# The Day Destroys the Night, Night Extends the Day:

## A Clientele Perspective on Equity Premium Variation

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**Abstract**

We provide a powerful new predictor of the equity premium by showing that smoothed overnight market returns strongly negatively forecast subsequent close-to-close quarterly market returns ($R^2$=16%). While our signal also negatively forecasts intraday market returns, we find that lagged smoothed intraday returns positively forecast the overnight component. Since both aspects of past market returns drive the price-to-earnings ratio ($PE$), this partially-offsetting effect explains $PE$'s relatively poor forecasting ability ($R^2$=2%). We interpret these patterns through a clientele perspective: Individual investor expectations and consumption growth strongly positively forecast overnight returns, while intermediary risk tolerance strongly negatively forecasts intraday returns.

*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.

In particular, we isolate the low frequency component of past overnight and intraday returns using an exponentially weighted moving average. Our main analysis then uses these smoothed variables to forecast subsequent close-to-close returns, revealing much stronger mean reversion in the equity premium. Take, for example, the classic measure of the conditional equity premium, the cyclically-adjusted price-earnings ratio ($PE$) of Campbell and Shiller (1988a). In our sample, $PE$'s relation to subsequent close-to-close quarterly returns is weak at best ($R^2$

of just 2%). However, isolating the variation in $PE$ due to smoothed past overnight returns provides roughly seven times the forecasting ability ($R^2$ of 16%). Smoothed past intraday returns, on the other hand, positively forecast future market returns, albeit insignificantly.

We then decompose the dependent variable – the close-to-close market return – in these forecasting regressions to better understand the drivers of the variation in the equity premium. We first find that mean reversion in stock prices linked to $PE$ occurs primarily intraday. Indeed, it is a much stronger phenomenon in the intraday period, as $PE$ is positively correlated with subsequent overnight returns. This positive relation partially offsets the intraday mean reversion in intraday returns that we document and thus explains the weak link between $PE$ and subsequent close-to-close returns that other researchers have documented (e.g., Goyal and Welch (2008) and Goyal, Welch, and Zafirov (forthcoming)). These initial results suggest (which we support with a bevy of additional subsequent tests) that the overnight clientele aligns with the mean *aversion* (extrapolation) component that pushes prices away from fundamentals (because of changes in either risk tolerance or sentiment) while the intraday clientele aligns with the mean reversion component.

When we forecast these two market return components with smoothed overnight and intraday returns, we find striking results. The stock market exhibits intraday mean 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 -3.96 and an $R^2$ of roughly 8% while the coefficient on the latter is economically small and statistically insignificant.

In contrast, $PE$'s positive relation with subsequent overnight returns reflects a 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 former remains negative and statistically significant while the coefficient on the latter is positive with a $t$-statistic of 3.39. The resulting $R^2$ is 15%.

Our ability to forecast the close-to-close market return is not only statistically and economically significant but also is robust to an extensive battery of horse races against other well-known predictors, as well as a careful sub-sample and out-of-sample analysis. Indeed, a simple out-of-sample strategy that times the market based on the smoothed overnight return produces a CAPM alpha of 2.0% per quarter with an associated $t$-statistic of 2.56. Including the five non-market factors of Fama and French (2015) and Carhart (1997) results in an alpha of 1.8% per quarter with a $t$-statistic of 2.76.

Interpreting this predictability from a clientele perspective naturally leads to the question of the ways in which overnight and intraday clienteles differ. Previous research by Lou, Polk, and Skouras (LPS 2019) argues that the overnight clientele is driven by the decisions of households while the intraday clientele is driven by the decisions of institutions. For example, they show that institutional ownership increases much more with intraday rather than overnight returns. LPS find these patterns not only in the 13F data but also in the high-frequency daily institutional flows of Campbell, Ramadorai, and Schwartz (2009).

We build off of their evidence in three ways. First, we analyze how subjective expectations in particular, and macro-finance data more broadly, differentially forecast these two components of returns. Second, 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. Finally, we examine the Tech boom/bust, the Global Financial Crisis (GFC), and the Covid crash/rebound through our clientele lens.

Our analysis of Greenwood and Shleifer's (2014) investor expectations reveals a novel fact. We find that individual investor expectations *positively* forecast subsequent overnight market returns ($t$-statistic of 2.63) but have no information about future intraday returns. Thus, our results help flesh out, at least partially, why Greenwood and Shleifer (2014) find that individual investor expectations are strongly negatively correlated with statistical-model-based expected close-to-close returns.

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 limited 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 2.66. In contrast, consumption growth has a negative and insignificant relation to subsequent intraday returns. Thus, our decomposition sheds light on this classic macro-finance variable.

In a similar fashion, we construct an intermediary risk tolerance measure that accumulates the shocks to the intermediary risk capacity measure introduced in Adrian et al. (2014) and find that the level of intermediary risk tolerance has an insignificant relation with subsequent overnight returns but strongly negatively forecasts intraday market returns. This finding adds nuance to the result in Haddad and Muir (2021) that return predictability is more linked to the financial health of intermediaries in asset classes where households are less active. We show that there is also a strong link in the equity market, as long as one examines the part of the day where intermediaries are more active.

In sum, the return predictability results based on individual investor expectations, as well as those results based on the macro-finance variables we study, 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 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.

Finally, we zoom in on three bubble/crisis episodes in the last three decades. We show that the Tech boom of the late 1990s and the Covid crash and rebound of 2020 were primarily overnight phenomena, consistent with the widespread view that individual investors were largely responsible for these events. 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 also 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.

In summary, all of the ways we 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 LPS, 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 summarizes related 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 a battery of tests confirming the out-of-sample strength of that predictability. Section 7 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.[1] 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; there is, in fact, evidence of own-component reversal. More interestingly, the aggregate cross component lead-lag effect is asymmetric: Smoothed past overnight returns negatively forecast intraday returns, while smoothed past intraday returns positively forecast overnight returns. 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. We provide an intuitive and easy-to-implement method to gauge the relative strength of retail vs. institutional trading, drawing on the notion that retail investors, relatively speaking, prefer to trade near the mar-

[1]For related studies at the firm level, see also Hendershott et al. (2020); Bogousslavsky (2021).

ket open while institutions prefer to trade near the market close. Our novel approach further allows us to study the characteristics and impact of retail vs. institutional trading.

Our paper is broadly related to the vast literature on forecasting the equity premium. Starting in the late 1980s, several papers document that aggregate stock returns are predictable using past returns (Fama and French (1988a), Poterba and Summers (1988)) or valuation ratios (Campbell and Shiller (1988a, 1988b), Fama and French (1988b), Kothari and Shanken (1997)). At the same time, authors raise concerns about econometric issues and poor out-of-sample performance. In terms of the former, Nelson and Kim (1993) and Stambaugh (1999) highlight that forecasting coefficients are biased if both the predictor in question is persistent and innovations in the predictor variable are correlated with returns. In terms of the latter, Goyal and Welch (2008) argue that historical average returns outperform out-of-sample forecasts based on the above predictor variables and conclude "the profession has yet to find some variable that has meaningful and robust empirical equity premium forecasting power, both [in-sample] and [out-of-sample]." Our work speaks directly to this literature by isolating the component of past returns and valuation ratios that better forecasts subsequent returns. By doing so, we not only significantly improve both in-sample and out-of-sample predictability, we also significantly reduce the problematic correlation that drives the coefficient bias noted above.

Since that early work exploiting the information in past returns and valuation ratios about time-variation in the equity premium, there have been many other types of predictor variables suggested in the literature (see Campbell (2018) for a textbook overview of this line of work). Recent research by Goyal, Welch and Zafirov (forthcoming) again questions whether any variable, either from the new generation of predictors or from the classic set of signals, usefully forecasts the equity premium.[2] We apply the key aspects of their demanding methodology for evaluating predictors and find that our predictor passes the high hurdles they propose. Indeed, our predictor, despite its simplicity, appears to be the strongest predictor of the equity

[2]Goyal, Welch, and Zafirov (forthcoming) conclude that "we are not confident that we can assess what variables would help us today to predict the equity premium forward-looking."

premium on record. Moreover, our key variable – smoothed past overnight market returns – remains statistically and economically significant in forecasting future close-to-close market returns even after controlling for the small set of variables that Goyal, Welch, and Zafirov (forthcoming) find have some predictive ability. We emphasize that our variable is a natural one to consider as it is a component of past returns, and any mean reversion in stock prices must be traceable back to a reversal with respect to some component of past returns.

Our work also builds on ideas in Haddad and Muir (2021). They highlight the natural difficulty in determining whether a subset of investors matters for aggregate asset prices. In their case, they are interested in whether the health of the financial sector, in particular, the amount of intermediary risk-bearing capacity, drives variation in risk premia. Haddad and Muir (2021) point out that, on the one hand, poor financial health of intermediaries such as hedge funds may cause risk premia to be high. On the other hand, they also acknowledge that the poor financial health of such institutions may simply reflect the fact that economy-wide risk aversion is high. To deal with this issue, Haddad and Muir (2021) compare variation in risk premia across more and less intermediated asset classes. In a similar spirit, we compare variation in risk premia across more and less intermediated times of the day.

The organization of our paper is as follows. Section 2 describes the data and empirical methodology. Section 3 presents our main results on time-series variation in the equity premium. Section 4 provides a battery of tests confirming the out-of-sample strength of that predictability. Section 5 presents evidence supporting our interpretation of the findings. Section 6 concludes.

# 3 Data and Methodology

Our core US sample spans the period 1993 to 2023, constrained by the availability of the TAQ data, which start in 1993. We take the SPDR S&P 500 Trust ETF, one of the most liquid financial instruments, as a proxy for the market index, as it allows for relatively easy calculation of a reliable open price.

## 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.[3] We rely on VWAP to ensure that our open prices are valid trade prices.

Following LPS, 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 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.[4] 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] We have 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 S&P 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).

[4] LPS provide evidence in the cross-section of firm-level returns that confirms the reasonableness of this assumption.

## 3.2 Smoothed Overnight and Intraday Returns

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., trading soon after the market opens), variation in the relative magnitudes of overnight and intraday returns provides useful insights into a clientele's collective behavior and its link to subsequent market performance.

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

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

We confirm that our results are robust to a reasonable range of smoothing parameters. For our primary analysis, we set $\lambda$ equal to $\frac{1}{120+1}$ which implies a center of mass of ten years and a half-life for the resulting weights of approximately seven years.[5] We also report results confirming that our main findings are robust to using other values, namely, $\frac{1}{100+1}$ and $\frac{1}{140+1}$.

## 3.3 Other Data

Following Lettau and Ludvigson (2019), we measure quarterly consumption growth ($cg$) using the change in log per-capita personal 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 future information. We also create a smoothed earnings variable, $EWMA_{EarnGrth,t-1}$, in a similar way as the smoothed returns defined in equation (1). To create intermediary risk tolerance ($IRT$), we take the intermediary

[5]We initialize the EWMA of each of these variables to zero at the beginning of the sample.

factor from Adrian et al. (2014) and accumulate the resulting factor shock to create a level variable. We measure individual investor expectations ($IIE$) using the American Association of Individual Investors. We choose this specific variable among the various measures of investor expectations studied in Greenwood and Shleifer (2014) because it has the longest history.

We download factor returns and risk-free rate data from Ken French's website. We follow Goyal, Welch, and Zafirov (forthcoming) in replicating key variables from the equity premium forecasting literature, listed in Section 4.3. Note that our main analysis forecasts quarterly market returns (and the associated intraday and overnight components) over the 1997Q1-2023Q4 period. However, some of the above variables are not yet available as of the third quarter of 2023. As a consequence, in Tables II, III, IV, and VIII, our sample only covers 1997Q1-2023Q2.

### 3.4 Summary Statistics

Table I reports summary statistics of our main variables, with two key takeaways. First, as shown in Panel A of Table I, the average quarterly overnight return is 1.83% while the average quarterly intraday return is 0.25%. This finding is consistent with a literature that finds that much of the equity premium is earned overnight.[6]

Another key takeaway, as shown in Panel B of Table I, is that the two smoothed past return components – smoothed overnight and intraday returns – are effectively uncorrelated with each other. Given the long-horizon reversal present in aggregate stock returns (Fama and French, 1988a), this fact immediately raises the question of whether the two components of past returns differentially forecast time variation in the equity premium.

Table I, Panel A, also confirms that the intraday component of returns is more volatile than their overnight counterpart. This finding echos the fact that researchers since at least

[6]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), and Branch and Ma (2012). LPS note that this effect is concentrated in large stocks.

Fama (1965) have shown that volatility is higher during trading hours than non-trading hours.[7] Figure 1 plots our two smoothed return components against $PE$.[8]

# 4 Main Empirical Results

A popular view in finance is that household risk tolerance / sentiment drives variation in the equity premium. Typically, researchers have identified this time-variation in the equity premium using scaled price ratios, like $PE$, which measure low-frequency movements away from fundamentals (Campbell and Shiller, 1988b). Of course, variation in PE is driven by variation in cumulative overnight returns, cumulative intraday returns, and cumulative earnings growth. Though reasonable arguments can be made that $PE$ is stationary, these three components are not. As a consequence, in our analysis, we use smoothed versions of these three components of $PE$ to guarantee stationarity. We will show that these three smoothed variables differentially forecast subsequent market returns (and return components).

Table II 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 Treasury bill return to the intraday and overnight periods based on their 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.

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

[8] Smoothed past overnight returns and smoothed past intraday returns explain a significant portion (72%) of the variation in $PE$.

## 4.1 Strong predictability of the standard equity premium (close-to-close returns)

Column (1) of Table II Panel A documents that $PE$ has a tenuous relation with subsequent close-to-close returns, at least in our sample, with a $t$-statistic of only -1.82 and an $R^2$ of just 2.3%. Despite this lack of close-to-close return predictability, the rest of the table shows that examining $PE$'s components reveals novel 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 past smoothed overnight returns is surprisingly strong, both statistically and economically speaking, which is the first key finding of the paper.[9] Statistically, the $t$-statistic is -5.41, almost three times the $t$-statistic on $PE$. The $R^2$, at 15.7%, is nearly seven times as large.

In all of the regressions in Table II, the right-hand side variables are normalized for the ease of interpretation. Therefore, a one-standard-deviation move in smoothed overnight returns forecasts an economically significant change in the quarterly equity premium of 3.38%. The third column in the table shows the results when we further include $EWMA_{EarnGrth}$. The ability of past smoothed overnight returns to forecast future market returns remains strong. In Columns 4 and 5, we show that our forecasting results are robust to different smoothing parameters for the EWMA of past returns.

[9] Our decomposition not only reveals striking differences in equity premium dynamics across these two parts of the day, it does so in a context where classic econometric issues associated with forecasting market returns are of limited concern. 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 II, and we have confirmed that $p$-values do not change significantly if we apply the correction of Polk, Thompson and Vuolteenaho (2006).

## 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 II, we forecast intraday excess market returns. As can be seen in the first column, $PE$ has a strong negative relation with subsequent intraday 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 identified by $PE$ in column (1) of this panel, and column (2) confirms that view. Thus, the second key result of the paper is that the mean reversion in close-to-close returns that is linked to $PE$ in general and to past overnight returns in particular, occurs primarily intraday. As in Panel A, column (3) shows that adding smoothed earnings growth does not change the result qualitatively. Columns (4) and (5) confirm that this result is robust to different smoothing parameters in the construction of $EWMA$.

Panel C of Table II 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, albeit statistically insignificant. Thus, part of the reason that $PE$ does a poor job predicting mean reversion in close-to-close market returns is because of 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.

Indeed, our predictability results imply that past smoothed intraday returns primarily reflect aggregate cash-flow news, as this variable has little information about subsequent 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 5. Again, our results are robust to controlling for smoothed earning growth and to different smoothing parameters in our construction of the $EMWA$.

## 4.3 Horse Races with other Market Return Predictors

We further control for a host of macro/aggregate variables that are known to forecast stock market returns in Table III. We compile this list based on those variables that Goyal, Welch, and Zafirov (forthcoming), in their reexamination of their well-known 2008 analysis (Goyal and Welch, 2008), argue are relatively robust in the ability to forecast aggregate returns. The list includes the aggregate investment rate (Cochrane, 1991), the Treasury bill yield (Campbell 1987), aggregate equity issuance (Baker and Wurgler, 2000), aggregate accruals (Hirshleifer, Hou, and Teoh, 2009), fourth-quarter consumption growth (Møller and Rangvid, 2015), and aggregate short interest (Rapach, Ringgenberg, and Zhou, 2016). We augment their list with three recent signals, $SVIX$ (Martin, 2017), the Gold-to-Platinum Price Ratio (Huang and Kilic, 2019), and the aggregate analyst long-term growth forecast (Bordalo et. al., forthcoming), that have recently been shown to be promising predictors of the equity premium.[10]

The left-hand side of Panel A of Table III measures the forecasting ability of each of the above variables in isolation. For our sample, only accruals, fourth-quarter consumption growth, and the aggregate long-term analyst growth forecast are able to predict returns at conventional levels of statistical significance. The $t$-statistics for these three variables are 2.35, -2.55, and -2.84 respectively.

As can be seen from the right-hand side of Panel A of Table III, in one-to-one horse races, $EWMA_{overnight}$ retains its economic and statistical significance in forecasting future market returns; the coefficients on $EWMA_{overnight}$ are similar to those reported in Table II and $t$-statistics always remain over 4.0. Out of the nine variables listed above, only $SVIX$ is statistically significant in these horse races.

Panel B of the same table reports results from a multiple regression that includes all of the above forecasting variables. Only two of them (our smoothed overnight return variable and Martin's (2017) SVIX measure) come out statistically and economically significant in

[10]We have also confirmed that smoothed overnight returns subsume the information in the default yield (Fama and French, 1989), the term spread (Fama and French, 1989), cay (Lettau and Ludvigson, 2001), the small-stock value spread (Campbell and Vuolteenaho, 2004), and market volatility (Campbell et. al., 2018).

forecasting close-to-close market returns. As shown in the panel, a one-standard-deviation increase in $EWMA_{over}$ forecasts a lower close-to-close quarterly market return of -4.5% ($t$-statistic = -4.15); a one-standard-deviation increase in $SVIX$ forecasts a higher quarterly market return of 2.6% ($t$-statistic = 2.46).

### 4.4 Forecasting Dividend Growth and Market Volatility

As a natural extension, in Table IV, we further examine the relations between smoothed overnight/intraday market returns and future aggregate dividend growth and market volatility, in the context of the key variables ($PE$, $DEF$, $RVAR$) used in the volatility-forecasting model of Campbell et al. (2018). As can be seen in Columns 1 and 2, neither smoothed overnight returns nor smoothed intraday returns help forecast future dividend growth. Columns 3 and 4 show a positive relation between lagged smoothed overnight market returns and future market volatility. This finding is consistent with the idea that potentially destabilizing trades by the overnight clientele may lead to an increase in market volatility.

## 5 In-Sample Robustness, Out-of-Sample Predictability

The in-sample evidence that smoothed overnight market returns forecast the equity premium is unusually strong compared to other predictors in the literature. In this section, we reinforce this evidence with standard out-of-sample statistical and economic (trading strategy) metrics. We adopt several of the metrics proposed by Goyal and Welch (2008) and Goyal, Welch and Zafirov (forthcoming) because they have shown that these metrics collectively provide a high hurdle that few, if any, equity premium predictors can clear. In sharp contrast to their conclusion that almost all equity premium prediction is weak and unstable out-of-sample, our predictor performs well out-of-sample, and its performance is stable across sub-samples.

In Table V, we show that the adjusted $R^2$ of a simple regression of the quarterly CRSP excess market return on smoothed overnight returns is stable and high (around 13%) across both our entire sample (1997Q1 to 2023Q4) and each of the two equal sub-samples. We also report the out-of-sample $R^2$ (OOS $R^2$) from an expanding-window regression, closely following the implementation of Welch and Goyal (2008). This OOS $R^2$ is also high (around 16%). The boostrapped p-value of McCracken's (2007) out-of-sample MSE-F statistic as implemented by Goyal, Welch and Zafirov (forthcoming) is only 0.002, confirming that our variable's out-of-sample performance is statistically significant. The consistency of the $R^2$ estimates across all the sub-samples we have considered, as well as the strong Newey-West $t$-statistics across all in-sample analyses confirm that the performance of our signal is stable.

Figure 2 shows the robustness of that out-of-sample performance throughout the sample. Following Goyal and Welch (2008), the figure compares the squared error of forecasts based on our predictor against the squared error of a "historical mean" forecast (the out-of-sample forecast from an expanding window OLS regression on a constant). We compare three types of forecasts: in-sample, out-of-sample (the forecasts evaluated in Table V, respectively in columns 1 and 4), and out-of-sample forecasts constrained to be non-negative (i.e., winsorized at zero), as proposed by Campbell and Thompson (2008).

The out-of-sample outperformance of our predictor closely tracks its in-sample outperformance and is reasonably stable throughout the sample, providing statistically significant outperformance, based on a confidence interval implemented as in Goyal and Welch (2008), on almost all dates after 2004 and always after 2010.[11] It is interesting that outperformance is especially strong *before*, during, and after the COVID recession and *before* the dot-com recession. It is also worth noting that the constrained forecasts are inferior to the unconstrained forecasts, suggesting that our predictor may be able to forecast negative market returns.

In Table VI, we consider the economic significance of equity premium predictability linked to our variables by evaluating the performance of predictor-driven trading strategies as studied in Goyal, Welch and Zafirov (2024). Their "z-score-scaled" strategy takes positions given by

[11] Strictly, this confidence interval is not appropriate because it requires that the models from which the forecasts are obtained are non-nested. However, Goyal, Welch and Zafirov (forthcoming) report that this approach to confidence intervals "corresponds well" to more appropriate bootstap estimates which are avoided because they are highly computationally burdensome as they require a separate bootstrap at each date.

the current value of the smoothed overnight return minus its expanding window historical median, divided by a similarly constructed standard deviation, and then signed according to its historical median.[12] The quadratic utility strategy of Campbell and Thompson (2008) (also studied by Goyal, Welch and Zafirov, 2024) takes positions given by the out-of-sample forecast analyzed in Table V and Figure 2, divided by the five-year rolling window historical variance of excess market returns, with positions scaled by the coefficient of risk aversion. We follow Goyal and Welch's (2008) implementation of Campbell and Thompson (2008) and use a risk-aversion coefficient of 3.[13] Finally, we also consider a quadratic utility strategy which uses forecasts for the volatility of returns in addition to forecasts for the mean, again based on our smoothed overnight return signal and using an identical expanding window methodology.

We consider two benchmark "unconditional" (i.e., assuming no predictability) strategies analyzed by Goyal, Welch and Zafirov (forthcoming) – the classic buy-and-hold strategy and a quadratic utility investment strategy based on the historical mean forecast analyzed also in Figure 2. We find that the mean return and Sharpe Ratio are all large and statistically significant for all predictor-driven trading strategies. Annualized means are in the 8-20% range (easily beating benchmarks delivering 3-7% annually), and Sharpe Ratios in the 0.5-0.7 range (benchmarks at 0.1-0.4). The performance of the strategy that also uses a volatility forecast based on our signal is especially strong, which confirms the in-sample statistical evidence of Table IV in the context of an out-of-sample trading strategy. In results not reported, we have examined the certainty equivalent of this strategy, finding it to be statistically significant.

It is worth noting that the quadratic utility predictor-driven strategies are significantly long-biased (long in 75 of the 96 quarters, with a mean position close to $1), but do predict a significant number of negative quarterly excess returns. The z-score-scaled strategy is by design more balanced in its positions. All predictor-driven strategies have a low turnover of

[12]Goyal, Welch and Zafirov (forthcoming) also consider unscaled and long-equity tilted versions of this strategy. In our analyses, such strategies do not provide additional insight, so have been omitted for brevity.

[13]Note that Campbell and Thompson (2008) apply winsorization to their strategy to force positions in the range $[0,1.5] It is not obvious why such constraints would be appropriate for investments based on a clientele-motivated predictor so we do not impose this winsorization (see also our discussion of Figure 2).

24-52% per quarter, implying high break-even transaction costs of 5-13%.

In Table VII, we consider whether the performance of the three predictor-driven trading strategies analyzed in Table VI can be explained by exposures to benchmark strategies. All strategies have large and statistically significant quarterly alphas with respect to the three sets of factors/benchmarks considered (in the range of 1.8% to 4.6%). Unsurprisingly, the z-score scaled strategy has no exposure to the market (since it is not long-biased), while the quadratic utility strategies do. Interestingly, both the z-score-scaled strategy and the quadratic utility strategy, where we forecast both the mean and the volatility, have exposure to the CMA investment factor, in line with our interpretation that the smoothed overnight return captures aggregate mean reversion.[14]

# 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 least relatively speaking, at the market open and others, at the market close. It is well-known that with the rise of institutional investors, trading volume associated with institutional investors has migrated to the end of the trading day. Indeed, LPS provide evidence showing that relatively less institutional trading occurs at the open and that firm-level institutional ownership is increasing in the intraday-overnight return. In this section, we build off of those findings to conduct additional analyses that shed more light on investor heterogeneity across the intraday and overnight periods. Thus, just as Haddad and Muir (2021) exploit the fact that intermediaries are more active in some markets than other, we exploit the fact that intermediaries are more active at certain times of the day than others. In particular, we offer three broad pieces of evidence.

We first examine three key macro-finance variables that are the focus of many prior studies and are also interesting in our context. In particular, we study two variables linked to

[14] The positive loading on CMA but not HML is consistent with Fama and French's (2015) finding that CMA, in conjunction with their profitability factor, subsumes HML in explaining the cross section of average returns.

households – individual investor expectations (Greenwood and Shleifer 2014) and consumption growth – and a third variable linked to institutions, intermediary risk tolerance (Haddad and Muir 2021). We study whether these three variables capture either continuation or reversal aspects of time-series variation in aggregate expected returns. We also examine the extent to which these variables differentially forecast the intraday and overnight components of market returns.

Second, we estimate a VAR-based return decomposition, based on an extension of the methodology of Campbell (1991). Our extension 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.

Third, 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 flush with cash and making aggressive investments in the equity market. Ortmann, Pelster, and Wengerek (2020) document that retail trading surged during the pandemic while Zheng, Li, Huang, and Chen (2022) show that the household equity share rose significantly as well. Indeed, Greenwood, Laarits, and Wurgler (2022) show that stimulus payments increased trading and prices of stocks popular with retail investors.[15] The Covid sub-period thus provides a unique opportunity to confirm when households are relatively more likely to trade – either overnight (including the market open) or intraday (up to the close of the trading day).

## 6.1 Macro-finance Variables

Greenwood and Shleifer (2014) show that individual investor expectations are consistent with extrapolation as they are positively correlated with past realized returns yet negatively cor-

[15]Thatte, Jalagani, and Chanda (2021) argue that up to 15% of the $814 billion of stimulus payments during the pandemic was invested in the stock market.

related with model-based expectations of future stock returns. Consistent with their findings and our interpretation of our results, we show that though those expectations are uninformative about future close-to-close returns in our sample, they positively forecast future overnight returns.

Consumption growth is an asset-pricing variable that is only weakly linked to close-to-close market returns. Campbell (2018) discusses not only the weak correlation between returns and consumption growth but also the broader empirical challenges of consumption-based asset pricing. We find that consumption growth positively forecasts the overnight component of returns.

Our final micro-finance variable measures intermediary risk tolerance. 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 at each point in time. We show that our level version of that variable negatively forecasts intraday market returns.

Before discussing the results, we first note that our sample includes the remarkable period of the Covid pandemic where the S&P 500 surged more than 40% in the second through fourth quarters of 2020, after the Federal Reserve and Congress took extraordinary measures to support financial markets and the economy. To ensure that our results are not driven by that extreme movement, we add a dummy variable capturing those three quarters. Note that we will directly examine the patterns in overnight and intraday returns during 2020, later in this section.

For the sake of comparison, in all panels of Table VIII, we repeat in column (1) the analysis in column (2) of Table III. We then study each of these macro-finance variables, first in isolation, then in conjunction with smoothed past overnight and intraday returns, and finally all-together in a single specification.

In Panel A, we examine predictability of close-to-close returns. Consistent with Greenwood and Shleifer (2014), column (2) of Table VIII Panel A confirms that there is no positive relation between individual investor expectations and subsequent close-to-close returns, either in isolation or, as reported in column (3), in conjunction with the two smoothed components of past market returns. Though consumption growth does not forecast subsequent close-to-close returns by itself (column (4)), controlling for our two smoothed variables reveals that consumption growth positively forecasts subsequent market returns (column (5)). That predictability continues to hold when the other variables are added to the regression in column (8). Columns (6) and (7) document that $IRT$ is not informative about close-to-close returns.

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 now $IRT$ tracks a strong intraday mean reversion. Moreover, neither $EWMA_{Overnight}$ or $EWMA_{Intraday}$ subsume that variable's ability to forecast intraday returns. Indeed, now $EWMA_{Intraday}$ also picks up some of the mean reversion that occurs intraday. We continue to find only mean reversion intraday, when institutions are relatively more likely to trade. Neither consumption growth nor individual investor expectations are statistically significant at the 5% level.

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, with a $t$-statistic of 2.63. Moreover, this predictive power is not subsumed by $EWMA_{Overnight}$ and $EWMA_{Intraday}$ in column (3). 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 and when they take them (namely, trading the market in a way consistent with their expectations and doing so relatively more at the open than at the close).

Column (4) shows that consumption growth strongly forecasts subsequent overnight returns, with a $t$-statistic of 2.66. That predictability is not subsumed by our two smoothed components of returns and continues to remain statistically significant in the full specification of column (8). In that regression, where all of our key variables (smoothed overnight and intraday market returns, individual investor expectations, consumption growth, and intermediary risk tolerance) are included in the regression, the coefficients on past smoothed intraday returns and consumption growth remain positive and statistically significant. We also continue to find that past smoothed overnight returns negatively forecasts subsequent overnight returns.

In sum, the return predictability results of our three macro-finance variables are consistent with the interpretation 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). In stark contrast, intraday returns (and the corresponding clientele) are where mean reversion primarily occurs (intermediary risk tolerance negatively forecasts intraday market returns).

## 6.2 Decomposing Discount-rate News

We next conduct a return decomposition exercise, extending 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 market return in excess of (6.5/24) * log risk-free rate, and $r^{Overnight}$, the log intraday market return in excess of (17.5/24) * log risk-free rate. The VAR is:

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

Since $r_{t+1} = r_{t+1}^{Intraday} + r_{t+1}^{Overnight}$, these two variables sum 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 entire close-to-close period into components related to news about expected future intraday and overnight returns.[16]

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

where $\mathbf{e}_1 = [1,0,0,0]$ and $\mathbf{e}_2 = [0,1,0,0]$. As in Campbell (1991), we measure cash-flow news as the residual.

Table IX Panel A reports estimates of the transition matrix $\mathbf{\Gamma}$. The findings are broadly consistent with the results of Table II which uses simple returns. Table IX Panel B shows that cash-flow news has the smallest volatility (2.4%) of the three components (the two discount-rate news terms have volatility that is roughly twice as large). Moreover, in comparison to a baseline VAR (unreported) which simply uses $PE$ to forecast close-to-close returns, there is much more discount rate news in total. The two components of discount-rate news are only weakly contemporaneously correlated (0.11). Figure 3 provides a graphical view of the forecasts from the VAR; together they imply significantly more variation in the close-to-close equity premium than a baseline VAR with simply close-to-close returns and the $PE$ ratio.[17]

Perhaps most interestingly, the correlations between two return components and cash-flow news change signs as we move from intraday to overnight. The change in the correlation is consistent with an extrapolation interpretation of our findings. For example, after good

[16] Note that our decomposition does not measure whether discount news arrives intraday or overnight.

[17] The dramatic increase in time-series variation in the equity premium uncovered by our decomposition also resurrects the conditional CAPM. In a companion paper, Lou, Polk, and Skouras (2024), we show that 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%. Appendix Table 1 repeats the key result found in that work.

news about fundamentals arrives, the overnight clientele is expected to push prices away from fundamentals, resulting in a positive correlation between cash-flow news and the component of discount rate news reflecting revisions in expected future overnight returns. The intraday clientele is expected to pull prices back, hence the negative correlation between cash-flow news and the component of discount rate news reflecting revisions in expected future intraday returns. The difference in these two correlations is not only economically large but also highly statistically significant.

### 6.3 The Covid Crash, GFC, and Tech Boom/Bust

Figure 4 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.[18]

We also examine two other well-know bubble/crisis episodes in recent decades through our intraday/overnight prism. Figure 5 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 6 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.

[18]Our companion paper (Lou, Polk, and Skouras 2024) 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 striking time-variation in 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 market returns negatively forecast future close-to-close market 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 market returns strongly positively forecast future overnight market returns.

We interpret this predictability as the outcome of interactions between overnight and intraday clienteles and attempt to characterize both groups. First, individual investor expectations positively forecast future overnight market returns (but not intraday market returns). Second, consumption growth positively forecasts overnight market returns, and the level of intermediary risk tolerance negatively predicts intraday market returns. Third, a cash-flow / discount-rate news decomposition reveals that news about future expected overnight market returns is positively correlated with cash-flow news while news about future expected intraday market 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 cross-sectional context. We aim to advance research that may benefit from our powerful signal of the equity premium. Indeed, in contemporaneous work (Lou, Polk, and Skouras, 2024), we show that the CAPM betas of the Fama-French non-market factors not only move with smoothed overnight market returns, but do so in a way that dramatically reduces their unconditional alphas in a conditional CAPM regression.

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## Table I. Summary Statistics

This table reports summary statistics of our main variables at the quarterly frequency. RMRF, $RMRF_{Intraday}$, $RMRF_{Overnight}$ are the quarterly close-to-close, intraday, and overnight market returns. PE is the standard price-to-earnings ratio. $EWMA_{Intraday}$, $EWMA_{Overnight}$, and $EWMA_{EarnGrth}$ are the exponential weighted moving average of $RMRF_{Intraday}$, $RMRF_{Overnight}$, and quarterly earnings growth, all with a half-life of roughly seven years. Panel A reports the summary statistics of our main variables, and Panel B reports the correlation matrix. The sample period is 1997 to 2023 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

Panel A: Summary Statistics

| | Mean | St. Dev. | P25 | Median | P75 |
|---|---|---|---|---|---|
| RMRF | 0.0209 | 0.0852 | -0.0237 | 0.0293 | 0.0699 |
| $RMRF_{Intraday}$ | 0.0025 | 0.0631 | -0.0351 | 0.0068 | 0.0412 |
| $RMRF_{Overnight}$ | 0.0183 | 0.0558 | -0.0012 | 0.0244 | 0.0468 |
| PE | 3.4304 | 0.2269 | 3.2839 | 3.4178 | 3.5475 |
| $EWMA_{Intraday}$ | 0.0002 | 0.0015 | -0.0009 | 0.0004 | 0.0015 |
| $EWMA_{Overnight}$ | 0.0054 | 0.0011 | 0.0046 | 0.0054 | 0.0062 |
| $EWMA_{EarnGrth}$ | 0.0082 | 0.0106 | 0.0080 | 0.0114 | 0.0135 |

Panel B: Correlation Matrix

| | RMRF | $RMRF_{Intraday}$ | $RMRF_{Overnight}$ | PE | $EWMA_{Intraday}$ | $EWMA_{Overnight}$ | $EWMA_{EarnGrth}$ |
|---|---|---|---|---|---|---|---|
| RMRF | 1 | | | | | | |
| $RMRF_{Intraday}$ | 0.75 | 1 | | | | | |
| $RMRF_{Overnight}$ | 0.66 | 0.00 | 1 | | | | |
| PE | 0.15 | -0.10 | 0.35 | 1 | | | |
| $EWMA_{Intraday}$ | 0.39 | 0.25 | 0.31 | 0.57 | 1 | | |
| $EWMA_{Overnight}$ | -0.13 | -0.30 | 0.15 | 0.63 | 0.00 | 1 | |
| $EWMA_{EarnGrth}$ | 0.10 | -0.06 | 0.24 | 0.49 | 0.49 | 0.27 | 1 |

## Table II. Forecasting 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. $EWMA_{Intraday}$, $EWMA_{Overnight}$, and $EWMA_{EarnGrth}$ are the exponential weighted moving average of $RMRF_{Intraday}$, $RMRF_{Overnight}$, and quarterly earnings growth, all with a half-life of roughly seven years. 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 next-quarter overnight excess market return. All independent variables are standardized to have a mean of zero and standard deviation of one. We report Newey-West *t*-statistics based on four lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997 to 2023 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 | -0.015* | | | | |
| | [-1.82] | | | | |
| $EWMA_{Overnight}$ | | -0.034*** | -0.032*** | | |
| | | [-5.41] | [-5.06] | | |
| $EWMA_{Intraday}$ | | 0.011 | 0.013 | | |
| | | [1.33] | [1.38] | | |
| $EWMA_{EarnGrth}$ | | | -0.005 | | |
| | | | [-0.57] | | |
| $EWMA_{Overnight}$ (100) | | | | -0.033*** | |
| | | | | [-5.22] | |
| $EWMA_{Intraday}$ (100) | | | | 0.011 | |
| | | | | [1.32] | |
| $EWMA_{Overnight}$ (140) | | | | | -0.033*** |
| | | | | | [-4.71] |
| $EWMA_{Intraday}$ (140) | | | | | 0.012 |
| | | | | | [1.37] |
| Adj-$R^2$ | 2.3% | 15.7% | 15.1% | 15.1% | 15.1% |

| Panel B: Forecasting Intraday Excess Market Returns | | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| PE | -0.021*** | | | | |
| | [-4.14] | | | | |
| $EWMA_{Overnight}$ | | -0.019*** | -0.017*** | | |
| | | [-3.96] | [-3.58] | | |
| $EWMA_{Intraday}$ | | -0.006 | -0.004 | | |
| | | [-1.05] | [-0.56] | | |
| $EWMA_{EarnGrth}$ | | | -0.005 | | |
| | | | [-1.00] | | |
| $EWMA_{Overnight}$ (100) | | | | -0.02*** | |
| | | | | [-5.04] | |
| $EWMA_{Intraday}$ (100) | | | | -0.006 | |
| | | | | [-1.15] | |
| $EWMA_{Overnight}$ (140) | | | | | -0.016*** |
| | | | | | [-3.01] |
| $EWMA_{Intraday}$ (140) | | | | | -0.006 |
| | | | | | [-0.96] |
| Adj-$R^2$ | 10.0% | 7.7% | 7.4% | 9.3% | 5.8% |

| Panel C: Forecasting Overnight Excess Market Returns | | | | | |
|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] |
| PE | 0.006 | | | | |
| | [1.16] | | | | |
| $EWMA_{Overnight}$ | | -0.015** | -0.015** | | |
| | | [-2.25] | [-2.29] | | |
| $EWMA_{Intraday}$ | | 0.018*** | 0.017*** | | |
| | | [3.39] | [2.87] | | |
| $EWMA_{EarnGrth}$ | | | 0.000 | | |
| | | | [0.08] | | |
| $EWMA_{Overnight}$ (100) | | | | -0.012* | |
| | | | | [-1.76] | |
| $EWMA_{Intraday}$ (100) | | | | 0.017*** | |
| | | | | [3.39] | |
| $EWMA_{Overnight}$ (140) | | | | | -0.016*** |
| | | | | | [-2.65] |
| $EWMA_{Intraday}$ (140) | | | | | 0.018*** |
| | | | | | [3.43] |
| Adj-$R^2$ | 0.3% | 15.0% | 14.1% | 13.2% | 16.6% |

## Table III. Horse Races Against Other Forecasting Variables

This table reports regressions forecasting the excess return on the market. $EWMA_{Intraday}$ and $EWMA_{Overnight}$ are the exponential weighted moving average of $RMRF_{Intraday}$ and $RMRF_{Overnight}$, both with a half-life of roughly seven years. The competing forecasting variables are the aggregate investment rate (I/K), the Treasury bill yield (TB), aggregate equity issuance (EQ Iss), aggregate accruals (Accruals), fourth-quarter consumption growth (4QCG), aggregate short interest (Short Interest), the SVIX, the Gold-to-Platinum Price Ratio, and the aggregate analyst long-term growth forecast (LTG). The left side Panel A reports the estimates of simple regressions with each of the above variables as the single predictor, while the right side of the panel estimates multiple regressions that add the smoothed overnight and intraday returns to the simple regression. We report coefficients in percentage units and Newey-West *t*-statistics based on four lags, in bold where significant. In Panel B, we report a kitchen-sink multiple regression that includes all variables of Panel A. We report coefficients in natural units and Newey-West standard errors based on four lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. In both panels, all forecasting variables are standardized to have a mean of zero and standard deviation of one. The sample period is 1997 to 2023 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

| Panel A: Depvar = Future Market Returns | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Simple Forecasting | | | Multiple Forecasting | | | | | | |
| | competitor | | | $EWMA_{Overnight}$ | | $EWMA_{Intraday}$ | | competitor | | |
| | coef | *t*-stat | $R^2$ | coef | *t*-stat | coef | *t*-stat | coef | *t*-stat | $R^2$ |
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] | [9] | [10] |
| I/K | -1.0% | -1.51 | 0.5% | **-3.4%** | **-4.27** | 1.1% | 1.06 | -0.1% | -0.10 | 14.7% |
| TB | -1.2% | -1.53 | 1.2% | **-3.4%** | **-4.61** | 1.0% | 1.25 | 0.0% | 0.00 | 14.7% |
| EQ Iss | 0.9% | 1.26 | 0.2% | **-3.4%** | **-5.28** | 1.0% | 1.24 | 0.0% | -0.06 | 14.7% |
| Accruals | **1.3%** | **2.35** | 1.4% | **-3.3%** | **-5.03** | 1.0% | 1.10 | 0.2% | 0.33 | 14.8% |
| 4QCG | **-1.6%** | **-2.55** | 2.7% | **-3.8%** | **-3.84** | 0.9% | 1.09 | 0.6% | 0.76 | 15.0% |
| Short Interest | -0.8% | -0.72 | -0.2% | **-3.9%** | **-5.58** | -0.4% | -0.50 | -2.1% | -1.79 | 17.5% |
| SVIX | 2.0% | 1.67 | 4.7% | **-3.1%** | **-5.38** | 1.7% | 1.97 | **2.1%** | **2.04** | 20.3% |
| Gold/Plat | 1.7% | 1.88 | 3.1% | **-3.3%** | **-5.07** | 0.3% | 0.25 | 1.1% | 1.37 | 15.7% |
| LTG | **-2.0%** | **-2.84** | 4.6% | **-3.2%** | **-4.58** | 1.0% | 1.26 | -0.5% | -0.76 | 15.0% |

| Panel B: Depvar = Future Market Returns | |
|---|---|
| Intercept | 0.020*** |
| | [2.94] |
| $EWMA_{Overnight}$ | -0.045*** |
| | [-4.15] |
| $EWMA_{Intraday}$ | 0.011 |
| | [0.68] |
| I/K | -0.007 |
| | [-0.52] |
| TB | 0.008 |
| | [0.77] |
| EQ Iss | -0.013* |
| | [-1.94] |
| Accruals | 0.007 |
| | [1.30] |
| 4QCG | 0.002 |
| | [0.17] |
| Short Interest | -0.042 |
| | [-1.56] |
| SVIX | 0.026** |
| | [2.46] |
| Gold/Plat | -0.030 |
| | [-1.32] |
| LTG | -0.006 |
| | [-0.79] |
| | |
| Adj-$R^2$ | 18.9% |

## Table IV. Forecasting Dividend Growth and Return Volatility

This table reports regressions forecasting quarterly dividend growth and realized variance (RVAR, measured using daily returns within the quarter). PE is the standard smoothed price-to-earnings ratio. $EWMA_{Intraday}$ and $EWMA_{Overnight}$ are the exponential weighted moving average of $RMRF_{Intraday}$ and $RMRF_{Overnight}$, both with a half-life of roughly seven years. DEF is the default yield spread. All independent variables are standardized to have a mean of zero and standard deviation of one. We report Newey-West *t*-statistics based on four lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997 to 2023 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

| | Div growth | Div growth | RVAR | RVAR |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| Intercept | 0.014*** | 0.014*** | 0.172*** | 0.172*** |
| | [6.94] | [3.78] | [22.17] | [23.36] |
| PE | 0.003 | | 0.023** | |
| | [1.22] | | [2.00] | |
| $EWMA_{Overnight}$ | | 0.000 | | 0.020** |
| | | [-0.10] | | [2.44] |
| $EWMA_{Intraday}$ | | 0.006 | | -0.005 |
| | | [1.20] | | [-0.64] |
| DEF | | | 0.032** | 0.036*** |
| | | | [2.56] | [3.72] |
| RVAR | | | 0.030* | 0.015 |
| | | | [1.85] | [1.30] |
| Adj-$R^2$ | 0.5% | 5.3% | 26.9% | 27.9% |

## Table V. In-Sample and Out-of-Sample Evidence

This table reports statistical performance metrics for a predictive regression of the quarterly excess CRSP market return on the lagged smoothed overnight return. The in-sample stability analysis presents the adjusted $R^2$ and the *t*-stat on the predictor across various subsamples (*t*-statistics are Newey-West based on four lags). The out-of-sample analysis reports the out-of-sample $R^2$ (following Goyal and Welch, 2008) for the same predictive regression and McCracken's (2007) MSE-F statistic and its bootstrapped value (following Goyal, Welch and Zafirov, 2024). Sample start and end dates refer to the realization date of LHS returns. The sample period is 2000-2023; in other words, we use an extra three-year burn-in period in the out-of-sample analysis.

| | In-Sample Stability | | | Out-of-Sample |
|---|---|---|---|---|
| | Full Sample | Subsample 1 | Subsample 2 | |
| Adjusted $R^2$ | 0.14 | 0.13 | 0.12 | |
| predictor *t*-statistic | -5.37 | -4.18 | -2.34 | |
| OOS $R^2$ | | | | 0.16 |
| MSE-F | | | | 38.09 |
| p-value (bootstrapped) | | | | 0.002 |
| start | 1997Q1 | 1997Q1 | 2010Q3 | 2000Q1 |
| end | 2023Q4 | 2010Q2 | 2023Q4 | 2023Q4 |
| # obs | 108 | 54 | 54 | 96 |

## Table VI. Out-of-Sample Performance

This table reports trading strategy performance metrics for strategies based on the out-of-sample forecasts of the predictive regression of the quarterly excess CRSP market return on the lagged smoothed overnight return as well as comparison metrics from benchmark strategies. The first column examines a trading strategy (introduced by Goyal, Welch and Zafirov, forthcoming) with investment period allocations determined as the current value of the smoothed overnight return minus its expanding window historical median, divided by a standard deviation estimate and signed according to its historical median. The second to fourth columns analyze a trading strategy (introduced by Campbell and Thomson, 2008) where positions are the optimal ones of a quadratic utility investor with risk aversion coefficient $\gamma$=3. In the second column, the out-of-sample forecasts are from our predictive regression and the volatility estimate is based on a five-year rolling window ending on each investment date. In the third column, this standard deviation estimate is replaced by a volatility forecast obtained using out-of-sample predictive regressions analogous to those used to obtain mean forecasts but forecasting quarterly realized volatility based on daily returns. In the fourth column, we reconsider the second column's strategy using forecasts based on the expanding-window historical mean. The final column considers the classic buy-and-hold strategy. In Panel A, we report the mean and Sharpe Ratio of annualized returns. We report Newey-West *t*-statistics based on four lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. We report *t*-stats for the Sharpe Ratio (SR) based on Lo (2002). In Panel B, we report statistics on the distribution of position sizes, turnover and break-even proportional transaction costs (in percent). The sample period is 2000 to 2023 as in the out-of-sample analysis of Table V.

| Panel A: Annualized Performance | | | | | |
|---|---|---|---|---|---|
| | Predictor-driven strategies | | | Benchmark Strategies | |
| | z-score-scaled | Quadratic utility mean-forecast-based | Quadratic utility mean-and-vol forecast-based | Quadratic utility historical-mean-based | Always long (buy-and-hold) |
| Mean | 0.080*** | 0.197*** | 0.132*** | 0.031 | 0.069* |
| | [2.69] | [2.83] | [3.78] | [0.58] | [1.86] |
| SR | 0.542*** | 0.641*** | 0.730*** | 0.113 | 0.392*** |
| | [4.96] | [5.72] | [6.36] | [1.10] | [3.71] |

| Panel B: Allocations | | | | | |
|---|---|---|---|---|---|
| | Predictor-driven strategies | | | Benchmark Strategies | |
| | z-score-scaled | Quadratic utility mean-forecast-based | Quadratic utility mean-and-vol-forecast-based | Quadratic utility historical-mean-based | Always long (buy-and-hold) |
| Mean(abs(allocation)) $ | 0.56 | 1.34 | 1.04 | 0.93 | 1.00 |
| Mean $ | -0.10 | 1.06 | 0.84 | 0.93 | 1.00 |
| Std $ | 0.70 | 1.60 | 0.97 | 0.41 | 0.00 |
| Median $ | -0.03 | 0.84 | 0.83 | 0.83 | 1.00 |
| Min $ | -1.67 | -1.56 | -1.10 | 0.33 | 1.00 |
| Max $ | 1.36 | 6.71 | 3.73 | 1.50 | 1.00 |
| # long | 44 | 75 | 75 | 96 | 96 |
| # short | 49 | 21 | 21 | 0 | 0 |
| quarterly turnover $ | 0.24 | 0.52 | 0.40 | 0.09 | 0.01 |
| break even t-cost | 0.05 | 0.13 | 0.12 | 0.07 | 1.66 |

## Table VII. Out-of-Sample Alphas and Factor Loadings

This table reports alphas and factor loadings of the three trading strategies analysed in the first three columns of Table VI. We control for exposure to the CAPM and the six-factor Fama-French-Carhart model, as well as to the trading strategy based on historical mean forecasts considered in the fourth column of Table VI. We report Newey-West $t$-statistics based on four lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 2000 to 2023 as in the out-of-sample analysis of Table V.

| | z-score-scaled | | | Quadratic utility mean-forecast-based | | | Quadratic utility mean-and-vol-forecast-based | | |
|---|---|---|---|---|---|---|---|---|---|
| Quarterly Alpha | 0.021*** | 0.020*** | 0.018*** | 0.046*** | 0.033** | 0.030** | 0.045*** | 0.032*** | 0.026*** |
| | [2.89] | [2.56] | [2.76] | [3.34] | [2.24] | [1.99] | [3.75] | [3.30] | [3.04] |
| Historical mean forecast | -0.123 | | | 0.477*** | | | 0.304** | | |
| quadratic utility | [-1.64] | | | [2.45] | | | [1.97] | | |
| MKT | | -0.007 | -0.052 | | 0.921*** | 0.961*** | | 0.914*** | 0.928*** |
| | | -0.039 | [-0.27] | | [3.01] | [3.12] | | [3.83] | [3.47] |
| SMB | | | -0.049 | | | -0.081 | | | 0.090 |
| | | | [-0.30] | | | [-0.30] | | | [0.39] |
| HML | | | -0.060 | | | 0.051 | | | -0.234 |
| | | | [-0.20] | | | [0.08] | | | [-0.48] |
| RMW | | | -0.062 | | | 0.081 | | | 0.037 |
| | | | [-0.31] | | | [0.27] | | | [0.103] |
| CMA | | | 0.570** | | | 0.165 | | | 0.71** |
| | | | [2.19] | | | [0.33] | | | [2.01] |
| MOM | | | -0.203 | | | -0.044 | | | -0.084 |
| | | | [-1.86] | | | [-0.22] | | | [-0.59] |

## Table VIII. Forecasting Market Returns: Mechanisms

This table reports regressions forecasting excess market returns and its intraday and overnight components. $EWMA_{Intraday}$ and $EWMA_{Overnight}$ are the exponential weighted moving average of $RMRF_{Intraday}$ and $RMRF_{Overnight}$, both with a half-life of roughly seven years. Individual Investor Expectations (IIE) are obtained from the Gallop survey. Consumption Growth (CG) is quarterly consumption growth, and IRT 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. We report Newey-West *t*-statistics based on 4 lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997 to 2023 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] | [7] | [8] |
| $EWMA_{Overnight}$ | -0.033*** | | -0.033*** | | -0.039*** | | -0.032*** | -0.039*** |
| | [-5.71] | | [-5.75] | | [-6.54] | | [-5.82] | [-6.54] |
| $EWMA_{Intraday}$ | 0.008 | | 0.008 | | -0.001 | | 0.004 | -0.007 |
| | [0.98] | | [1.02] | | [-0.20] | | [0.58] | [-0.96] |
| IIE | | -0.001 | 0.000 | | | | | -0.003 |
| | | [-0.09] | [-0.01] | | | | | [-0.40] |
| CG | | | | 0.006 | 0.021*** | | | 0.024*** |
| | | | | [0.74] | [2.65] | | | [2.69] |
| IRT | | | | | | -0.009 | -0.007 | -0.009 |
| | | | | | | [-1.09] | [-1.02] | [-1.21] |
| Covid | 0.096*** | 0.119*** | 0.096*** | 0.138*** | 0.165*** | 0.109*** | 0.091*** | 0.164*** |
| | [7.72] | [5.76] | [6.76] | [4.29] | [5.91] | [5.56] | [6.61] | [5.32] |
| Adj-$R^2$ | 18.3% | 3.7% | 17.5% | 4.1% | 20.9% | 4.9% | 18.0% | 20.4% |

| Panel B: Forecasting Intraday Excess Market Returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| $EWMA_{Overnight}$ | -0.019*** | | -0.018*** | | -0.020*** | | -0.018*** | -0.021*** |
| | [-3.95] | | [-4.33] | | [-3.72] | | [-4.25] | [-3.93] |
| $EWMA_{Intraday}$ | -0.006 | | -0.005 | | -0.008 | | -0.017*** | -0.020*** |
| | [-1.02] | | [-0.86] | | [-1.25] | | [-3.36] | [-3.60] |
| IIE | | -0.011 | -0.010 | | | | | -0.007 |
| | | [-1.67] | [-1.68] | | | | | [-1.17] |
| CG | | | | -0.007 | 0.004 | | | 0.011 |
| | | | | [-1.08] | [0.59] | | | [1.35] |
| IRT | | | | | | -0.013** | -0.022*** | -0.021*** |
| | | | | | | [-2.53] | [-4.32] | [-3.72] |
| Covid | 0.001 | -0.013 | -0.013 | -0.019 | 0.014 | -0.014 | -0.012 | 0.012 |
| | [0.15] | [-1.07] | [-1.30] | [-0.90] | [0.60] | [-1.52] | [-1.44] | [0.49] |
| Adj-$R^2$ | 6.8% | 1.2% | 8.4% | -0.8% | 6.1% | 2.1% | 14.4% | 14.5% |

| Panel C: Forecasting Overnight Excess Market Returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| $EWMA_{Overnight}$ | -0.013** | | -0.014*** | | -0.018*** | | -0.014** | -0.018*** |
| | [-2.30] | | [-2.74] | | [-3.20] | | [-2.35] | [-3.06] |
| $EWMA_{Intraday}$ | 0.014*** | | 0.013*** | | 0.007 | | 0.022*** | 0.014** |
| | [2.77] | | [2.96] | | [1.28] | | [4.00] | [2.39] |
| IIE | | 0.012*** | 0.011*** | | | | | 0.005 |
| | | [2.63] | [2.70] | | | | | [1.08] |
| CG | | | | 0.014*** | 0.017*** | | | 0.013*** |
| | | | | [2.66] | [3.28] | | | [3.41] |
| IRT | | | | | | 0.003 | 0.015*** | 0.011* |
| | | | | | | [0.51] | [2.60] | [1.91] |
| Covid | 0.093*** | 0.133*** | 0.109*** | 0.158*** | 0.149*** | 0.121*** | 0.102*** | 0.151*** |
| | [8.25] | [11.07] | [9.66] | [7.57] | [6.93] | [8.51] | [8.70] | [8.72] |
| Adj-$R^2$ | 21.6% | 14.7% | 24.6% | 15.5% | 26.1% | 10.7% | 26.0% | 29.1% |

## 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 into intraday and overnight components. $r_{Intraday}$ and $r_{Overnight}$ are, respectively, the quarterly intraday and overnight log market returns excess of the log risk-free rate. $EWMA_{intra}$ and $EWMA_{over}$ are the exponentially weighted moving average of past intraday and overnight returns, respectively, with a half-life of roughly seven years. Panel A reports the VAR estimates, and Panel B shows the standard deviations and correlations of the various return components. We report Newey-West t-statistics based on 4 lags below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1997 to 2023 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

| Panel A: VAR Analysis | | | | |
|---|---|---|---|---|
| | $r_{Intraday}$ | $r_{Overnight}$ | $EWMA_{intra}$ | $EWMA_{over}$ |
| | [1] | [2] | [3] | [4] |
| Intercept | 0.0991*** | 0.0789*** | 0.0008*** | 0.0006*** |
| | [4.23] | [2.82] | [4.35] | [2.67] |
| $r_{Intraday}$ | -0.1291 | 0.0558 | -0.0011 | 0.0004 |
| | [-1.30] | [0.78] | [-1.31] | [0.67] |
| $r_{Overnight}$ | -0.0838 | -0.0329 | -0.0007 | -0.0002 |
| | [-0.85] | [-0.28] | [-0.82] | [-0.23] |
| $EWMA_{Intraday}$ | -1.4914 | 11.0300*** | 0.9637*** | 0.0923*** |
| | [-0.46] | [2.79] | [36.88] | [2.79] |
| $EWMA_{Overnight}$ | -17.9299*** | -11.8504** | -0.1436*** | 0.8861*** |
| | [-4.00] | [-2.16] | [-4.05] | [18.96] |
| Adj-$R^2$ | 7.6% | 12.9% | 89.4% | 83.3% |

| Panel B: Cash Flow vs. Discount Rate News | | | |
|---|---|---|---|
| News Std. Dev./Corr. | $N_{CF}$ | $-N_{DR\_Intraday}$ | $-N_{DR\_Overnight}$ |
| $N_{CF}$ | 2.4% | 0.70 | -0.61 |
| $-N_{DR\_Intraday}$ | 0.70 | 4.9% | 0.11 |
| $-N_{DR\_Overnight}$ | -0.61 | 0.11 | 4.9% |

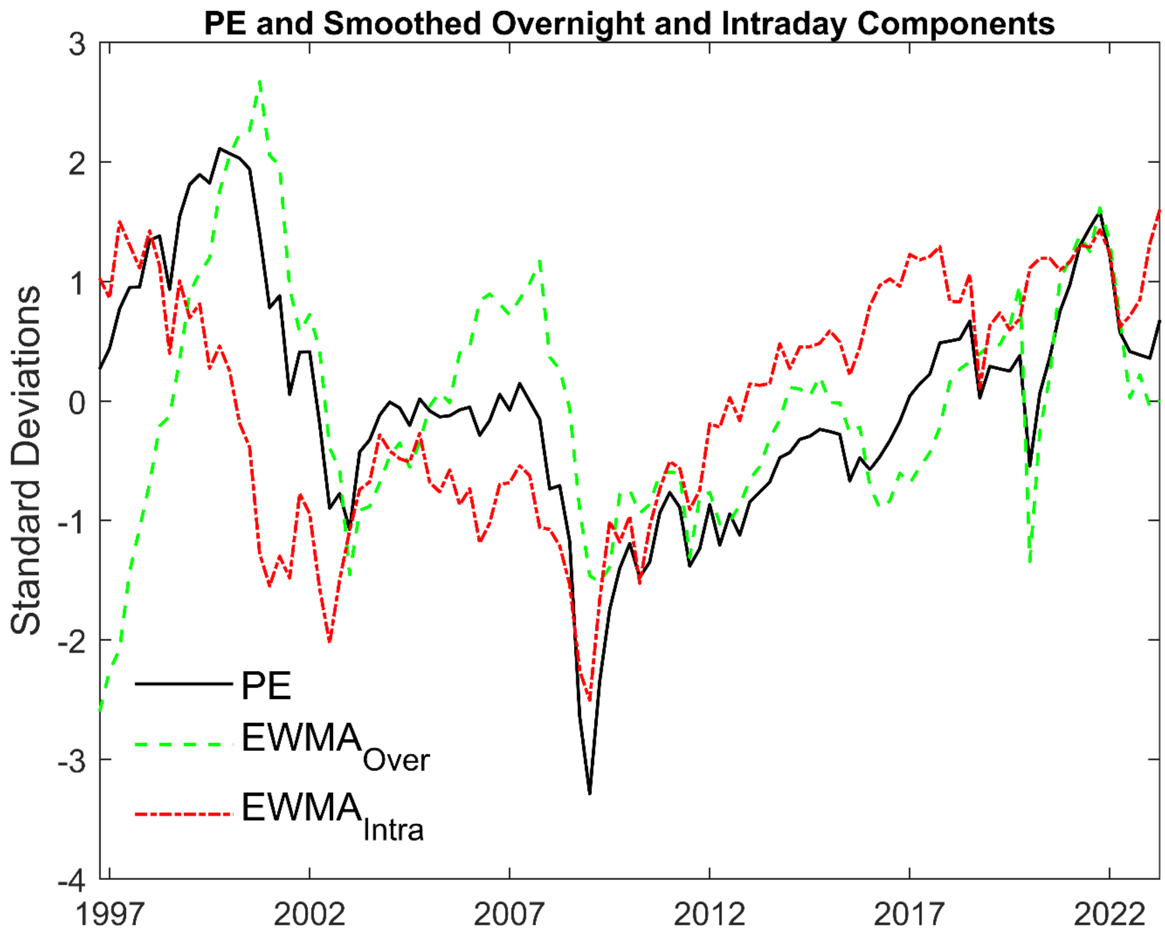


**Figure 1.** This figure shows the PE ratio and smoothed (exponential-weighted average) overnight/intraday returns for the period 1997-2023.

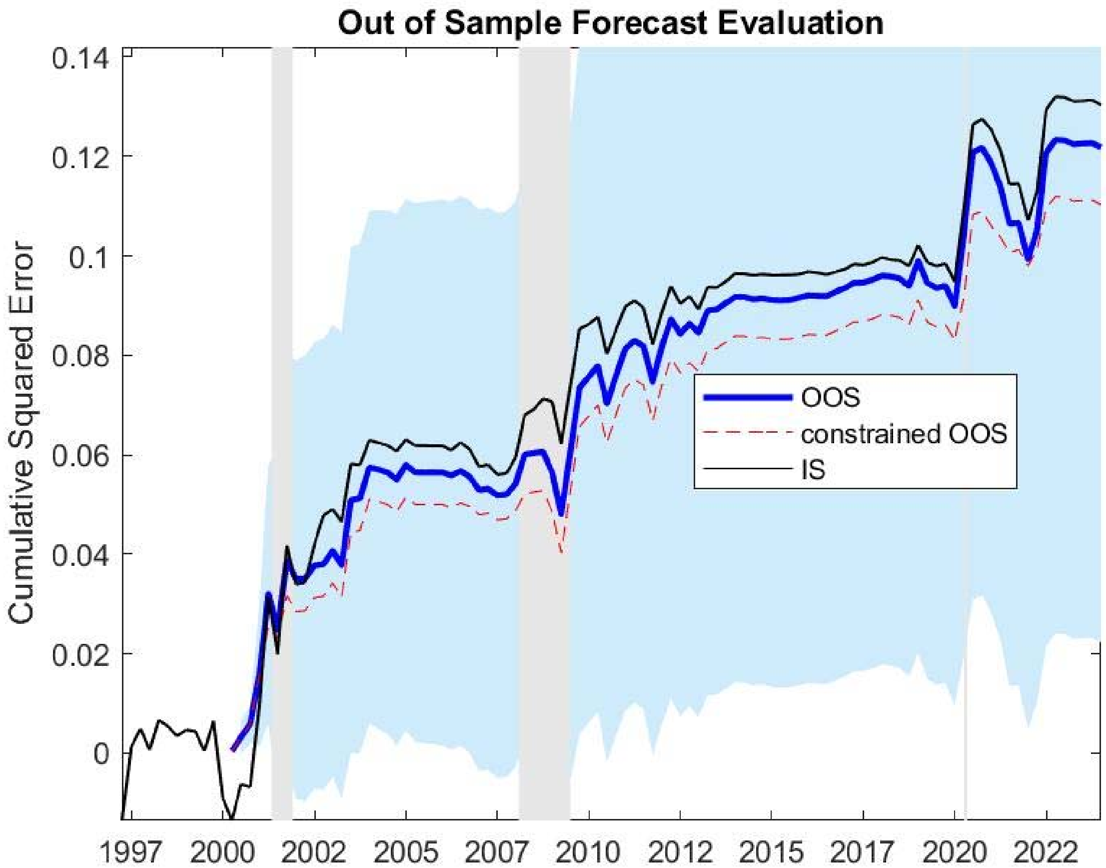


Figure 2. This figure plots the cumulative squared forecast error from our smoothed overnight predictor minus the cumulative squared forecast error from a benchmark forecast based on the historical mean. The thin black line plots that comparison for in-sample (IS) forecasts, the thick blue plots that comparison for out-of-sample (OOS) forecasts, and the red dashed line constrains the out-of-sample forecasts to be non-negative, following Campbell and Thomson (2008). The shaded blue confidence interval is for the OOS forecasts and is constructed as in Goyal and Welch (2008). NBER recessions are highlighted using grey intervals.

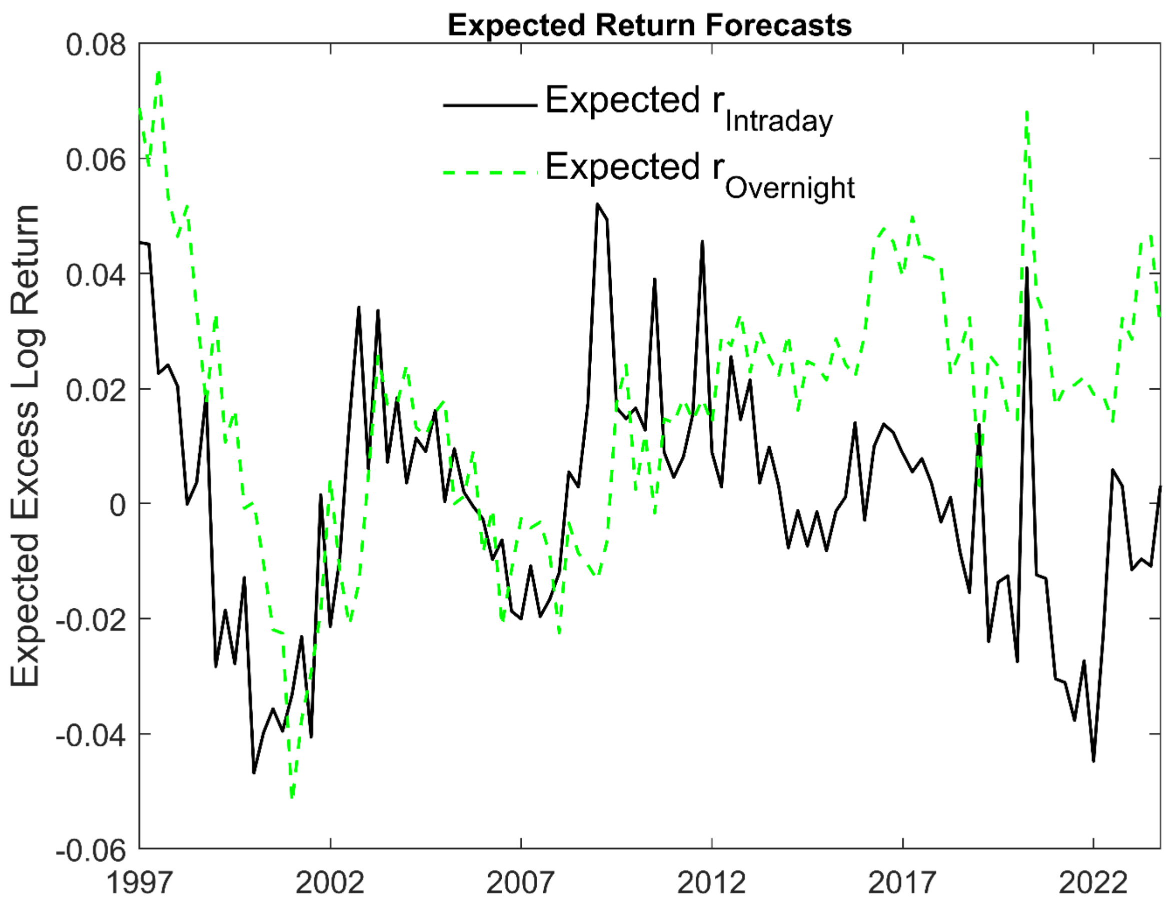


**Figure 3.** The figure shows the time-series of expected overnight and intraday returns from the VAR in Table VIII.

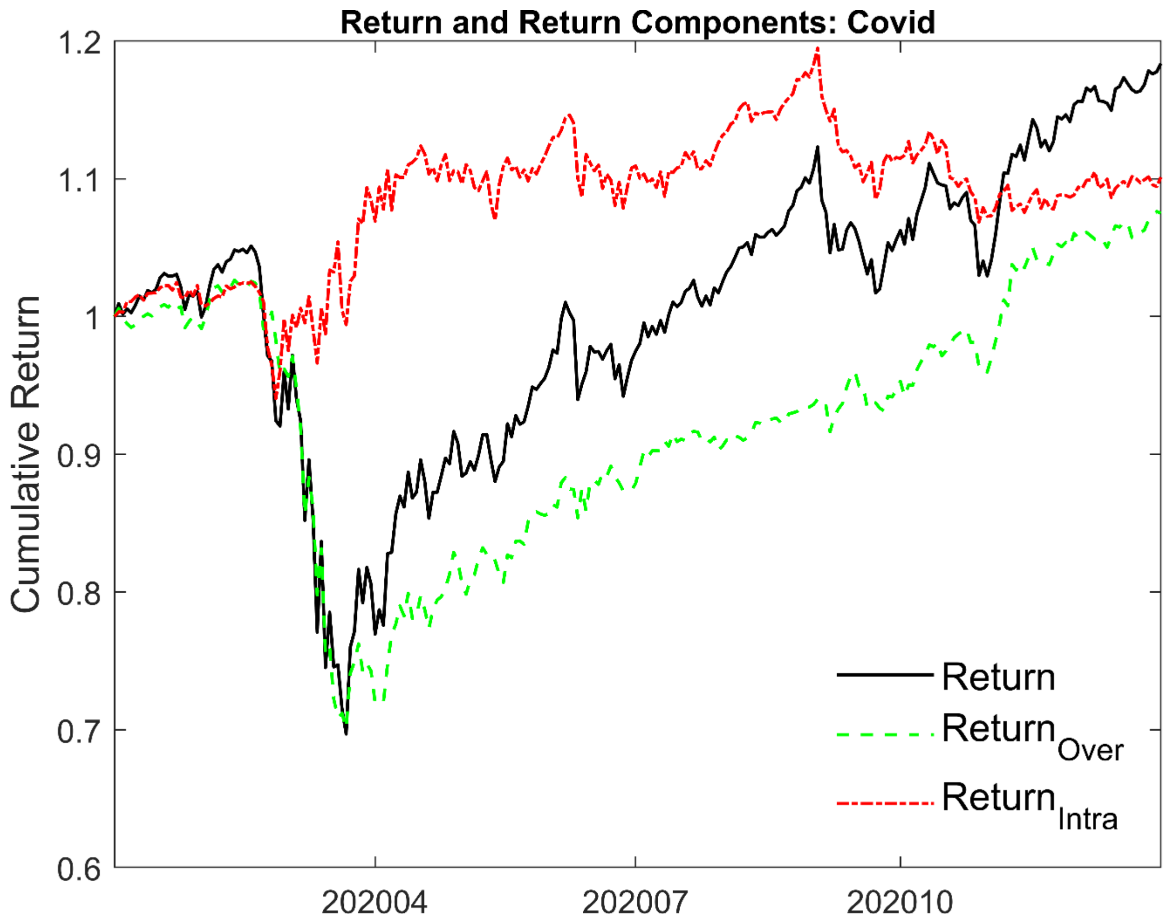


**Figure 4.** This figure plots the cumulative returns of an investment in the stock market ("Return", black line), an investment in the market during only overnight periods ("$\text{Return}_{\text{Over}}$", green line), and an investment during only intraday periods ("$\text{Return}_{\text{Intra}}$", red line) in 2020 (the COVID-19 pandemic).

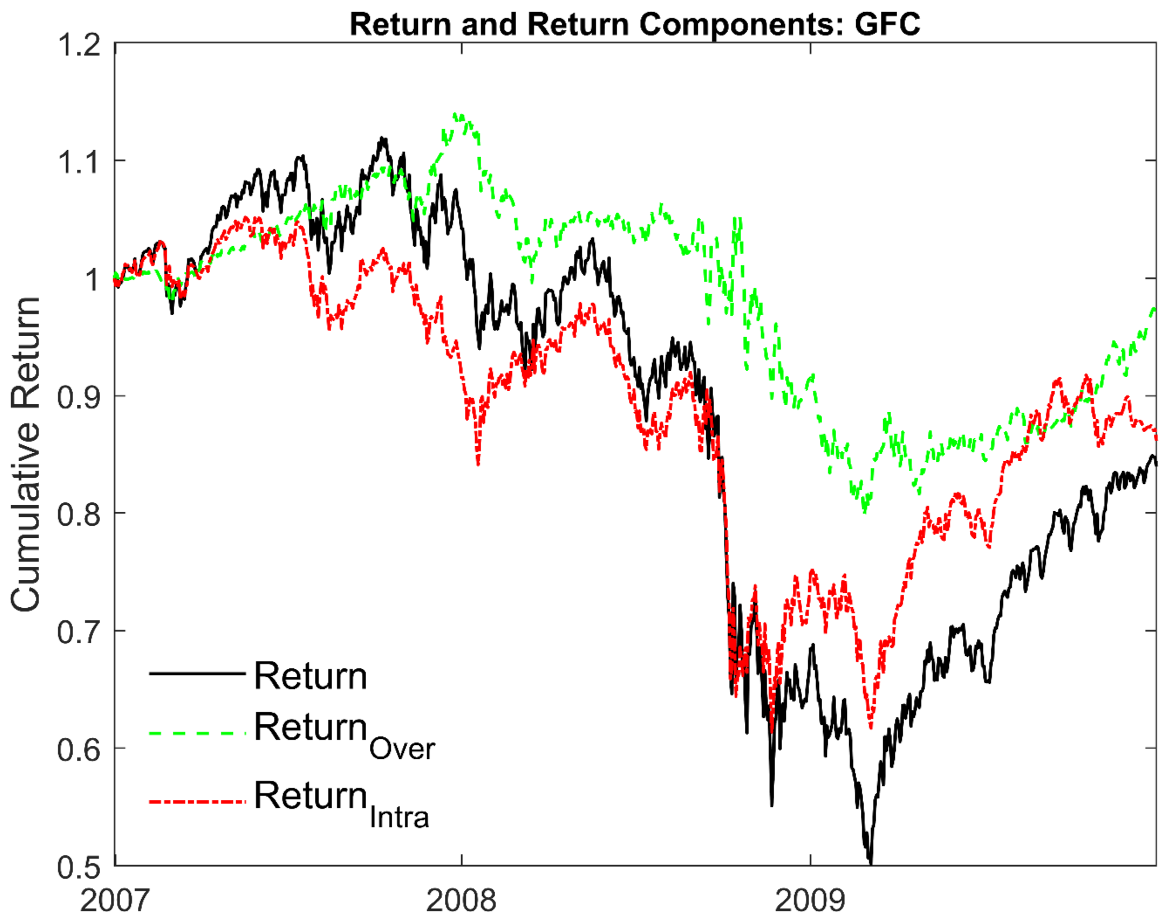


**Figure 5.** This figure plots the cumulative returns of an investment in the stock market ("Return" black line), an investment in the market during only overnight periods ("Return$_{\text{Over}}$", green line), and an investment during only intraday periods ("Return$_{\text{Intra}}$", red line) in the Global Financial Crisis (GFC).

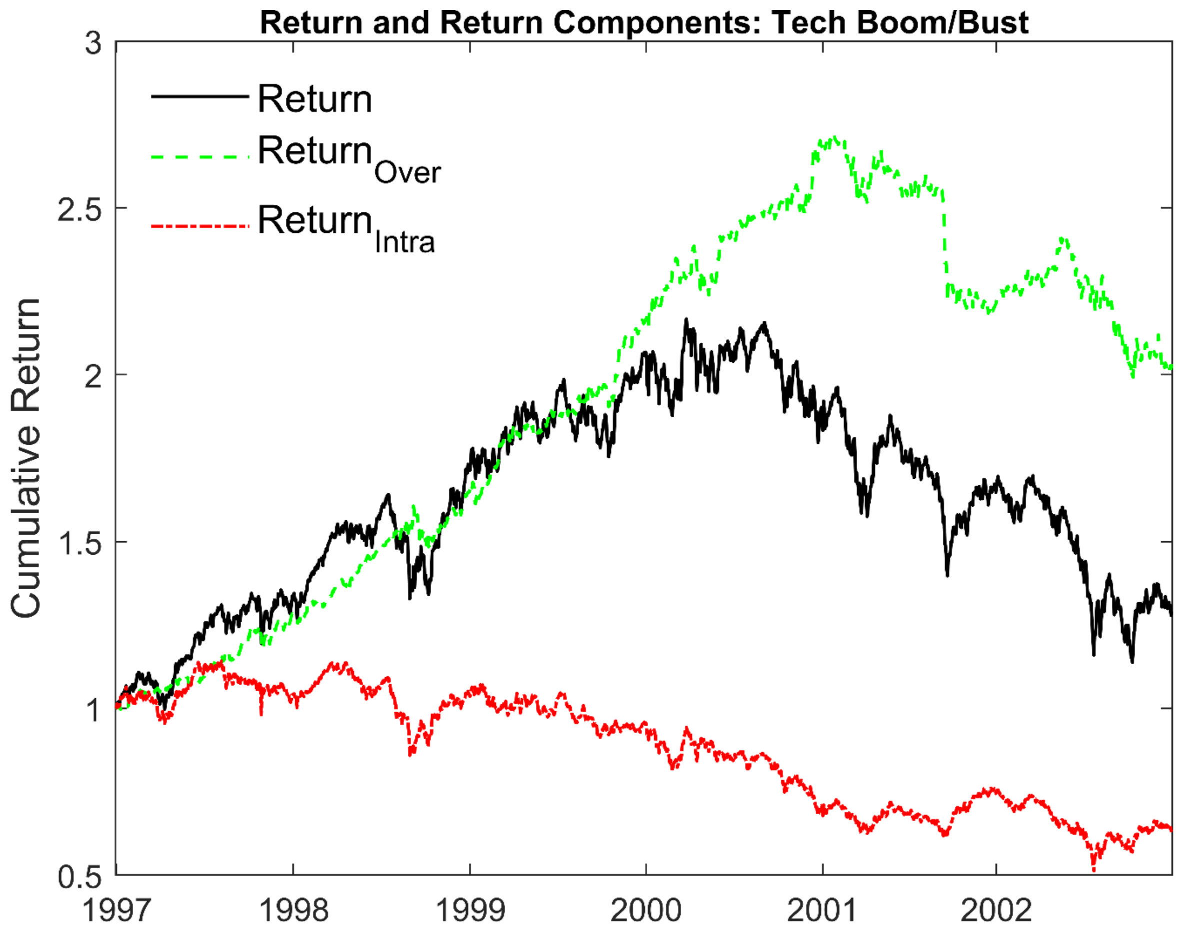


**Figure 6.** This figure plots the cumulative returns of an investment in the stock market ("Return" black line), an investment in the market during only overnight periods ("Return$_{\text{Over}}$", green line), and an investment during only intraday periods ("Return$_{\text{Intra}}$", red line) in the Tech Boom and Bust.

## Appendix Table I. Conditional CAPM

This table reports time-series regressions of common factor returns on market returns. The dependent variables in the first four columns are the quarterly 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 $EWMA_{Intraday}$. In Panel C, we further include lagged $EWMA_{Overnight}$ and $EWMA_{Intraday}$ in the regression to forecast the conditional CAPM alpha. In both Panels B and C, $EWMA_{Overnight}$ and $EWMA_{Intraday}$ are standardized to have a mean of zero and standard deviation of one. Standard errors are reported below each estimate. In all three panels, we report intercepts in percentage units. We indicate statistical significance at the 10%, 5%, and 1% levels with *, **, and ***, respectively. The sample period is 1997 to 2023 to allow a four-year burn-in period for the calculation of the exponentially weighted moving averages.

| 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] |
| Intercept (%) | 0.017 | 0.532 | 1.67*** | 0.945** | 0.791** | 1.697** | 1.403 |
| | [0.04] | [0.76] | [3.43] | [2.10] | [2.08] | [2.09] | [1.61] |
| $RMRF_{t+1}$ | 0.211*** | -0.093 | -0.268*** | -0.140*** | -0.073* | -0.368*** | -0.993*** |
| | [4.14] | [-1.22] | [-5.10] | [-2.87] | [-1.77] | [-4.21] | [-10.54] |
| Adj-$R^2$ | 13.2% | 0.5% | 19.1% | 6.4% | 2.0% | 13.6% | 50.9% |

| 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] |
| Intercept (%) | -0.199 | -0.150 | 0.984** | 0.472 | 0.277 | 1.693** | 0.630 |
| | [-0.39] | [-0.21] | [2.02] | [1.03] | [0.72] | [2.01] | [0.68] |
| $RMRF_{t+1}$ | 0.216*** | -0.098 | -0.234*** | -0.145*** | -0.065 | -0.324*** | -0.975*** |
| | [4.16] | [-1.32] | [-4.67] | [-3.10] | [-1.65] | [-3.76] | [-10.32] |
| $EWMA_{Overnight,t}$*$RMRF_{t+1}$ | -0.051 | -0.202*** | -0.132*** | -0.143*** | -0.132*** | 0.077 | -0.188** |
| | [-1.12] | [-3.12] | [-3.05] | [-3.52] | [-3.86] | [1.02] | [-2.29] |
| $EWMA_{Intraday,t}$*$RMRF_{t+1}$ | 0.020 | -0.049 | 0.137*** | -0.043 | 0.016 | 0.205*** | 0.052 |
| | [0.44] | [-0.77] | [3.20] | [-1.08] | [0.48] | [2.77] | [0.64] |
| Adj-$R^2$ | 12.7% | 8.2% | 29.7% | 16.3% | 12.7% | 19.3% | 52.5% |

| Panel C: Conditional CAPM Allowing for Conditional Alpha | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $SMB_{t+1}$ | $HML_{t+1}$ | $RMW_{t+1}$ | $CMA_{t+1}$ | EW[FF] | $MOM_{t+1}$ | $BAB_{t+1}$ |
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| Intercept (%) | -0.380 | -0.370 | 0.883* | 0.275 | 0.102 | 1.628* | 0.579 |
| | [-0.78] | [-0.51] | [1.79] | [0.61] | [0.27] | [1.93] | [0.62] |
| $EWMA_{Overnight,t}$ (%) | 0.991** | 1.471** | 0.621 | 1.258*** | 1.085*** | 0.617 | 0.438 |
| | [2.03] | [2.02] | [1.26] | [2.79] | [2.88] | [0.73] | [0.47] |
| $EWMA_{Intraday,t}$ (%) | -1.422*** | 0.210 | -0.289 | -0.244 | -0.436 | 1.381* | 0.747 |
| | [-3.13] | [0.31] | [-0.63] | [-0.58] | [-1.25] | [1.76] | [0.86] |
| $RMRF_{t+1}$ | 0.284*** | -0.034 | -0.201*** | -0.085 | -0.009 | -0.318*** | -0.967*** |
| | [5.18] | [-0.42] | [-3.63] | [-1.67] | [-0.22] | [-3.36] | [-9.19] |
| $EWMA_{Overnight,t}$*$RMRF_{t+1}$ | -0.053 | -0.226*** | -0.139*** | -0.161*** | -0.145*** | 0.055 | -0.201** |
| | [-1.23] | [-3.47] | [-3.15] | [-3.98] | [-4.30] | [0.73] | [-2.39] |
| $EWMA_{Intraday,t}$*$RMRF_{t+1}$ | 0.047 | -0.055 | 0.142*** | -0.040 | 0.023 | 0.176** | 0.036 |
| | [1.08] | [-0.85] | [3.24] | [-1.01] | [0.70] | [2.36] | [0.44] |
| Adj-$R^2$ | 21.3% | 10.2% | 29.6% | 20.9% | 18.6% | 20.6% | 52.0% |