The Day Destroys the Night, Night Extends the Day:

A Clientele Perspective on Equity Premium Variation

Dong Lou, Christopher Polk, and Spyros Skouras*

This version: May 2026

*Lou: Hong Kong University of Science and Technology and CEPR. Email: dlou@ust.hk. Polk: London School of Economics and CEPR. Email: c.polk@lse.ac.uk. Skouras: Athens University of Economics and Business. Email: skouras@aueb.gr. We thank John Campbell, Ralph Koijen, Jon Lewellen, Dimitri Vayanos, Tuomo Vuolteenaho, and seminar and conference participants at Amsterdam Business School, Chinese University of Hong Kong (Shenzhen), Collegio Carlo Alberto, Hong Kong University of Science and Technology, London School of Economics, Peking University HSBC Business School (Shenzhen), Stockholm Business School, Texas A&M University, University of Georgia, University of Texas Dallas, the 2019 Conference on the Regulation and Operation of Modern Financial Markets, the 2021 CRETE conference, the 2022 Conference in Honour of Ramon Marimon, the 2022 Bristol Financial Markets Conference, and the 2022 NBER Asset Pricing Summer Institute for helpful comments. We thank Ken French, Ian Martin, and Ran Shi for sharing data used in the analysis. Lou is grateful for financial support from the National Natural Science Foundation of China (Grant No. 72425006, 72342020). We also thank The Doors for inspiring our paper's title.

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Abstract

We provide a powerful new predictor of the equity premium: Smoothed past overnight market returns strongly negatively forecast the quarterly close-to-close excess return on the market. Decomposing this predictability, our novel signal negatively forecasts both overnight and intraday components of close-to-close returns, while smoothed intraday returns positively forecast the overnight component. We interpret these patterns from a clientele perspective: Individual investor expectations and consumption growth strongly positively forecast overnight returns, while intermediary risk tolerance strongly negatively forecasts intraday returns. We show that the predictability we document is stronger in settings where overnight returns are more likely to reflect household sentiment.

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 involves 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 only the net effect of the clienteles in play. This paper exploits the fact that different types of investors likely prefer to trade stocks at different points in time, allowing 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.[1]

We use this clientele perspective, along with the distinction between overnight versus 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 highlight that these two components of returns behave quite differently over our sample period. We estimate quarterly regressions of these components of returns on contemporaneous changes in a host of macroeconomic and financial variables. Interestingly, we find that variables summarizing the broad economy – GDP growth, consumption growth, percentage change in the level of the Industrial Production index, and Private Nonresidential Investment growth – are all much more correlated with the overnight component of market returns. Our interpretation of these findings is that broad macroeconomic conditions are an important driver of household confidence/sentiment. Thus, when these variables increase, it is reasonable for households to become more bullish on the market. Consistent with that view, we also find that

[1]Though we use the term "overnight", we do not imply that these investors tend to trade during the night, or even while the market is closed. In our baseline specification, the overnight / intraday decomposition is based on an open price defined as the VWAP from trades in the first half hour after market open, so trading just after the open and at the close will affect overnight returns.

overnight (intraday) returns are positively (negatively) correlated with Baker and Wurgler's (2006) sentiment measure. These facts suggest that overnight returns may contain important information about subsequent expected returns.

To formally test that hypothesis, we isolate the low frequency component of past overnight and intraday returns using an exponentially weighted moving average. We first show that these smoothed variables behave differently across well-known periods of booms and busts in the U.S. stock market. For example, we find that smoothed overnight returns increased throughout the late 1990s, while smoothed intraday returns sharply decreased. Similarly, we find that smoothed overnight returns moved dramatically during the COVID pandemic, while smoothed intraday returns did not. In contrast, the Global Financial Crisis of 2008 was primarily an intraday phenomenon.

Our main analysis then uses these smoothed variables as signals to forecast subsequent close-to-close market returns, revealing much stronger mean reversion in the equity premium. Take, for example, the classic measure of the conditional equity premium, the cyclically-adjusted log 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 2% and a t-statistic of -1.8). In stark contrast, smoothed past decomposed market returns provide roughly seven times the forecasting power of PE (R^2 of 16%) with a t-statistic of -5.4 associated with our novel signal. Smoothed past intraday returns, instead, positively forecast future market returns, albeit insignificantly.

Our ability to forecast the close-to-close market return is not only statistically and economically significant but also highly robust; we provide extensive evidence in support of that claim. For example, we confirm that our findings are robust to a wide range of smoothing and initialization parameter values when constructing our signal. Moreover, our results are not driven by days with macroeconomic announcements or by days in which prominent firms' announce their earnings in clusters. We continue to find strong predictability if we exclude those days from either the calculation of our signal or the returns that we forecast.

Our results are also robust to the securities we use to document these findings. Our primary tests use the S&P 500 SPY ETF as our market proxy. However, the smoothed overnight return on the SPY ETF forecasts not only the excess return on SPY but also the real return on the SPY ETF, the excess return on the underlying SPY index, the excess return on the CRSP value-weight market, the excess return on the CRSP equal-weight market portfolio, and the return on E-mini S&P 500 futures. Moreover, if we smooth the overnight and intraday components of past E-mini S&P 500 futures returns instead of those of the ETF, the resulting signal forecasts the equity premium just as well.

In addition to these robustness tests, we run a battery of horse races against other well-known predictors, as well as a careful sub-sample and out-of-sample analysis. Our smoothed overnight return signal maintains a t-statistic with an absolute value over four in both head-to-head and kitchen sink regressions against the variables that previous work has deemed the best predictors of the equity premium (e.g., Goyal, Welch, and Zafirov, 2024). Our signal works in both halves of the sample period and generates an annualized Sharpe Ratio of around 0.7 in a simple out-of-sample strategy that times the market.

Although our primary contribution is to document this striking degree of predictability of the equity premium, we also study and discuss potential explanations for our findings. To facilitate that discussion, we decompose the dependent variable in these forecasting regressions into its intraday and overnight components. We emphasize that these regressions are not meant to be interpreted as potential trading strategies. Instead, they are simply used to shed light on possible economic explanations.

The decomposition reveals that mean reversion in stock prices linked to PE occurs primarily intraday. Indeed, mean reversion is a much stronger phenomenon during the intraday period (t-statistic of -4.18), as PE is positively correlated with subsequent overnight returns.[2]

When we then forecast these two market return components with past 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 -3.98 and an R^2 of 7%, 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 occurs 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 2.82.

Interpreting this predictability using a clientele perspective naturally raises the question: Which investors are key members of these overnight and intraday clienteles? Previous research by Lou, Polk, and Skouras (2019) (LPS) argues that the overnight clientele is relatively more

[2]These results may provide interesting context for the weak link between PE and subsequent close-to-close returns documented in the literature (e.g., Goyal and Welch (2008) and Goyal, Welch, and Zafirov (2024)).

driven by the decisions of households, while the intraday clientele is more driven by the decisions of institutions. For example, they show that firm-level 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).

This interpretation is also supported by several strands of recent research. Aboody, Even-Tov, Lehavy and Trueman (2018) argue that overnight returns are a good proxy for sentiment. Barardehi, Bernhadt, Da and Warachka (2025) conclude that overnight returns are positively correlated with a popular measure of retail order flow, while Ahn, Fan, Noh and Park (2023) provide direct evidence from trader IDs that overnight returns are driven by retail order flow around the open in Korea. In addition, Berkman, Kock, Tuttle, and Zhang (2012) provide evidence that retail sentiment drives the overnight-intraday gap. There is also broader evidence that returns at specific times of the day can act as proxies for the flow of different investors. For example, Heston, Korajczyk and Sadka (2010) argue that return continuations at half-hour intervals across days is due to periodicities in fund flows and trading algorithms. Jiang (2019) and Ranaldo (2009) argue that diurnal return patterns in currencies are due to heterogeneous clienteles active at different times. From a theoretical perspective, Admati and Pfleiderer (1988) develop a theory in which diurnal trading patterns emerge endogenously through the strategic interaction of informed and liquidity traders.

We build on LPS's interpretation by studying the manner in which variables linked to households (individual investor return expectations and consumption growth) and institutions (intermediary risk tolerance) differentially forecast these two components of market returns. We find that individual investor expectations *positively* forecast subsequent overnight market returns (t-statistic of 2.59) but do not forecast intraday returns. Similarly, past consumption growth positively forecasts subsequent overnight returns (t-statistic of 2.21) but has a negative and insignificant coefficient when forecasting subsequent intraday returns. Furthermore, as we discussed earlier, macroeconomic and financial variables that summarize the broad state of the economy tend to be contemporaneously positively correlated with overnight returns, as is sentiment.

In contrast, an intermediary risk tolerance measure that accumulates shocks to the intermediary risk capacity of Adrian, Etula, and Muir (2014) negatively forecasts intraday market returns (t-statistic of -2.54). 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 when intermediaries are more active.

To flesh out this household interpretation, we further examine how variation in investor sentiment, both in the time series and across stocks, relates to the ability of smoothed overnight returns to forecast close-to-close returns. For the time-series test, we exploit Baker and Wurgler's sentiment measure. In particular, we split past months into those where market returns move in the same direction as sentiment and those where they do not. Our predictability primarily comes from the former.

For the cross-sectional test, we first document that overnight returns are responsible for the price spikes of meme stocks during the COVID period. Using this fact as motivation, we then sort stocks into groups based on their likely exposure to investor sentiment and compute separate smoothed overnight return signals from these high and low sentiment subsets. We find that predictability based on smoothed overnight market returns is driven entirely by the subset of "high-sentiment" stocks.

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 expected future intraday and overnight components of market returns. Consistent with our clientele interpretation, news about expected future overnight (intraday) returns is positively (negatively) correlated with cash-flow news. In other words, when good news about fundamentals arrives, the overnight clientele pushes 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.

We grant that the above findings are suggestive and that other explanations might be at play. However, we examine the alternative explanations that seem plausible and find clear evidence against them.[3] For example, a natural clientele that could potentially drive overnight returns consists of foreign investors. Indeed, Bondarenko and Muravyev (2023) argue that the majority of the equity premium is earned from 11:30pm – 3:30am, while Boyarchenko, Larsen, and Whelan (2023) further show that the resulting overnight drift from foreign investors arrives mostly during the hour of 2am - 3am.

Nevertheless, our tests do not support such a foreign investor interpretation. Using S&P 500 futures data, we show that the component of overnight returns driving predictability is orthogonal to the component of overnight returns explained by returns in non-US markets. Furthermore, a granular examination of overnight sub-intervals reveals that the predictive subinterval occurs *after* the time associated with the European open. Specifically, predictability is driven by US-specific returns (orthogonalized to international overnight returns) in the period

[3]We thank our referees for suggesting the alternatives we consider.

7-10am NY time, i.e., the early-morning period around the time of the US open. As discussed earlier, we also consider whether announcements might be driving our predictor (e.g. it could be that our predictability reflects systematic overreaction to announcements occurring during the overnight interval), but this is not the case. Our effect is also not related to micro-structural issues specific to ETFs which might have seemed plausible in light of recent evidence that ETF pricing may be subject to ETF-specific effects (Ben-David, Franzoni and Moussawi (2018) and Brown, Davies and Ringgernberg (2020)).

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 presents evidence supporting our interpretation of the findings. Section 6 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.[4] 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 (whereas at the firm level, LPS find that this effect is negative). Therefore, the equity premium predictability studied here is distinct from the cross-sectional patterns documented in earlier research, and it is this distinction that makes the overnight predictor effective for close-to-close returns at the aggregate level.

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

[4]For related studies at the firm level, see also Hendershott, Livdan, and Rösch (2020); Bogousslavsky (2021).

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 build on LPS' 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 market open while institutions prefer to trade near the market close. Our interpretation 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)). On the other hand, the literature raises concerns about poor out-of-sample performance. 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 significantly improve both in-sample and out-of-sample predictability.

Since that early work exploiting the information in past returns and valuation ratios about time-variation in the equity premium, many other types of predictor variables have been suggested in the literature (see Campbell (2018) for a textbook overview of this line of work). Recent research by Goyal, Welch, and Zafirov (2024) again questions whether any variable, either from the new generation of predictors or from the classic set of signals, usefully forecasts the equity premium.[5] 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 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 (2024) find have had some predictive ability historically. 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

[5] Goyal, Welch, and Zafirov (2024) conclude that "we are not confident that we can assess what variables would help us today to predict the equity premium forward-looking."

be traceable back to a reversal with respect to some component of past returns.

Our work also builds on the ideas presented 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 address 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.

3 Data and Methodology

Our core US sample spans the period from 1993 to 2023, constrained by the availability of the TAQ data, which starts in 1993. We take the SPDR S&P 500 Trust ETF, one of the most liquid financial instruments, as our primary proxy for the market index, as it allows for relatively easy calculation of a reliable open price. However, we confirm in subsequent tests that our findings are robust to the use of other market proxies, both in terms of what we predict and what we use to construct our signals.

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 valid trade prices.[7] For close prices, we use CRSP.

Following LPS, we define the intraday return, $R^M_{Intraday,s}$, as the price appreciation between

[6]The VWAP is computed from cleaned TAQ trades with positive prices and sizes and without correction, cancellation, or error flags. The first TAQ trade is defined as the first cleaned transaction during the first half-hour after the market open. For September 11, 2002 and January 8, 1996, when the market opened one hour late, we use the first half-hour after the delayed open.

[7]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.

market open and close of the same day s, and impute the overnight return, $R^M_{overnight,s}$, based on this intraday return and the standard daily close-to-close return, $R^M_{close-to-close,s}$,

$$\begin{aligned} R^M_{Intraday,s} &= \frac{P^M_{close,s}}{P^M_{open,s}} - 1, \\ R^M_{Overnight,s} &= \frac{1 + R^M_{close-to-close,s}}{1 + R^M_{Intraday,s}} - 1. \end{aligned}$$

In other words, we assume that dividend adjustments, share splits, and other corporate events that could mechanically move prices take place overnight.[8] We then accumulate these overnight and intraday returns across days in each month t:

$$\begin{aligned} R^M_{Intraday,t} &= \prod_{s \in t}(1 + R^M_{Intraday,s}) - 1, \\ R^M_{Overnight,t} &= \prod_{s \in t}(1 + R^M_{Overnight,s}) - 1, \\ (1 + R^M_{Intraday,t})(1 + R^M_{Overnight,t}) &= (1 + R^M_t). \end{aligned}$$

3.2 Smoothed Overnight and Intraday Returns

We hypothesize that there are different investor clienteles. For example, on any specific day, 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 around the market open or close, 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 overnight and intraday returns using monthly log returns (to ensure that they add up to smoothed close-to-close returns) as follows:

$$\begin{aligned} EWMA_{Overnight,t} &= \lambda log(1 + R^M_{Overnight,t}) + (1 - \lambda)EWMA_{Overnight,t-1}, \\ EWMA_{Intraday,t} &= \lambda log(1 + R^M_{Intraday,t}) + (1 - \lambda)EWMA_{Intraday,t-1}. \end{aligned} \tag{1}$$

We confirm that our results are robust to a reasonable range of smoothing parameters. For our primary analysis, we set λ equal to $\frac{1}{120+1}$, which implies a center of mass of ten years

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

and a half-life for the resulting weights of approximately seven years.[9] We choose this value as it corresponds to the ten year period that Campbell and Shiller (1988a) use to smooth earnings and covers the long-horizon reversal that Fama and French (1988a) measure up to ten years out. Furthermore, a large value of λ is necessary to have a signal with persistence comparable to PE. In our robustness analysis, we report results confirming that our main findings are robust when using other values that correspond to long-term smoothing, and we examine a wide range of parameters from $\frac{1}{24+1}$ and $\frac{1}{204+1}$.[10] In certain variants of our signal used to understand and further interpret our baseline results, we exclude returns on specific dates (e.g. dates with announcements or inconsistent direction of sentiment and returns) from the EWMA calculation, which is equivalent to setting those returns to zero on those dates.

3.3 Other Data

We use futures data from LSEG's Tick History database for the E-mini S&P 500 from its launch on 9th September 1997 until the end of 2023 to create a continuous VWAP-based return series over half hour intervals. From this, we derive returns for the overnight and intraday intervals, as well as more granular segments of the overnight interval. We also use data for the S&P 500 index from the same source.

In addition, we use data for monthly S&P 500 returns from January 1926 to December 1992 in certain pre-sample analyses and CPI for inflation adjustments from Rob Shiller's website. We also take the log smoothed price-earnings ratio PE from Shiller's website but ensure that we remove any interpolation so that the resulting variable does not use future information. We follow standard practice and lag smoothed earnings by a quarter to ensure that they are available in real time.

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 also create a smoothed earnings variable, $EWMA_{EarnGrth,t-1}$, in a manner similar to the smoothed returns defined in equation (1). To create intermediary risk tolerance (IRT), we take the intermediary factor from Adrian, Etula, and Muir (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

[9] We initialize the EWMA of each of these variables to zero at the beginning of the sample and require a four-year burn-in period before using the resulting smoothed variable as a signal.

[10] See Table III, columns (4) and (5), and Table IV, Panel E.

Greenwood and Shleifer (2014) because it has the longest history.

Our macroeconomic variables from FRED are the growth in real gross domestic product (GDPC1), the growth in personal consumption expenditures (PCE), the percentage change in the level of Industrial Production (INDPRO), growth in Private Nonresidential Investment (PNFI), the percentage change in the unemployment rate (UNRATE), the percentage change in the U.S. Dollar Index (DXY), the growth in Housing Starts (HOUST), and inflation (the percentage change in the Personal Consumption Expenditures Price Index (PCEPI)).[11] Growth in S&P 500 earnings comes from Bob Shiller's website. We also study the change in Baker and Wurgler's (2005) Sentiment measure, the change in the 90-day Treasury yield, and the shock to Intermediary Risk Capacity of Adrian, Etula, and Muir (2014). When measuring growth in flow variables such as consumption for the contemporaneous returns in Table II, we compute growth over quarter t as $(X_{t+1} + X_t)/(X_t + X_{t-1}) - 1$ to align with calendar-quarter returns. When measuring consumption growth to predict returns in Table VIII, we use the definition $(X_{t+1})/(X_t) - 1$ and lag the variable appropriately.

We download the risk-free rate for excess return calculations from Ken French's website. We follow Goyal, Welch, and Zafirov (2024) in replicating key variables from the equity premium forecasting literature, which are listed in Section 4.3.

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 1.84% while the average quarterly intraday return is 0.21%. This finding is consistent with a literature that finds that much of the equity premium is earned overnight.[12]

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 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

[11] Variable identifiers on FRED are in parentheses.

[12] 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, Kock, Tuttle, and Zhang (2009), and Branch and Ma (2012). LPS note that this effect is concentrated in large stocks.

their overnight counterpart. 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.[13] Figure 1 plots our two smoothed return components against PE.[14]

3.5 The COVID Crash, GFC, and Tech Boom/Bust

Figure 2 Panel A plots how the intraday and overnight components of market returns moved during the COVID crash and rebound of 2020. 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, which we discuss further in Section 5.[15]

We also examine two other well-known bubble/crisis episodes in recent decades through our intraday/overnight prism. Figure 2 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 institutions playing a key role in driving market prices during this episode.

Figure 2 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 during 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. In sum, in our view, the patterns in these figures are stark and support the relevance of a clientele interpretation.

3.6 Contemporaneous Correlations with Macro Variables

Table II reports the results of contemporaneous simple regressions of quarterly close-to-close returns, overnight returns, intraday returns, and the difference between overnight and intraday returns on many key macroeconomic variables.

Interestingly, we find that variables that summarize the broad economy – GDP growth, consumption growth, percentage change in the level of the Industrial Production index, and

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

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

[15] These striking patterns are a useful out-of-sample confirmation of the LPS hypothesis that households are a key member of the overnight clientele.

Investment growth – are all much more correlated with the overnight than with the intraday component of returns. To the extent that broad macroeconomic conditions are an important driver of household sentiment (that is, when these variables increase, it is reasonable for households to become more bullish on the market), these results support the view that the overnight clientele, relatively speaking, reflects more of household views on the stock market. Consistent with this interpretation, we find that the change in Baker and Wurgler's (2005) sentiment measure is positively correlated with overnight returns and negatively correlated with intraday returns.

4 Main Empirical Results

A popular view in finance is that risk tolerance / investor 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.

4.1 Predicting the close-to-close equity premium

Column (1) of Table III documents that PE has a tenuous relation with subsequent close-to-close returns, at least in our sample, with a t-statistic of only -1.80 and an R^2 of just 2.2%. 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. Statistically, the t-statistic is -5.44, almost three times the t-statistic on PE. The R^2, at 15.5%, is nearly seven times as large.

In all of the regressions in Table III, 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 3.36%. 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. In tests in Table IV Panel E, we confirm that this robustness holds across a broader range of smoothing parameter values.

Appendix Table I reports bias-corrected coefficient estimates and adjusted p-values for Table III using the method of Kostakis, Magdalinos, and Stamatogiannis (2015). We find that coefficients barely change and that all estimates remain highly statistically significant. Given that the bias is small and the conclusions are robust to these more sophisticated estimates, we report in the paper the more familiar OLS estimates and Newey-West adjusted t-statistics (we have also checked that our other key findings are also robust to using their method).

4.2 In-Sample Robustness

The in-sample evidence from Table III shows that smoothed overnight market returns forecast the equity premium and is particularly strong compared to other predictors in the literature. In Table IV, we demonstrate that this result is also highly robust, with coefficient estimates (as well as t-statistics and adjusted R^2's) remaining close to their values in our baseline regression.[16]

In Panel A, we vary the returns we forecast by replacing the excess return on the SPY ETF with several alternative, plausible measures of the equity premium and show that the key coefficient and its t-statistics remain stable. These include real returns on the SPY ETF, the percent change in the S&P 500 index minus the risk free rate, the excess return on the standard CRSP value-weight market portfolio, the excess return on the CRSP equal-weight market portfolio, and the quarterly return from investing in the front expiration E-mini S&P 500 futures contract rolled at 11 a.m. on the last Monday before expiration.

In Panel B, we instead vary our predictors, replacing the overnight and intraday returns with alternative measures and again confirm stable coefficients on our predictor. In the first two rows, our measures derive from replacing the VWAP used for our open price with (i) the price of the first trade in TAQ after 9:30 (which typically is the opening auction); and (ii)

[16]Since these robustness tests involve futures data that is not available for the entire sample, the top of Table IV not only repeats the baseline result from Table III column (2) but also re-estimates that finding for the SPY data over the different sample periods that are necessary when using futures data to construct either the LHS or RHS variables in our forecasting regression.

the open price reported in CRSP. In the third row, we instead use the open and close prices from the front E-mini S&P 500 futures contract, switching contracts for the intraday return calculation on the last Monday before expiration.

It is worth considering whether the predictability we report is driven by important announcements. We test this possibility by excluding the days on which these announcements occur from the construction of our predictor or by excluding those days from the calculation of the return being predicted. Panel C shows that our findings remain robust if we exclude from the calculation of our predictors either dates of macroeconomic announcements in general (Savor and Wilson, 2014), FOMC announcements in particular (Lucca and Moench, 2015), or earning announcements of influential firms that cluster together (using either Chan and Marsh's (2022) or Chen, Cohen, and Wang's (2022) definitions). Panel D shows that our findings are also robust to similarly excluding these dates from the calculation of the returns we are forecasting.

As discussed previously, our choice to implement decennial smoothing is intended to follow Campbell and Shiller (1988a) who smooth earnings over 10 years in their calculation of their smoothed PE ratio. This window has been motivated as appropriate for a predictor that is intended to be unaffected by business cycles and which might capture long-term reversal effects. In Panel E, we consider the sensitivity of our results to our choice of smoothing parameter and show that our predictor works well across a range of long-term smoothing parameters. As we vary the parameter from 2 years to 17 years, the absolute value of our t-statistics are always above 2.5 with R^2's always above 6.8%. This robustness is quite impressive, given that the PE ratio generates a t-statistic of only -1.8 with an R^2 of just 2.2% in Table III. Indeed, over an arguably more reasonable range of 5 to 15 years, R^2's are always five times larger than that for PE and roughly 10 times larger than those for smoothed close-to-close returns.

Furthermore, in Appendix Table II, we use smoothed close-to-close returns, rather than their overnight and intraday components, to forecast the excess return on the S&P 500. In Panel A, we report that a researcher who would have used the pre-1993 sample to study the most effective way to smooth past close-to-close returns would settle on 11 years as the appropriate parameter value. Panel B confirms that such a choice also works well in our baseline sample period. Though 8 years provides the highest R^2 (0.82%), 11 years is the second best and not much different in magnitude (R^2 of 0.72%). Our choice of a round number of 10 years seems reasonable in light of these findings.

In Panel F we consider the sensitivity of return predictability to our choice of initialization parameter. We note that we use a four-year burn-in period to limit the relevance of the initialization parameter; this panel is intended to confirm this empirically. Indeed, Panel F confirms that this is the case, as our findings are robust to a wide range of initialization values, from -20 to 120 bps/month. In all cases, the absolute value of the resulting t-statistic from our forecasting regression is 4.36 or larger, and R^2's are always greater than 10%. Thus, we conclude that our findings are robust to the choice of initialization value, at least if one uses a reasonable burn-in window.

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 V. We compile this list based on those variables that Goyal, Welch, and Zafirov (2024), 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, Gennaioli, Porta, and Shleifer, 2024), that have been shown to be promising predictors of the equity premium.[17]

The left-hand side of Panel A of Table V measures the forecasting ability of each of the above variables in isolation. For our sample, only accruals and the Gold-to-Platinum price ratio are able to predict returns at conventional levels of statistical significance. The t-statistics for these two variables are 2.45 and 2.01 respectively.

As can be seen from the right-hand side of Panel A of Table V, 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 III and the absolute value of the associated 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

[17]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, Giglio, Polk, and Turley, 2018).

and Martin's (2017) SVIX measure) come out statistically and economically significant in forecasting close-to-close market returns. As shown in the panel, a one-standard-deviation increase in $EWMA_{Overnight}$ forecasts a lower close-to-close quarterly market return of -4.22% (t-statistic = -4.36); a one-standard-deviation increase in $SVIX$ forecasts a higher quarterly market return of 2.37% (t-statistic = 2.16).

4.4 Out-of-Sample Predictability

In sub-section 4.2, we showed that the key result in our baseline predictability regression was robust. In this sub-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 (2024) 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 that out-of-sample performance is unstable or inconsistent across evaluation metrics, our predictor performs well across all the metrics they consider.

In Table VI, we show that the adjusted R^2 of a simple regression of the quarterly SPY excess return on lagged smoothed overnight returns is stable and high (around 15%) 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 (2024) is only 0.003, 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, both here and in Table IV, as well as the strong Newey-West t-statistics across all in-sample analyses confirm that the performance of our signal is stable.

Figure 3 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 VI, respectively in column 1), 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.[18] 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 VII, 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 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 the prevailing coefficient in an expanding window predictive regression.[19] 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 VI and Figure 3, divided by the five-year rolling window historical variance of excess market returns, with positions scaled inversely 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.[20] 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 (2024) – the classic buy-and-hold strategy and a quadratic utility investment strategy based on the historical mean forecast analyzed also in Figure 3. 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 7-20% 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. In results not reported, we have examined the certainty equivalent of this strategy, finding it to be statistically significant.

[18]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 (2024) 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.

[19]Goyal, Welch, and Zafirov (2024) 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.

[20]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 3).

It is worth noting that the quadratic utility predictor-driven strategies are significantly long-biased (long in 72 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 24-57% per quarter, implying high break-even transaction costs of 4-13%.

5 Economic Interpretations

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, around the market open, and others around 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. As discussed in the introduction, 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 (and other research further corroborates this clientele interpretation). In this section, we build on 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 others, we exploit the fact that intermediaries are more active at certain times of the day than others. In particular, we offer several pieces of evidence that support this interpretation.

We first return to Figure 2A that examines the COVID crash and rebound of 2020 through our clientele prism. Researchers have shown 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) find 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.[21] Thus, the patterns during COVID, which occurred after the publication of LPS as well as after the first draft of this paper, are consistent with households as a key driver of the overnight clientele.

Armed with that qualitative evidence, we then conduct empirical tests to provide evidence

[21] 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.

consistent with our economic interpretation. Our first round of tests decompose the market return on the left-hand side of the regression equation. We first examine how smoothed past overnight and intraday returns differentially forecast future overnight and intraday returns. We then add to that analysis 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 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 next examine how variation in investor sentiment, both in the time series and cross section, relates to the return predictability of smoothed overnight returns. Finally, 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.

Finally, we also consider an alternative interpretation based on foreign investors driving the overnight clientele, as well as discuss the implications of earlier evidence regarding the potential role of information arrival / earnings announcements and microstructure effects in explaining the performance of our signal.

5.1 Mean reversion intraday and mean aversion overnight

In Table VIII, we decompose the market return on the left-hand side of the regression into its intraday and overnight components.[22] In Panel A of Table VIII, 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, mean reversion in close-to-close returns that is linked to PE in general and to past overnight returns in particular, occurs primarily intraday. We view this as another key result of our work, as it provides a more granular view into the mechanism underlying our main

[22] We 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 in Table VIII. Note that we directly examine the patterns in overnight and intraday returns during 2020 in Figure 2A, discussed above.

result (i.e. that the close-to-close equity premium is predictable with overnight returns).

Panel B of Table VIII 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 focus on components of returns, e.g. in column (2), refines this result considerably, as it is clear that smoothed intraday returns are what drive the overnight continuation. One possible interpretation of the predictability of intraday and overnight returns is that the overnight clientele extrapolates information in intraday returns, which is subsequently corrected by the intraday clientele.

5.2 Macro-finance Variables

We examine three macro-finance variables that are plausibly linked to household sentiment and/or institutional trading. First, Greenwood and Shleifer (2014) show that individual investor expectations are consistent with extrapolation as they are positively correlated with past realized returns yet negatively correlated with model-based expectations of future stock returns. Second, consumption growth is a variable that reflects the intertemporal decisions of households. Finally, 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, Etula, and Muir (2014) and accumulate the shocks to back out a proxy for the *level* of intermediary risk tolerance at each point in time.

We return to Panel A of Table VIII, where the dependent variable is the intraday market return in the next quarter. Column (7) of this panel shows that IRT tracks strong intraday mean reversion. Moreover, neither $EWMA_{Overnight}$ nor $EWMA_{Intraday}$ 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.

In Panel B of Table VIII, when we return to forecasting overnight returns, we find evidence consistent with the overnight clientele reflecting household investment decisions. Column (3) of the panel shows that individual investors' expectations positively forecast subsequent overnight returns in isolation, with a t-statistic of 2.59. Moreover, this predictive power is not subsumed by $EWMA_{Overnight}$ and $EWMA_{Intraday}$ in column (4). These results suggest 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 (5) shows that consumption growth strongly forecasts subsequent overnight returns, with a t-statistic of 2.21. 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).

5.3 Household Sentiment

In Table IX, we further examine how variation in investor sentiment, both in the time series and across stocks, relates to the return predictability of smoothed overnight returns.

Panel A conducts a time-series exercise. Specifically, we divide all months in our sample into a two-by-two matrix based on (i) the previous month's Baker and Wurgler (2006) (BW) sentiment index and (ii) the current month's market return. We label months in which the BW index and market return are both above the sample median, or both below the median, as "consistent" months. Conversely, we label months in which the two measures fall on opposite sides of their respective medians as "inconsistent" months. Our conjecture is that market returns in consistent months are more likely to reflect investor sentiment, whereas market returns in inconsistent months are more likely to be driven by other factors, such as cash-flow news.

We then construct two smoothed overnight market return series: one using only consistent months and the other using only inconsistent months (i.e. the two series form two disaggregated signals that sum to our original overnight signal). We repeat the same procedure to construct two smoothed intraday market return series for consistent and inconsistent months.

As shown in Column (4) of Panel A, the coefficient on smoothed overnight market returns in consistent months is a statistically significant -3.90, with a t-statistic of -5.41, whereas the coefficient on smoothed overnight market returns in inconsistent months is over 40% smaller at -2.17. The difference between the two coefficients is statistically significant at the 10% level.

Panel B conducts a cross-sectional test. At the end of each month, we sort stocks into groups based on their likely exposure to investor sentiment. Specifically, we rank all stocks into percentiles using three stock characteristics: daily return skewness, daily Fama-French three-factor idiosyncratic volatility, and the maximum daily return measure of Bali, Cakici, and Whitelaw (2011). We then sort stocks into deciles based on the average of these three percentile rankings. Finally, we construct two smoothed overnight market return series: one based on the subset of "high-sentiment" stocks and the other based on the subset of "low-sentiment" stocks.

Before describing the results, we first motivate this cross-sectional test with a figure documenting that firm-level evidence of the overnight/intraday patterns in meme stocks echo the aggregate patterns around the tech and COVID booms/busts. Figure 4 plots the intraday, overnight, and total cumulative returns from January 2020 to January 2022 for four well-known meme stocks: AMC; GameStop; Bed, Bath, and Beyond; and Koss. It is very clear from these graphs that the explosive price behavior associated with households trading these stocks occurs primarily in the overnight return. Of course, meme stocks are particularly striking examples of high-sentiment stocks; our hope is that we find a similar pattern more systematically using our cross-sectional test.

In Column (1) of Panel B, we define high- and low-sentiment stocks as those in the top and bottom 20% of the sentiment ranking, respectively. In Column (2), we use a 30% cutoff, and in Column (3), a 50% cutoff. Across all three columns, the return predictability of smoothed overnight market returns is driven entirely by the subset of stocks most likely to be affected by investor sentiment. For example, as shown in Column (3), the coefficient on smoothed overnight market returns for the top 50% high-sentiment stocks is -5.42, with a t-statistic of -3.14, while the coefficient for the bottom 50% low-sentiment stocks is 2.56, with a t-statistic of 1.42. The difference between the two is statistically significant at the 5% level.

In sum, Table IX shows that the predictive power of smoothed overnight returns for future market returns is concentrated precisely in settings where overnight returns are more likely to reflect household sentiment: in months when overnight market returns align with investor sentiment, and among stocks that are more sentiment-sensitive. This evidence supports our interpretation that smoothed overnight market returns reflect persistent sentiment-driven trades from the household sector rather than from other clienteles.

5.4 Decomposing Discount-rate News

Finally, we 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 $r^M_{Intraday}$, the log intraday market return in excess of $(6.5/24) \times$ log risk-free rate, and $r^M_{Overnight}$, the log overnight market return in excess of $(17.5/24) \times$ log risk-free rate. The VAR is:

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

Since $r^M_{t+1} = r^M_{Intraday,t+1} + r^M_{Overnight,t+1}$, 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.[23]

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

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. We set ρ to $.95^{1/4}$.

Table X Panel A reports estimates of the transition matrix $\boldsymbol{\Gamma}$. The findings are broadly consistent with the results of Table III which uses simple returns. Table X Panel B shows that

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

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 (0.13). Figure 5 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 close-to-close returns and the PE ratio.

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 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.

5.5 The Potential Role of Foreign Investors

An alternative explanation of our findings is that the predictive power of smoothed overnight returns is driven by the activity of foreign investors in their own markets during this period. One reason to consider this possibility is the evidence in Boyarchenko, Larsen, and Whelan (2023) and Bondarenko and Muravyev (2023), who argue that the equity premium in the US market is earned entirely in overnight windows around the European open. Boyarchenko, Larsen, and Whelan (2023) primarily focus on the 2 - 3 am EST interval, while Bondarenko and Muravyev (2023) focus on the broader 11:30 pm – 3:30 am interval. Of course, any implication of their work for the interpretation of our findings can only be suggestive, as it can also be the case that news or flows affecting future equity premia arrive at times other than when the equity premium is earned.

We address this issue in Table XI, where we show that the component of overnight returns driving predictability is orthogonal to the component of overnight returns explained by returns in non-US markets. Furthermore, the return sub-interval containing predictive power occurs after the time associated with the European open and, more specifically, is driven by US-specific returns in the period from 7 to 10 am NY time, i.e., the early-morning period around the US open. That time frame is clearly outside the Euro open windows studied in Bondarenko and Muravyev (2023) and Boyarchenko, Larsen, and Whelan (2023).

In terms of our specific findings, column (1) of Table XI shows that smoothing lagged SPY returns over the sample for which we have data for ETF international indexes provides similar (in fact, even stronger) predictability. The t-statistic associated with the smoothed overnight return is -5.65 and the resulting R^2 is 18.8%. Column (2) of Table XI constructs our smoothed overnight (intraday) signal using the residuals of daily regressions of overnight (intraday) SPY returns on the corresponding overnight (intraday) returns of 10 highly liquid international index ETFs (for Australia, France, Germany, Hong Kong, Japan, Malaysia, Mexico, Singapore, Switzerland, and the UK). The predictability we find remains strong, indicating that our signal is driven by US-specific return variation.

To benchmark our subsequent analysis in this table, Column (3) replicates our key result using returns from the Emini S&P 500 futures market for the predictor variables (see Table IV in section 4.2 for details). Column (4) then splits the overnight period into the pre-European opening period (4 pm to midnight), the European opening period (midnight to 4 am), and the post-European opening period (4 am to 10 am). We then smooth the returns occurring only within those sub-periods when forming our predictors. We find that the coefficient on smoothed returns accrued around the European opening is both economically and statistically small (t-statistic of -0.78).

In sharp contrast, the coefficient on returns smoothed during the post-European opening period is economically and statistically significant, with a t-statistic of -4.00. Column (5) examines a more granular decomposition of the overnight period, documenting that the effect is entirely located during the 7 am to 10 am window. In fact, the coefficient during the European opening window of 1 am to 4 am is not only statistically insignificant, but of the opposite sign of our paper's key finding. Column (6) reports the result when we divide the smoothed overnight returns into only two components in order to compare the importance of the 7-10 am slice against the earlier overnight period. Our results remain striking, with a t-statistic on our predictor of -4.46 and an insignificant coefficient on the earlier component of smoothed overnight returns.

Column (7) combines the two previous techniques to provide what we view as compelling evidence against the explanation that a foreign investor clientele is responsible for our striking empirical findings. We repeat the orthogonalization approach of column (2), but with just the 7-10 am futures return on the RHS, removing any exposure with respect to the entire overnight component of those 10 non-US ETFs. We view this as a tough test; nevertheless, our results remain strong.

In summary, these results provide strong evidence against the hypothesis that our signal reflects transitory variation in prices driven by overseas markets.

5.6 Other potential explanations

Table XI column (8) excludes all days with macro announcements (Savor and Wilson, 2014) from the monthly returns used to construct the predictor. That regression shows that the smoothed non-macro-announcement component of the return on E-mini S&P 500 futures from 7-10 am negatively forecasts the subsequent quarterly close-to-close futures return with a coefficient of -3.86% (t-statistic of -4.27) and an adjusted R^2 of 16.2%. Thus, though many announcements occur during this interval, they do not seem to be driving the predictability we report.

These results are consistent with the findings presented in Table IV, Panels C and D, but focus on the 7-10 am interval. Together, the results of Table IV and Table XI make it unlikely that our predictor works because it contains information related to announcements.

In addition, the results of Table IV Panel B help to preclude that price pressure specific to the SPY ETF is the driver of our documented predictability. In sum, we find no evidence that international markets, macro- or firm-announcements, or ETF-specific microstructure effects can explain the predictability we report, while we find good suggestive evidence corroborating our interpretation that the predictability we find reflects clientele effects.

6 Conclusions

We decompose close-to-close market returns into their overnight and intraday components to reveal striking time-variation in the standard close-to-close equity premium. In particular, we show that smoothed overnight market returns negatively forecast future close-to-close market returns. Our novel finding is robust to a variety of ways of constructing our signal, is not subsumed by any competing predictors, and survives the latest out-of-sample tests proposed in the literature.

We interpret this predictability as the outcome of interactions between overnight and intraday clienteles and attempt to characterize both groups. First, we note that the predictability we document is primarily driven by smoothed overnight returns forecasting subsequent intraday returns. In contrast, we show that smoothed intraday returns positively forecast subsequent overnight returns. Second, we show that both individual investor expectations and consumption growth positively forecast future overnight market returns (but not intraday market returns), while intermediary risk tolerance negatively forecasts subsequent intraday returns. Third, we show that the predictability of smoothed overnight returns is linked to household sentiment as our predictability primarily comes from months where aggregate market returns move in the same direction as Baker and Wurgler's (2005) sentiment measure. Moreover, if we compute separate smoothed overnight return signals from subsets of high or low sentiment stocks, it is only the signal from the former that has predictive power. Fourth, a cash-flow / discount-rate news decomposition reveals that news about expected future overnight market returns is positively correlated with cash-flow news while news about expected future 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. Moreover, the empirical evidence suggests that the overnight clientele has characteristics typically associated with households while the intraday clientele has characteristics associated with institutions, in line with the findings of Lou, Polk and Skouras (2019) in a cross-sectional context. Nevertheless, we grant that other investors may be important constituents of the overnight and intraday clienteles. In particular, we consider the possibility that foreign investors are responsible for the patterns we document and provide evidence inconsistent with that interpretation. Moreover, we also consider and reject alternative interpretations of our results, showing that news announcements do not explain our results, nor is our effect driven by price movements specific to the SPY ETF, which might emerge from microstructural effects.

We hope to advance research that may benefit from our powerful signal of the equity premium. For example, in contemporaneous work (Lou, Polk, and Skouras, 2026), we show that the CAPM betas of the Fama and French (2015) 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 key variables at the quarterly frequency. SPYRF, $\text{SPYRF}_{\text{Intraday}}$, $\text{SPYRF}_{\text{Overnight}}$ are the quarterly close-to-close, intraday, and overnight excess returns on the S&P 500 ETF (SPY). To compute excess returns on the overnight or intraday component of close-to-close returns, we use a pro rata portion of the quarterly risk-free return. PE is the Shiller smoothed price-to-earnings ratio for the S&P 500 index. $\text{EWMA}_{\text{Intraday}}$, $\text{EWMA}_{\text{Overnight}}$, and $\text{EWMA}_{\text{EarnGrth}}$ are the exponential weighted moving average of monthly log intraday returns on SPY, monthly log overnight returns on SPY, and quarterly earnings growth for the S&P 500, all with a half-life of roughly seven years. In particular, $\text{EWMA}_{\text{Intraday}}$ and $\text{EWMA}_{\text{Overnight}}$ are based on a smoothing parameter value of 120. Panel A reports summary statistics of these variables, and Panel B reports the correlation matrix. The sample period is 1997Q1 to 2023Q4 for the first three variables and 1996Q4-2023Q3 for the last four variables.

Panel A: Summary Statistics

	Mean	St. Dev.	P25	Median	P75
SPYRF	0.0206	0.0853	-0.0247	0.0292	0.0710
$\text{SPYRF}_{\text{Intraday}}$	0.0021	0.0633	-0.0353	0.0041	0.0423
$\text{SPYRF}_{\text{Overnight}}$	0.0184	0.0555	-0.0010	0.0251	0.0471
PE	3.4318	0.2263	3.2894	3.4186	3.5548
$\text{EWMA}_{\text{Intraday}}$	0.0002	0.0015	-0.0010	0.0004	0.0016
$\text{EWMA}_{\text{Overnight}}$	0.0054	0.0011	0.0047	0.0054	0.0061
$\text{EWMA}_{\text{EarnGrth}}$	0.0155	0.0105	0.0146	0.0189	0.0207

Panel B: Correlation Matrix

	SPYRF	$\text{SPYRF}_{\text{Intraday}}$	$\text{SPYRF}_{\text{Overnight}}$	PE	$\text{EWMA}_{\text{Intraday}}$	$\text{EWMA}_{\text{Overnight}}$	$\text{EWMA}_{\text{EarnGrth}}$
SPYRF	1						
$\text{SPYRF}_{\text{Intraday}}$	0.75	1					
$\text{SPYRF}_{\text{Overnight}}$	0.66	0.01	1				
PE	-0.18	-0.33	0.12	1			
$\text{EWMA}_{\text{Intraday}}$	0.12	-0.10	0.31	0.58	1		
$\text{EWMA}_{\text{Overnight}}$	-0.40	-0.29	-0.26	0.62	-0.01	1	
$\text{EWMA}_{\text{EarnGrth}}$	-0.09	-0.18	0.08	0.53	0.45	0.27	1

Table II. Explaining SPY Excess Returns

This table reports quarterly regressions of SPYRF, $SPYRF_{Overnight}$, $SPYRF_{Intraday}$, and the difference (DIFF) $SPYRF_{Overnight}$-$SPYRF_{Intraday}$ on contemporaneous changes in selected macroeconomic and financial variables. The explanatory variables are GDP growth, consumption growth, the percentage change in Industrial Production, Private Nonresidential Investment growth, the change in Baker and Wurgler's (2006) sentiment index, the change in the 90-day Treasury Bill rate, the shock to Adrian et al.'s (2014) Intermediary Risk Tolerance measure, the percentage change in the unemployment rate, the percentage change in the U.S. Dollar index, S&P 500 earnings growth, Housing Starts growth, and Inflation. The sample period is 1997Q1-2023Q4. We report *t*-statistics in parentheses, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

Variable (97Q1-23Q4)	SPYRF		$SPYRF_{Overnight}$		$SPYRF_{Intraday}$		DIFF	
	coef.	Adj-R^2	coef.	Adj-R^2	coef.	Adj-R^2	coef.	Adj-R^2
GDP growth	4.41***	16%	3.96***	31%	0.33	-1%	3.62***	11%
	[4.64]		[7.08]		[0.43]		[3.76]	
Consumption growth	2.66***	10%	2.67***	24%	-0.08	-1%	2.75***	11%
	[3.52]		[5.91]		[-0.14]		[3.72]	
Industrial Production %chg	1.22**	4%	1.28***	13%	-0.06	-1%	1.35***	6%
	[2.45]		[4.16]		[-0.17]		[2.77]	
Investment growth	1.31***	8%	1.17***	16%	0.14	-1%	1.03**	5%
	[3.22]		[4.60]		[0.44]		[2.52]	
Baker-Wurgler Sentiment chg	0.01	-1%	0.04**	3%	-0.02	0%	0.06**	3%
	[0.48]		[2.05]		[-1.00]		[2.12]	
Bill Rate chg	0.04**	5%	0.04***	10%	0.00	-1%	0.03**	3%
	[2.53]		[3.58]		[0.30]		[2.05]	
Intermediary Risk Tolerance shk	-0.05	-1%	-0.08	0%	0.04	-1%	-0.12	0%
	[-0.44]		[-1.00]		[0.46]		[-1.01]	
Unemployment Rate %chg	0.04	1%	0.04*	2%	0.01	-1%	0.03	0%
	[1.31]		[1.68]		[0.23]		[0.92]	
Dollar Index %chg	-0.47**	4%	-0.16	0%	-0.31**	3%	0.15	0%
	[-2.36]		[-1.21]		[-2.09]		[0.75]	
Earn growth	0.12***	12%	0.05**	4%	0.07***	7%	-0.02	-1%
	[3.86]		[2.38]		[2.96]		[-0.61]	
Housing Starts growth	0.60***	15%	0.33***	11%	0.27**	5%	0.06	-1%
	[4.49]		[3.71]		[2.55]		[0.44]	
Inflation	-0.10	-1%	0.38	-1%	-0.35	-1%	0.73	-1%
	[-0.06]		[0.32]		[-0.26]		[0.41]	

Table III. Forecasting Excess SPY Returns

This table reports quarterly regressions forecasting SPYRF using PE, $\text{EWMA}_{\text{Overnight}}$, $\text{EWMA}_{\text{Intraday}}$, and $\text{EWMA}_{\text{EarnGrth}}$, defined in Table I. Columns (4) and (5) repeat the regression in Column (2) using versions of $\text{EWMA}_{\text{Overnight}}$ and $\text{EWMA}_{\text{Intraday}}$ based on a smoothing parameter value of 100 and 140 respectively. 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 for the dependent variable is 1997Q1-2023Q4.

	Depvar = SPYRF				
	[1]	[2]	[3]	[4]	[5]
PE	-1.51%*				
	[-1.80]				
$\text{EWMA}_{\text{Overnight}}$		-3.36%***	-3.24%***		
		[-5.44]	[-5.09]		
$\text{EWMA}_{\text{Intraday}}$		1.03%	1.23%		
		[1.29]	[1.34]		
$\text{EWMA}_{\text{EarnGrth}}$			-0.43%		
			[-0.52]		
$\text{EWMA}_{\text{Overnight}}$ (100)				-3.28%***	
				[-5.23]	
$\text{EWMAI}_{\text{ntraday}}$ (100)				0.98%	
				[1.24]	
$\text{EWMA}_{\text{Overnight}}$ (140)					-3.30%***
					[-4.71]
$\text{EWMA}_{\text{Intraday}}$ (140)					1.12%
					[1.36]
# obs.	108	108	108	108	108
Adj-R^2	2.2%	15.5%	14.9%	14.9%	14.9%

Table IV. Robustness

This table reports several variants of our baseline regression of Table III column (2), focusing on the coefficient of our proposed smoothed overnight predictor and its t-stat (we suppress coefficients on the smoothed intraday return component to focus on the coefficient of interest). In all cases, we are forecasting quarterly returns using smoothed overnight and intraday returns while examining robustness with respect to design decisions in the LHS (predictand) or RHS (predictor) variables. In the first three rows we report results for our baseline specification, differing only with respect to the subsample considered, with subsamples matched to certain regressions of subsequent panels (non-benchmark samples marked in italics). In Panel A we consider various specifications of the predictand, including in the last row the return from holding the E-mini futures for the S&P500 and rolling on the last Monday before expiration at the VWAP of the [10:59,11:00) interval (the E-mini was launched in 1997Q3, hence the slightly different sample range). Panel B reports results when the definition of overnight and intraday returns changes. Here the futures markets open and close prices are based on VWAP in the intervals [9:30,10:00) and [15:30,16:00). Panel C defines monthly overnight and intraday returns which are then smoothed to form our predictors so that they exclude those days on which there was a certain type of announcement which changes across rows. Panel D keeps the usual predictors but excludes the returns on dates with announcements from the quarterly SPY return predictand. Panel E varies the smoothing parameter and Panel F the initialization parameter used in the definition of our signals in equation (1). We report Newey-West t-statistics based on four lags next to each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively.

	Estimate	t-stat	Adj-R^2	# obs
baseline - full sample 1997Q1-2023Q4	-3.36%***	-5.44	15.5%	108
baseline - LHS futures sample 1997Q3-2023Q4	-3.34%***	-5.39	15.2%	106
baseline - RHS futures sample 2001Q3-2023Q4	-3.73%***	-4.30	17.9%	90
Panel A. Alternative specifications of holding returns (LHS)				
inflation-adjusted ETF return	-3.37%***	-5.47	15.4%	108
SP500 index minus risk free return	-3.28%***	-5.29	14.8%	108
CRSP market excess return (RMRF)	-3.49%***	-5.14	14.5%	108
CRSP equal weighted market excess return	-3.59%***	-3.40	9.1%	108
futures return	-2.87%***	-4.43	10.4%	106
Panel B. Alternative specifications of predictor returns (RHS)				
open price: first TAQ trade for SPY	-3.34%***	-5.40	15.4%	108
open price: CRSP open for SPY	-3.24%***	-4.88	13.2%	108
over & intra returns from SP500 futures market	-3.67%***	-3.60	12.3%	90

	Estimate	t-stat	Adj-R^2	# obs
Panel C. Predictor excludes returns on announcement dates				
excluding Macro announcement days (Mungo & Wilson)	-3.37%***	-4.02	14.3%	108
excluding FOMC announcement days	-3.44%***	-5.42	15.5%	108
excluding earnings announcement days (Marsh et al.)	-3.31%***	-5.22	15.8%	108
excluding earnings announcement days (Cohen et al.)	-3.30%***	-5.05	15.2%	108
Panel D. Predictand excludes returns on announcement dates				
excluding Macro announcement days (Mungo & Wilson)	-2.95%***	-4.09	12.1%	108
excluding FOMC announcement days	-3.40%***	-5.37	15.4%	108
excluding earnings announcement days (Marsh et al.)	-3.53%***	-5.74	18.3%	108
excluding earnings announcement days (Cohen et al.)	-3.39%***	-5.77	17.3%	108
Panel E. Sensitivity to predictor smoothing parameter				
2 years	-2.01%**	-2.55	6.8%	108
5 years	-2.75%***	-3.75	11.0%	108
8 years	-3.24%***	-5.09	14.6%	108
11 years	-3.34%***	-5.06	15.2%	108
14 years	-3.08%***	-3.70	12.6%	108
17 years	-2.71%***	-3.14	9.4%	108
Panel F. Sensitivity to predictor initialization parameter				
-20 bps/month	-3.25%***	-4.36	14.4%	108
10 bps/month	-3.36%***	-5.47	15.5%	108
40 bps/month	-3.23%***	-4.81	13.5%	108
60 bps/month	-3.23%***	-4.76	12.1%	108
80 bps/month	-3.38%***	-4.71	11.2%	108
100 bps/month	-3.64%***	-4.62	10.6%	108
120 bps/month	-3.97%***	-4.52	10.3%	108

Table V. Horse Races Against Other Forecasting Variables

This table reports quarterly regressions forecasting SPYRF using $EWMA_{Overnight}$ and $EWMA_{Intraday}$ as defined in Table I. 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 of 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. In Panel B, we report a kitchen-sink multiple regression that includes all the variables studied in Panel A. 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. In both panels, all forecasting variables are standardized to have a mean of zero and standard deviation of one. The sample period for the dependent variable is 1997Q1-2023Q4.

Panel A: Depvar = Future Market Returns

	Simple Regression			Multiple Regression						
	competitor			$EWMA_{Overnight}$		$EWMA_{Intraday}$		competitor		
	Coef.	*t*-stat	Adj-R^2	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Adj-R^2
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
I/K	-1.0%	-1.46	0.4%	-3.3%***	-4.29	1.0%	1.08	0.0%	-0.05	14.7%
TB	-1.1%	-1.39	0.7%	-3.4%***	-4.63	1.0%	1.27	0.1%	0.07	14.7%
EQ Iss	0.8%	1.05	-0.1%	-3.4%***	-5.30	1.0%	1.25	-0.1%	-0.17	14.7%
Accruals	1.3%**	2.45	1.5%	-3.3%***	-5.04	1.0%	1.10	0.2%	0.37	14.7%
4QCG	-1.2%	-1.68	1.2%	-4.1%***	-4.17	0.7%	0.97	1.2%	1.43	15.7%
Short Interest	-0.6%	-0.60	-0.4%	-3.7%***	-5.64	0.1%	0.12	-1.4%	-1.11	16.1%
SVIX	2.0%	1.67	4.6%	-3.0%***	-5.37	1.7%**	2.02	2.1%**	2.04	20.1%
Gold/Plat	1.7%**	2.01	3.3%	-3.2%***	-5.08	0.2%	0.18	1.2%	1.42	15.7%
LTG	-1.4%	-1.92	1.7%	-3.8%***	-4.25	0.8%	0.96	0.8%	0.98	15.1%

Panel B: Depvar = Future Market Returns	
Intercept	2.06%***
	[3.05]
$EWMA_{Overnight}$	-4.22%***
	[-4.36]
$EWMA_{Intraday}$	0.88%
	[0.56]
I/K	-0.54%
	[-0.39]
TB	0.44%
	[0.44]
EQ Iss	-1.18%
	[-1.56]
Accruals	0.73%
	[1.17]
4QCG	1.00%
	[1.04]
Short Interest	-1.72%
	[-0.95]
SVIX	2.37%**
	[2.16]
Gold/Plat	-0.72%
	[-0.53]
LTG	0.04%
	[0.04]
# obs.	108
Adj-R^2	16.9%

Table VI. Sub-Sample and Out-of-Sample Predictive Ability

This table reports statistical performance metrics for a regression forecasting SPYRF with 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 2000Q1-2023Q4 so that three-years are used for initial estimation (burn-in) before out-of-sample evaluation.

	Full Sample	Subsample 1	Subsample 2
In-sample Stability			
Adj-R^2	14.8%	15.3%	10.4%
predictor t-stat	-5.73	-4.80	-2.09
Start	31-Mar-97	31-Mar-97	30-Sep-10
End	31-Dec-23	30-Jun-10	31-Dec-23
# obs.	108	54	54
Out-of-sample Stability			
OOS R^2	16.5%		
MSE-F	36.46		
MSE-F bootstrapped p-value	0.003		
start	31-Mar-00		
end	31-Dec-23		
# obs.	96		

Table VII. Out-of-Sample Trading Strategy Performance

This table reports performance metrics for trading strategies based on out-of-sample forecasts from a regression forecasting SPYRF with the lagged smoothed overnight return. We also report performance metrics for two benchmark strategies for the sake of comparison. The first column examines a trading strategy (introduced by Goyal, Welch and Zafirov, 2024) 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 the sign of the prevailing coefficient in an expanding window predictive regression. 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 γ=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 a benchmark implementation, namely, one 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 VI.

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	7.12%***	20.32%***	15.67%***	3.05%	6.56%*
	[2.52]	[2.95]	[3.54]	[0.56]	[1.82]
SR	51.33%***	66.22%***	70.28%***	11.27%	39.00%***
	[4.73]	[5.88]	[6.17]	[1.10]	[3.68]

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)) $	0.55	1.43	0.93	1.31	1.00
Mean $	-0.09	1.08	0.71	1.31	1.00
Std $	0.70	1.75	0.88	1.14	0.00
Median $	-0.01	0.86	0.73	0.90	1.00
Min $	-1.64	-1.93	-1.14	0.38	1.00
Max $	1.37	7.34	3.48	5.20	1.00
# long	44	72	72	96	96
# short	50	24	24	0	0
quarterly turnover %	24	57	36	22	
break even t-cost %	4	13	10	5	

Table VIII. Forecasting Market Return Components: Mechanisms

This table reports regressions forecasting the intraday ($SPYRF_{Intraday}$) (Panel A) and overnight ($SPYRF_{Overnight}$) (Panel B) components of SPYRF. Forecasting variables in these quarterly regressions are PE, $EWMA_{Overnight}$, and $EWMA_{Intraday}$, defined in Table I. We also include the following additional variables as predictors: Individual Investor Expectations (IIE) obtained from AAII, quarterly consumption growth (CG), and Intermediary Risk Tolerance (IRT). IRT accumulates the intermediary risk tolerance shocks of Adrian, Etula, and Muir (2014). Covid is a dummy that is set to one when the dependent variable is measured during 2020Q2-2020Q4.

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 for the dependent variables is 1997Q1-2023Q4.

Panel A: Forecasting Intraday Excess Market Returns									
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
PE	-2.07%***								
	[-4.18]								
$\text{EWMA}_{\text{Overnight}}$		-1.85%***		-1.81%***		-1.87%***		-1.80%***	-1.82%***
		[-3.98]		[-4.38]		[-3.96]		[-4.22]	[-4.21]
$\text{EWMA}_{\text{Intraday}}$		-0.63%		-0.53%		-0.65%		-1.79%***	-1.69%***
		[-1.13]		[-0.96]		[-1.17]		[-3.55]	[-3.49]
IIE			-1.18%*	-1.04%*					-0.54%
			[-1.73]	[-1.72]					[-0.89]
CG					-0.34%	0.09%			0.23%
					[-1.15]	[0.39]			[0.77]
IRT							-1.24%**	-2.16%***	-1.99%***
							[-2.54]	[-4.30]	[-3.44]
Covid	0.28%	0.18%	-1.25%	-1.34%	-0.04%	0.30%	-1.17%	-1.08%	-1.45%
	[0.49]	[0.22]	[-1.04]	[-1.36]	[-0.06]	[0.35]	[-1.38]	[-1.40]	[-1.30]
# obs.	108	108	108	108	108	108	108	108	108
Adj-R^2	9.0%	6.9%	1.4%	8.6%	-1.6%	6.0%	1.9%	14.3%	13.3%

Panel B: Forecasting Overnight Excess Market Returns									
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
PE	0.65%								
	[1.22]								
$\text{EWMA}_{\text{Overnight}}$		-1.32%**		-1.37%***		-1.43%**		-1.35%**	-1.47%***
		[-2.30]		[-2.75]		[-2.48]		[-2.36]	[-2.71]
$\text{EWMA}_{\text{Intraday}}$		1.42%***		1.32%***		1.29%***		2.22%***	1.89%***
		[2.82]		[3.03]		[2.59]		[4.07]	[3.41]
IIE			1.16%***	1.09%***					0.72%
			[2.59]	[2.69]					[1.54]
CG					0.72%**	0.71%***			0.59%***
					[2.21]	[2.83]			[3.68]
IRT							0.27%	1.49%***	1.20%*
							[0.42]	[2.60]	[1.93]
Covid	11.60%***	9.20%***	13.16%***	10.80%***	12.43%***	10.16%***	11.90%***	10.07%***	11.75%***
	[9.52]	[8.46]	[11.04]	[9.74]	[7.12]	[6.48]	[8.62]	[8.92]	[8.73]
# obs.	108	108	108	108	108	108	108	108	108
Adj-R^2	11.6%	21.4%	14.3%	24.4%	11.8%	22.2%	10.4%	25.8%	27.1%

Table IX. Forecasting Market Returns: Household Sentiment

This table reports regressions forecasting SPYRF. Panel A reports a time-series mechanism test. We divide sample months into a two-by-two classification based on (i) the previous month's Baker and Wurgler (2006) sentiment index (BW) and (ii) the current month's market return. Months in which both variables are above their respective sample medians, or both are below their respective sample medians, are classified as consistent months. Months in which the two variables fall on opposite sides of their respective medians are classified as inconsistent months. We then construct separate smoothed overnight market return series using only consistent months and only inconsistent months. We apply the same procedure to construct separate smoothed intraday market return series for consistent and inconsistent months.

Panel B reports a cross-sectional mechanism test. At the end of each month, we sort S&P 500 stocks by their likely exposure to investor sentiment. Specifically, we rank stocks into percentiles based on daily return skewness, daily Fama-French three-factor idiosyncratic volatility, and the maximum daily return measure of Bali, Cakici, and Whitelaw (2011). All three characteristics are stock-level measures obtained from Open Asset Pricing at the portfolio-formation month. We then sort stocks based on the average of the three percentile rankings and form high- and low-sentiment-exposure portfolios. Portfolio returns are value-weighted. We construct the smoothed overnight market return series separately for the high- and low-sentiment-exposure portfolios by first forming the monthly value-weighted portfolio return series with time-varying constituents and then applying the smoothing procedure to the resulting portfolio-level return series. In Column (1), high- and low-sentiment stocks are defined as stocks in the top and bottom 20% of the sentiment ranking, respectively. Columns (2) and (3) use 30% and 50% cutoffs, respectively.

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 for the dependent variables is 1997Q1-2023Q4.

Panel A: Forecasting Excess Market Returns by Sentiment Consistency				
	[1]	[2]	[3]	[4]
$\text{Consistent}_{\text{Overnight}}$	-3.38%***	-3.17%***	-3.69%***	-3.90%***
	[-4.20]	[-3.72]	[-4.23]	[-5.41]
$\text{Consistent}_{\text{Intraday}}$	0.90%	0.71%	1.52%*	1.07%
	[1.15]	[0.89]	[1.89]	[1.46]
$\text{Inconsistent}_{\text{Overnight}}$			-1.91%**	-2.17%***
			[-2.62]	[-3.31]
$\text{Inconsistent}_{\text{Intraday}}$			-0.82%	-2.93%***
			[-1.27]	[-3.13]
BW		-0.64%		-2.68%***
		[-1.06]		[-2.86]
# obs.	108	108	108	108
Adj-R^2	0.139	0.136	0.174	0.207

Panel B: Forecasting Excess Market Returns by Stock Sentiment			
Sentiment ranking	20%	30%	50%
	[1]	[2]	[3]
$\text{High}_{\text{Overnight}}$	-4.19%***	-3.93%***	-5.42%***
	[-4.13]	[-3.63]	[-3.14]
$\text{High}_{\text{Intraday}}$	1.95%**	1.89%**	1.80%
	[2.15]	[2.02]	[1.59]
$\text{Low}_{\text{Overnight}}$	1.33%	0.74%	2.56%
	[1.14]	[0.58]	[1.42]
$\text{Low}_{\text{Intraday}}$	0.86%	0.58%	0.59%
	[0.61]	[0.44]	[0.39]
# obs.	108	108	108
Adj-R^2	0.0633	0.0908	0.0711

Table X. Cash-Flow and Discount-Rate News

This table reports a quarterly vector autoregression (VAR) and the associated Campbell (1991) decomposition of market returns into cash flow (N_{CF}) and discount rate news, with the latter being further decomposed into intraday ($N_{DR\_Intraday}$) and overnight ($N_{DR\_Overnight}$) components. The state variables in the VAR are $r_{Intraday}$, $r_{Overnight}$, $EWMA_{Intraday}$, and $EWMA_{Overnight}$. The first two variables are the quarterly intraday and overnight log S&P 500 ETF return in excess of the log risk-free rate. The last two variables are defined in Table I. 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 for the dependent variable is 1997Q1-2023Q4.

Panel A: VAR Analysis

	constant	$r_{Intraday}$	$r_{Overnight}$	$EWMA_{Intraday}$	$EWMA_{Overnight}$	Adj-R^2
$r_{Intraday}$	0.11***	-0.14	-0.07	-0.99	-19.93***	8.9%
	[3.47]	[-1.38]	[-0.68]	[-0.24]	[-3.44]	
$r_{Overnight}$	0.08***	0.05	-0.03	11.19***	-12.47**	12.8%
	[2.95]	[0.60]	[-0.31]	[3.04]	[-2.46]	
$EWMA_{Intraday}$	0.00***	0.00	0.00	0.97***	-0.16***	89.5%
	[3.44]	[-1.39]	[-0.65]	[28.20]	[-3.37]	
$EWMA_{Overnight}$	0.00***	0.00	0.00	0.09***	0.88***	82.4%
	[2.79]	[0.52]	[-0.25]	[3.03]	[20.82]	

Panel B: Cash Flow vs. Discount Rate News

News Std. Dev./Corr.	N_{CF}	$-N_{DR\_Intraday}$	$-N_{DR\_Overnight}$
N_{CF}	2.4%	0.63	-0.66
$-N_{DR\_Intraday}$	0.63	4.9%	0.13
$-N_{DR\_Overnight}$	-0.66	0.13	5.0%

Table XI. International Returns and the Smoothed Overnight Predictor

This table presents versions of our baseline regression with our overnight predictor decomposed into multiple predictors defined as smoothed components of the overnight return. All predictors are standardized to have a mean of zero and standard deviation of one. The first column reproduces our baseline analysis for 2000Q1 to 2023Q4 during which data is also available for US-traded liquid ETFs for 10 international market indexes (Australia, France, Germany, Hong Kong, Japan, Malaysia, Mexico, Singapore, Switzerland, and UK). The second column is the same, but with overnight and intraday returns that are first orthogonalized to the respective overnight or intraday components of the 10 ETF's returns (international ETF return components are calculated from TAQ data in the same way as for the SPY ETF). The residual returns are aggregated to monthly and then smoothed in the usual way. The third column reproduces our baseline analysis for 2001Q3 to 2023Q4 during which data is also available for smoothed signals based on returns from the E-mini S&P500 futures market (see row 3 of Table IV for details). The fourth, fifth and sixth columns further decompose the overnight return into returns over sub-intervals of the overnight interval. In all cases, returns are calculated using VWAPs over half hour intervals ending just before the hour stated in the name of the corresponding predictor. The seventh column is like the sixth, but with returns in the [7,10)am interval residualized with respect to the 10 ETFs' overnight component. The eighth column is like the sixth, but with all dates on which the macro announcements of Savor and Wilson (2014) occur excluded from each component of 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.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$\text{EWMA}_{\text{Overnight}}$	-3.71%***	-3.70%***	-3.67%***					
	[-5.65]	[-3.79]	[-3.60]					
$\text{EWMA}_{\text{04to10}}$ (post-Euro open)				-3.06%***				
				[-4.00]				
$\text{EWMA}_{\text{00to04}}$ (Euro open)				-1.46%				
				[-0.78]				
$\text{EWMA}_{\text{16to00}}$ (pre-Euro open)				-0.75%				
				[-0.71]				
$\text{EWMA}_{\text{07to10}}$					-4.31%**	-3.65%***	-3.60%***	-3.86%***
					[-2.46]	[-4.46]	[-3.06]	[-4.27]
$\text{EWMA}_{\text{04to07}}$					-2.55%			
					[-1.28]			
$\text{EWMA}_{\text{01to04}}$					1.98%			
					[1.02]			
$\text{EWMA}_{\text{22to01}}$					-1.60%			
					[-0.91]			
$\text{EWMA}_{\text{19to22}}$					-1.49%			
					[-1.24]			
$\text{EWMA}_{\text{16to19}}$					0.37%			
					[0.35]			
$\text{EWMA}_{\text{16to07}}$						-1.23%	-1.17%	-2.57%
						[-1.07]	[-0.95]	[-1.83]
$\text{EWMA}_{\text{Intraday}}$	1.35%	1.87%	2.92%**	2.28%	0.01%	1.63%	3.93%**	3.31%**
	[1.55]	[1.52]	[2.42]	[1.29]	[0.14]	[1.51]	[2.41]	[2.38]
# obs.	96	96	90	90	90	90	90	90
Adj-R^2	18.8%	8.3%	12.3%	10.5%	15.3%	15.4%	7.8%	16.2%

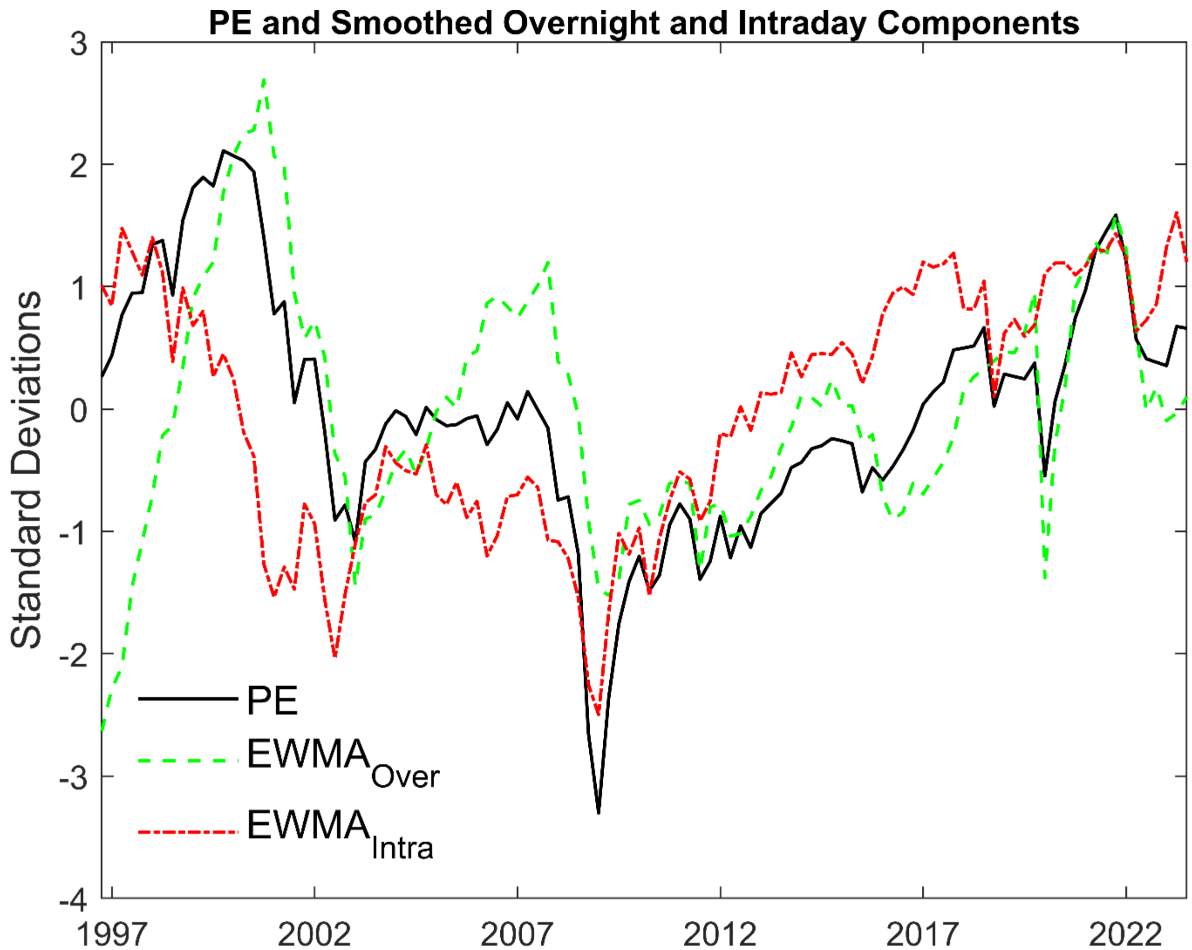

Figure 1. This figure shows the PE ratio and smoothed (exponential-weighted average) overnight/intraday returns for the period 1997-2023. All variables standardized to mean of zero and standard deviation of one.

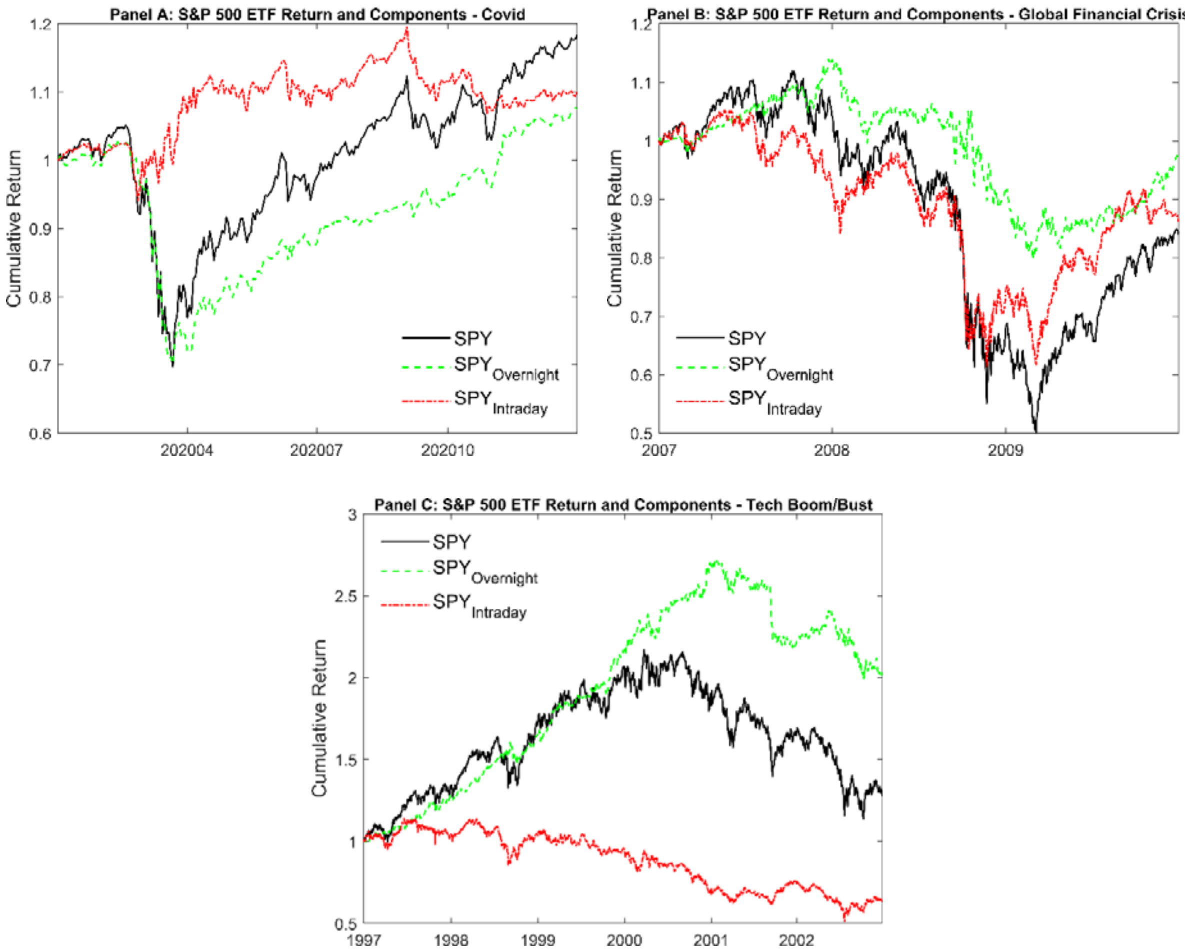

Figure 2. This figure plots the cumulative returns to the SPY S&P 500 ETF ("SPY", black line), an investment in SPY during only overnight periods ("$\text{SPY}_{\text{Overnight}}$", dashed green line), and an investment in SPY during only intraday periods ("$\text{SPY}_{\text{Intraday}}$", dotted red line). Panel A plots the period of Covid (1/2/2020—12/31/2020); Panel B plots the period of the Global Financial Crisis (1/03/2007—12/31/2009); and Panel C plots the period of the Tech Boom and Bust (1/2/1997—12/31/2002).

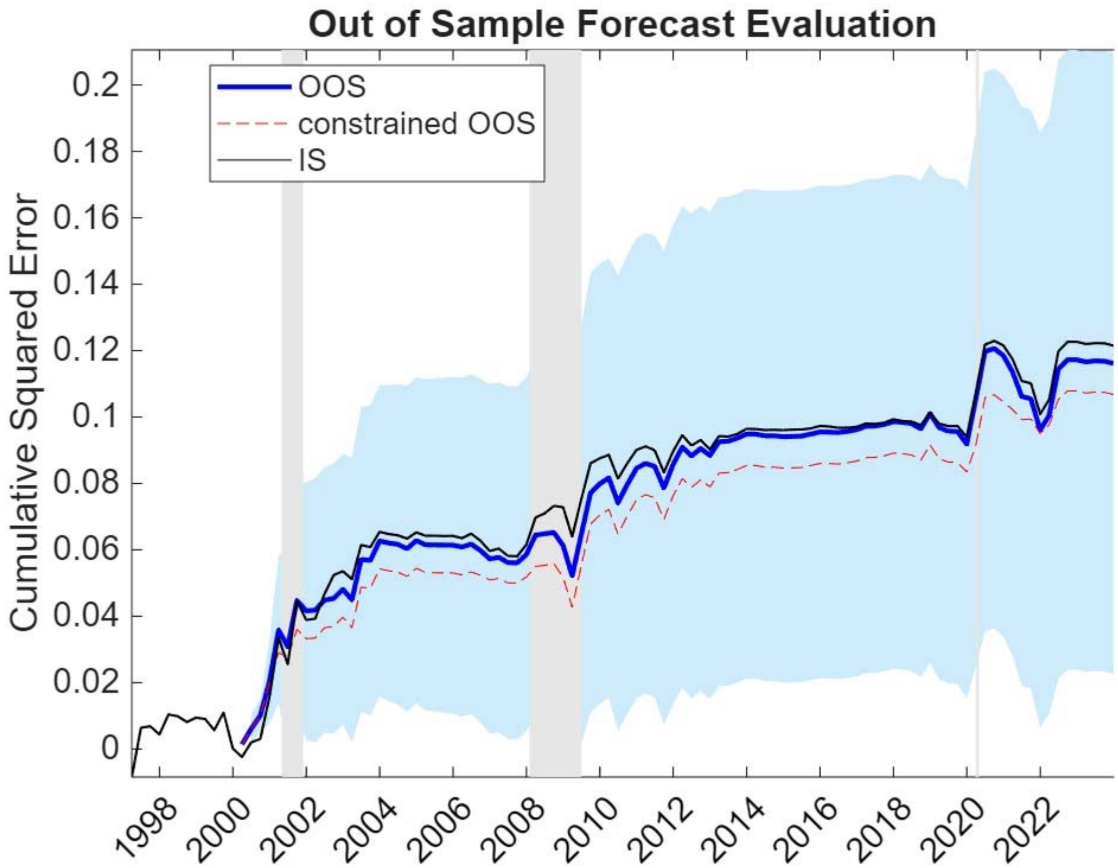

Figure 3. This figure plots the cumulative squared forecast error from our smoothed overnight predictor minus the cumulative squared forecast error from a benchmark forecast based on the historical mean. The thin black line plots that comparison for in-sample (IS) forecasts, the thick blue line plots 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.

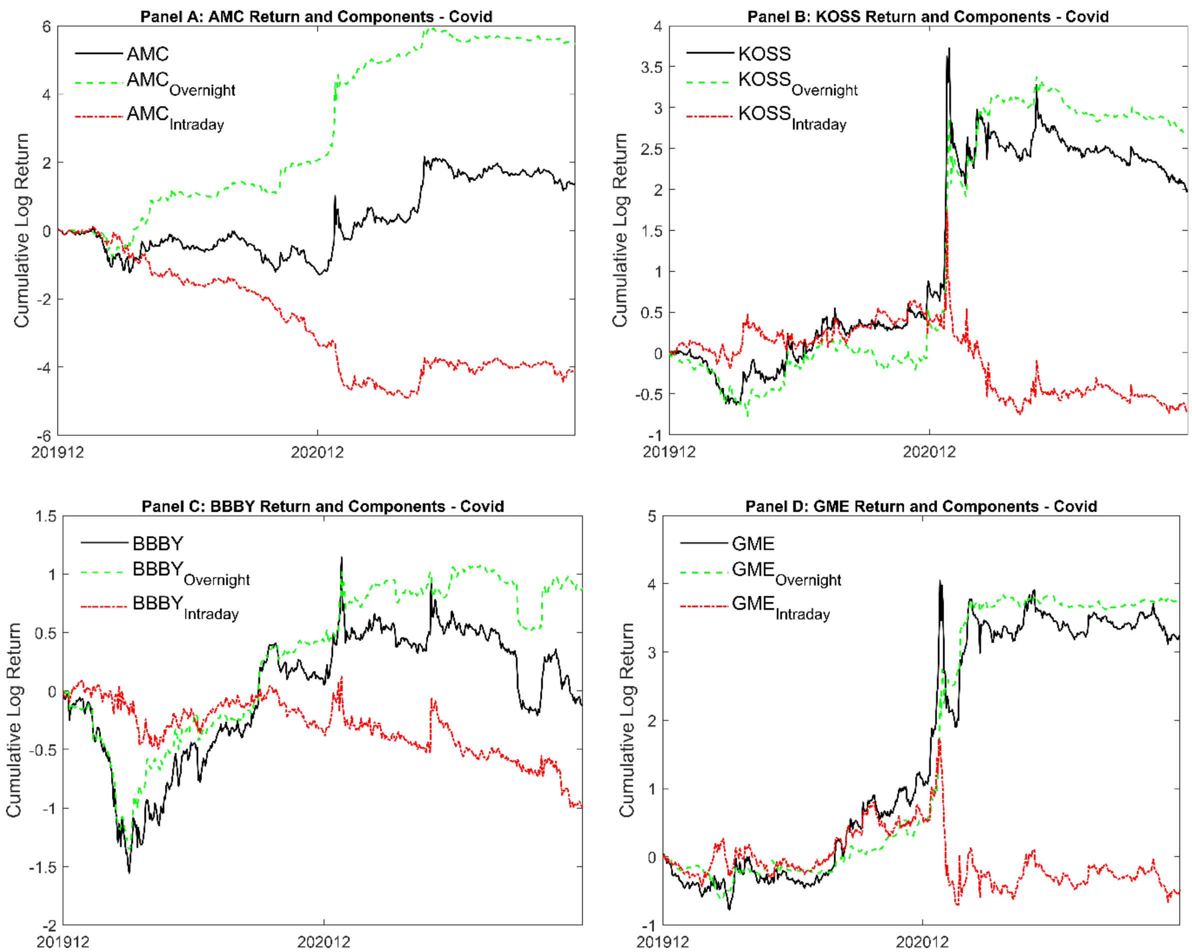

Figure 4. This figure plots the cumulative log return to a meme stock, (solid black line), an investment in that stock during only overnight periods (dashed green line), and an investment in that meme stock during only intraday periods (dotted red line) over the 1/2/2020—12/31/2021 period. The meme stocks are AMC Entertainment Holdings (Panel A: AMC), Koss Corporation (Panel B: KOSS), Bed Bath & Beyond Inc (Panel C: BBBY), and GameStop Corp (Panel D: GME).

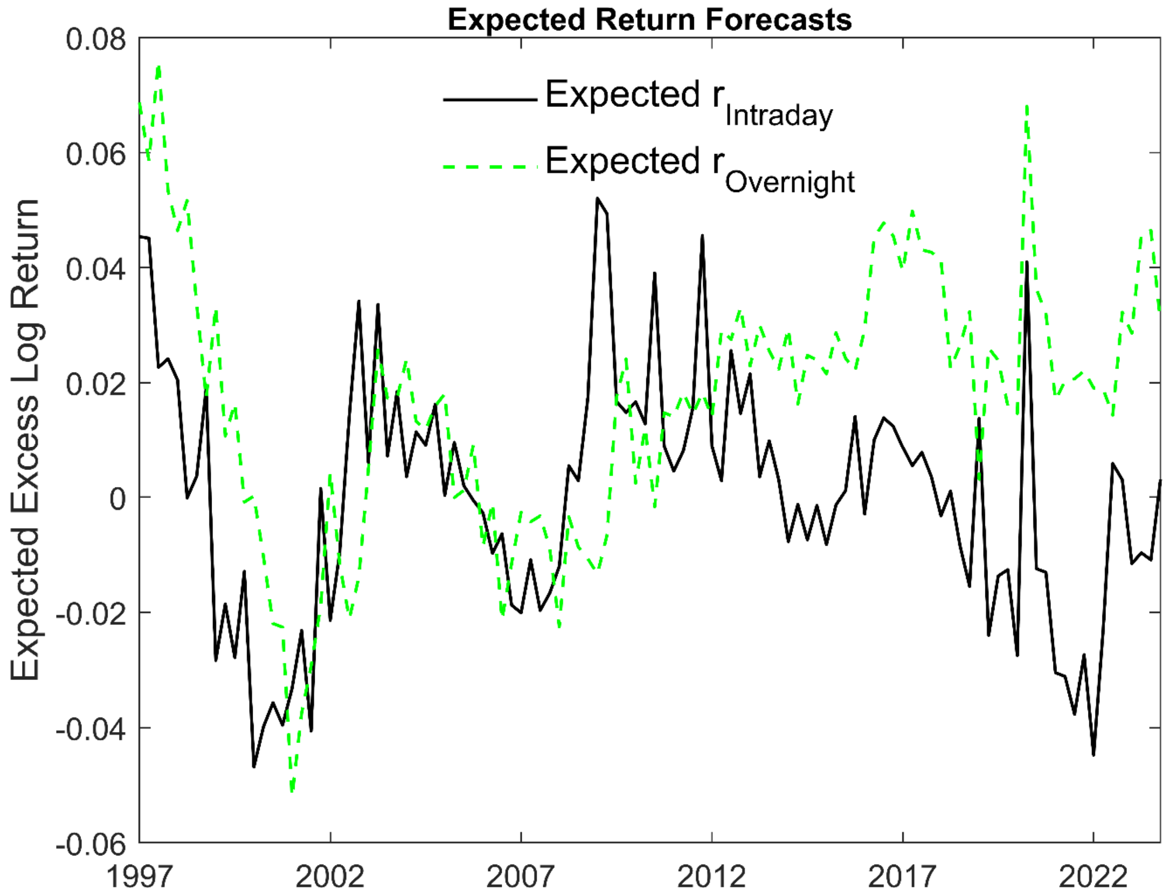

Figure 5. The figure shows the time-series of expected overnight and intraday returns from the VAR in Table X.

Appendix Table I. Forecasting Excess SPY Returns: Bias-adjusted Estimates

This table presents the same regressions as Table III, but with bias adjusted estimates. This table reports quarterly regressions forecasting SPYRF using PE, $EWMA_{Overnight}$, $EWMA_{Intraday}$, and $EWMA_{EarnGrth}$, defined in Table I. Columns (4) and (5) repeat the regression in Column (2) using versions of $EWMA_{Overnight}$ and $EWMA_{Intraday}$ based on a smoothing parameter value of 100 and 140 respectively. All independent variables are standardized to have a mean of zero and standard deviation of one. We report bias-adjusted coefficient estimates and *p* values based on the method of Kostakis, Magdalinos, and Stamatogiannis (2015) below each estimate, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period for the dependent variable is 1997Q1-2023Q4.

LHS: 97Q1-23Q4	Forecasting Excess SPY Returns				
	[1]	[2]	[3]	[4]	[5]
PE	-5.42%				
	[0.14]				
$EWMA_{Overnight}$		-3.42%***	-3.30%***		
		[0.00]	[0.01]		
$EWMA_{Intraday}$		1.00%	1.15%		
		[0.21]	[0.18]		
$EWMA_{EarnGrth}$			-0.34%		
			[0.73]		
$EWMA_{Overnight}$ (100)				-3.08%***	
				[0.00]	
$EWMA_{Intraday}$ (100)				0.008	
				[0.30]	
$EWMA_{Overnight}$ (140)					-3.80%***
					[0.01]
$EWMA_{Intraday}$ (140)					1.28%
					[0.13]
# obs.	108	108	108	108	108
Adj-R^2	2.2%	15.5%	14.9%	14.9%	14.9%

Appendix Table II. Smoothing-Parameter Sensitivity: Close-to-Close Returns

This table reports variants of our baseline regression of Table III column (2) with the predictor based on regular close-to-close returns rather than overnight and intraday components. In all cases, we are forecasting quarterly excess returns to the S&P500 using smoothed monthly returns for various smoothing parameters across rows and distinct samples in Panel A (1930Q1 to 1996Q4) and Panel B (1997Q1 to 2023Q4). The S&P500 return data are from Robert Shiller's website. We report Newey-West t-statistics based on four lags next to each estimate.

Panel A. Sensitivity to close-to-close smoothing parameter (pre-sample)

	Estimate	t-stat	Adj-R^2	# obs.
2 years	-1.18%	-0.92	0.9%	284
5 years	-1.27%	-1.16	1.1%	284
8 years	-1.28%	-1.26	1.1%	284
11 years	-1.28%	-1.32	1.1%	284
14 years	-1.26%	-1.34	1.1%	284
17 years	-1.22%	-1.32	1.0%	284

Panel B. Sensitivity to close-to-close smoothing parameter (baseline sample)

	Estimate	t-stat	Adj-R^2	# obs.
2 years	-0.49%	-0.54	-0.6%	108
5 years	-0.97%	-1.16	0.4%	108
8 years	-1.13%	-1.39	0.8%	108
11 years	-1.10%	-1.36	0.7%	108
14 years	-0.98%	-1.22	0.4%	108
17 years	-0.86%	-1.06	0.1%	108