Return Extrapolation and Day/Night Effects*

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Abstract

We propose that differences between overnight and daytime returns are the result of return extrapolation. After high daytime returns, morning order imbalances are high in the first 15 minutes of regular trading the next day, which is consistent with higher overnight returns. The effect is asymmetric, with positive returns having larger response than negative returns, and it is stronger in more overpriced stocks and stocks with more retail interest. At the portfolio level, extrapolative effects can explain most of the cross-sectional variation in the "tug of war" between overnight and daytime returns. Extrapolative trading is also consistent with the upward sloping relation between market beta and average overnight returns.

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1 Introduction

In recent years, a variety of surprising intraday patterns in average stock returns have been identified. Kelly and Clark (2011) observe that the stock market, as a whole, only tends to appreciate overnight. Lou et al. (2019) show, in the cross section, that stocks with relatively high past overnight returns tend to exhibit similar performance going forward, and that characteristic-sorted portfolios typically have average daytime and overnight returns that are of opposite sign. Hendershott et al. (2020) find that the CAPM holds overnight, failing only during the day.

Lou et al. (2019) argue that the "tug of war" between daytime and overnight returns is driven by opposing clienteles, who systematically trade against one another in the morning and reverse their trades in the afternoon. While this is a plausible explanation, we argue that a behavioral foundation is missing. It is unclear why individuals tend to buy stocks with certain characteristics in the morning and whether/how institutions behave differently in this regard.

Other existing explanations for these patterns focus on investor rationales for closing positions prior to the end of the day. Bogousslavsky (2021), for example, hypothesizes that arbitrageurs avoid overnight holdings because of greater risk, higher margin requirements, and the requirement to pay stock lending fees. Similarly, Hendershott et al. (2020) suggest that the risk of holding high beta positions may only be undesirable during periods of market closure.

While these explanations have substantial appeal, they are lacking in some respects. The profitability of daytime arbitrageurs implies that other investors take losses as the result of the intraday timing of their trades, but these theories do not explain why these investors are prone to this error. And while overnight risk, margin, and lending fees are significant concerns for some market participants, most investors hold positions at longer horizons, making widespread concerns about overnight holdings less plausible.

In this paper, we propose a new explanation of these intraday patterns built on three well-accepted stylized facts. One is that investors, on average, display extrapolative beliefs. The second is that unsophisticated investors tend to trade in the morning. The third is that short selling is relatively uncommon, either as the result of constraints or preferences. When combined, these three components suggest that traders with extrapolative beliefs may have a tendency to trade in the morning, driving up prices at the start of the day when past returns are positive. Negative past returns have relatively little effect, as the result of short selling constraints, producing unconditionally high opening prices.

There is ample evidence that investors possess extrapolative beliefs. They appear to extrapolate their own performance (Vissing-Jorgensen 2003), the performance of the companies they work for (Benartzi 2001), and the performance of the market as a whole (Greenwood and Shleifer 2014). More recently, Da et al. (2021) find evidence that investors extrapolate the returns on individual stocks at a weekly horizon. In his recent review article, Barberis (2018) identifies extrapolation as one of the three key behavioral components that can explain a variety of findings regarding asset prices and trading volume.

The idea that extrapolative trading would disproportionately take place in the morning follows from the results of Berkman et al. (2012) and Lou et al. (2019), who suggest that nonprofessional traders are more likely to trade in the morning, and from Da et al. (2021), who find that nonprofessionals are more prone to extrapolative biases. Other indirect evidence further suggests that such exptrapolative trading can result in large price dislocations at the open. The opening minutes of the market is a period of high volume (Jain and Joh 1988) and high bid-ask spreads (Brock and Kleidon 1992). Della-Corte et al. (2016) find that opening prices exhibit much stronger short-term reversal than do closing prices.

For extrapolation to have unconditional effects on opening prices, asymmetry in the response to positive and negative past returns is necessary. Motivated by Miller (1977), studies such as Jones and Lamont (2002) and Asquith et al. (2005) find that short-sale constraints lead to overpricing. While evidence is limited on the constraints to short selling faced by different classes of investors, Gamble and Xu (2017) report that only 13% of the retail investors in their sample sell short. Even among investors with margin accounts, the number is still just 24%. While it is difficult to say whether the infrequency of short selling is the result of true constraints or other factors, these statistics suggest that the response of nonprofessional investors to any negative signal will be muted.

The combination of extrapolative beliefs and short sale constraints is also central to the model of Barberis et al. (2018). In that model, in which extrapolative beliefs lead to asset market bubbles, short sale constraints serve two purposes. One is to eliminate the possibility of "anti-bubbles," in which prices persist below their fundamental values. The other is to amplify extrapolation effects by causing rational traders to exit the market once the bubble has become severe. In this paper, one may view routinely inflated opening prices as a sequence of "mini bubbles" that are small enough to not require the amplification provided by short selling constraints on rational traders.

We examine extrapolative effects in stocks and portfolios. At the stock level, we find that morning order imbalances are strongly positively related to lagged daytime returns. The relationship weakens or turns negative when we examine order imbalances later in the day. Consistent with this observation, higher lagged daytime returns predict higher overnight returns, though this finding requires us to compute lagged returns over an interval that ends some time before the close. Moreover, these effects are asymmetric, with positive lagged returns having a much larger impact than negative returns, consistent with the presence of constraints on short selling.

A comparison of the overnight returns on equally weighted and value weighted portfolios suggests that extrapolative trading is more apparent in larger stocks. This may be due to extrapolative trading being stronger in those stocks, but it could also be the result of countervailing liquidity effects being weaker.

Using the mispricing measure of Stambaugh et al. (2015), we find that extrapolative trading appears to be stronger for overvalued stocks. It is also stronger for stocks favored by retail traders, where we measure retail trading using the approach of Boehmer et al. (2021). Lastly, we follow Da et al. (2011) by using Google search volume as a proxy for retail attention and find similar effects. Each of these factors makes morning order flows more responsive to lagged daytime returns and afternoon order flows less responsive, and each leads to a stronger relationship between overnight and lagged daytime returns.

We also find substantial evidence of extrapolation in portfolios. Using 130 decile portfolios corresponding to the 13 stock characteristics studied by Lou et al. (2019), we document relationships between portfolio-level order flow and portfolio returns that are similar to those found for individual stocks. We argue that the asymmetry between positive and negative returns observed for stocks should manifest itself as a sensitivity of order flows and returns to lagged return dispersion. We show significant evidence of this effect. Return dispersion is positively related to next day order imbalances, most strongly in the first few minutes of the day. Consistent with this observation, it is also positively related to overnight returns but negatively related to subsequent daytime returns.

For long/short portfolios formed on the basis of the same 13 characteristics, we find that the "tug of war" of Lou et al. (2019), or the difference between overnight and daytime returns, is strongly predictable for the majority of the 13 portfolios, either using the lagged market return, lagged return dispersion, or both. Portfolio-level order imbalances are similarly predictable. Providing a consistent view, the anomaly portfolios whose overnight returns are most predictable also tend to have the most predictable order imbalances. A particularly important finding is that the anomaly portfolios whose overnight returns are most predictable using lagged intraday returns or return dispersion also exhibit the largest differences between average overnight and daytime returns. In other words, there appear to be a very strong link between the "tug of war" effect of Lou et al. (2019) and the strength of extrapolative trading.

We then revisit the finding of Hendershott et al. (2020), who report that the price of market beta is positive in overnight returns but not in daytime returns. Rather than being the result of risk preferences, as Hendershott et al. (2020) suggest, we argue that this pattern is more likely the result of investors' extrapolative beliefs about market returns. When lagged market returns are high, extrapolative traders expect even higher market prices. Therefore, next day morning prices tend to be high, especially for high-beta stocks, driving up their overnight returns but leading to a daytime return reversal.

Consistent with this hypothesis, we find that the relation between market betas and overnight returns is upward sloping only following positive market returns. When past returns are negative, high beta stocks have lower overnight returns. The latter effect is weak, however, as the result of short selling constraints. Unconditionally, therefore, overnight beta is associated with higher average returns.

We complete our portfolio-level analysis with an examination of the market portfolio. We find that morning order flows show a strong tendency to follow lagged market returns, though this result is sensitive to what controls are in place. Lagged daytime returns also forecast higher nighttime market returns and lower daytime returns, consistent with extrapolation-caused price pressure.

Our final result sheds light on differences in the degree of extrapolative trading between retail and professional traders. We use the approach of Boehmer et al. (2021) to identify retail order imbalances, and we use intermarket sweep orders to proxy for institutional trades. We find that both retail and institutional traders behave in a manner consistent with extrapolative beliefs. For retail, extrapolative order flow is concentrated near the open, while institutional traders exhibit extrapolative tendencies at the start and the end of the day. More importantly, it is the retail investors whose morning trading respond asymmetrically to lagged returns, suggesting that unconditional differences between daytime and overnight returns are retail-driven.

Our paper adds to the growing literature on extrapolative trading in asset markets. Early models of extrapolative trading include Cutler et al. (1990) and De Long et al. (1990), who show that the existence of feedback traders generates positive short-term return autocorrelation, overreaction to news, and asset market bubbles. There is now a substantial literature documenting empirical evidence of extrapolative beliefs, with Greenwood and Shleifer (2014) showing evidence of extrapolation of market returns and Da et al. (2021) showing extrapolative beliefs about the cross-section of stock returns. While previous work has demonstrated the importance of extrapolative trading in a number of settings, we believe that we are the first to show that it has implications for intraday market behavior.

Our paper also relates to the literature examining intraday patterns in the stock market. Early work found intraday U-shaped patterns in volatility (Wood et al. 1985; Harris 1986), volume (Jain and Joh 1988), and bid-ask spreads (McInish and Wood 1992). Both Wood et al. (1985) and Harris (1986) also find evidence of higher returns at the beginning and the end of the day.

More recently, Heston et al. (2010) find evidence of intraday periodicity, in that stocks that performed relatively well in a certain half hour interval are likely to repeat their good performance in the same interval on subsequent days. Gao et al. (2018) show that the market return in the first half hour of trading positively forecasts the return in the last half hour. Bogousslavsky (2016) argues that both of these findings can be explained by infrequent rebalancing trades.

The first finding of large differences between daytime and overnight returns appears to be Kelly and Clark (2011) for market returns, while Berkman et al. (2012) find cross-sectional variation. Lou et al. (2019) show that return differences are observed in long-short portfolios, attributing the differences to clientele effects. Hendershott et al. (2020) find greater overnight returns for high beta stocks, suggesting that market beta risk is priced overnight. Bogousslavsky (2021) argues that all of these effects are driven, at least in part, by the desire of arbitrageurs to exit positions before the end of the day. Relative to this literature, our contribution is to show that the "tug of war" between daytime and overnight returns is highly predictable and to provide a new interpretation of existing results based on extrapolative trading.

In the next section, we discuss data and methodology. Section 3 examines evidence of extrapolative trading at the individual stock level, while Section 4 studies portfolios. Section 5 concludes.

2 Data and methodology

We examine returns and order imbalances on U.S. common stocks from 1993 to 2021. We base both variables on high frequency trade and quote data. We use Trade and Quote (TAQ) data over the 1993-2014 sample period and Polygon data from 2015-2021. Both data providers supply a record of all transactions in the U.S. equities market as well as the National Best Bid and Offer (NBBO) prices. We use CRSP to adjust overnight returns for dividends, splits, and other corporate actions.

Our main return measures approximately capture appreciation over the day and at night. Following Bogousslavsky (2021) and others, we compute returns based on bid-ask midpoints and treat 9:45am Eastern Time as the start of the day, which avoids noise due to noisy quotes in the first few minutes of the day. We end the day at 3:59pm to avoid quotes that may widen abruptly at the end of the day. The day return on day t is therefore the return from 9:45am to 3:59pm. The day t night return is from 3:59pm on day $t-1$ to 9:45am on day t.[1]

[1] On days when regular trading ends at 1:00pm (typically the day before a major holiday), the end of the day is taken as 12:59pm.

The daytime return on day t for stock i is simply

$$R(9{:}45 \text{ to } 3{:}59, t, i) = \text{midpoint}(3{:}59\text{pm}, t, i)/\text{midpoint}(9{:}45\text{am}, t, i) - 1, \tag{1}$$

while the return from 3:59pm on day $t-1$ to 9:45am on day t follows the formula used by CRSP to calculate returns:

$$\begin{aligned} R(3{:}59 \text{ to } 9{:}45, t, i) = &\left((1 + \text{facpr}(t, i)) \times \text{midpoint}(9{:}45\text{am}, t, i) + \text{dividend}(t-1, i)\right) \\ &/ \ \text{midpoint}(3{:}59\text{pm}, t-1, i) - 1, \end{aligned} \tag{2}$$

where facpr(t, i) denotes the price adjustment factor from CRSP, which corrects for stock splits.

Our sample covers common stocks traded on NYSE, Nasdaq, and AMEX. We exclude stocks whose market capitalizations fall below the 20^{th} percentile of NYSE stocks and stocks whose share prices fall below \$5 at the end of the previous calendar month.

Aside from returns, our other major variable of interest is order imbalance. Following Lee and Ready (1991), we designate each trade as either a buy or sell depending on whether the price of the transaction is above or below the previous NBBO midpoint. Specifically, following Holden and Jacobsen (2014), we compare the trade price against the midpoint that prevailed one second earlier. When the transaction price and midpoint are equal, we classify the trade based on the "tick test," which compares the transaction price to the most recent (but different) price.

We impose a number of filters when using tick data. We exclude transactions from the opening and closing crosses, corrected trades, and a handful of unusual trade conditions that mostly indicate a transaction that did not occur at the time reported.[2] We exclude

[2] We exclude bunched trades (TAQ code B/Polygon code 4), bunched sold trades (G/5), average price trades (W/2), Rule 155 trades (K/23), sold last trades (L/30), and sold out of sequence trades (Z/33). We also exclude Rule 127 trades (TAQ code J) and pre- and post-market close trades (TAQ code T) from TAQ data, though there is no similar trade condition in Polygon.

observations for which the bid or ask price is missing or when the ask is not greater than the bid. We also eliminate large reversals, defined as transactions prices that are more than 25% greater than or less than both the previous and subsequent transaction.

We construct order imbalance measures over different time intervals by taking the difference between buy and sell volume and dividing by shares outstanding. In addition, we express each imbalance measure on an hourly basis by dividing by the number of hours within the interval over which imbalance is computed.

When we study portfolio returns using time-series regressions in Section 4, we calculate aggregate order imbalances by taking value-weighted averages of the stock-level imbalances. In addition, to limit the impact of long-term trends in market microstructure, we divide these aggregate order imbalances by the 200-day moving averages of aggregate turnover rates, where the aggregate turnover rate on each trading day is the value-weighted average of the stock-level turnover rates.

Finally, we include data on the same 13 firm characteristics examined by Lou et al. (2019). Size is the market capitalization at the end of the previous month. Market betas are calculated using daily stock and market returns over the lagged 12 months. For each regression, we require at least 150 valid daily observations, and we also apply the method proposed by Dimson (1979) with five lags of daily returns. Monthly idiosyncratic volatilities are calculated as the standard deviations of the residuals of the Fama-French three-factor model, following Ang et al. (2006).

Monthly turnover rates are defined as trading volume divided by the number of shares outstanding. To address the double-counting issue with Nasdaq stocks, we divide their volumes by 2 prior to February 2001, by 1.8 between February and December 2001, and by 1.6 in 2002 and 2003.

Momentum is the cumulative stock return from month $t-13$ to month $t-2$ when we study daily stock returns in month t, and the reversal effect is captured by the stock return in month $t-1$. We obtain post-earnings drift and industry momentum from Andrew Chen's website.

The variables described so far are updated at the monthly frequency. The following variables related to firm fundamentals are updated at the annual frequency, primarily using COMPUSTAT annual items. Corporate investments are calculated as the percentage annual change in total assets (AT). Gross profitability is given by the ratio between the gross profits (GP) and total assets of the same fiscal year. Accruals are given by the following formula: [Change in current assets (ACT) + Change in cash holding (CH) − Change in current liabilities (LCT) + Change in debt in current liabilities (DLC) + change in income tax payable (TXP) − Depreciation (DP)]/Average total assets over the two years. The book value in book-to-market ratio is given by the stock holdings' equity (SEQ) + deferred taxes (TXDB) + investment tax credit (ITCB) − Preferred stocks (PSTKRV). Net issuance is the change in the logarithm of adjusted number of shares outstanding.

3 Stock-level extrapolation

In this section, we ask whether past returns forecast the cross section of order imbalances and returns. For order imbalances, our focus is on patterns around the open, but we also examine the rest of the day. For returns, we are mainly interested in nighttime returns.

Our primary predictor is the lagged daytime return. We focus on the daytime return, as opposed to the more common close-to-close return, for several reasons that have mostly to do with the return regressions we present below.

In particular, the strong evidence presented by Lou et al. (2019) suggests that high average overnight returns predict higher future overnight returns. The intraday periodicity found by Heston et al. (2010) suggests that the most recent overnight return is likely to be particularly predictive. Both papers argue that these effects may be driven by autocorrelated order flows. Were we to find that full day returns, which include overnight returns, predict future overnight returns, it would be difficult to rule out that persistence in overnight returns was the explanation. Similarly, our main focus is on predicting nighttime returns because of the difficulty of distinguishing extrapolation from other explanations in explaining evidence on daytime-to-daytime return continuation.

In contrast, existing results do not suggest the positive relation between daytime and subsequent overnight returns that the extrapolation hypothesis suggests. If anything, the results of Lou et al. (2019) suggest that a negative relation is more likely. A negative relation is also consistent with the well known tendency of stocks to exhibit short-run reversal (Jegadeesh 1990, Lehmann 1990).

A secondary reason for using daytime returns as our primary predictor relates to our maintained hypothesis that unsophisticated investors tend to trade at the open. If these investors traded daily at this time, then they might have already acted based on the lagged overnight return. The daytime return therefore represents information that was not available prior to their most recent trading episode.

3.1 Extrapolation evidence from stock-level order imbalances

We begin in Table 1 with an examination of stock-level order imbalances (Imb). Panel A reports results of Fama-MacBeth regressions of the form

$$\begin{aligned}\text{Imb}(\mathit{interval}, t, i) \;=\; & \alpha \;+\; \beta\; R(\text{9:45 to 3:59}, t-1, i) \;+\; \delta_1\; \text{Imb}(\text{9:30 to 9:45}, t-1, i) \\ & +\; \delta_2\; \text{Imb}(\text{9:45 to 10:30}, t-1, i) \;+\; \delta_3\; \text{Imb}(\text{10:30 to 4:00}, t-1, i) \;+\; \epsilon(t, i), \quad (3)\end{aligned}$$

where *interval* is either 9:30-9:45, 9:45-10:30, or 10:30-4:00. Our primary interest is on the coefficient β, which we interpret as a measure of potential extrapolative trading. Coefficients on lagged order imbalances are always positive and significant. However, because they are not our main focus, we do not report these coefficients in the table.

The R-squares in Table 1 are designed to capture cross-sectional fit and are computed based on the suggestion of Lewellen (2015). We compute fitted values using the averaged Fama-MacBeth coefficient estimates, but we cross-sectionally demean both the errors and the dependent variables in each period. Loosely speaking, this R-square represents the improvement in fit from going from a model with time fixed effects only to a model with both time fixed effects and constant betas with respect to some set of predictors. We report these R-squares for all other Fama-MacBeth regressions in the paper as well.

Panel A shows that order imbalances in the first 15 minutes of trading are strongly related to past returns. The effect is highly significant, with a t-statistic of 26.9. Imbalances over the next 45 minutes also indicate extrapolation, though the effect weakens. In the remainder of the day, from 10:30-4:00, the impact of past daytime returns reverses, with high past returns leading to a higher fraction of sell orders. While smaller, this effect remains highly significant, with a t-statistic of -9.7.

Our division of the day into the intervals 9:30-9:45, 9:45-10:30, and 10:30-4:00 is somewhat arbitrary. Figure 1(a) therefore presents an alternative set of regression results in which the order imbalance in each half-hour interval of the trading day is regressed on the lagged daytime return (again with controls for lagged order imbalance).

The figure shows that order imbalances in the first 30 minutes of trading are strongly positively related to lagged daytime returns. However, the effect becomes slightly negative by the second hour of the day, remaining at roughly that level until the close. The figure implies that the beginning of the day has a unique role in extrapolative trading.

If investors have extrapolative beliefs, then there is little reason to think that it is only the previous daytime return that they extrapolate. As discussed above, we focus on daytime returns because alternative hypotheses might explain a positive relationship between lagged returns and current order flows or returns. For example, Heston et al. (2010) hypothesize that continuation in returns over the same intraday period might be driven by persistence in institutional trading.

Nevertheless, in panel B of Table 1 we ask whether lagged overnight and weekly returns are consistent with extrapolation, acknowledging that other hypotheses, such as autocorrelated order flow (e.g., Heston et al. 2010) cannot be excluded. The lagged overnight (3:59-9:45) return that is included is the one ending on the previous trading day. That is, it is part of the full close-to-close return that an investor would have observed in the evening prior to making the trades that we are attempting to predict. Thus, if extrapolative trades are made on day t based on the close-to-close return on day $t-1$, the overnight return we include should have effects that are similar to those observed for daytime returns. The weekly returns included in panel B are from the prior five days, or $t-6$ to $t-2$. They do not overlap with the lagged daytime or overnight returns.

The table shows that lagged overnight returns have qualitatively the same effect as lagged daytime returns, at least for the 9:30-9:45 and 10:30-4:00 intervals. The coefficients are smaller, but they remain highly significant. Lagged weekly returns, however, are different, as they are positively related to order imbalances in the early morning, but even more so throughout the rest of the day. While the coefficients are still consistent with extrapolation, they do not imply the same intraday effects on prices. One may imagine that investors perceive less urgency when acting on older information, like the lagged weekly return, leading them to defer trades until later in the day.

The last panel in Table 1 repeats the same regression, except that it adds an asymmetric response to lagged day returns. If investors face constraints on short selling, then we would expect that positive past returns would have a stronger effect than negative past returns.

We find strong evidence of asymmetry, as evidenced by highly significant positive coefficients on the maximum of zero and the lagged daytime return. In the first 15 minutes of the day, the inclusion of the asymmetric term reduces the coefficient on the lagged day return by more than half, suggesting a relatively low response to negative returns. Later in the day, the asymmetric effect remains positive, unlike the linear effect, though the magnitude is lower.

The greater sensitivity to lagged positive returns in the opening minutes is also illustrated in panels (b) and (c) of Figure 1. Panel (b) shows the coefficient on the lagged day returns, whereas panel (c) shows the coefficient on the asymmetry term. While the coefficients on the asymmetric term are now positive and significant during almost every 30-minute interval, they are clearly largest in the first 30 minutes. Again, therefore, the very beginning of the day shows the greatest degree of extrapolative trading.[3]

3.2 Implications of extrapolative trading for individual stock returns

If extrapolative trading following a positive return produces buying pressure in the morning, it is easy to imagine that stock prices will rise as a result. Similarly, if there is less buying pressure or even selling pressure in the afternoon, the high prices may weaken by the afternoon. We explore these possibilities in this section.

As discussed above, our primary focus will be on the relation between daytime returns and the overnight returns that immediately follow them. Our extrapolative trading hypothesis predicts a positive relation, as a high daytime return induces traders to buy stock the following morning. This prediction, however, runs counter to the well-known phenomenon of short-term return reversal, first demonstrated by Jegadeesh (1990) and Lehmann (1990). While short-run reversal is most often investigated using weekly returns, it is present in daily returns as well (e.g., Nagel 2012).

Reversal at high-frequencies may in part be due to transient noise in prices that results from short-run microstructure effects or wide bid-ask spreads. This reversal is mechanical in

[3]We do not show the coefficients capturing the symmetric extrapolation effects in regressions that include the asymmetric term because they are extremely similar to those reported in Figure 1(a).

the sense that it arises as the result of using the same price at the end of the formation period and at the start of the holding period. We therefore attempt to separate mechanical reversal from extrapolative effects, at least partially, by inserting a gap between the formation and holding periods, as is common in the momentum literature (e.g., Jegadeesh and Titman 1993).

Table 2 shows the results of Fama-MacBeth regressions in which we regress overnight or daytime returns on lagged return measures. The table begins with a regression of overnight (3:59-9:45) returns on lagged daytime (9:45-3:59) returns. There is no relation, which subsequent results will suggest is the result of extrapolation and reversal effects offsetting one another.

The second regression in the table replaces the lagged 9:45-3:59 return with a return computed over the same day, but in the 9:45-3:00 interval. The results reveal strong return continuation, which is consistent with high overnight returns resulting from buying pressure in the opening minutes of the market following high daytime returns. This finding runs counter to the widely known tendency of stock returns to reverse at short horizons, and it is also inconsistent with Lou, Polk, and Skouras' finding of an inverse relation between daytime and overnight returns.

Ending the lagged return intervals at 3:00 is arbitrary, and we have made no attempt to fine tune this choice. The true effects of extrapolation may be larger than what our results suggest, because it is unlikely that we completely avoid the forces behind return reversal simply by ending the formation period at 3:00 rather than 3:59. Nevertheless, the regression is sufficient to show an underlying dynamic of continuation in returns that is consistent with extrapolation and, to our knowledge, is new to the literature.

Ending the formation period at 3:00 has another advantage in terms of ruling out explanations based on program trading resulting, for example, from option hedging or other types of rebalancing trades. If algorithmic trading produces a relation between order imbalances and price changes, then one would expect these trades to occur soon following the change in prices. There would be no reason for an option hedger to wait until the next morning to rebalance following a positive return from 9:45-3:00, as such a delay would result in greater risk and would cause the rebalancing trades to occur at a time when liquidity is relatively low.

The third regression in Table 2 adds the lagged nighttime return, whose coefficient is positive and highly significant. This result is consistent with extrapolation, but it is also consistent with the effects of persistent order flows, as hypothesized by Heston et al. (2010) and Lou et al. (2019).

We next add an asymmetric effect, motivated by the possibility of short selling constraints. The results show a positive and highly significant dependence on the positive part of lagged daytime returns, as our hypothesis would predict. Comparing the coefficients on the symmetric and asymmetric terms, it appears that positive daytime returns exhibit continuation, while negative daytime returns tend to reverse.

The final overnight returns regression includes all of these variables in addition to controls for lagged weekly and monthly returns as well as size, book-to-market, momentum, idiosyncratic volatility, beta, investment, gross profitability, turnover, net issuance, and accruals. To save space, we do not report coefficient estimates for these controls, though most are statistically significant. While including so many controls has a noticeable effect on the relation between nighttime and lagged daytime returns, the evidence for extrapolation of positive returns remains strong.

The last two regressions in the table use daytime returns as dependent variables. These regressions are identical except that the second includes the 12 additional controls described above.

If the only cause of lead-lag effects in returns was morning extrapolation, we would expect negative coefficients on all of the slope coefficients in the regressions of daytime returns. This negative relation would be obtained assuming that the price impact of the morning extrapolative trading was at least partially transient, so that high opening prices would lead to a return reversal over the course of the day. The regression results show that this is not the case, however, as there is evidence of a positive relation between lagged and current daytime returns. This positive relation is observed for both negative returns (the coefficient on the lagged 9:45-3:00 return) and for positive returns (the coefficient on the lagged 9:45-3:00 return plus the coefficient on the maximum of that return and zero).

The interpretation of these results is not straightforward. They might mean that extrapolative trading continues beyond the opening minutes of the day, even though this was not suggested by our order flow results. They also might show effects unrelated to extrapolation, such as autocorrelated order flows, or any other force responsible for the intraday periodicity found by Heston et al. (2010). While we report these results for completeness, as with similar results below, we do not view them as evidence for or against our extrapolative trading hypothesis. Our portfolio analysis below further demonstrates that the positive autocorrelation of daytime returns is not found among large stocks, as the sign changes for value-weighted portfolios. This favors a liquidity-based explanation of this persistence in daytime returns.

We augment these regression results with portfolio sorts. These provide a check on the particular assumption made about the form of the asymmetric relation between past and future returns. In addition, examining value weighted portfolios provides an easy way to check whether our results are driven mainly by small firms.

Table 3 examines overnight and daytime portfolio returns that are formed on the basis of lagged daytime returns, computed either from 9:45-3:59 or 9:45-3:00. Panels A and B examine equally weighted portfolios. Panels C and D use value weighting.

Turning first to equally weighted nighttime returns in panel A, we see no relation with past 9:45-3:59 returns, consistent with our regression results, but a significant positive relationship when using past 9:45-3:00 returns. In that case, the difference between high and low deciles is about 7 bps. per night. Looking more closely, however, we see few differences among the first eight deciles. Only the top two deciles have average returns that are substantially higher than the rest.

Panel B examines equally weighed daytime returns. The holding and formation periods are separated by many hours regardless of whether lagged returns are measured from 9:45-3:59 or 9:45-3:00, so the choice of one or the other has little effect. In both cases, we see a strong and generally increasing relation with past returns. This, as noted above, is consistent with a number of hypotheses, including extrapolative trading.

Panel C again considers overnight returns, but each decile portfolio is now value weighted. As in panel A, we see no significant relation when lagged returns are computed from 9:45-3:59. When we use 9:45-3:00 returns, however, the positive relation is strong, with an average return spread that is greater than that of the equally weighted portfolio. Thus, return extrapolation does not appear to primarily be a feature of smaller stocks.

Panel D examines value weighted daytime returns. Using lagged 9:45-3:59 returns, we now see significant evidence of return reversal, but this evidence disappears when we use the earlier period to compute lagged returns. Thus, even if we interpret panel B as evidence of investors conducting intraday extrapolative trading based on lagged intraday returns, this effect only seems to apply to small stocks.

Taken together, these four panels suggest that the impact of extrapolative trading is particularly pronounced in the relation between lagged returns over the 9:45-3:00 daytime period and the subsequent nighttime returns. The effect is similarly strong for large and small stocks, and it is not canceled out by reversals due to market illiquidity. As a result, we focus on this relationship in subsequent analysis.

3.3 Extrapolation and investor sophistication

Bogousslavsky (2021) argues that intraday return patterns are affected by the desire of some investors to close positions overnight, either to meet margin requirements or to avoid overnight risk or stock lending fees. He finds that mispricing is greatest at the beginning of the trading day, gradually reducing until the half hour between 3:30pm and 4:00pm, when traders appear to exit positions before the close. The unanswered question is why other less sophisticated traders are motivated to take the opposite positions.

The evidence presented so far suggests that extrapolative trading is one reason mispricing may be severe near the market open, with unsophisticated traders buying from arbitrageurs taking short positions. But for this effect to be consistent with Bogousslavsky's findings, it must be the case that the strength of extrapolative trading varies across stocks, specifically that it is greater among stocks that are more overpriced.

In the Chinese stock market, Liang (2022) connects various firm characteristics to the strength of extrapolative trading. Growth stocks, for example, are far more more likely to be favored by extrapolative traders than value stocks. While her focus is on extrapolation over multi-month rather than intraday horizons, her results nevertheless suggest that different stock characteristics correlate with the degree of extrapolative trading.

In this section, we provide evidence that extrapolative trading around the market open is particularly strong for stocks that are overpriced and more likely to be favored by less sophisticated traders. As in Bogousslavsky (2021), we measure mispricing using the measure constructed by Stambaugh et al. (2015). A high value of this measure indicates an overpriced stock, one that Bogousslavsky's arbitrageurs would short sell. We also examine Google search frequency, which Da et al. (2011) view as a measure of attention by retail traders, as well as the fraction of trading volume identified as being from retail investors.

The Stambaugh et al. (2015) mispricing measure is available over our entire sample period. Google search volume is available starting in 2004. To measure the fraction of retail trading, we rely on the approach of Boehmer et al. (2021), which identifies retail orders based on the common practice of price improvement, whereby retail (but not institutional) orders may be executed at prices that are a fraction of a cent better than the prevailing bid or ask. We follow Boehmer et al. (2021) by only using data from 2010, around which time the practice of subpenny price improvement seems to have stabilized.

We investigate the links between these measures and extrapolation using Fama-MacBeth regressions in which order imbalances or returns are regressed on lagged 9:45-3:00 returns, the measure of mispricing or retail focus, and an interaction term, which is our main focus. The results of this analysis are reported in Table 4.

Panel A shows how order imbalances at different times of the day relate to past returns, and how that relation is modulated by firm characteristics. The first regression, which analyzes order imbalances in the first 15 minutes of trading, finds only one significant coefficient, which is on the interaction of mispricing and lagged returns. The positive sign of this coefficient indicates that more overpriced stocks tend to be the subject of more extrapolative trading. This is consistent with extrapolative trading being one of the sources of morning mispricing that Bogousslavsky (2021) documents.

While extrapolation continues somewhat in the 9:45-10:30 time interval, its dependence on mispricing disappears. In the 10:30-4:00 period, overpricing is associated with a more negative relation between past returns and imbalances. Thus, the tendency of extrapolative trading to occur around the market open is even stronger among more overpriced stocks.

We obtain similar patterns using Google search volume or the fraction of retail trading. Higher search volume or retail trading both lead to an increase in extrapolative trading around the open, and both are negatively related to the degree of extrapolative trading later in the day. Interestingly, these significance of these results is very strong despite the shorter sample periods used in these regressions.

Panel B of Table 4 examines whether the same explanatory variables predict overnight and daytime returns. We find that overpricing significantly increases the response of overnight returns to past daytime returns, consistent with order imbalances. However, higher mispricing also increases the tendency for continued extrapolative effects in the daytime period. Because the effect on daytime returns is smaller, extrapolative effects in the difference between overnight and daytime returns, what Lou et al. (2019) refer to as the "tug of war" effect, appear to be stronger for more overpriced stocks as well.

Results using Google search volume and retail trading volume are stronger. More search volume is highly related to the tendency of overnight returns to move in the same direction as previous daytime returns, but it has no effect on the following daytime returns. A higher fraction of retail trading is also associated with stronger overnight extrapolative effects in returns. It is also negatively related to these effects for daytime returns. For both of these variables, tug of war effects are therefore strongly related to past returns.

We believe that these results are complementary to Bogousslavsky's hypothesis. By highlighting one source of morning mispricing, we provide a rationale for why sophisticated arbitrageurs can profitably engage in intraday trading. Our results also demonstrate that the impact of extrapolative trading varies across stocks. This raises the possibility that extrapolative trading could impact the returns of long/short portfolios, if one leg is more subject to these effects. We address this possibility below.

4 Portfolio effects

In this section, we ask whether extrapolative trading affects the returns on portfolios.

Portfolio-level effects may be the result of investors extrapolating the performance of common factors, such as the return on the market, or from the extrapolation of idiosyncratic returns. Both forms have been documented in the literature, with Greenwood and Shleifer (2014) showing evidence of extrapolative beliefs about market returns and Da et al. (2021) showing that investors extrapolate the relative performance of different stocks. It is also possible that investors may extrapolate the performance of a stock based on the past returns of similar stocks that share some common characteristics.

With asymmetries in extrapolative trading, perhaps due to short selling constraints, portfolio-level predictions are somewhat different from those for individual stocks. Suppose, for a given stock i, that the extrapolative belief about returns in period $t+1$ is formed from a linear combination of asset returns in the previous period, $x_{i,t}$. This combination might heavily weight the own stock, but it might also put weight on the market return or a set of similar stocks. Then, for simplicity, assume that the time $t+1$ order imbalance for that stock is proportional to $\max\{x_{i,t}, 0\}$, reflecting short selling constraints. Under the assumption that the signal $x_{i,t}$ is normally distributed in the cross section with a mean of μ_t and a standard deviation of σ_t, the equally weighted average order imbalance is proportional to the cross-sectional average of $\max\{x_{i,t}, 0\}$, which is

$$\mu_t \Phi(\mu_t/\sigma_t) + \sigma_t \phi(\mu_t/\sigma_t), \tag{4}$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the normal CDF and PDF, respectively.[4]

Figure 2 shows the form of equation (4). It is increasing in the cross-sectional mean μ_t and in the cross-sectional standard deviation σ_t. The dispersion effect is the result of positive returns resulting in buy orders, with negative returns having no effect.

This model is meant to be illustrative. It cannot, in fact, be implemented directly given that the signals (the $x_{i,t}$s) are unobserved. The model nevertheless demonstrates that positivity constraints imposed at the stock level imply a sensitivity to dispersion at the portfolio level. We explore this implication throughout the rest of this section.

4.1 Characteristic-sorted portfolios

Lou et al. (2019) find remarkably large differences between the daytime and overnight re-

[4]This equation follows from the property of a truncated normal distribution since $E[\max\{x_{i,t}, 0\}] = E[x_{i,t}|x_{i,t} > 0]Pr(x_{i,t} \geq 0) + 0 \cdot Pr(x_{i,t} < 0)$, and $E[x_{i,t}|x_{i,t} > 0] = \mu_t + \sigma_t \phi(\mu_t/\sigma_t)/\Phi(\mu_t/\sigma_t)$.

turns on long/short portfolios formed on the basis of firm characteristics. Many of these characteristics are used in the construction of the mispricing measure of Stambaugh et al. (2015), which we showed was related to the strength of extrapolative trading. This suggests the possibility that extrapolation has differential effects on the long and short legs of the portfolios considered by Lou et al. (2019). In this section, we ask whether the findings in that paper are consistent with the market impact resulting from extrapolative trading.

Following Lou et al. (2019), we examine 13 different characteristics, namely beta, size, book-to-market, gross profits, investment, accruals, momentum, industry momentum, lagged one-month return, earnings surprise, net issuance, idiosyncratic volatility, and turnover. For each characteristic, we form decile portfolios, where the sort is either ascending or descending such that portfolio 10 always includes the values of the characteristic associated with positive risk-adjusted returns. We compute portfolio-level order imbalances by taking the value weighted average of the order imbalances of the component stocks. Portfolio returns are also value weighted, and portfolios are rebalanced at the end of each month.

Our portfolio analysis begins in Table 5 with a set of cross-sectional regressions similar to those used for individual stocks. We regress the 9:30-9:45, 9:45-10:30, and 10:30-4:00 order imbalances for the 130 decile portfolios on lagged day and night portfolio returns. We also show the regression for excess morning imbalance, defined as the difference between the 9:30-9:45 and 10:30-4:00 imbalances, each expressed on a per-hour basis. The results are on the left side of panel A.

Similar to Table 1, past daytime returns positively predict order imbalances in the first 15 minutes of the trading day but negatively predict them later in the day. The lagged overnight return has little effect. The final regression in this group examines the difference between the early and late periods, showing that the stronger response of morning order imbalance to lagged daytime returns is statistically significant.

The right side of Panel A shows corresponding return regressions. As with Table 2, overnight returns are highly positively related to past daytime returns, presumably as a result of morning buying pressure. They are also positively related to lagged night returns, which is consistent with extrapolation but that is also consistent with other explanations.

Daytime returns do not significantly depend on lagged daytime returns, though they are positively related to lagged overnight returns. Recall that the lagged overnight returns are from the previous day, so that they are observed a full 24 hours before the interval over which the dependent variable is measured. This effect is not particularly strong, but it is different from what we observed for individual stocks.

The last regression in panel A shows regressions of the difference between overnight and daytime returns, what Lou et al. (2019) refer to as the "tug of war" effect. The regression shows that the differences between daytime and overnight coefficients are significant.

Panel B of 5 adds the lagged cross sectional standard deviation of the returns in each portfolio as an additional explanatory variable. As discussed above, return dispersion should positively predict morning order imbalances and overnight portfolio returns if the response to lagged returns is asymmetric, for example, as the result of short sale constraints.

The left side of panel B shows that the dispersion effect is strong in order imbalances, particularly in the first 15 minutes of the day. The positivity of this coefficient throughout the day is consistent with the individual stock regressions in Table 2, which show a positive response to lagged positive returns both in the morning and the afternoon. In both cases, the decreasing coefficient as the day progresses suggests a special role for extrapolation around the open.

The right side of panel B examines return regressions that include return dispersion. The effect is positive and highly significant for overnight returns and negative for daytime returns. In the final regression, which examines the night/day return difference, all coefficients are positive, which is again consistent with greater extrapolative trading near the market open, which is stronger when past returns are positive.

4.2 The tug of war in long/short portfolios

One of the most striking results in Lou et al. (2019) is the finding that long/short anomaly portfolios tend to earn their average return either entirely during the day or entirely overnight. In many cases, average long/short returns are statistically significant both during the day and overnight, but with opposite signs.

Results thus far indicate that morning extrapolative trading is a pervasive feature of characteristic-sorted portfolios and that the degree of extrapolative trading varies across stocks, being stronger among more overpriced stocks, for example. These results suggest the possibility that the high and low deciles experience different levels of extrapolation-based price pressure, which we test directly in this section by examining long/short strategies.

Although mispricing is, by construction, correlated with many of the variables used to construct the long/short portfolios we analyze, these portfolios undoubtedly differ in many other respects. It is therefore not obvious that extrapolative trading pressure will be observed in long/short portfolios. In addition, the previous regressions all measure extrapolation as the sensitivity of order imbalances or returns to each portfolio's own lagged return. Since portfolios have different levels of return variance, the same regression coefficient may in fact imply different degrees of extrapolative trading.

To compare high and low deciles, it is therefore necessary to measure the response to the same measure. Testing for differences in the effects of extrapolation is then a simple matter of comparing coefficients for the long and short portfolios. We therefore focus on the extrapolative trading that occurs as the result of market-level returns and return dispersion. Given that diversified portfolios tend to be highly correlated with the market, it seems reasonable to expect that market returns may proxy for the extrapolative signal that investors are using for other diversified portfolios.

We approximate the lagged 9:45-3:00 return on the market using the SPY ETF, a widely traded S&P 500 Index ETF that is available throughout our sample.[5] Return dispersion is again measured using the cross-sectional standard deviation of 9:45-3:00 returns on all individual stocks. As with earlier results, order imbalance regressions control for lagged values over all three intraday periods.

Panel A of Table 6 shows regressions in which the dependent variable is the net excess morning imbalance. This is defined as the difference between the excess morning imbalances of decile ten, which is held long, and decile one, which is held short. If morning extrapolative trading is stronger for more overpriced stocks, which tend to be part of decile one, then the coefficient on lagged market returns should be negative.

We find that lagged market returns are significant predictors of net excess morning order imbalance for eight out of 13 anomaly portfolios. Six out of the eight significant coefficients are negative, which is consistent with earlier results on mispricing. The other two, industry momentum and ($-1\times$) size, are consistent with extrapolative trading being more prevalent among underpriced stocks. In the case of industry momentum, the result may be expected given that momentum strategies are naturally prone to attract extrapolative trading, and which in this case turns out to be profitable. The size result suggests that extrapolative traders are more drawn to small stocks, which is consistent the well documented (e.g., Barber et al. 2008) tendency of retail traders to favor small stocks.

The relationship with market dispersion tends to be weak. Only two long/short portfolios have significant coefficients on lagged return standard deviation, and both coefficients are positive, indicating more extrapolation among underpriced stocks.

The weakness these results may due to the effects of extrapolation being absorbed into the lagged order imbalances we include as control variables. High lagged returns may be the result of positive order imbalances, so including lagged imbalances may be controlling away

[5]We obtain similar results using market portfolio returns constructed by aggregating individual stock returns.

the effects we seek to identify. We therefore show, in panel B, regressions without these controls, bearing in mind that the persistence of order imbalances may not be fully captured in these specifications.

With this caveat in place, the results are striking, showing that most coefficients on lagged market returns and return dispersion are highly significant. While most of the significant coefficients are negative, momentum and industry momentum present exceptions, similar to before. Thus, while the evidence in order flow data for extrapolative trading is not overwhelmingly strong, we also cannot rule out the possibility of economically important effects.

Panel C of Table 6 examines the difference between night and day returns, measuring how the "tug of war" of Lou et al. (2019) is affected by past returns and return dispersion. We find that the coefficient on past returns is statistically significant in eight out of 13 cases, and all of these eight estimates are negative. Again, this result confirms the strength of morning extrapolative trading in overvalued stocks.

Return dispersion effects are weaker, being statistically significant in six out of 13 regressions. For industry momentum, the coefficient is positive and significant, consistent with earlier results, while the others are negative or insignificant. Overall, we conclude that extrapolative trading is, for the most part, more prevalent among overpriced stocks, though industry momentum is a notable exception.

A natural question to ask is whether the extrapolative effects in order imbalances line up with those in prices. The match between these two is unlikely to be perfect, in part because portfolios do not all have the same degree of liquidity, so that the same order imbalance is unlikely to produce the same price impact. Nevertheless, in Figure 3 we examine this relation. Specifically, we plot the coefficient estimates in panels A and B, measuring the effect of extrapolation on order imbalances, on the corresponding return regression coefficients from panel C.

Figure 3(a) shows how the effects of lagged daytime market returns compare between order imbalance and return regressions, comparing estimates from panels A and C from Table 6. The relationship is positive and strong, with a correlation coefficient of 0.889. Portfolios whose excess morning order flows respond most strongly to past daytime market returns also have the greatest tendency to respond with high morning prices, resulting in high overnight returns and low daytime returns.

Figure 3(b) shows a similar relation for return dispersion. That is, we are again comparing estimates from panels A and C from Table 6, but it is now the coefficients on lagged return dispersion that are being plotted. The relation here is weaker, but it is still clearly positive.

Given the possibility that the controls for lagged order imbalance in panel A of Table 6 are hiding the full effects of extrapolative trading, Figures 3(c) and 3(d) show results using order imbalance regressions without those controls, which are from panel B of Table 6. We find that the relation between lagged daytime return coefficients becomes even stronger, with a correlation of 0.933. The relation between dispersion coefficients strengthens slightly as well, with a correlation of 0.633.

In sum, there is strong evidence that order flows and prices respond in consistent ways to lagged daytime market returns. The evidence is weaker that dispersion effects in order flows and prices are related.

The final issue we examine regarding long/short portfolios is whether extrapolative trading could be the cause of the unconditional means of night/day return differences, or what Lou et al. (2019) label the "tug or war" effect. Asymmetry between positive and negative returns, which is observed at the portfolio level in the sensitivity to lagged return dispersion, means that positive lagged returns will generate positive price pressure around the open, while negative returns will have little effect. The result is an unconditionally positive order imbalance at the open, raising overnight returns and possibly lowering daytime returns.

We investigate this hypothesis by analyzing the relationship between average overnight minus daytime returns, shown in panel D of Table 6, and the two slope coefficients from panel C. Out hypothesis is that the dispersion coefficient will be positively related to average night/day return differences.

In fact, Figures 4(a) and 4(b) show that both the lagged daytime market return coefficient and the lagged return dispersion coefficient are strongly related to the average tug of war effect, with correlation coefficients of about 0.96 and 0.90, respectively. The fact that both of these correlations are high implies that the correlation between the two slope coefficients is also high. This is apparent in Figure 4(c), which shows that the correlation between the two slope coefficients is 0.85.

The relation between the average tug of war effect and the two slope coefficients can be tested formally using Fama-MacBeth regression. We do so using the Shanken (1992) adjustment to account for measurement errors in betas. The resulting estimates and t-statistics are

Intercept	Lagged Day Return	Lagged Return Dispersion
0.0386	0.6648	0.2951
(2.96)	(4.91)	(1.54)

Furthermore, the cross-sectional R-square is 0.934, indicating a very close fit.

Our hypothesis is not directly supported, as it is the coefficient on the lagged daytime market return, rather than the lagged return dispersion, that has a significant relation with the average tug of war effect. On the other hand, the high correlation between the two betas included in the second-pass regression likely makes it difficult to distinguish between these two effects.

Furthermore, our hypothesis suggests that any asset affected by extrapolative trading will have betas on both past daytime returns and return dispersion. Either coefficient should therefore be equally able to explain variation in the tug of war effect, which is approximately what is suggested by Figure 4. The dominance of the lagged return in the Fama-MacBeth regression may simply be the result of estimation error, as the dispersion slope coefficients in Table 6 are generally estimated with lower t-statistics compared with the coefficients on lagged returns.

4.3 The CAPM during the day and overnight

Hendershott et al. (2020) present a remarkable finding that the high beta stocks do in fact have higher returns, but only over the overnight period. We replicate their finding in Figure 5(a), which shows stark differences between the relation between market beta and returns during the day and overnight.

Hendershott et al. (2020) suggest that market risk may primarily be undesirable over periods of market closure, when asset illiquidity eliminates the option to reduce exposures. A heightened aversion to risk over non-trading periods is also featured in the models of Brock and Kleidon (1992) and Bogousslavsky (2021), among others.

Extrapolative trading that is stronger when lagged returns are positive implies a different explanation of the findings of Hendershott et al. (2020). Table 6 implied that high beta stocks are more prone to high opening prices the day after a positive daytime market return relative to low beta stocks. If the effect of negative daytime returns is relatively muted, then the unconditional effect on high beta stocks is to raise their opening prices, increasing their overnight returns.

To investigate this hypothesis, we use the same beta-sorted decile portfolios examined earlier. For each portfolio, we compute the average daytime and overnight return. We also compute the betas of daytime and overnight returns by regressing 9:45am-3:59pm and 3:59pm-9:45am returns on corresponding returns on the SPY ETF. These are the values displayed in Figure 5(a).

Our hypothesis is that these relations should look very different in the subsample of days that follow positive daytime returns relative to the subsample following negative return days. Specifically, the positive upward slope between betas and overnight returns should be stronger on days following positive returns.

Figures 5(b) and 5(c) show the results of this analysis. In Figure 5(b), which examines the sample of days following positive market returns, we see a more extreme version of the unconditional relation that Hendershott et al. (2020) uncovered. In contrast, Figure 5(c) examines the days following negative returns and finds a completely different result. In this subsample, the relation between beta and average returns is no longer positive for overnight periods.

Both of these results are consistent with extrapolative trading in the morning. Following positive returns, traders appear to buy high-beta stocks, leading to high overnight returns and low daytime returns. Following negative returns, traders sell high-beta stocks, leading to low overnight returns. The response to negative returns is much weaker, however, and no reversal is observed in the following daytime return. The asymmetric response to positive and negative returns is also important because it results in an unconditionally positive relation between betas and average overnight returns.

Table 7 examines the statistical significance of these relations, again using the Shanken (1992) adjustment. The results that use the sample of days following positive market returns are overwhelmingly significant. The results based on days following negative returns are much less significant, especially the overnight returns following negative market returns.

Our results suggest that a desire to avoid overnight risk is not the primary explanation of the findings of Hendershott et al. (2020). If investors sought to avoid market risk overnight, there is no reason why they would not do so following negative market returns. In fact, given the negative relation between market returns and innovations to market volatility, it is reasonable to imagine that investors would become even more averse to holding market beta following negative returns, which is the opposite of what we find.

4.4 Market return extrapolation

Kelly and Clark (2011) show that average U.S. equity market returns are positive overnight and close to zero, if not negative, during the day. Our hypothesis is that this effect is driven, at least in part, by extrapolative trading.

We examine the evidence for market-level return extrapolation in Table 8. As in Section 4.2, we use the SPY ETF as a proxy for the market index. All regressions include the lagged 9:45-3:00 SPY return, and some include the cross-sectional standard deviation of 9:45-3:00 returns on individual stocks as a measure of dispersion.

Panel A show regressions in which the dependent variable is a market-level order imbalance, which is computed by taking the value weighted average of the order imbalances of all U.S. common equities. As before, these are computed over three different time intervals, and each imbalance is measured on a per-hour basis. These regressions do not control for lagged order imbalances. As discussed in Section 4.2, these controls may absorb the effects we seek to identify, and when we include them we find essentially no significant relationships. Given this lack of robustness, the panel A regressions must be viewed with some caution.

Bearing this in mind, the results in panel A are are highly consistent with morning extrapolation, with a large and significant positive coefficient on the lagged SPY return only for the 9:30-9:45 interval. Dispersion coefficients are also uniformly positive. The final two columns show regressions in which the dependent variable is the excess morning imbalance, or the difference between the 9:30-9:45 and 10:30-4:00 per-hour imbalances. The last column shows that the dispersion effects is significantly stronger in the first 15 minutes of the day than it is over the 10:30-4:00 period.

Panel B examines the regressions with overnight and daytime market returns, or their difference, as the dependent variable. Consistent with the cross-sectional regressions on individual stocks, we find that higher past daytime returns predict high overnight returns to follow. Subsequent daytime returns are negative however, which may reflect a reversal of the market impact caused by extrapolative trading. Lagged returns are even more significant in the regression of overnight minus daytime. Note that we do not see any evidence of a dispersion effect.

Overall, we believe that the results in Table 8 suggest that extrapolation plays a role in the differences between daytime and overnight market returns. The lack of a dispersion effect suggests, however, that explaining Kelly and Clark's (2011) results likely require more than just extrapolation with asymmetry to positive and negative returns.

5 Who drives the extrapolation effect?

Table 4 showed strong evidence that morning extrapolation effects in order imbalances and returns are stronger among stocks in which retail traders comprise a larger fraction of trading volume. In this section, we add to this evidence by examining the intra-day behavior of retail order imbalances, which are identified using the procedure of Boehmer et al. (2021).

We complement this analysis by also examining intermarket sweep orders (ISOs), a type of order designed for use by institutional investors. These orders allow large investors, who trade on multiple exchanges simultaneously, to bypass the usual requirement that orders be rerouted to another exchange posting a better price. In general, retail investors will not use ISOs given that their trades tend to occur off-exchange, and most on-exchange trades would be small enough to be filled at the exchange posting the best price. Chakravarty et al. (2012) confirm that ISOs are most often used by institutions and further show that they are more likely to be informed than non-ISOs.

We construct order imbalance measures similarly to before, except that we now include only retail orders or ISOs. These imbalances (Imb) are used in the same specifications estimated in Figure 1, namely

$$\text{Imb}(interval, t, i) = \alpha + \beta\, R(\text{9:45-3:59}, t-1, i) + \gamma \max\left(R(\text{9:45-3:59}, t-1, i), 0\right) + \text{controls} + \epsilon(t, i), \tag{5}$$

where *interval* is one of the 13 half-hour intervals within regular trading hours. As in earlier results, our focus is on the estimates of the symmetric (β) and asymmetric (γ) extrapolation effects.

We begin by comparing symmetric extrapolation effects (β) in models without the asymmetric term ($\gamma = 0$) and where controls include only the lagged order imbalances over the 9:30-9:45, 9:45-10:30, and 10:30-4:00 intervals. Panel (a) of Figure 6 shows estimates based on retail order imbalances, while (b) examines imbalances in ISOs.

The graphs show that both retail and institutional investors exhibit patterns in order imbalances consistent with extrapolation. For both types of investors, this effect is strongest in the first half hour of the day. With the intermarket sweep orders favored by institutional investors, extrapolation strengthens in the last 30 minutes of the day. Because this end-of-day peak is smaller, and also because it happens at a time that the market is particularly liquid, it is likely that the price effects of extrapolative trading are still much stronger in the morning, even for institutional traders.

Since our hypothesis is that asymmetric extrapolation is necessary for generating unconditional tug of war effects, the more relevant question is whether the incremental effect of positive lagged returns is stronger for retail or institutional traders. We answer this question in Figure 7, which analyzes the more general specification that includes an asymmetric return effect and additional controls for lagged overnight and weekly returns. Panels (a) and (b) show coefficients on the lagged daytime return, while panels (c) and (d) show the coefficients on the maximum of the lagged daytime return and zero. Thus, the response to negative returns can be seen in panels (a) and (b), while the response to positive returns is observed by summing one of the top panels with the corresponding bottom panel.

We find that retail and institutional traders exhibit strikingly different asymmetries in their responses to positive and negative returns. Most importantly, by comparing panels (c) and (d), we see that the asymmetric response to positive returns in the first half hour of the day appears to be driven entirely by retail traders. Retail traders show no tendency to extrapolate negative returns near market open, while institutional traders appear to extrapolate positive and negative returns symmetrically in the first 30 minutes of trading.

Near the market close, retail shows some tendency to sell following negative returns, as indicated by the positive coefficients on the right side of panel (a). However, they also tend to sell at the end of the day following positive returns (summing the right sides of panels (a) and (c)). Thus, while the behavior of retail traders near the close cannot be described as extrapolative, their tendency to be net sellers following both positive and negative returns likely contributes to lower average prices at the close.

While the tendency of retail traders to sell near the close should lead to greater differences between overnight and daytime returns, this effect is at least partially offset by the behavior of institutions. Specifically, the right side of panel (d) shows that institutional trades show a strong pattern of asymmetric extrapolation late in the day. By buying at the close following positive returns, institutions push closing prices higher, leading to higher daytime and lower overnight returns.

Overall, these results indicate that both retail and institutional traders show highly significant tendencies to extrapolate past returns. However, the asymmetric response to lagged positive returns is much different between the two groups, and it is retail traders whose order imbalances, both right after the open and just before the close, are more consistent with the tug of war that we observe in daytime and overnight stock returns.

6 Conclusion

Prior work has shown large differences in daytime and overnight returns, which it has attributed to clientele effects or different attitudes towards risk during the day versus overnight. We find that the "tug of war" between night and day returns is highly predictable and is consistent with extrapolative trading that is concentrated in the first 15 minutes of the trading day.

Morning order imbalances and overnight returns are strongly related to lagged daytime returns at the individual stock level and for portfolios. These effects are stronger for more overpriced stocks and for stocks favored by retail investors. Positive returns have much stronger effects than negative returns, suggesting that extrapolation of downside returns is hindered, possibly by short selling constraints.

The returns on long/short portfolios are predictable using lagged daytime market returns and lagged return dispersion, which captures the effects of asymmetry in portfolios. Across different long/short portfolios, the sensitivity to lagged market returns or return dispersion is highly related to the average difference between daytime and overnight returns, suggesting that the tug of war in portfolio returns documented by Lou et al. (2019) is largely the outcome of extrapolative trading.

We also find evidence that morning extrapolative trading if stronger among high beta stocks. Reexamining the relation between beta and average overnight returns, which Hendershott et al. (2020) finds to be strongly positive, we find that the result is highly dependent on whether the previous day's market return was positive or negative. When the lagged return is positive, then the upward sloping relation between beta and overnight returns is strong. When the lagged return is negative, then the relation between beta and overnight returns turns weakly negative. This dependence is consistent with extrapolative trading, not with risk attitudes that differ between daytime and overnight periods.

We show that both retail and institutional traders exhibit patterns in order imbalances that are consistent with extrapolative beliefs. However, the incremental tendency to buy at the open following positive returns is found only among retail traders. These traders then reverse their order imbalances just prior to market close, which may cause even greater differences between overnight and daytime returns.

Our results help to understand the rationale for day trading by sophisticated arbitrageurs, who Bogousslavsky (2021) argues are responsible for a gradual decrease in mispricing over the course of the trading day. The existence of extrapolative traders, concentrated in the morning and in overpriced stocks, creates a natural incentive for arbitrageurs to short sell these stocks at the start of the day.

More broadly, we demonstrate the relevance of extrapolative trading for studying high frequency phenomenon, which have traditionally been seen as the outcome of information, risk, and liquidity effects. Whether or not extrapolative trading is capable of explaining other high frequency patterns, such as volatility and volume clustering, is an interesting area for future research.

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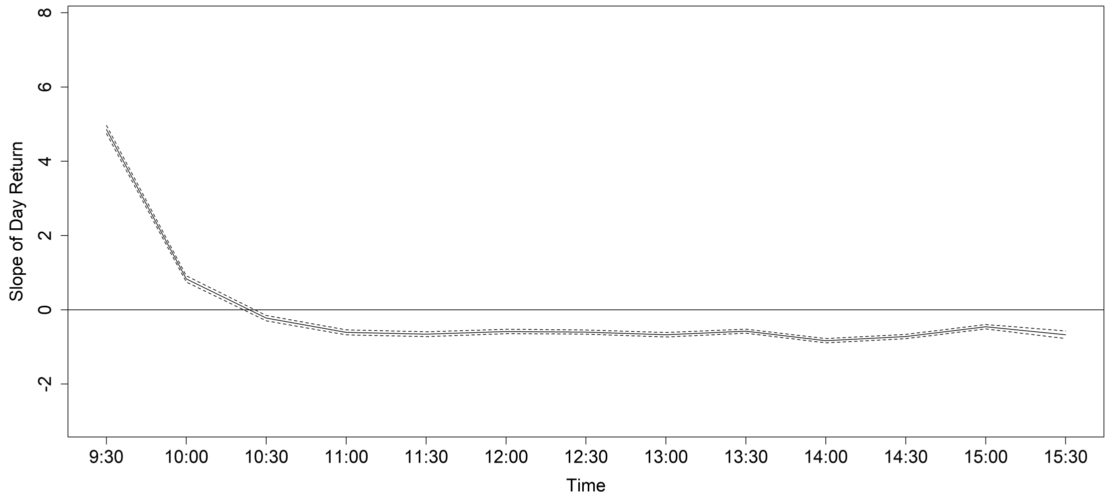
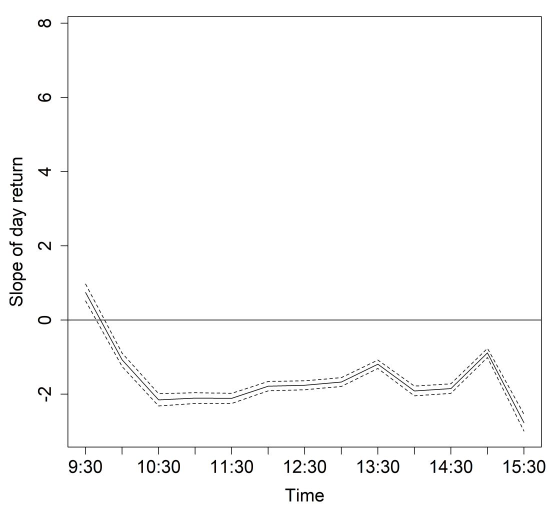
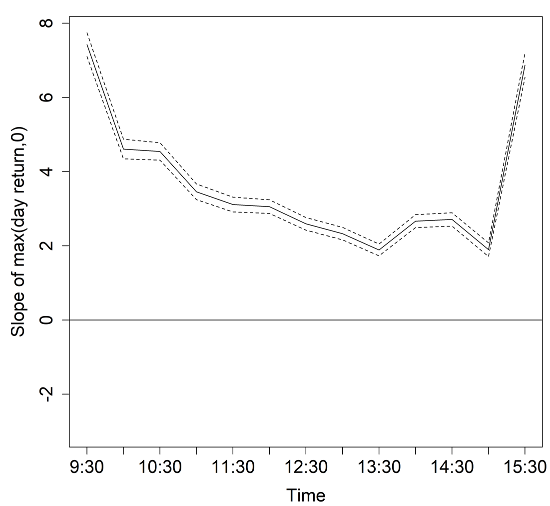


(a) Regression slope of order imbalance regressed on lagged daytime returns



(b) Slope of lagged daytime returns



(c) Slope of max(lagged daytime returns, 0)

Figure 1. Past daytime returns and intraday order imbalances.
This figure shows the slopes of the Fama-MacBeth regressions in which half hour order imbalances are regressed on lagged returns and other variables. Panel (a) is the slope of the simple predictive regression without controlling for past returns (similar to Table 1, panel A) and panel (b) and (c) are the slopes on the lagged daytime returns and on max(lagged day return, 0), respectively, controlling for lagged day, night, and week returns (similar to Table 1, panel C). Dotted lines represent 95% confidence bands.

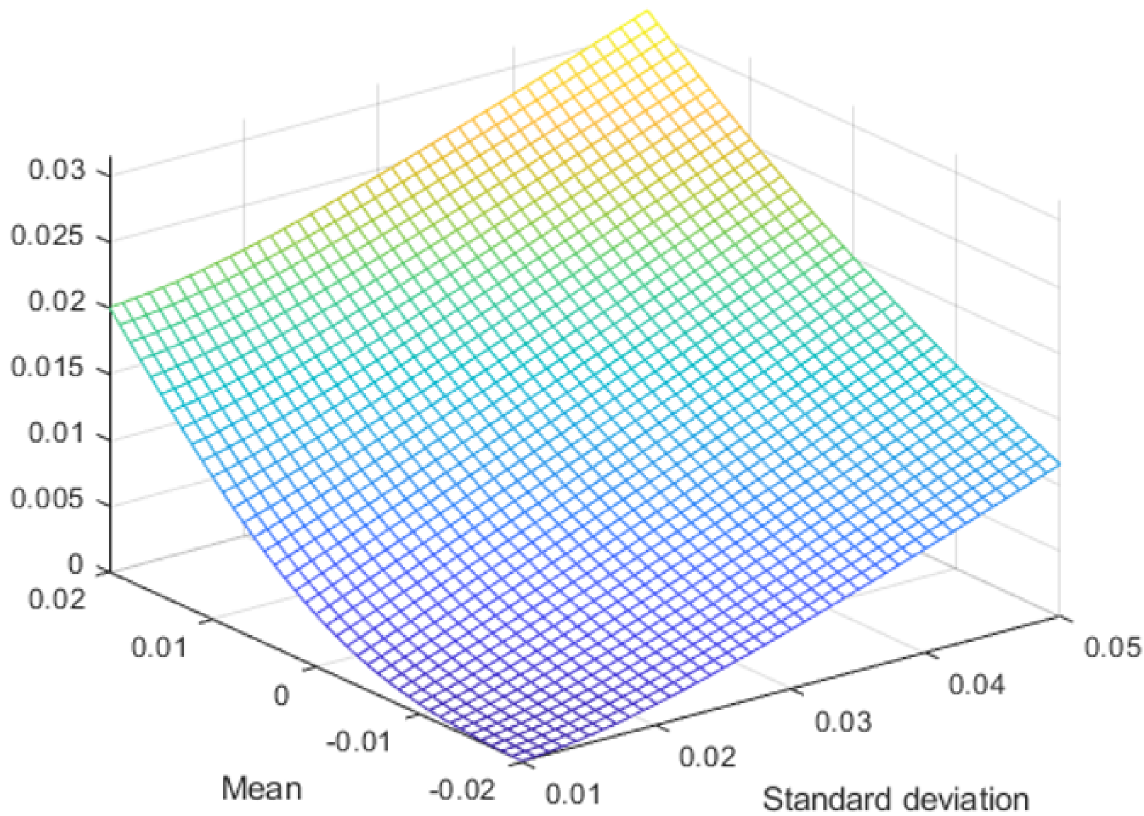


Figure 2. Extrapolative trading effects and return dispersion
This figure shows the value of Equation (4) across different values of mean (μ_t) and standard deviation(σ_t).

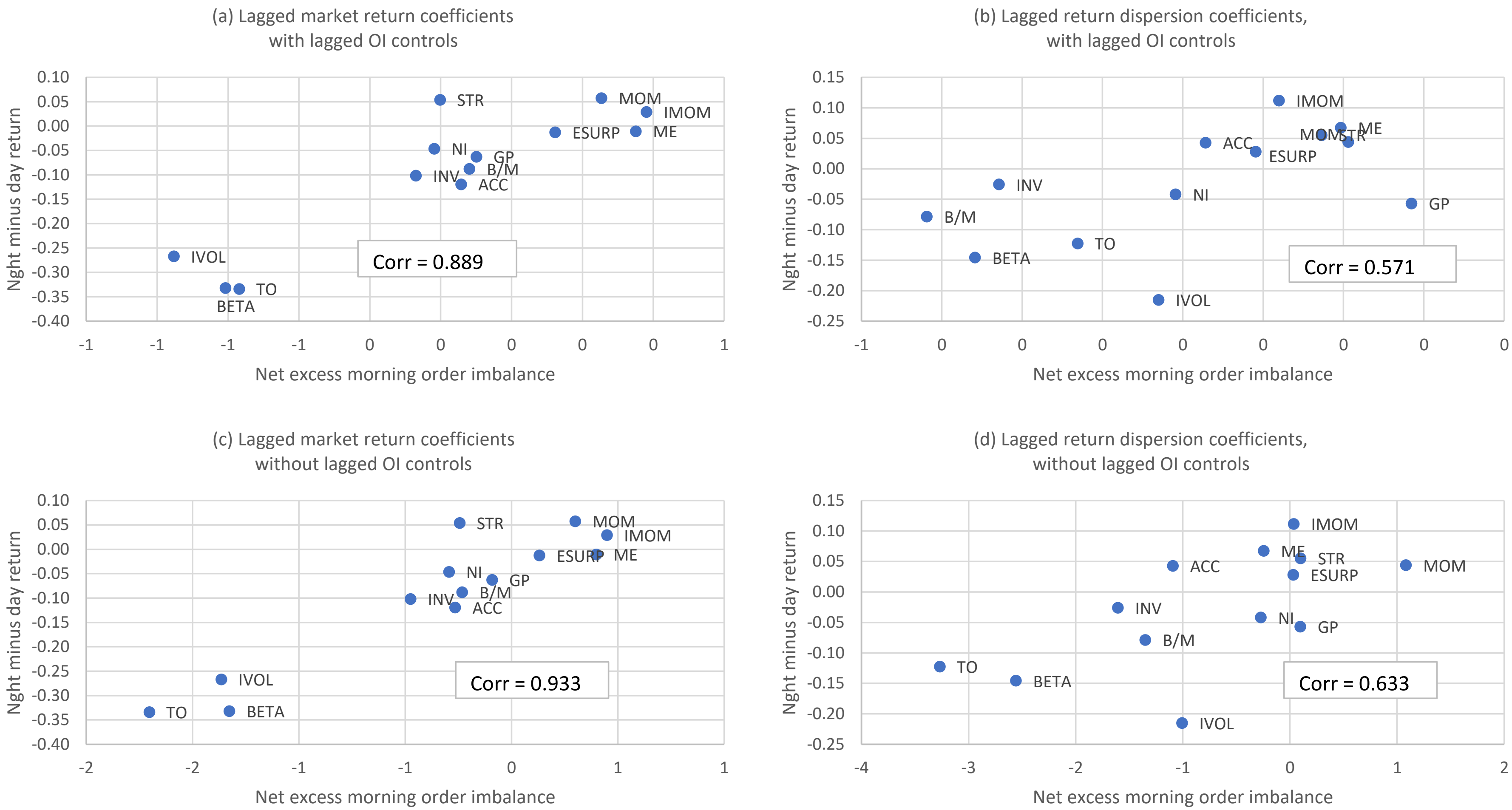


Figure 3. The relation between extrapolative effects in order imbalances and returns.
This figure shows the relation between the corresponding slope coefficients from order imbalance and return regressions. Panel (a) shows the lagged daytime return coefficients from Panels A and C of Table 6. Panel (b) shows the lagged return dispersion coefficients from the same regressions. Panels (c) and (d) are identical except that they use order imbalance regression coefficients from Panel B of Table 6, which does not include controls for lagged order imbalances.

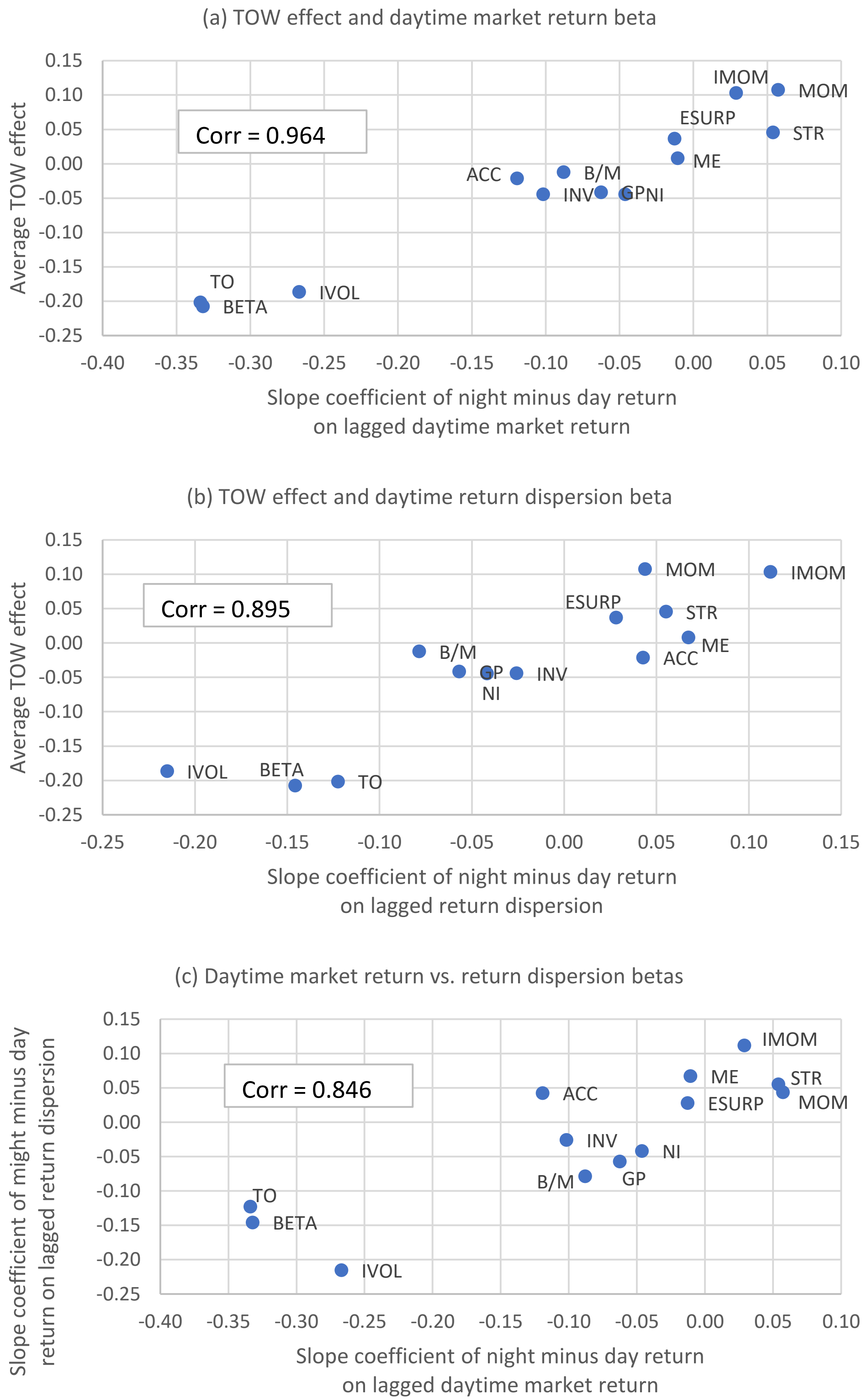
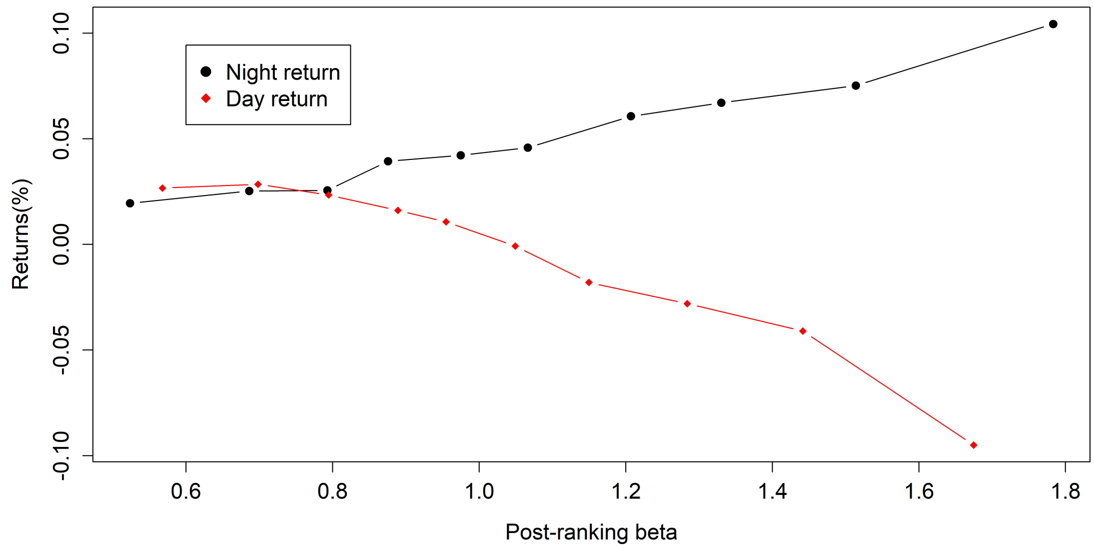
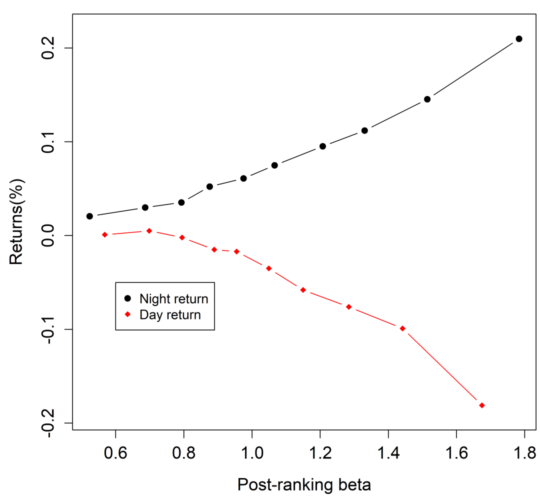


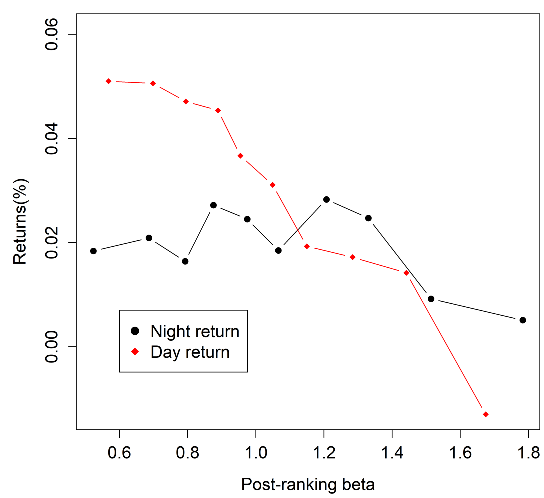
Figure 4. The relation between extrapolative effects and average night/day return differences.
Panel (a) shows the relation between the slope coefficients on lagged daytime returns from Panel C of Table 6 and the average night minus day return on each long/short portfolio. Panel (b) shows the relation between the slope coefficient on lagged return dispersion and the average night minus day return. Panel (c) shows the relation between the two slope coefficients in the first two panels.



(a) All sample

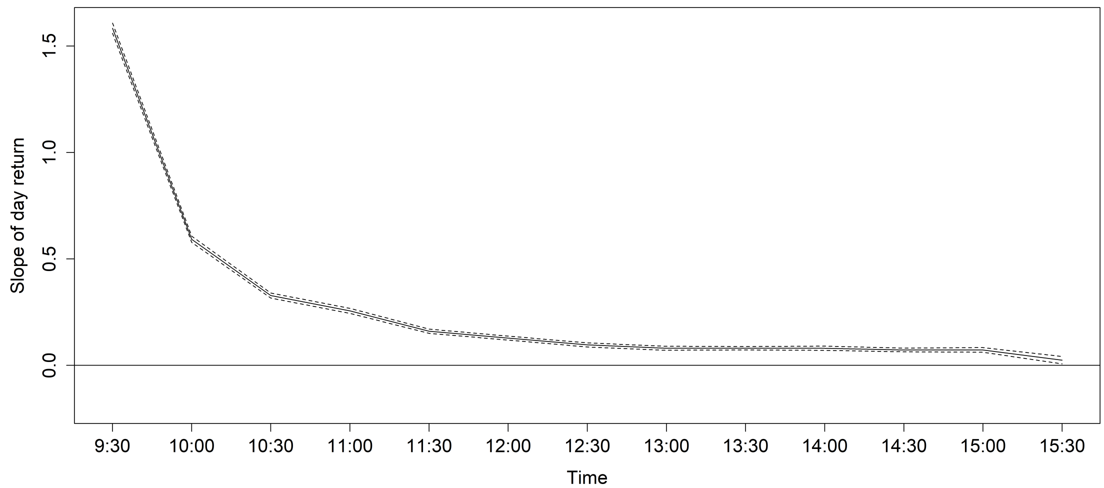


(b) Days following positive daytime returns

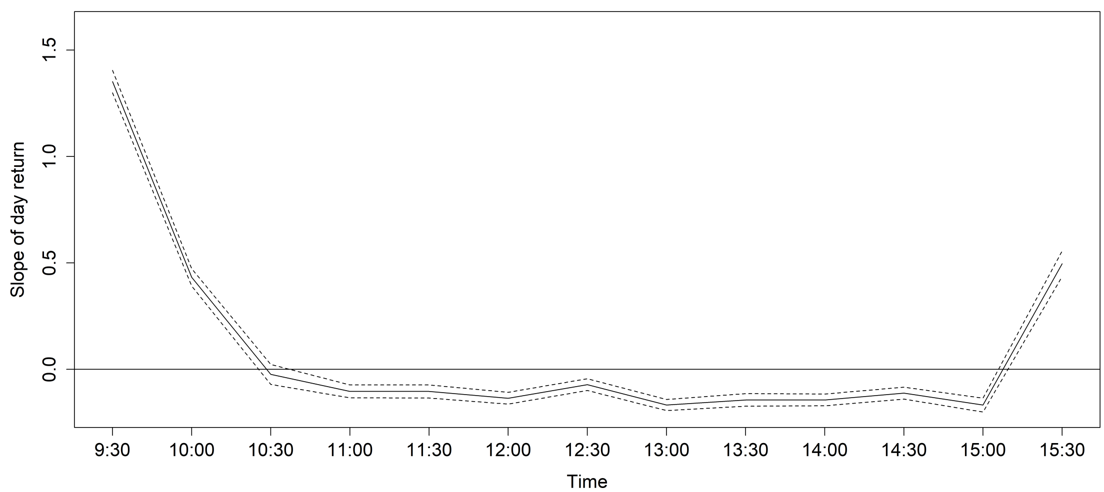


(c) Days following negative daytime returns

Figure 5. Extrapolative return relations and market beta.
This figure illustrates the relationship between daytime/overnight market betas and daytime/overnight returns. Panel (a) shows the relationship for the entire sample. Panel (b) is the average returns for days following positive daytime returns, and panel (c) is for days following negative returns.

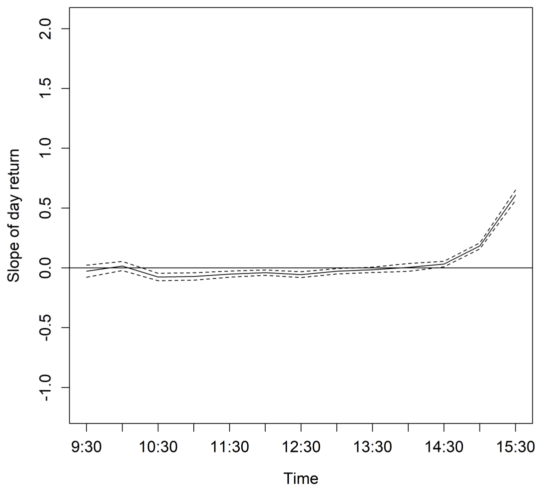


(a) The slope of retail imbalance on lagged daytime returns

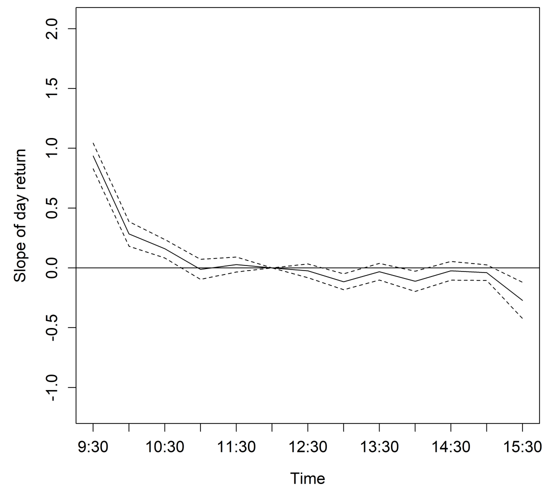


(b) The slope of ISO imbalance on lagged daytime returns

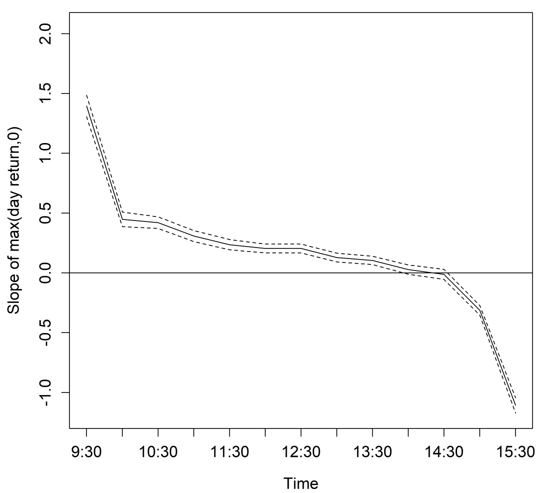
Figure 6. Linear extrapolation in retail and intermarket sweep imbalances. This figure shows the slopes of the Fama-MacBeth regressions in which half hour retail order (panel (a)) or intermarket sweep order (ISO) (panel (b)) imbalances are regressed on lagged returns and other variables. The figure shows the slopes of simple predictive regressions that include only lagged daytime returns and controls for lagged order imbalances (similar to Table 1, panel A). Dotted lines represent 95% confidence bands.



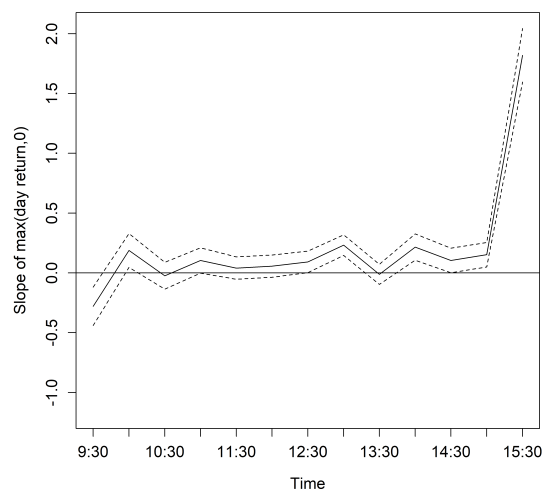
(a) The slope of retail imbalance on on lagged daytime returns



(b) The slope of ISO imbalance on on lagged daytime returns



(c) The slope of retail imbalance on on max(lagged daytime returns, 0)



(d) The slope of ISO imbalance on on max(lagged daytime returns, 0)

Figure 7. Nonlinear extrapolation in retail and intermarket sweep imbalances. This figure shows the slopes of the Fama-MacBeth regressions in which half hour retail order (panels (a) and (c)) or intermarket sweep order (ISO) (panels (b) or (d)) imbalances are regressed on lagged returns and other variables. The figure shows the slopes of predictive regressions that include lagged daytime returns, the maximum of that return and zero, and controls for lagged overnight and weekly returns as well as lagged order imbalances (similar to Table 1, panel C). Dotted lines represent 95% confidence bands.

Table 1: Fama-MacBeth regressions of order imbalances

This table reports results of Fama-MacBeth regressions in which order imbalances are regressed on lagged returns and other variables. Order imbalance is defined as 1000 times the share volume of buy orders minus the share volume of sell orders divided by shares outstanding, where trade sign is determined using the Lee and Ready (1991) test, divided by the number of hours in the interval over which they are compted, either 9:30am-9:45am, 9:45am-10:30am, or 10:30am-4:00pm. Lagged day returns are over the 9:45am-3:59pm interval on the previous day. Lagged night returns are from the 3:59pm-9:45am interval ending one day prior to the order imbalance being predicted. The lagged week return is computed over the week ending two days before the variables being predicted. All regressions also include the previous day's order imbalances over all three intervals (coefficients unreported). T-statistics are in parentheses.

Panel A: No controls except for lagged order imbalances

	9:30-9:45	9:45-10:30	10:30-4:00
Lagged day return	1.8620	0.3332	-0.1537
	(26.88)	(9.51)	(-9.68)
R-square (%)	0.68	1.41	3.27

Panel B: Adding controls for lagged overnight and weekly return

	9:30-9:45	9:45-10:30	10:30-4:00
Lagged day return	1.8828	0.3565	-0.1266
	(27.1)	(10.15)	(-8.07)
Lagged night return	0.4100	-0.3211	-0.0918
	(4.15)	(-6.08)	(-4.18)
Lagged week return	0.1236	0.0101	0.0737
	(5.63)	(0.9)	(14.87)
R-square (%)	0.68	1.41	3.28

Panel C: Adding asymmetric effect

	9:30-9:45	9:45-10:30	10:30-4:00
Lagged day return	0.8032	-0.3041	-0.4571
	(5.39)	(-3.98)	(-14.43)
Max(lagged day return, 0)	2.0664	1.3060	0.7893
	(9.56)	(11.66)	(18.14)
Lagged night return	0.4104	-0.3128	-0.0907
	(4.2)	(-5.96)	(-4.17)
Lagged week return	0.1336	0.0151	0.0758
	(6.14)	(1.36)	(15.56)
R-square (%)	0.70	1.43	3.33

Table 2: Fama-MacBeth regressions of daytime and nighttime returns

This table reports Fama-MacBeth regression estimates in which the dependent variable is either the return from 3:59pm to 9:45am of the next day or from 9:45am to 3:59pm of the same day. Lagged returns over the 9:45am-3:59pm or 9:45am-3:00pm intervals are from the previous day. Lagged night returns are from the 3:59pm-9:45am interval ending on the day prior to the return being predicted. In the two regressions indicated, we also include controls for lagged weekly and monthly returns, as well as size, book-to-market, momentum, idiosyncratic volatility, beta, investment, gross profitability, turnover, net issuance, and accruals. T-statistics are in parentheses.

Dependent variable:			**--------------------------- Nighttime return ---------------------------**			**----- Daytime return -----**	
Intercept	0.0438	0.0441	0.0377	0.0257	-0.0163	0.0174	0.0950
	(5.49)	(5.52)	(5.23)	(3.64)	(-1.67)	(1.88)	(5.76)
Lagged 9:45-3:59 return	-0.1000						
	(-0.87)						
Lagged 9:45-3:00 return		0.9533	0.8807	-1.2440	-0.3839	3.2505	1.1716
		(8.12)	(7.92)	(-6.58)	(-2.76)	(13.87)	(6.89)
Max(Lagged 9:45-3:00 return, 0)				3.1559	1.0215	-2.0523	-0.2479
				(10.29)	(4.72)	(-5.77)	(-1.05)
Lagged 3:59-9:45 return			4.2489		3.7447	-2.3795	-3.2472
			(25.93)		(30.05)	(-12.7)	(-23)
R-square (%)	0.00	0.03	0.09	0.05	0.14	0.05	0.06
Additional controls	no	no	no	no	yes	no	yes

Table 3: Portfolios formed on the basis of lagged daytime returns

In each panel of the table, we perform decile sorts based on returns on either the 9:45am-3:59pm or 9:45am-3:00pm interval from the previous day. Based on these sorts, we compute nighttime (3:59pm-9:45am) or daytime (9:45am-3:59pm) portfolio returns. Portfolios are equally weighted in panels A and B and value weighted in panels C and D. T-statistics are in parentheses.

Decile:	Low	2	3	4	5	6	7	8	9	High	High - Low
Sorting variable											
						Panel A: Equal weighted nighttime returns					
Lagged 9:45-3:59 return	0.0008	0.0006	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004	0.0008	0.0000
	(6.88)	(5.59)	(5.20)	(4.51)	(4.09)	(3.81)	(3.95)	(3.93)	(4.62)	(7.17)	(-0.40)
Lagged 9:45-3:00 return	0.0005	0.0004	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004	0.0006	0.0012	0.0007
	(3.84)	(4.08)	(4.06)	(4.05)	(3.94)	(4.20)	(4.45)	(5.30)	(6.45)	(10.65)	(8.91)
						Panel B: Equal weighted daytime returns					
Lagged 9:45-3:59 return	-0.0007	-0.0006	-0.0004	-0.0002	0.0000	0.0002	0.0003	0.0005	0.0005	0.0003	0.0010
	(-4.14)	(-4.11)	(-3.14)	(-1.60)	(0.10)	(1.76)	(3.04)	(4.24)	(4.50)	(2.02)	(9.21)
Lagged 9:45-3:00 return	-0.0007	-0.0005	-0.0003	-0.0001	0.0000	0.0002	0.0003	0.0004	0.0005	0.0003	0.0010
	(-4.36)	(-3.60)	(-2.70)	(-1.21)	(0.36)	(1.68)	(2.82)	(3.73)	(3.98)	(1.85)	(9.50)

Table 3, continued

Sorting variable / Decile:	Low	2	3	4	5	6	7	8	9	High	High - Low
Panel C: Value weighted nighttime returns											
Lagged 9:45-3:59 return	0.0006	0.0005	0.0004	0.0004	0.0004	0.0004	0.0004	0.0004	0.0005	0.0007	0.0001
	(4.76)	(4.78)	(4.48)	(4.42)	(5.12)	(4.83)	(5.41)	(4.47)	(5.55)	(4.50)	(0.79)
Lagged 9:45-3:00 return	0.0003	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004	0.0005	0.0006	0.0011	0.0009
	(2.01)	(3.28)	(3.39)	(4.12)	(4.98)	(5.00)	(5.55)	(6.23)	(7.40)	(7.49)	(6.20)
Panel D: Value weighted daytime returns											
Lagged 9:45-3:59 return	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	-0.0005	-0.0004
	(-0.39)	(0.10)	(0.14)	(0.44)	(0.50)	(0.50)	(0.89)	(0.37)	(-0.42)	(-3.43)	(-2.91)
Lagged 9:45-3:00 return	-0.0002	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000	-0.0003	0.0000
	(-1.51)	(-0.23)	(-0.11)	(-0.04)	(0.86)	(0.98)	(1.20)	(0.58)	(-0.05)	(-2.17)	(-0.33)

Table 4: Determinants of extrapolative trading

This table examines how extrapolative trading effects depend on the mispricing measure of Stambaugh, Yu, and Yuan (2015), the Google search volume, and the fraction of trading volume identified as retail. Higher values of mispricing indicate a more overpriced stock. Retail trades are classified using the approach of Boehmer, Jones, Zhang, and Zhang (2021). Each column table reports stock-level Fama-MacBeth regression estimates in which the dependent variable is either an order imbalance (Panel A) or return (Panel B). Night returns are from 3:59pm to 9:45am of the next day, while day returns are from 9:45am to 3:59pm of the same day. Lagged returns over the 9:45am-3:00pm interval are from the previous day. Order imbalance regressions also include the previous day's order imbalances over all three intervals (coefficients unreported). T-statistics are in parentheses.

Panel A: Order Imbalances

	Z = Mispricing			Z = Google Search Volume			Z = Retail / Total Volume		
	9:30-9:45	9:45-10:30	10:30-4:00	9:30-9:45	9:45-10:30	10:30-4:00	9:30-9:45	9:45-10:30	10:30-4:00
Intercept	0.0088	0.0068	0.0019	-0.0004	0.0017	0.0054	-0.0108	-0.0104	-0.0054
	(2.67)	(3.81)	(2.3)	(-0.1)	(1.72)	(8.07)	(-4.36)	(-8.89)	(-10.28)
Lagged 9:45-3:00 return	0.9892	0.2744	0.0969	2.4352	0.5052	-0.0361	0.4656	0.8216	0.4903
	(4.07)	(2.16)	(1.96)	(28.55)	(12.99)	(-2.19)	(2.96)	(11.07)	(18.44)
Z x lagged 9:45-3:00 return	0.0132	0.0001	-0.0056	11.0916	-2.8555	-2.8402	46.2576	-2.9020	-8.7669
	(2.69)	(0.03)	(-5.75)	(5.39)	(-3.35)	(-9.03)	(13.21)	(-1.95)	(-17.63)
Z	0.0004	0.0001	0.0003	0.1028	0.0749	0.0186	-0.1656	0.0271	0.0068
	(5.05)	(5.04)	(15.71)	(4.3)	(8.38)	(5.47)	(-2.46)	(0.76)	(0.57)

Panel B: Returns

	Z = Mispricing		Z = Google Search Volume		Z = Retail / Total Volume	
	Night	Day	Night	Day	Night	Day
Intercept	0.1291	0.0579	0.0496	0.5004	0.0422	0.0344
	(4.75)	(5.08)	(3.72)	(1.03)	(2.43)	(2.42)
Lagged 9:45-3:00 return	-2.7646	-0.5491	-1.0307	-2.1700	-2.7459	0.6721
	(-2.15)	(-1.17)	(-2.72)	(-0.83)	(-3.62)	(2.58)
Z x lagged 9:45-3:00 return	0.0642	0.0323	13.6811	1.3157	33.1346	-8.6307
	(2.93)	(3.09)	(6.74)	(0.13)	(6.12)	(-2.71)
Z	-0.0004	-0.0009	0.0322	-3.8893	0.3486	-0.4663
	(-0.89)	(-4.26)	(0.87)	(-1.03)	(3.82)	(-4.25)

Table 5: Characteristic-sorted portfolios

This table reports Fama-MacBeth regressions for 130 decile portfolios formed on the basis of beta, size, book-to-market, gross profits, investment, accruals, momentum, industry momentum, lagged one-month return, earnings surprise, net issuance, idiosyncratic volatility, and turnover. Panel A regresses order imbalances or returns on past daytime (9:45am to 3:00pm) and nighttime (3:59pm to 9:45am) returns. Panel B adds the lagged cross-sectional standard deviation of the daytime returns of the stocks within each portfolio. Portfolio order imbalances and returns are value-weighted averages of stock-level values. Order imbalance regressions also include the previous day's order imbalances over all three intervals (coefficients unreported). T-statistics are in parentheses.

Panel A: Without return dispersion

	Order imbalances (x1000)				Returns		
	9:30-9:45	9:45-10:30	10:30-4:00	9:30-9:45 minus 10:30-4:00	Night	Day	Night minus day
Intercept	0.0068	-0.0005	0.0009	0.0059	0.0003	0.0001	0.0002
	(3.44)	(-0.68)	(2.47)	(3.03)	(4.01)	(1.04)	(1.58)
Lagged 9:45 to 3:00 return	0.9792	-0.5307	-0.7132	1.6924	0.0296	0.0076	0.0220
	(6.67)	(-7.66)	(-23.27)	(11.71)	(8.39)	(1.62)	(3.83)
Lagged 3:59 to 9:45 return	0.0304	-0.0957	-0.0782	0.1090	0.0403	0.0158	0.0245
	(0.17)	(-1.07)	(-1.94)	(0.63)	(8.87)	(2.59)	(3.32)
R-square (%)	12.59	25.53	35.62	3.60	0.49	0.06	0.10

Panel B: Including return dispersion

	Order imbalances (x1000)				Returns		
	9:30-9:45	9:45-10:30	10:30-4:00	9:30-9:45 minus 10:30-4:00	Night	Day	Night minus day
Intercept	-0.0072	-0.0075	-0.0053	-0.0019	-0.0001	0.0007	-0.0009
	(-2.52)	(-6.92)	(-10.59)	(-0.67)	(-2)	(7.26)	(-7.45)
Lagged 9:45 to 3:00 return	0.9288	-0.5449	-0.6603	1.5892	0.0207	0.0044	0.0163
	(6.58)	(-8.52)	(-23.37)	(11.47)	(6.4)	(1.09)	(3.2)
Lagged 3:59 to 9:45 return	-0.0144	-0.1263	-0.0979	0.0836	0.0376	0.0128	0.0248
	(-0.09)	(-1.53)	(-2.62)	(0.51)	(9.25)	(2.45)	(3.83)
Lagged daytime return dispersion	0.9456	0.5147	0.4047	0.5409	0.0264	-0.0386	0.0650
	(6.16)	(7.2)	(12.96)	(3.59)	(7.67)	(-7.68)	(11.73)
R-square (%)	12.59	25.66	36.05	3.57	0.55	0.26	0.45

Table 6: Extrapolative effects in long-short portfolios

This table reports the results of time series regressions examining long-short portfolios formed on the basis of firm characteristics. For each characteristic, we buy the stocks in the top decile, which includes stocks with positive alphas, and short the stocks in the bottom decile, which includes stocks with negative alphas. Portfolio order imbalances, returns, and uninformed trading proxies are value-weighted averages of stock-level values. The dependent variable in Panels A and B is the difference between excess morning order imbalance of the long and short legs. The dependent variable in Panel C is the difference between the overnight and daytime returns on each long-short portfolio. Regressors include the lagged return on the SPY ETF over the 9:45am to 3:00pm interval and the standard deviation of returns (on all stocks) over the same interval. Regressions in Panel A also include the previous day's net exces morning order imbalances over all three time intervals (coefficients unreported). T-statistics are in parentheses.

	-1 x Accruals	Industry Momentum	-1 x Investment	Gross Profits	-1 x Idiosync. Volatility	Book to Market	-1 x Beta	Momentum	-1 x Net Issuance	-1 x Size	-1 x Monthly return	Earnings Surprise	-1 x Turnover
Panel A: Net excess morning order imbalance													
Intercept	-0.0002	0.0008	0.0038	-0.0028	-0.0036	0.0065	-0.0012	-0.0008	0.0001	-0.0020	0.0000	0.0007	-0.0055
	(-0.08)	(0.42)	(1.67)	(-1.88)	(-1.06)	(3.24)	(-0.27)	(-0.24)	(0.07)	(-1.01)	(-0.00)	(0.46)	(-1.25)
Lagged 9:45 to 3:00 SPY return	-0.1423	0.3811	-0.2699	-0.0992	-0.9526	-0.1187	-0.8071	0.2537	-0.2179	0.3509	-0.2018	0.1232	-0.7685
	(-0.76)	(2.52)	(-2.40)	(-1.11)	(-5.23)	(-1.07)	(-4.50)	(1.53)	(-3.08)	(3.68)	(-1.53)	(1.74)	(-3.54)
Lagged 9:45-3:00 return dispersion	-0.0716	0.0198	-0.3288	0.1847	-0.1302	-0.4186	-0.3587	0.1060	-0.1090	0.0967	0.0727	-0.0092	-0.2309
	(-0.36)	(0.16)	(-2.25)	(1.96)	(-0.58)	(-3.32)	(-1.21)	(0.53)	(-1.10)	(0.77)	(0.45)	(-0.11)	(-0.78)
Adjusted R-square (%)	4.15	6.36	10.56	1.22	4.47	6.22	11.47	6.38	1.32	0.93	5.08	0.50	14.76
Panel B: Net excess morning order imbalance, without controlling for lagged order imbalances													
Intercept	0.0136	0.0021	0.0203	-0.0012	0.0068	0.0200	0.0253	-0.0128	0.0017	0.0019	-0.0022	0.0003	0.0276
	(3.73)	(0.93)	(6.44)	(-0.77)	(1.91)	(9.10)	(4.71)	(-3.52)	(1.03)	(1.13)	(-0.74)	(0.18)	(4.59)
Lagged 9:45 to 3:00 SPY return	-0.2648	0.4485	-0.4747	-0.0915	-1.3645	-0.2324	-1.3268	0.2996	-0.2938	0.3988	-0.2442	0.1314	-1.7032
	(-1.39)	(2.79)	(-3.94)	(-1.00)	(-7.54)	(-2.07)	(-7.00)	(1.76)	(-4.11)	(4.31)	(-1.78)	(1.84)	(-7.28)
Lagged 9:45-3:00 return dispersion	-1.0930	0.0364	-1.6062	0.0977	-1.0064	-1.3498	-2.5575	1.0819	-0.2712	-0.2442	0.0998	0.0311	-3.2683
	(-4.65)	(0.26)	(-8.05)	(0.98)	(-4.50)	(-10.01)	(-7.56)	(4.66)	(-2.69)	(-2.46)	(0.52)	(0.35)	(-8.72)
Adjusted R-square (%)	0.84	0.41	3.91	0.02	1.83	3.05	5.00	0.91	0.44	0.37	0.04	0.03	5.93
Panel C: Difference between night and day returns													
Intercept	-0.0010	-0.0008	0.0000	0.0006	0.0019	0.0012	0.0005	0.0003	0.0003	-0.0011	-0.0005	-0.0001	0.0001
	(-1.71)	(-1.29)	(0.03)	(0.85)	(2.39)	(2.03)	(0.44)	(0.42)	(0.85)	(-3.04)	(-0.58)	(-0.30)	(0.12)
Lagged 9:45 to 3:00 SPY return	-0.1193	0.0289	-0.1018	-0.0626	-0.2669	-0.0879	-0.3321	0.0573	-0.0463	-0.0107	0.0538	-0.0128	-0.3338
	(-5.07)	(0.90)	(-4.37)	(-2.13)	(-6.65)	(-3.15)	(-6.63)	(1.60)	(-2.69)	(-0.50)	(1.48)	(-0.81)	(-7.59)
Lagged 9:45-3:00 return dispersion	0.0427	0.1118	-0.0258	-0.0568	-0.2150	-0.0786	-0.1457	0.0438	-0.0419	0.0674	0.0552	0.0281	-0.1225
	(1.20)	(2.64)	(-0.84)	(-1.36)	(-4.15)	(-2.09)	(-2.06)	(0.89)	(-1.83)	(3.00)	(0.98)	(1.26)	(-2.09)
Adjusted R-square (%)	0.77	0.41	0.69	0.26	2.39	0.59	1.73	0.08	0.42	0.33	0.12	0.07	2.36
Panel D: Unconditional mean difference between night and day returns (%)													
	-0.0212	0.1033	-0.0443	-0.0415	-0.1866	-0.0123	-0.2074	0.1075	-0.0445	0.0080	0.0455	0.0367	-0.2016
	(-1.76)	(6.93)	(-4.15)	(-3.10)	(-9.95)	(-0.97)	(-8.84)	(5.71)	(-5.59)	(0.86)	(2.67)	(4.50)	(-10.16)

Table 7: The CAPM overnight and during the day

This table reports Fama-MacBeth coefficients in which beta-sorted decile portfolio returns are regressed on post-ranking betas. Decile portfolios are formed on the basis of a 250-day rolling market model regression using close-to-close stock and market returns. Post-ranking betas are estimated separately for the daytime (9:45am to 3:59pm) and overnight (3:59pm to 9:45am) periods. The table shows regression results in which overnight or daytime returns are regressed on the corresponding post-ranking beta. We show results for the full sample as well as subsamples chosen on the basis of the sign of the previous daytime market return (from 9:45am to 3:00pm). T-statistics, which are based on the Shanken (1992) method, are in parentheses.

	Overnight returns				**Daytime returns**		
	All days	Following positive daytime market returns	Following negative daytime market returns		All days	Following positive daytime market returns	Following negative daytime market returns
Intercept	-0.0218	-0.0696	0.0386	Intercept	0.1090	0.1080	0.0959
	(-4.86)	(-5.91)	(5.13)		(8.86)	(6.14)	(14.26)
Night Beta	0.0650	0.1337	-0.0155	Day Beta	-0.1109	-0.1588	-0.0651
	(7.61)	(8.84)	(-1.25)		(-7.87)	(-7.18)	(-4.98)
CS R-square (%)	96.99	95.40	31.10	CS R-square (%)	91.71	89.86	92.77

Table 8: Market order imbalances and returns

This table reports OLS regressions of market-level order imbalances or returns on past daytime (9:45am to 3:00pm) returns and return dispersion. Market returns are proxied using the SPY ETF. Market order imbalances and returns are value-weighted averages of stock-level values. T-statistics are in parentheses.

Panel A: Order imbalances

	9:30-9:45		9:45-10:30		10:30-4:00		9:30-9:45 minus 10:30-4:00	
Intercept	0.0433	-0.0436	0.0334	-0.0594	0.0222	-0.0372	0.0211	-0.0064
	(24.09)	(-6.21)	(31.67)	(-14.86)	(35.57)	(-13.63)	(13.00)	(-1.17)
9:45-3:00 SPY return	2.1022	1.9691	0.2987	0.1567	-0.1509	-0.2419	2.2531	2.2110
	(6.44)	(5.66)	(1.45)	(0.75)	(-1.26)	(-1.91)	(7.55)	(7.24)
9:45-3:00 return SD		5.0021		5.3396		3.4186		1.5835
		(11.89)		(21.36)		(20.31)		(4.86)
R-square (%)	1.06	6.56	0.05	18.50	0.03	21.62	1.49	2.15

Panel B: Returns

	Night		Day		Night minus day	
Intercept	0.0003	0.0007	0.0001	-0.0001	0.0003	0.0008
	(4.23)	(2.06)	(0.55)	(-0.25)	(2.17)	(1.54)
9:45-3:00 SPY return	0.0387	0.0392	-0.0549	-0.0551	0.0936	0.0943
	(2.04)	(2.07)	(-2.00)	(-2.00)	(2.90)	(2.91)
9:45-3:00 return SD		-0.0187		0.0095		-0.0283
		(-0.91)		(0.35)		(-0.88)
R-square (%)	0.17	0.19	0.19	0.18	0.39	0.41