual Investor Expectations

Greenwood and Shleifer (2014) argue that individual investors extrapolate past returns in forming their expectations; this view has been part of an exciting and growing literature in behavioral economics. Table VI reports regressions of individual investors' expectations on smoothed overnight and intraday returns. We find that individual investors' expectations vary primarily with $EWMA_{Intraday}$ (column (1)); $EWMA_{Overnight}$ has no explanatory power, either in isolation (column (2)) or in tandem (column (3)). The regressions in Table VI are contemporaneous; if one lags the right-hand side by a quarter, the same qualitative finding holds. This evidence linking survey expectations to a particular component of returns is consistent with the idea that individual investors extrapolate news about fundamentals (which mainly drive intraday returns, as the results in Table III imply, and we confirm in Section 6.3).

6.2 Macro-finance Variables

Prior research in asset pricing has trouble linking consumption growth to close-to-close stock returns as predicted by theory. Table VII Panel A regresses consumption growth on both components of market returns to reveal a strong link between consumption growth and overnight returns and no link with intraday returns. Of course, one might worry that consumption data are released with a lag. However, we find a strong relation using consumption anywhere from quarter t-2 to quarter t+2. Moreover, our finding is robust to reversing the regression specification and instead regressing each component of market returns on consumption growth (Panels B and C). Across leads and lags, and regardless of whether it is on the left-hand side or right-hand side, consumption growth has no relation to intraday returns and a strong relation to overnight returns.

Haddad and Muir (2021) argue that shocks to intermediary risk tolerance have little predictive power for equity returns, but strong predictive power for returns in intermediated markets such as the market for credit default swaps (CDS). We take the intermediary factor from Adrian et al. (2014) and accumulate the shocks to back out the level of intermediary risk tolerance / risk appetite at each point in time.

For the sake of comparison, in all panels of Table VIII, we first report in column (1) the analysis in column (2) of Table III. Consistent with Greenwood and Shleifer (2014), column (2) of Table VIII Panel A confirms that there is no link between individual investor expectations and subsequent close-to-close returns, either in isolation or in conjunction with the two smoothed components of past market returns. Column (4) shows that consumption growth does not forecast subsequent close-to-close returns either. Column (5) shows that *Intermediary RT* is informative, at least in isolation, about close-to-close returns. However, column (6) documents that *Intermediary RT* is driven out by $EWMA_{Overnight}$.

Panel B of Table VIII then repeats the exercise in Panel A but replaces the dependent variable, next month's close-to-close return, with the intraday return component. This panel shows that the mean reversion picked up in close-to-close returns by *Intermediary RT* is particularly strong intraday. However, $EWMA_{Overnight}$ also subsumes that variable's ability to forecast intraday returns. We continue to find only mean reversion intraday, when institutions typically trade. As with close-to-close returns, neither consumption growth nor individual investor expectations have any predictive power.

Finally, in Panel C of Table VIII, we forecast overnight returns and find strong confirming evidence of the importance of the overnight clientele and its reflection of household investment decisions. Column (2) of the panel shows that individual investors' expectations positively forecast subsequent overnight returns in isolation. As might be expected, given how noisy these expectation estimates are, they are subsumed by $EWMA_{Overnight}$ and $EWMA_{Intraday}$ in column (3). Nevertheless, these results indicate that the expectations data studied in Greenwood and Shleifer (2014) not only reveal extrapolation but are also informative about the actions these investors take (buying into the market, primarily at the open).

Column (4) shows that consumption growth strongly forecasts subsequent overnight returns, with a t-statistic of 4.88. In column (7), where all of our key variables (smoothed overnight and intraday market returns, consumption growth, and intermediary risk tolerance) are included in the regression, the coefficients on past smoothed intraday returns and consumption growth remain statistically positive.

In sum, the return predictability results of individual investor expectations, as well as those of our macro-finance variables, all support the notion that overnight returns (and the corresponding clientele) are where mean aversion primarily occurs (both individual investor expectations and consumption growth positively predict overnight market returns), while intraday returns are where mean reversion primarily occurs (both the intermediary risk tolerance and household equity share negatively forecast overnight market returns).

6.3 Decomposing Discount-rate News

We next conduct a return decomposition exercise, following Campbell (1991). We assume that a first-order VAR describes the transition of the state variables where the first and second elements are $r^{Intraday}$, the log intraday return in excess of (6.5/24) * log risk-free rate, and $r^{Overnight}$, the log intraday return in excess of (17.5/24) * log risk-free rate.

$$\begin{aligned}
\boldsymbol{x}_{t+1} &= \bar{\boldsymbol{x}} + \boldsymbol{\Gamma}\left(\boldsymbol{x}_t - \bar{\boldsymbol{x}}\right) + \boldsymbol{u}_{t+1}, \\
\boldsymbol{x}_{t+1} &= [r_{t+1}^{Intraday}, r_{t+1}^{Overnight}];\; r_{t+1} = r_{t+1}^{Intraday} + r_{t+1}^{Overnight}.
\end{aligned}$$

These two variables sum up to the excess log return on the market and therefore allow a straightforward decomposition of the standard Campbell (1991) discount-rate news term into its intraday and overnight components. Importantly, we are decomposing discount-rate news that arrives throughout the close-to-close period into components related to news about expected intraday and overnight returns (note that this decomposition is not the same as measuring whether discount news arrives intraday or overnight).

$$\begin{aligned}
r_{t+1} - \mathrm{E}_t r_{t+1} &= N_{CF,t+1} - N_{DR,t+1}, \\
N_{DR,t+1} &= N_{DR,t+1}^{Intraday} + N_{DR,t+1}^{Overnight}, \\
N_{DR,t+1}^{Intraday} &= (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}^{Intraday} = \mathbf{e}_1' \sum_{j=1}^{\infty} \rho^j \mathbf{\Gamma}^j \mathbf{u}_{t+1} = \mathbf{e}_1' \rho \mathbf{\Gamma} (\mathbf{I} - \rho \mathbf{\Gamma})^{-1} \mathbf{u}_{t+1}, \\
N_{DR,t+1}^{Overnight} &= (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}^{Overnight} = \mathbf{e}_2' \sum_{j=1}^{\infty} \rho^j \mathbf{\Gamma}^j \mathbf{u}_{t+1} = \mathbf{e}_2' \rho \mathbf{\Gamma} (\mathbf{I} - \rho \mathbf{\Gamma})^{-1} \mathbf{u}_{t+1}.
\end{aligned}$$

As in Campbell (1991), we measure cash-flow news (which technically includes both news about dividend growth and news about the log real interest rate) as the residual.

Table IX Panel A reports estimates of the transition matrix. The findings are broadly consistent with the results of Table III which uses simple returns. Table IX Panel B shows that cash-flow news has the smallest volatility of the three components. Consistent with our interpretation of the data, we find that intraday discount-rate news is significantly more volatile than overnight discount-rate news. Moreover, in comparison to a baseline VAR (unreported) which simply uses PE to forecast close-to-close returns, there's a lot more discount rate news in total. The two components of discount-rate news are only weakly contemporaneously correlated (0.177), far from a perfect correlation.

Figure 3 provides a graphical view of the forecasts from the VAR and shows how together they imply significantly more variation in the close-to-close equity premium than the baseline VAR (where we do not include the intraday and overnight components of the market return).

Perhaps most interestingly, the correlations between two return components and cash-flow news change signs as we move from intraday to overnight. Indeed, a regression (not tabulated) of $N_{DR,t+1}^{Overnight} - N_{DR,t+1}^{Intraday}$ on $N_{CF,t+1}$ has a coefficient of 4.18 with a t-statistic of 20.95, and an R^2 of 83%.

Moreover, the change in the correlation is consistent with an extrapolation interpretation of our findings. For example, after good news about fundamentals arrives, the overnight clientele will push prices away from fundamentals, resulting in a positive correlation between the discount rate news about future overnight returns and cash-flow news. The intraday clientele will pull prices back, hence the negative correlation between the discount rate news about future intraday returns and cash-flow news.

In line with that interpretation, we find that intraday returns are primarily driven by cash-flow news while overnight returns are primarily driven by discount-rate news. The correlation between cash-flow news and the spread between intraday and overnight realized returns is 0.76. Since Table VI documents that individual investors expectations are driven by past intraday returns, this finding suggests that individual investors extrapolate fundamentals rather than returns.

6.4 The Covid Crash, GFC, and Tech Boom/Bust

Figure 4 Panel A plots how the intraday and overnight components of market returns moved during the Covid crash and rebound of 2020. The patterns in 2020 are stark and confirm the importance of our clientele story. The majority of the Covid crash and rebound comes overnight. This finding is consistent with anecdotal evidence of increased retail participation due to Covid lockdowns.

We also examine two other well-know bubble/crisis episodes in recent decades through our intraday/overnight prism. Figure 4 Panel B plots the intraday/overnight components of aggregate returns during the Global Financial Crisis. This event was much more of an intraday phenomenon, consistent with declining intermediary risk tolerance playing a key role in driving market prices in this episode.

Figure 4 Panel C uses our approach to study the tech boom and bust of the late 1990s and early 2000s. As far back as 1997, intraday returns were flat at best and then became slowly negative. In contrast, the striking rise in valuations in this episode is entirely driven by overnight returns. This episode highlights how a PE measure based on close-to-close market returns effectively combines the much earlier intraday peak in early 1998 with the much later overnight peak in 2001.

Figure F documents that these patterns occur for well-known meme stocks – AMC; GameStop; Bed, Bath, and Beyond; and Koss. The patterns in these meme stocks are known to be driven by retail investors and their remarkable price spikes occur entirely overnight. In contrast, their intraday returns tend to go the opposite way.

7 Conclusions

In this paper, we decompose close-to-close market returns into their overnight and intraday components, which reveals strong predictability of the equity premium. This phenomenon is a much stronger version of the well-known mean reversion in returns linked to the price-earnings ratio. Smoothed overnight returns negatively forecast future close-to-close returns, particularly the intraday component. The ability of PE to forecast close-to-close returns is hamstrung by the partially-offsetting effect that smoothed intraday returns strongly positively forecast future overnight returns.

Our decomposition also resurrects the conditional CAPM: If we allow beta to vary with past smoothed overnight returns, the unconditional alpha of the four Fama-French non-market factors decreases by 84%. Nevertheless, once we also allow CAPM alphas to also vary with our conditioning variables, we find that the conditional CAPM alpha of these four factors varies positively with smoothed overnight market returns. In contrast, the conditional CAPM alpha of the momentum strategy varies positively with smoothed intraday market returns.

We interpret this predictability as the outcome of the interaction of overnight and intraday clienteles and attempt to characterize these clienteles. First, survey evidence reveals that retail investor expectations are driven by past intraday market returns but not overnight returns. In addition, these expectations positively forecast future overnight returns (but not future intraday returns). Second, an analysis exploiting macro-finance variables reveals that overnight returns (but not intraday returns) are strongly correlated with consumption growth, and that intermediary risk tolerance negatively predict intraday market returns. Third, a cash-flow / discount-rate news decomposition reveals that news about future expected overnight returns is positively correlated with cash-flow news, and that news about future expected intraday returns is negatively correlated with cash-flow news.

These facts are consistent with the idea that the overnight clientele extrapolates cash-flow news while the intraday clientele pulls prices back. All of these results suggest that the overnight clientele has characteristics typically associated with households, and the intraday clientele has characteristics associated with institutions, in line with the findings of Lou, Polk and Skouras (2019) in a different cross-sectional context. Moreover, our findings help resolve a debate in behavioral economics as to whether investors extrapolate fundamentals or returns, a distinction that has important policy implications (Fontanier (2022)).

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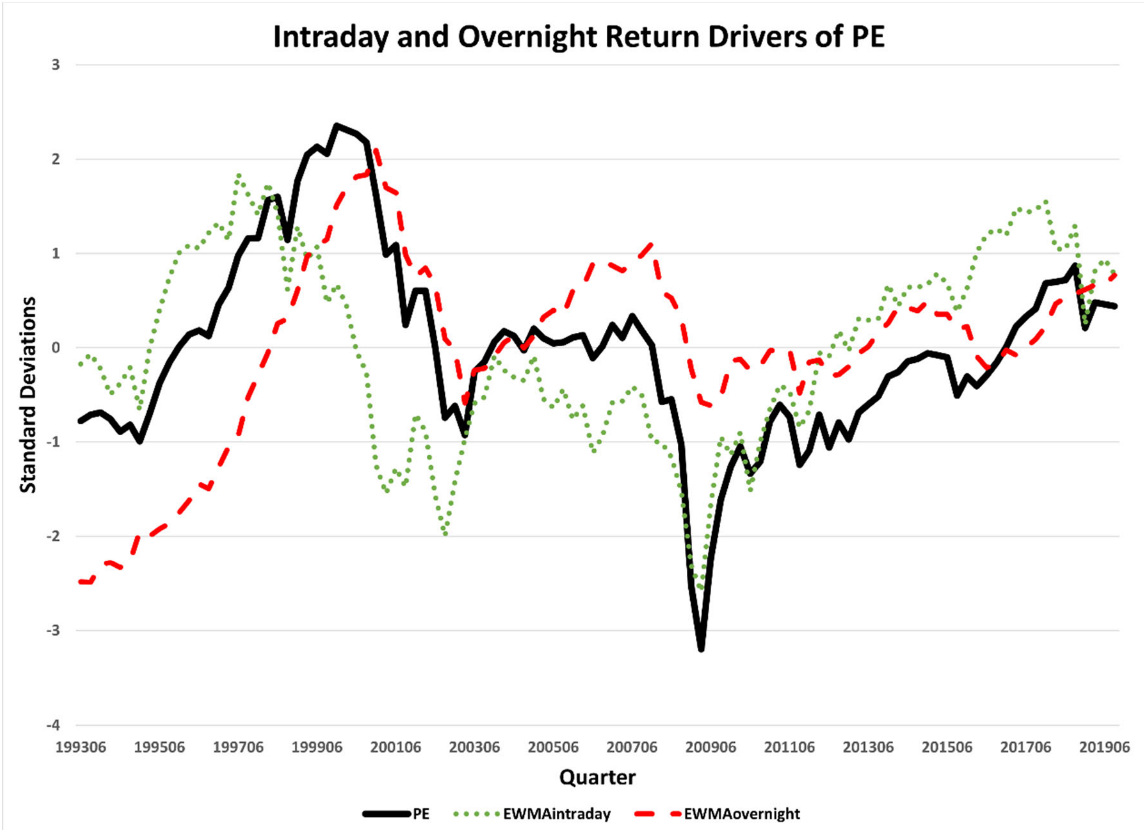


Figure 1. This figure shows the PE ratio and smoothed (exponential-weighted average) overnight/intraday returns for the period 1993-2019.

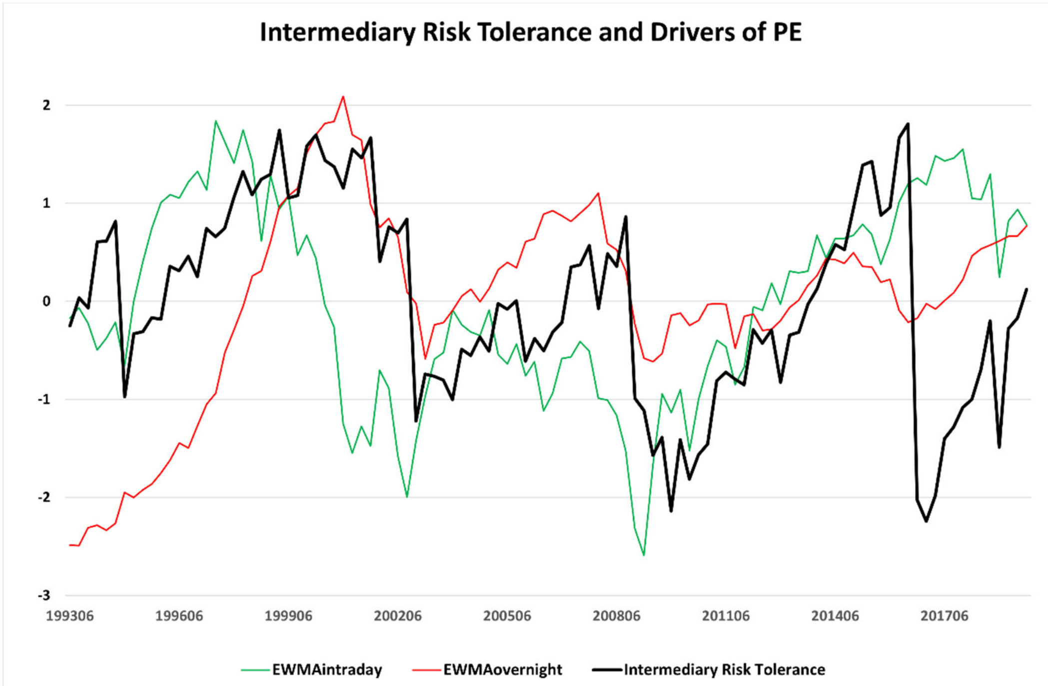
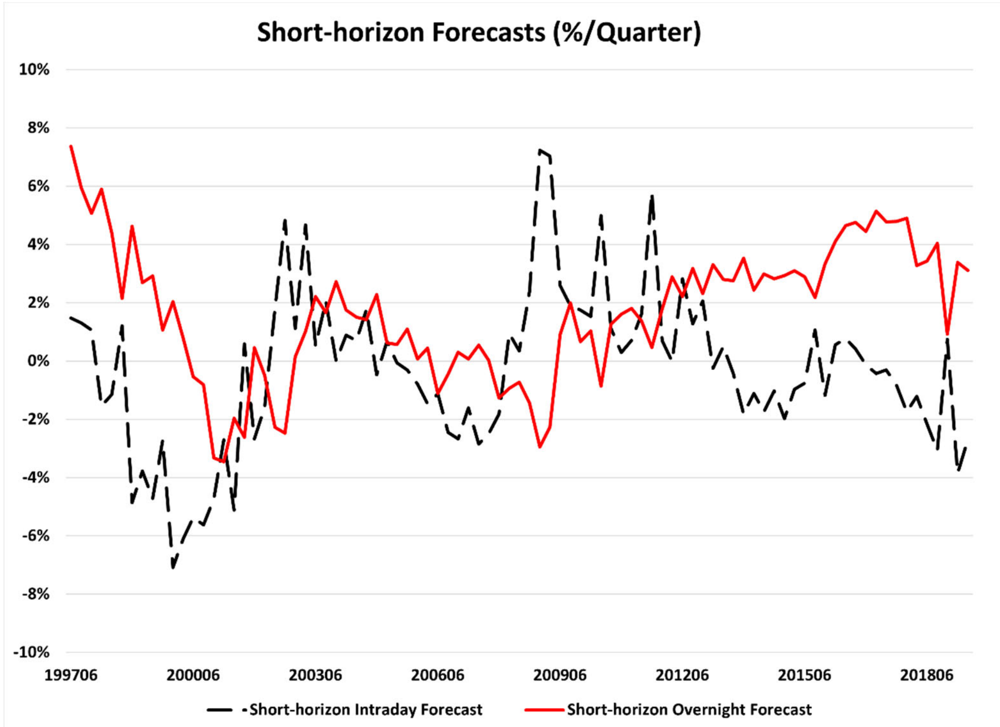


Figure 2. The figure shows the time series of smoothed overnight and intraday returns together with our measure of intermediary risk tolerance.



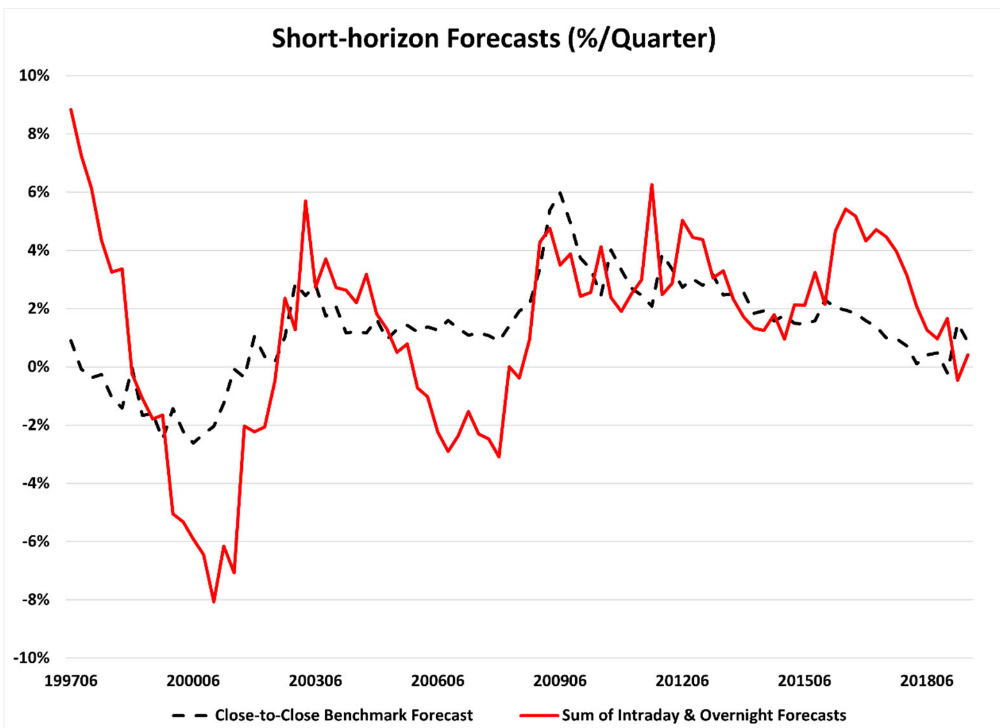


Figure 3. The figure shows the time-series of expected overnight and intraday returns from the VAR in Table IX. The first panel plots the time-series of return forecasts while the second panel plots the sum of those component forecasts, comparing it to the close-to-close forecast from a benchmark PE-only VAR.

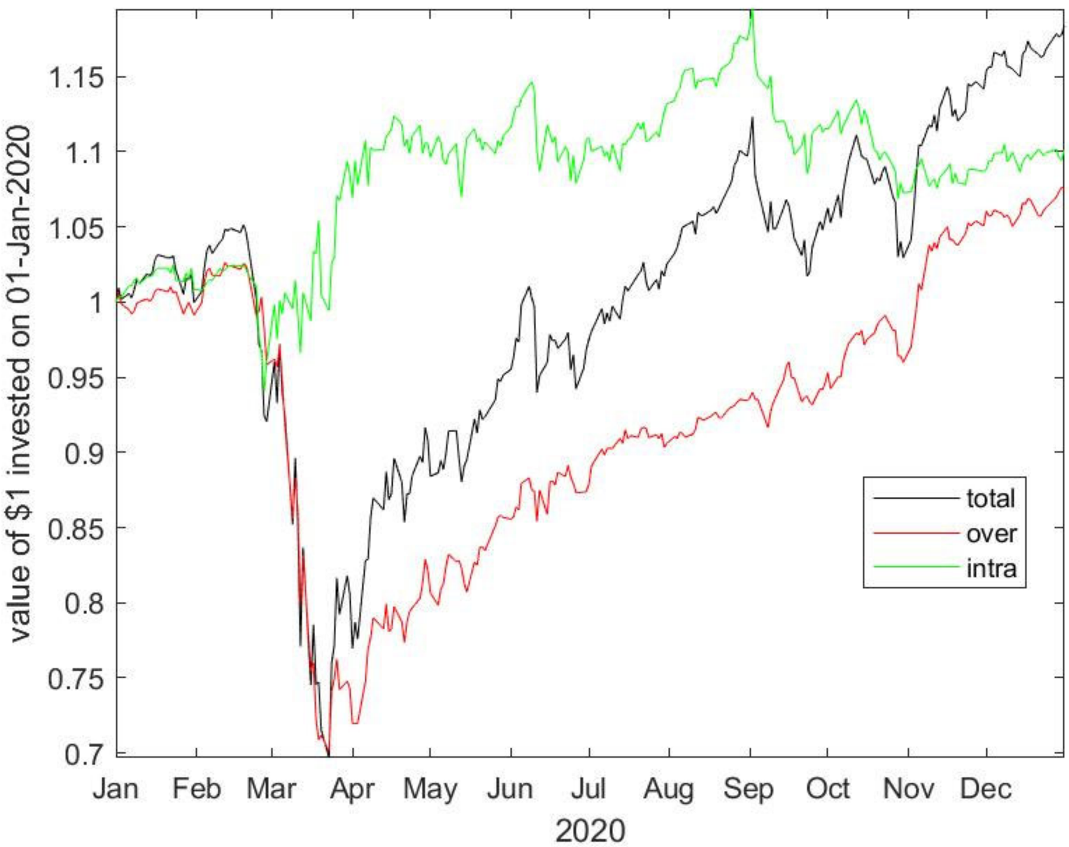


Figure 4 Panel A. This figure plots the cumulative returns of an investment in the stock market ("total" black line), an investment in the market during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in 2020 (the COVID-19 pandemic).

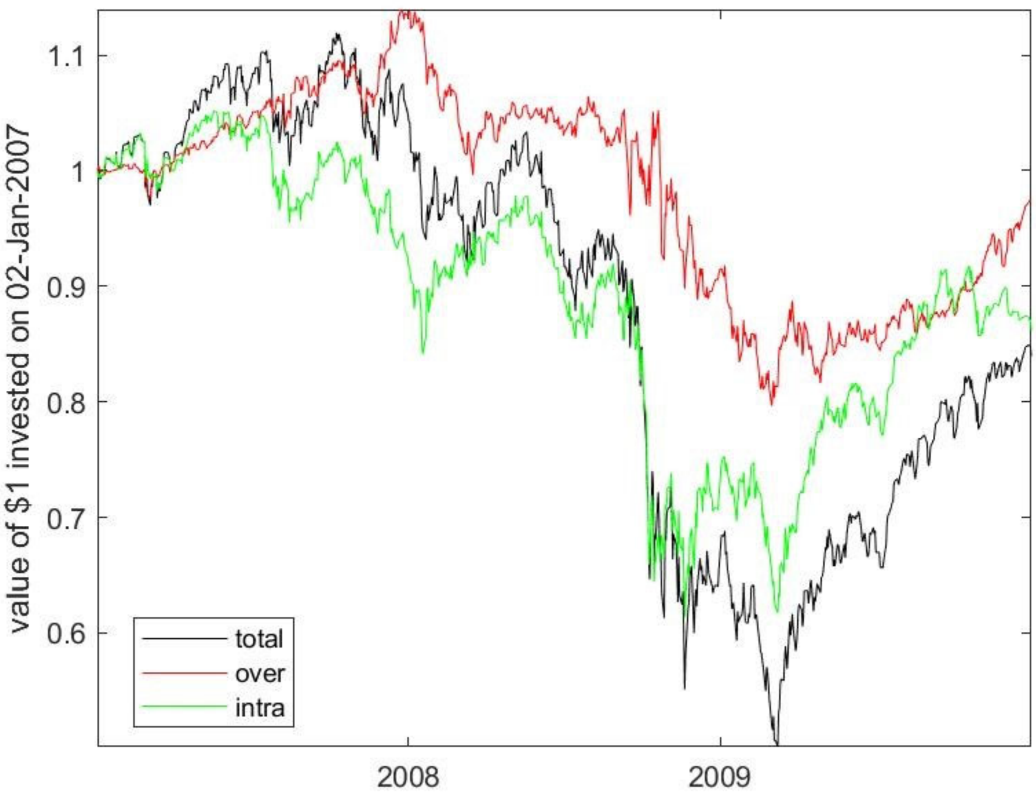


Figure 4 Panel B. This figure plots the cumulative returns of an investment in the stock market ("total" black line), an investment in the market during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the Global Financial Crisis (GFC).

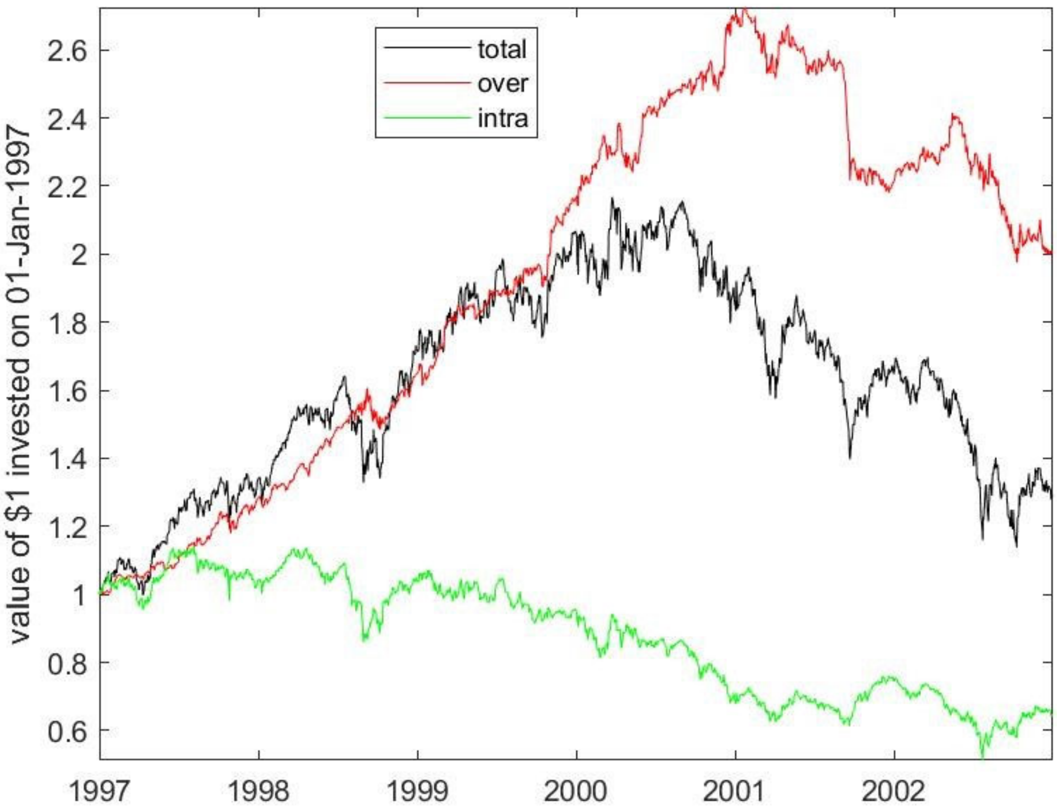


Figure 4 Panel C. This figure plots the cumulative returns of an investment in the stock market ("total" black line), an investment in the market during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the NASDAQ bubble.

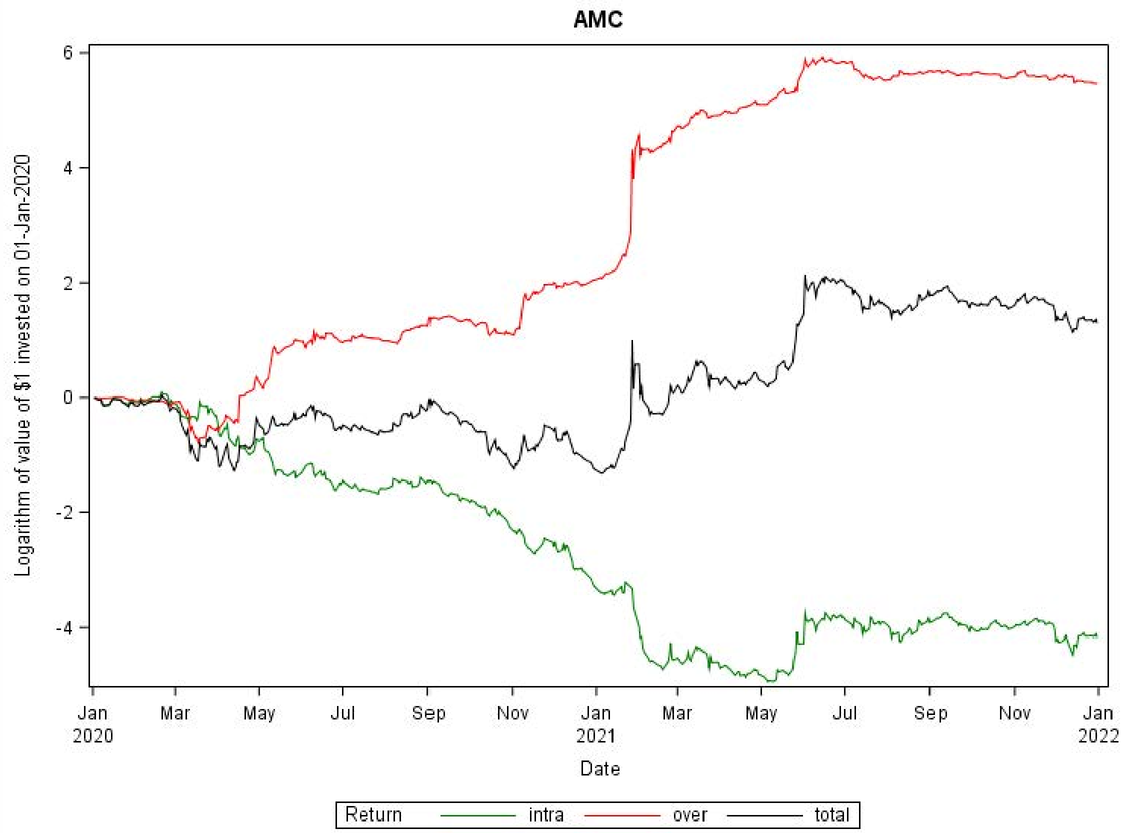


Figure 5 Panel A. This figure plots the cumulative log returns of an investment in the AMC ("total" black line), an investment in AMC during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the meme stock subperiod.

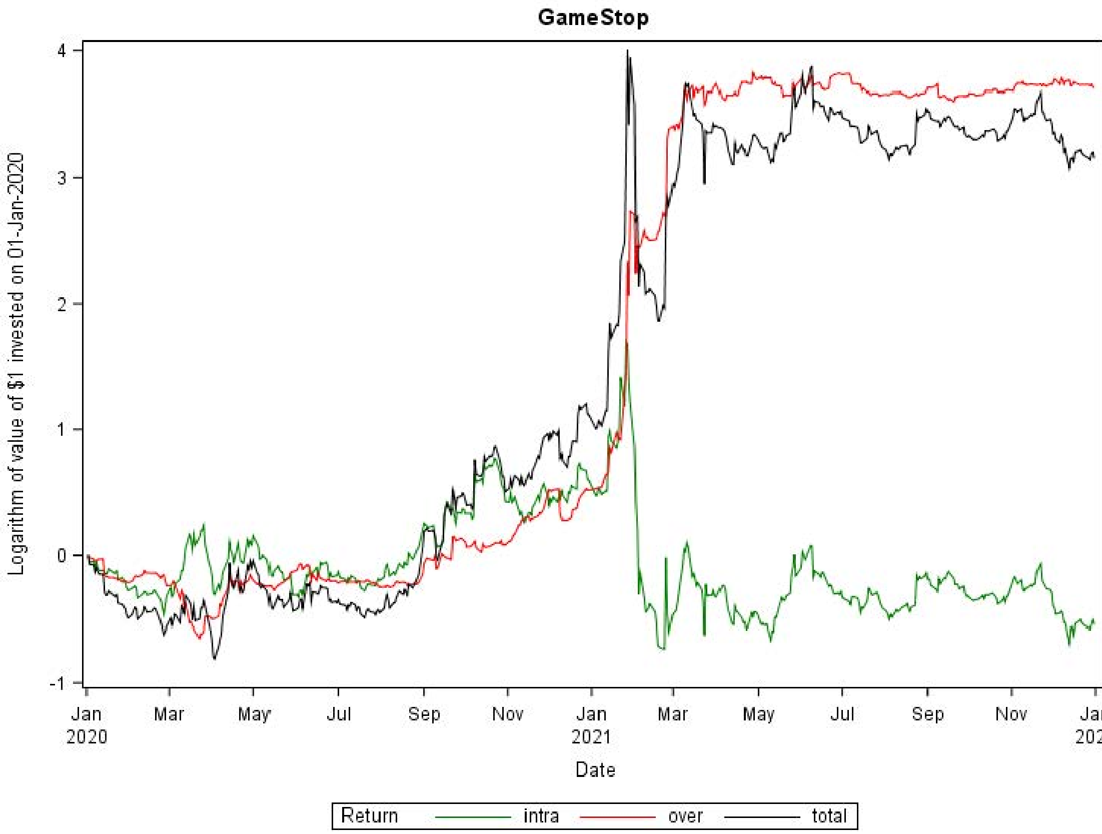


Figure 5 Panel B. This figure plots the cumulative log returns of an investment in the GameStop ("total" black line), an investment in GameStop during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the meme stock subperiod.

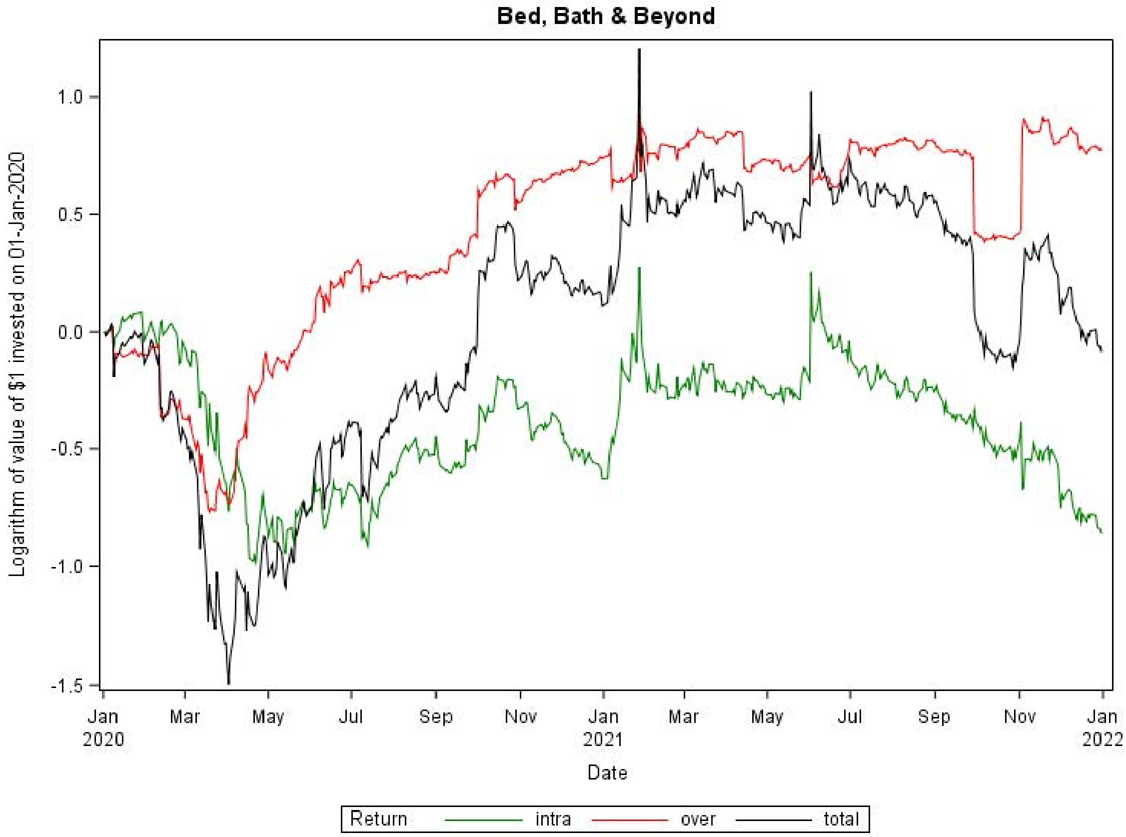


Figure 5 Panel C. This figure plots the cumulative log returns of an investment in the Bed, Bath, and Beyond ("total" black line), an investment in Bed, Bath, and Beyond during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the meme stock subperiod.

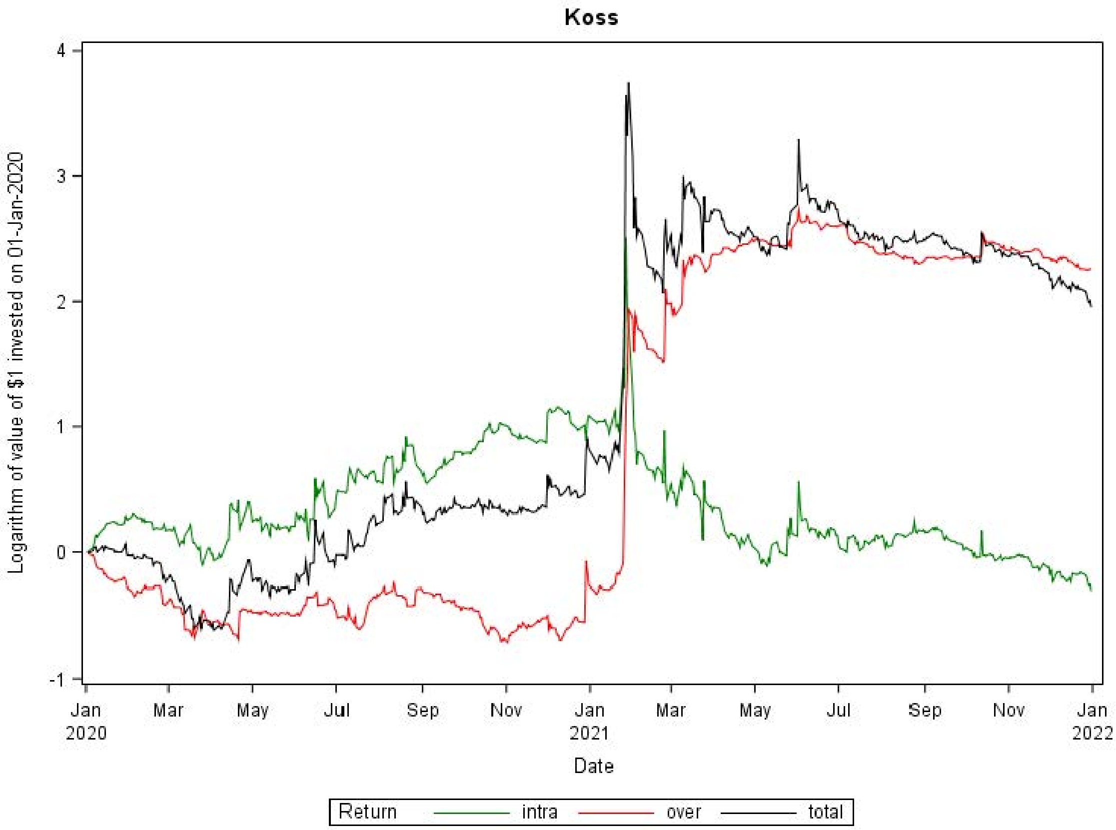


Figure 5 Panel D. This figure plots the cumulative log returns of an investment in Koss ("total" black line), an investment in Koss during only overnight periods ("over", red line), and an investment during only intraday periods ("intra", green line) in the meme stock subperiod.

Table I. Summary Statistics

This table reports summary statistics of our main variables at the quarterly frequency. RMRF, Intraday RMRF, Overnight RMRF are the quarterly close-to-close, overnight and intraday market returns. PE is the standard price-to-earnings ratio. EWMA Intraday, EWMA Overnight, and EWMA earnings are the exponential weighted moving average of Intraday RMRF, Overnight RMRF, and quarterly earnings growth, all with a half-life of roughly 7 years. CAY and VS are the Lettau and Ludvigson (2001) consumption-to-wealth ratio and the value spread, respectively. RVOL is the realized daily market volatility in the quarter. Cons. Growth is the quarterly consumption growth and Intermediary RT is a measure accumulating the intermediary risk tolerance shocks of Adrian et al. (2014). Panel A reports the summary statistics of our main variables, and Panel B reports the correlation matrix. The sample period is 1993Q3 to 2019Q4.

Panel A: Summary Statistics

	mean	stdev	P25	Median	P75
RMRF	0.018	0.082	-0.024	0.027	0.061
$\text{RMRF}_{\text{Intraday}}$	0.000	0.066	-0.040	0.001	0.042
$\text{RMRF}_{\text{Overnight}}$	0.018	0.045	0.000	0.024	0.042
PE	3.404	0.232	3.259	3.395	3.517
$\text{EWMA}_{\text{Intraday}}$	0.000	0.001	-0.001	0.000	0.001
$\text{EWMA}_{\text{Overnight}}$	0.005	0.001	0.005	0.005	0.006
$\text{EWMA}_{\text{Earn}}$	0.013	0.006	0.009	0.013	0.019
CAY	-0.003	0.016	-0.015	-0.001	0.009
VS	1.567	0.178	1.411	1.596	1.680
RVOL	1.061	0.571	0.675	0.899	1.303
Cons. Growth	0.005	0.005	0.002	0.005	0.007
Intermediary RT	0.975	1.689	-0.262	0.808	2.393

Panel B1: Correlation Matrix

	RMRF	$\text{RMRF}_{\text{Intra}}$	$\text{RMRF}_{\text{Over}}$	PE	$\text{EWMA}_{\text{Intra}}$	$\text{EWMA}_{\text{Over}}$	$\text{EWMA}_{\text{Earn}}$
RMRF	1						
$\text{RMRF}_{\text{Intraday}}$	0.84	1					
$\text{RMRF}_{\text{Overnight}}$	0.58	0.05	1				
PE	0.13	-0.12	0.43	1			
$\text{EWMA}_{\text{Intraday}}$	0.44	0.23	0.46	0.53	1		
$\text{EWMA}_{\text{Overnight}}$	-0.22	-0.35	0.13	0.66	-0.07	1	
$\text{EWMA}_{\text{Earn}}$	-0.01	-0.06	0.07	0.07	0.50	0.09	1

Panel B2: Correlation Matrix							
	$EWMA_{Intra}$	$EWMA_{Over}$	CAY	VS	RVOL	Cons. Growth	Inter. RT
$EWMA_{Intra}$	1						
$EWMA_{Over}$	-0.07	1					
CAY	-0.39	0.18	1				
VS	0.28	0.17	-0.55	1			
RVOL	-0.49	-0.03	0.41	0.04	1		
Cons. Growth	0.55	0.20	0.02	-0.05	-0.41	1	
Inter. RT	0.18	0.54	0.35	0.07	0.12	0.29	1

Table II. Decomposing the PE Ratio

This table reports regressions explaining the PE ratio. The dependent variable in all columns is the price-to-earnings ratio in quarter t. The main independent variables are the log cumulative overnight return, the log cumulative intraday return, the log cumulative earning growth, $EWMA_{overnight}$, $EWMA_{intraday}$, and $EWMA_{earn}$. $EWMA_{overnight}$, $EWMA_{intraday}$, and $EWMA_{earn}$ are standardized to have a mean of zero and standard deviation of one. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997Q3 to 2019Q4 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Decomposing the PE Ratio						
	[1]	[2]	[3]	[4]	[5]	[6]
$Ln(CumRet_{over})$	0.98***					
	[76.98]					
$Ln(CumRet_{Intra})$	0.98***					
	[85.22]					
$Ln(E/E_0)$	-1.00***					
	[-78.38]					
$EWMA_{overnight}$		0.15***			0.16***	0.17***
		[8.32]			[13.94]	[20.59]
$EWMA_{intraday}$			0.12***		0.14***	0.18***
			[5.92]		[11.53]	[18.54]
$EWMA_{earn}$				0.02		-0.09***
				[0.67]		[-9.17]
Adj-R^2	99.2%	43.4%	27.7%	-0.6%	77.4%	88.4%

Table III. Forecasting Future Market Returns

This table reports regressions forecasting the excess return on the market as well as its intraday and overnight components. PE is the standard price-to-earnings ratio. $EWMA_{overnight}$, $EWMA_{intraday}$, and $EWMA_{earn}$ are the exponential weighted moving average of intraday RMRF, overnight RMRF, and quarterly earnings growth, all with a half-life of roughly 7 years. CAY and VS are the Lettau and Ludvigson (2001) consumption-to-wealth ratio and the value spread, respectively. RVOL is the realized daily market volatility in the quarter. The dependent variable in Panel A is the next-quarter close-to-close excess market return; the dependent variable in Panel B is the next-quarter intraday excess market return, and in Panel C, the dependent variable is the overnight excess market return. All independent variables are standardized to have a mean of zero and standard deviation of one. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997Q3 to 2019Q4 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Panel A: Forecasting Excess Market Returns					
	[1]	[2]	[3]	[4]	[5]
PE	-0.017*				
	[-1.77]				
$EWMA_{overnight}$		-0.032***	-0.030***	-0.031***	-0.029***
		[-5.53]	[-5.10]	[-5.33]	[-3.83]
$EWMA_{intraday}$		0.006	0.003	0.007	0.010
		[0.74]	[0.50]	[0.54]	[1.11]
$EWMA_{earn}$				-0.002	
				[-0.18]	
CAY					-0.004
					[-0.36]
VS					-0.007
					[-0.64]
$RVOL$					0.007
					[0.43]
Adj-R^2	3.0%	14.1%	11.7%	13.1%	11.6%

Panel B: Forecasting Intraday Excess Market Returns					
	[1]	[2]	[3]	[4]	[5]
PE	-0.025***				
	[-4.88]				
$EWMA_{overnight}$		-0.022***	-0.018***	-0.023***	-0.018***
		[-5.67]	[-3.31]	[-5.86]	[-3.94]
$EWMA_{intraday}$		-0.013**	-0.011**	-0.017*	-0.011**
		[-2.34]	[-2.25]	[-1.70]	[-2.20]
$EWMA_{earn}$				0.007	
				[0.74]	
CAY					-0.013*
					[-1.95]
VS					-0.004
					[-0.59]
$RVOL$					0.011
					[0.83]
Adj-R^2	14.4%	12.9%	7.9%	12.8%	12.7%

Panel C: Forecasting Overnight Excess Market Returns					
	[1]	[2]	[3]	[4]	[5]
PE	0.010*				
	[1.81]				
$EWMA_{overnight}$		-0.009*	-0.011**	-0.008	-0.010**
		[-1.65]	[-2.26]	[-1.52]	[-2.07]
$EWMA_{intraday}$		0.020***	0.015***	0.025***	0.022***
		[3.96]	[3.30]	[4.93]	[4.01]
$EWMA_{earn}$				-0.010*	
				[-1.74]	
CAY					0.009
					[1.33]
VS					-0.003
					[-0.42]
$RVOL$					-0.005
					[-0.91]
Adj-R^2	3.5%	22.2%	16.5%	24.6%	24.8%

Table IV. A Conditional CAPM Model

This table reports time-series regressions of common factor returns on market returns. The dependent variables in the first four columns are the monthly returns on the Fama French size, value, investment, profitability factors, respectively. The dependent variable in the fifth column is the equal-weighted average return of the Fama French four factors, the dependent variable in the sixth column is the momentum factor return, and the dependent variable in the seventh column is the betting-against-beta factor return. In Panel A, we simply regress these factor returns on the contemporaneous market return. In Panel B, we also interact the market return with lagged $EWMA_{overnight}$ and $EWMA_{intraday}$ (as conditioning variables, both standardized to mean of zero and standard deviation of 1). In Panel C, we further include lagged $EWMA_{overnight}$ and $EWMA_{intraday}$ in the regression to forecast the conditional CAPM alpha. A four-year burn-in period is used to calculate $EWMA_{overnight}$ and $EWMA_{intraday}$, so strategy returns cover 1997Q3 to 2019Q4. All returns are expressed in percentage terms. $EWMA_{overnight}$ and $EWMA_{intraday}$ are standardized to have a mean of zero and standard deviation of one. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Unconditional CAPM Regressions

	SMB_{t+1}	HML_{t+1}	RMW_{t+1}	CMA_{t+1}	$EW\ FF$	MOM_{t+1}	BAB_{t+1}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Constant (%)	0.200	0.596	1.602***	0.959**	0.837**	1.773**	1.746**
	[0.41]	[0.85]	[3.29]	[2.16]	[2.22]	[1.96]	[1.99]
$RMRF_{t+1}$	0.184***	-0.133*	-0.380***	-0.156***	-0.121***	-0.357***	-1.024***
	[3.27]	[-1.70]	[-6.82]	[-3.08]	[-2.81]	[-3.45]	[-10.19]
Adj-R^2	9.9%	2.1%	34.1%	8.8%	7.3%	11.0%	53.9%

Panel B: Conditional CAPM Regressions

	SMB_{t+1}	HML_{t+1}	RMW_{t+1}	CMA_{t+1}	$EW\ FF$	MOM_{t+1}	BAB_{t+1}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Constant (%)	-0.080	-0.530	0.879*	0.283	0.138	1.785**	0.887
	[-0.15]	[-0.87]	[1.80]	[0.71]	[0.42]	[2.00]	[0.96]
$RMRF_{t+1}$	0.193***	-0.139**	-0.336***	-0.167***	-0.112***	-0.217**	-0.971***
	[3.14]	[-1.97]	[-5.93]	[-3.62]	[-2.94]	[-2.10]	[-9.03]
$RMRF_{t+1}$ *	-0.080	-0.361***	-0.184***	-0.226***	-0.213***	0.150*	-0.218***
$EWMA_{over,t}$	[-1.58]	[-6.23]	[-3.95]	[-5.97]	[-6.79]	[1.76]	[-2.47]
$RMRF_{t+1}$ *	0.003	-0.089	0.057	-0.070*	-0.025	0.336***	0.069
$EWMA_{intra,t}$	[0.06]	[-1.47]	[1.18]	[-1.77]	[-0.75]	[3.80]	[0.75]
Adj-R^2	10.5%	34.1%	43.2%	37.7%	39.8%	26.0%	56.1%

Panel C: Conditional CAPM with Additional Timing Variables							
	SMB_{t+1}	HML_{t+1}	RMW_{t+1}	CMA_{t+1}	$EW\ FF$	MOM_{t+1}	BAB_{t+1}
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Constant (%)	-0.151	-0.608	0.844*	0.208	0.073	1.644*	0.809
	[-0.30]	[-1.00]	[1.71]	[0.53]	[0.23]	[1.89]	[0.88]
$EWMA_{over,t}$	0.843*	0.815	0.399	0.826**	0.721**	1.445	0.762
	[1.70]	[1.36]	[0.82]	[2.13]	[2.26]	[1.68]	[0.84]
$EWMA_{intra,t}$	-1.394***	0.636	-0.279	-0.010	-0.262	1.760**	1.706**
	[-2.91]	[1.10]	[-0.60]	[-0.03]	[-0.85]	[2.13]	[1.96]
$RMRF_{t+1}$	0.256***	-0.115	-0.314***	-0.130***	-0.076*	-0.186*	-0.969***
	[4.09]	[-1.53]	[-5.12]	[-2.67]	[-1.90]	[-1.72]	[-8.50]
$RMRF_{t+1}$ *	-0.061	-0.376***	-0.182***	-0.230***	-0.212***	0.114	-0.249***
$EWMA_{over,t}$	[-1.26]	[-6.41]	[-3.82]	[-6.07]	[-6.82]	[1.36]	[-2.82]
$RMRF_{t+1}$ *	0.032	-0.106*	0.062	-0.072*	-0.021	0.291***	0.028
$EWMA_{intra,t}$	[0.63]	[-1.72]	[1.25]	[-1.82]	[-0.64]	[3.30]	[0.30]
Adj-R^2	20.0%	34.8%	42.6%	39.5%	42.6%	30.1%	57.2%

Table V. Pricing Tests: In-Sample and Out-of-Sample Evidence

This table reports OLS regressions of the returns from a managed investment in the excess market return on various factor models, which use combinations of Fama-French market, size, value, investment, profitability, and momentum factors. In Panel A, the investment in the market is scaled by minus the standardized (mean zero, standard deviation one) exponentially weighted moving average of the overnight return, with a half-life of roughly 7 years. In Panel B, the standardization uses an expanding sample up to the investment date. A four-year burn-in period for the standardization is also used, so strategy returns cover 1997Q3 to 2019Q4. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: In-Sample Analysis

	[1]	[2]	[3]	[4]
Alpha	0.021***	0.018***	0.013***	0.014***
	[2.75]	[3.91]	[2.99]	[3.16]
RMRF	-0.399**	-0.325***	-0.242**	-0.265**
	[-2.12]	[-3.00]	[-2.09]	[-2.32]
SMB		-0.001	0.027	0.005
		[-0.01]	[0.20]	[0.04]
HML		0.538***	0.313***	0.252**
		[5.22]	[2.83]	[2.29]
RMW			0.170	0.192*
			[1.47]	[1.82]
CMA			0.356*	0.399**
			[1.87]	[2.03]
MOM				-0.097
				[-1.15]
Adj-R^2	24.3%	47.6%	50.0%	50.7%

Panel B: Out-of-Sample Analysis				
	[1]	[2]	[3]	[4]
Alpha	0.016***	0.013***	0.008**	0.010**
	[2.68]	[3.58]	[2.08]	[2.43]
RMRF	-0.494**	-0.424***	-0.340**	-0.390***
	[-2.51]	[-3.51]	[-2.54]	[-2.64]
SMB		-0.023	0.022	-0.006
		[-0.20]	[0.15]	[-0.05]
HML		0.522***	0.300***	0.177*
		[5.39]	[2.71]	[1.79]
RMW			0.183	0.224**
			[1.44]	[2.09]
CMA			0.338**	0.436***
			[2.32]	[2.72]
MOM				-0.179**
				[-1.96]
Adj-R^2	34.3%	56.0%	58.2%	62.0%

Table VI. Explaining Individual Investors' Expectations

This table reports regressions of individual investors' expectations on smoothed overnight and intraday returns. The dependent variable in all columns is individual investors' expectations of future market returns (following Greenwood and Shleifer, 2014). The main independent variables are the smoothed intraday market returns and smoothed overnight market returns measured in the previous quarter. $EWMA_{overnight}$ and $EWMA_{intraday}$ are standardized to have a mean of zero and standard deviation of one. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997Q3 to 2019Q4 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Explaining Individual Investors' Expectations			
	[1]	[2]	[3]
$EWMA_{intraday}$	0.471***		0.471***
	[3.41]		[3.52]
$EWMA_{overnight}$		0.065	0.059
		[0.38]	[0.52]
Adj-R^2	20.8%	-1.3%	19.8%

Table VII. Consumption Growth and Market Returns

This table reports the lead-lag relations between quarterly consumption growth rates and overnight and intraday market returns. In Panel A, the dependent variable is the consumption growth rate measured in quarters t-2 to t+2. The main independent variables are the overnight and intraday components of the excess market return in quarter t. In Panels B and C, the dependent variables are the overnight and intraday components of the excess market return measured in quarters t-2 to t+2, respectively, and the main independent variable is the consumption growth rate in quarter t. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1993Q3 to 2019Q4.

Panel A: Consumption Growth					
	t-2	t-1	t	t+1	t+2
$RMRF_{intraday}$	-0.031%	-0.041%	0.045%	0.041%	0.039%
	[-0.64]	[-0.84]	[0.91]	[0.70]	[0.81]
$RMRF_{overnight}$	0.133%***	0.180%***	0.183%***	0.154%**	0.132%**
	[2.55]	[2.80]	[2.55]	[2.35]	[1.93]
Adj-R^2	7.2%	14.9%	15.6%	10.6%	7.4%

Panel B: Intraday RMRF					
	t-2	t-1	t	t+1	t+2
$Cons.Growth$	0.357%	0.822%	0.710%	-0.760%	-0.387%
	[0.55]	[1.14]	[1.02]	[-0.86]	[-0.58]
Adj-R^2	-0.7%	0.7%	0.2%	0.4%	-0.6%

Panel C: Overnight RMRF					
	t-2	t-1	t	t+1	t+2
$Cons.Growth$	1.327%***	1.491%***	1.799%***	1.855%***	1.235%***
	[2.84]	[3.53]	[3.94]	[4.88]	[2.61]
Adj-R^2	8.0%	10.4%	15.6%	16.6%	4.6%

Table VIII. Horse Races Forecasting Excess Market Returns

This table reports regressions forecasting the excess market returns and its intraday and overnight components. $EWMA_{overnight}$ and $EWMA_{intraday}$ are the exponential weighted moving average of past overnight RMRF and past intraday RMRF respectively with a half-life of roughly 7 years. Individual Investor Expectations are obtained from the Gallop survey. Cons. Growth is quarterly consumption growth, and Intermediary RT is a measure accumulating the intermediary risk tolerance shocks of Adrian et al. (2014). The dependent variable in Panel A is the next-quarter close-to-close excess market return; the dependent variable in Panel B is the next-quarter intraday excess market return, and in Panel C it is the overnight excess market return. All independent variables are standardized to have a mean of zero and standard deviation of one. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997Q3 to 2019Q4 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Panel A: Forecasting Excess Market Returns						
	[1]	[2]	[3]	[4]	[5]	[6]
$EWMA_{overnight}$	-0.032***		-0.038***			-0.038**
	[-5.53]		[-5.30]			[-5.02]
$EWMA_{intraday}$	0.006		0.008			0.002
	[0.74]		[0.75]			[0.34]
$Indiv. Inv. Exp.$		0.003	0.001			
		[0.28]	[0.12]			
$Cons.\ Growth$				0.008		0.017
				[0.64]		[1.42]
$Intermediary\ RT$					-0.021***	-0.009
					[-2.82]	[-1.11]
Adj-R^2	14.1%	-1.2%	13.1%	-0.3%	5.4%	15.5%

Panel B: Forecasting Intraday Excess Market Returns						
	[1]	[2]	[3]	[4]	[5]	[6]
$EWMA_{overnight}$	-0.022***		-0.024***			-0.021***
	[-5.67]		[-5.21]			[-3.70]
$EWMA_{intraday}$	-0.013**		-0.019***			-0.014**
	[-2.34]		[-3.09]			[-2.55]
$Indiv. Inv. Exp.$		-0.010	-0.002			
		[-1.12]	[-0.17]			
$Cons.\ Growth$				-0.010		0.002
				[-1.1]		[0.21]
$Intermediary\ RT$					-0.017***	-0.003
					[-2.64]	[-0.45]
Adj-R^2	12.9%	0.7%	15.9%	1.4%	5.5%	11.1%

Panel C: Forecasting Overnight Excess Market Returns						
	[1]	[2]	[3]	[4]	[5]	[7]
$EWMA_{overnight}$	-0.009*		-0.013**			-0.009*
	[-1.65]		[-2.42]			[-1.97]
$EWMA_{intraday}$	0.020***		0.027***			0.012**
	[3.96]		[4.23]			[2.22]
$Indiv. Inv. Exp.$		0.014***	0.004			
		[2.85]	[0.79]			
$Cons.\ Growth$				0.019***		0.016***
				[4.88]		[3.53]
$Intermediary\ RT$					-0.004	-0.005
					[-0.64]	[-1.13]
Adj-R^2	22.2%	7.3%	33.0%	16.5%	-0.4%	28.9%

Table IX. Cash-Flow and Discount-Rate News

This table reports a vector autoregression (VAR) and the associated Campbell (1991) decomposition of market returns into cash flow and discount rate news, with the latter being further decomposed in to intraday and overnight components. $r_{intraday}$ and $r_{overnight}$ are, respectively, the quarterly intraday and overnight market returns. $EWMA_{intraday}$ and $EWMA_{overnight}$ are the exponentially weighted moving average of past $r_{intraday}$, and $r_{overnight}$, respectively, with a half-life of roughly 7 years. Panel A reports the VAR estimates, and Panel B shows the standard deviations and correlations of the various return components. Newey-West standard errors with 12 lags are reported below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997Q3 to 2019Q4 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Panel A: VAR Analysis

	$r_{intraday}$	$r_{overnight}$	$EWMA_{intraday}$	$EWMA_{overnight}$
	[1]	[2]	[3]	[4]
constant	0.120***	0.055**	0.096***	0.040**
	[3.46]	[2.38]	[3.38]	[2.02]
$r_{intraday}$	-0.147	0.056	-0.121	0.044
	[-1.38]	[0.79]	[-1.38]	[0.73]
$r_{overnight}$	-0.138	0.055	-0.107	0.053
	[-0.85]	[0.50]	[-0.81]	[0.58]
$EWMA_{intraday}$	-0.052	0.126***	0.933***	0.106***
	[-0.99]	[3.56]	[21.69]	[3.55]
$EWMA_{overnight}$	-0.226***	-0.073*	-0.179***	0.931***
	[-3.52]	[-1.70]	[-3.41]	[25.57]
Adj-R^2	13.2%	21.3%	87.6%	89.6%

Panel B: Cash Flow vs. Discount Rate News

News Std. Dev./Corr.	N_{cf}	$-N_{DR\_Intraday}$	$-N_{DR\_Overnight}$
N_{cf}	1.347%	0.542	-0.696
$-N_{DR\_Intraday}$	0.542	5.625%	0.177
$-N_{DR\_Overnight}$	-0.696	0.177	3.714%