A Tug of War: Overnight Versus Intraday Expected Returns

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Abstract

We provide new evidence about the cross-section of average stock returns through a careful examination of exactly when expected returns occur. Momentum and short-term reversal profits accrue entirely overnight while profits to all other trading strategies studied occur entirely intraday. In fact, for many of these anomalies, their overnight/intraday returns are larger than close-to-close returns as there is a partially-offsetting intraday/overnight premium of the opposite sign. We postulate that our findings are potentially consistent with a clientele explanation. We first document strong overnight and intraday return continuation, as well as cross-period reversal effects, all lasting for years. Using this novel overnight/intraday clientele lens, we argue that a relatively large difference between overnight and intraday returns reveals the extent to which investor clienteles are engaged in a "tug of war" over the direction of the strategy in question. All else equal, if the current tug of war is more contentious, the side betting to take advantage of the close-to-close pattern is more likely to be constrained and thus are more likely to leave part of the abnormal returns unexploited. Indeed, a one-standard-deviation increase in a strategy's smoothed overnight-intraday return spread forecasts a close-to-close strategy return in the following month that is 1% higher.

JEL classification: G02, G12, G23, N22

1 Introduction

Understanding cross-sectional variation in average returns is crucial for testing models of market equilibrium. Indeed, over the last three decades, researchers have documented a rich set of stock characteristics that forecast returns which provide a tough test to our standard asset-pricing models.[1] In this paper, we shed new light on this risk-return trade-off by decomposing the abnormal profits associated with these characteristics. Analogous to the large literature on the attribution of unexpected returns to cash-flow vs. discount-rate news, we decompose characteristics' average close-to-close returns into their intraday and overnight components. We argue that this is a reasonable and informative exercise because intraday and overnight periods differ along several important dimensions – for example, in terms of the arrival of both macro and firm-specific information, trading activity, investors' risk bearing capacity, and the funding costs of professional investors' capital.

We deliver remarkable new evidence about the cross-section of expected returns through a careful examination of exactly when expected returns accrue: our list of stock characteristics includes the factors of the Fama-French-Carhart model as well as eight popular anomalies relative to that model (and several variants of momentum such as earnings, industry and time-series momentum).[2] First, we find that all of the abnormal returns to momentum strategies occur overnight. The average intraday component of momentum profits, on the other hand, is economically and statistically insignificant; it is even negative for large-cap stocks and stocks with relatively high prices and institutional ownership. In stark contrast, the profits on size and value (and many other strategies, as discussed below) occur entirely intraday; on average, the overnight components of the profits on these two strategies are economically and statistically insignificant. More formally, we can easily reject the hypothesis that returns to these three strategies (as well as the many additional anomalies we also study) are distributed evenly across hours. Further, we find no evidence that standard risk factors or the arrival of macro and micro news explain these results.

Our analysis then turns to patterns in the cross-section not captured by the four-factor

[1] Both risk-based, behavioral, and limits-to-arbitrage explanations of the value and/or momentum effects have been offered in the literature. A partial list includes Barberis, Shleifer, and Vishney (1998); Hong and Stein (1999); Daniel, Hirshleifer, and Subramanyam (2001); Lettau and Wachter (2007); Vayanos and Woolley (2012); and Campbell, Giglio, Polk, and Turley (2016).

[2] A more precise description of our analysis is that we decompose returns into components based on exchange trading and non-trading periods. However, we refer to these two as intraday and overnight for simplicity's sake. Though the weekend non-trading period contains two intraday periods, we show in the paper that our results are not particularly different for this non-trading period. Thus, the weekend is not special in this regard.

Fama-French-Carhart model. We show that the premiums for profitability, investment, beta, idiosyncratic volatility, equity issuance, discretionary accruals, and turnover occur intraday. Indeed, by splitting abnormal returns into their intraday and overnight components, we find that the intraday premiums associated with these characteristics are significantly higher than that from close to close. These results thus imply, which we then confirm, the striking finding that these characteristics have an economically and statistically significant overnight premium that is opposite in sign to their well-known and often-studied total effect.

A closer look reveals that in every case a positive risk premium is earned overnight for the side of the trade that might naturally be deemed as riskier. In particular, firms with low return-on-equity, or firms with high investment, market beta, idiosyncratic volatility, equity issuance, discretionary accruals, or share turnover all earn a positive premium overnight.[3]

We also include the short-term reversal effect associated with one-month past returns in our analysis. Interestingly, we find that the negative premium that previous research has documented in close-to-close returns is realized entirely overnight. Thus, the two past-return based strategies, momentum and short-term reversal, are alike in our overnight/intraday decomposition. We also find that the overnight premium for short-term reversal is more negative than the corresponding close-to-close estimate, and thus there is, on average, a partially offsetting positive premium intraday.

Of course, to be persuasive, our decomposition must be reliable and robust. We exclude microcaps (i.e., stock in the bottom size quintile of the NYSE sample) and low-price stocks (< \$5 per share). When sorting stocks into portfolios, we only examine value-weight strategies and generate breakpoints using only NYSE stocks. We confirm our results using four different measures of open price, including the volume-weighted average price during the first half-hour the market is open as well as the midpoint of the quoted bid-ask spread at the open. The former measure ensures that our open price is tradable while the latter ensures that bid-ask bounce is not responsible for any of our findings.

As our results are inconsistent with simple neoclassical models of risk and returns (as risk exposures are unlikely to fluctuate at such a high frequency), we instead consider the possibility that preferences of investor clienteles drive these overnight-intraday differences. The core idea is that for various reasons (e.g., time-varying risk capacity, funding costs, institutional constraints), some investors prefer to trade (hold) a particular set of stocks at

[3]Merton (1987) argues that both beta and idiosyncratic volatility can have positive premiums in a world where investors cannot fully diversify. Campbell, Polk, and Vuolteenaho (2010) link accounting risk measures to cash-flow beta.

particular times (i.e. at the open of the market or near the market close), leading to the observed within-day variation in abnormal returns. To this end, we employ two different but complimentary ways of identifying the effect of investor clienteles. In our first, more general approach, without taking a stand on the exact classification of investor clienteles, we exploit the simple idea that clienteles should be relatively persistent. In particular, we start by documenting the extent to which past components of returns (either intraday or overnight) predict subsequent components in the cross-section of stocks. Under a clientele story, stocks that experience relatively strong overnight (intraday) returns do so in part because of the demand (and thus price pressure) from the clientele. If the clientele is persistent, those stocks should continue to perform relatively well overnight (intraday) in the near future. Furthermore, that price pressure (to the extent that it is not fully informative) should reverse during subsequent intraday (overnight) periods.

We confirm that stocks with relatively-high lagged overnight returns in the past month have relatively-high average overnight returns in the next month; these stocks also have average intraday returns in the next month that are relatively low. Specifically, a portfolio that buys the value-weight overnight winner decile and sells the value-weight overnight loser decile has a three-factor overnight alpha of 3.47% per month with an associated t-statistic of 16.83 and a three-factor intraday alpha of -3.02% per month (t-statistic of -9.74). Similarly, stocks with relatively-high lagged intraday returns have relatively-high average intraday returns over the next month coupled with relatively-low average overnight returns. A portfolio that buys the value-weight intraday winner decile and sells the value-weight intraday loser decile has a three-factor intraday alpha of 2.41% per month (t-statistic of 7.70) and a three-factor intraday alpha of -1.77% per month (t-statistic of -7.89).

More surprisingly, these striking patterns persist even when we lag past return signals by as much as 60 months. Indeed, the corresponding t-statistics for the resulting joint tests are over 20. We emphasize that one should interpret these abnormal returns and t-statistics with caution. Needless to say, transaction costs will make the actual profitability of such overnight/intraday strategies less economically attractive. But the t-statistics themselves strongly confirm that the patterns are not a statistical fluke and thus represent a clear economic phenomenon in the market that we hope has the potential to explain broader asset-pricing questions.[4] Nevertheless, to confirm that these findings are robust, we show that these results also strongly hold in each of the nine countries in our international sample.

[4] See Harvey, Liu, and Zhu (2016) for a discussion of the extent to which the usual hurdle for establishing significance should be increased to account for data mining. Our findings significantly exceed their proposed hurdle of 3.0.

We argue that our measure of the general clientele effect reveals an important piece of information about the popularity of the strategy in question. Specifically, one way of thinking about the intraday-overnight return pattern we have documented when decomposing average returns on anomalies is that there are heterogenous groups of investors (clienteles); some investors trade to eliminate the anomaly in question, and others trade in the opposite direction, thus helping the anomaly to perpetuate. However, until now, understanding heterogenous reactions to anomalies has been hamstrung when taken to the data since the standard way of measuring anomaly returns (close-to-close) only captures the net effect of these two groups.

In sharp contrast, with our novel overnight/intraday clientele prism, we can separate out a relatively large difference between overnight and intraday returns, which reveals the extent to which these two investor clienteles are effectively engaged in a tug of war over the direction of the stock/strategy in question. All else equal, if the current tug of war is more contentious, the side betting to take advantage of the close-to-close pattern is more likely to be constrained with regards to their investment activity in the strategy in question, and thus are more likely to leave part of the abnormal returns unexploited. We naturally interpret the side trading to eliminate the anomaly as the constrained party, since the average returns on these anomalies have continued to persist since their discovery. Consequently, we expect that contentious periods are followed by higher returns to the strategy. Thus, by exploiting the overnight versus intraday periods, which we have shown effectively sorts investors into clienteles with different preferences about key stock characteristics, we are able to measure the investment intensities of these two opposing clienteles.

As an example, to make our argument concrete, recall that we have shown that the profitability effect is primarily an intraday phenomenon, but has an economically-large, statistically-significant, and partially-offsetting overnight negative premium. Thus, when the past intraday minus overnight return spread is particularly *large*, the tug of war over the impact of that characteristic is particularly fierce, the clientele actively trading to take advantage of the profitability effect must be particularly constrained, and thus, we argue that the subsequent close-to-close returns on strategies trading the profitability effect should be particularly large.

In summary, we argue that our initial overnight-intraday decomposition provides a novel way to learn about the cross-section of average close-to-close returns. As a consequence, we use our smoothed measure of the past overnight minus intraday returns to forecast close-to-close returns of key anomalies. Our results show that this measure of a strategy's tug of war forecasts subsequent close-to-close returns just as predicted. All but one of the anomalies have the predicted sign for the forecasting coefficient, and seven of the eleven anomalies are statistically significant. The null hypothesis that these forecasting coefficients are jointly zero is strongly rejected ($p < 0.001$). In terms of economic importance, for a typical strategy in our sample, a one-standard-deviation increase in the smoothed overnight-intraday return spread forecasts a 1.01% higher close-to-close strategy return, or about 18% of its monthly return volatility.

With this insight, our second approach to measuring the clientele effect zooms in on the momentum strategy to illustrate a specific source of investor heterogeneity – individuals vs. institutions. Since it is reasonable to suspect that these two groups have different preferences, not only in terms of whether they buy or sell momentum stocks but also in terms of when they prefer to trade (when the market is open vs. when the market is closed), we therefore link institutional activity to our momentum decomposition in two steps.

We first examine when institutional investors likely initiate trades. Specifically, we link changes in institutional ownership to the components of contemporaneous firm-level stock returns. We find that for all institutional ownership quintiles, institutional ownership increases more with intraday than with overnight returns. Indeed, in some of these quintiles, institutional ownership tends to decrease with overnight returns. To the extent that collective trading can move prices, this evidence is consistent with the notion that institutions tend to initiate trades throughout the day and particularly at the close while individuals are more likely to initiate trades at the open. We then turn to the TAQ database and confirm that large trades (linked to institutions) are more likely to occur near the close while small trades (linked to individuals) are more likely to occur near the open.[5]

We next examine the extent to which institutions, relative to individuals, trade momentum stocks. We find that on a value-weight basis, institutions as a whole trade against the momentum characteristic. We then extend this finding by refining our understanding of why this intraday/overnight tug of war occurs and how it relates to intraday/overnight momentum returns. To this end, we condition both our trading and decomposition results on two key variables. The first variable is a time series measure of the degree of investment activity in momentum strategies introduced by Lou and Polk (2014). The second variable is a cross-sectional measure of the aggregate active weight (in excess of the market weight) of

[5]These results are consistent with the narrative of how these two classes of investors approach markets. Professional investors tend to actively trade during the day, and particularly near the close, taking advantage of the relatively high liquidity at that time. Conversely, individuals may be more likely to evaluate their portfolios in the evening after work and thus may tend to initiate trades that execute when markets open.

all institutions invested in a stock, which is likely related to institutions' rebalancing motives.

Either in the time series, when the amount of momentum activity is particularly low, or in the cross-section, when the typical institution holding a stock has a particularly strong need to rebalance, we find that momentum returns are relatively more negative during the day (when institutions actively put on their trades) and relatively more positive overnight. Both sorting variables generate variation in the spread between overnight and intraday momentum returns in the order of 2% per month. Moreover, consistent with the results from our general measure of investor clienteles, the average close-to-close return on momentum is stronger during these times when the momentum tug of war is relatively high.

Taken all together, our findings further challenge theories of the risk-return trade-off by revealing striking temporal patterns as to when trading profits on well-known strategies occur. We argue that investor heterogeneity plays an important role in understanding these patterns, in particular why momentum profits accrue overnight, and especially so for stocks whose institutional owners have relatively strong preferences to trade against the momentum characteristic. More generally, by showing strong overnight and intraday return continuation, as well as cross-period reversal effects, we document a remarkable tug of war across the overnight and intraday periods that we tie to time variation in average close-to-close returns on central asset-pricing anomalies.

The organization of our paper is as follows. Section 2 motivates our work and briefly summarizes existing literature. Section 3 describes the data and empirical methodology. Section 4 presents our main results. Section 5 presents evidence supporting our clientele interpretation. Section 6 concludes.

2 Motivation and Related Literature

Though we are the first to decompose the cross section of average returns into their intraday and overnight components, we argue that such a decomposition is a natural one as these two periods are different along several key dimensions.

One key difference between these two periods is that much of the overnight return may reflect more firm-specific information. The United States stock market is open from 9:30 am to 4:00 pm but a significant portion of earnings announcements occur outside of these times. More generally, firms tend to submit important regulatory filings after the market has closed.

Second, it is reasonable to assume that the overnight return is predominantly driven by trading of investors less concerned with liquidity and price impact, as after-hours trading is much thinner than trading while markets are open. Though the pre-open auctions on the NYSE and NASDAQ may average anywhere from one to four percent of median daily volume, depending on the type of stock, this is significantly less than the volume one observes intraday, particularly near or at the close. Consistent with this idea, Barclay and Hendershott (2003) find that though prices are more efficient and more information is revealed during the day, individual after-hours trades contain more information than those made when markets are open.

Alternatively, trading at the open could reflect trades that are not purely information-based. Presumably, many of these trades are made to rebalance portfolios that were previously optimal but no longer are. Indeed, some of the trading overnight may be a result of institutional capital flows. Perhaps some institutional investors' mandates effectively require capital to be invested immediately in the strategies those investors pursue, once that capital arrives.

Researchers have shown since at least Fama (1965) that volatility is higher during trading hours than non-trading hours.[6] Recent work by Kelly and Clark (2011) suggests that stock returns on average are higher overnight than intraday.[7] To our knowledge, we are the first paper decomposing the returns to popular characteristics into their overnight and intraday components. By providing this evidence, our decomposition brings new and important constraints to risk-, intermediary-, or behavioral-based explanations of these empirical regularities.

Many prior papers have linked investor heterogeneity (possibly tied to institutions) to patterns in the cross section of returns. A partial list includes Sias and Starks (1997); Sias and Nofsinger (1999); Cohen, Gompers, and Vuolteenaho (2002); Griffen, Harris, and Topaloglu (2003); Sias (2004); and Dasgupta, Prat, and Verardo (2011). Our paper contributes to this literature by providing relatively direct evidence of how investor clienteles may affect stock returns differentially across day and night.

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

[7]See related work by Branch and Ma (2008), Cliff, Cooper, and Gulen (2008), Tao and Qiu (2008), Berkman et al. (2009), and Branch and Ma (2012).

3 Data and Methodology

To decompose the close-to-close return into its overnight and intraday components, we use the open price from various sources: a) open prices as reported by the Center for Research in Security Prices (CRSP), b) the first trade price from the Trade and Quote (TAQ) database, c) the volume-weighted average price (VWAP) in the first half hour of trading (9:30-10am) as reported in TAQ, and d) the midpoint of the quoted bid-ask spread at the open. In almost all of the results presented below, we use VWAP during this first half hour as the daily open price. Our findings are robust to using the other three proxies for the open price (results available upon request). To further ensure that our VWAP is not driven by very small orders, we exclude observations where there are fewer than 100 shares traded in the first half hour (we have also checked that our results are not sensitive to this restriction.)

For each firm i, we define the intraday return, $r^i_{intraday,s}$, as the price appreciation between market open and close of the same day s, and impute the overnight return, $r^i_{overnight,s}$, based on this intraday return and the standard daily close-to-close return, $r^i_{close-to-close,s}$, taken directly from CRSP,

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

In other words, we assume that dividend adjustments, share splits, and other corporate events that could mechanically move prices take place overnight.[8] Furthermore, to ensure that the returns are actually achievable, if the open price on day s for a particular stock is missing (which happens very rarely as we exclude small-cap stocks from our sample), we hold the overnight position from the closing of day $s-1$ to the next available open price. Put differently, we construct our return measures such that the overnight and intraday returns aggregate up to exactly the close-to-close return. Though conceptually clean, this aspect of our methodology has no appreciable impact on our relative decomposition of average returns into their overnight and intraday components.

We then accumulate these overnight and intraday returns across days in each month t.

[8] We know of no violation of this assumption in our sample. However, we have redone our analysis excluding months in which dividends are paid, and our results are nearly identical.

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

Thus, all of our analysis examines the intraday and overnight components of the standard CRSP monthly return, r^i_t.

We mostly focus on portfolios, where we typically report the following three components:

$$
\begin{aligned}
r^p_t &= \sum_i w^i_{t-1} r^i_t, \\
r^p_{intraday,t} &= \sum_i w^i_{t-1} r^i_{intraday,t}, \\
r^p_{overnight,t} &= \sum_i w^i_{t-1} r^i_{overnight,t}.
\end{aligned}
$$

Of course $(1 + r^p_t) \neq (1 + r^p_{intraday,t})(1 + r^p_{overnight,t})$, due to $\sum_i w^i_{t-1} r^i_{intraday,t} r^i_{overnight,t}$ (i.e the interaction term), so our portfolio decomposition does not sum to the close-to-close return. This discrepancy is small and can be easily backed out from our tables.

Our core US data sample spans 1993-2013, constrained by the availability of TAQ data. We exclude microcap stocks—i.e., those with a price below \$5 a share and those whose market capitalization is in the bottom NYSE size quintile—from the sample to mitigate microstructure issues. We augment these data with information on institutional ownership from Thompson Financial.

The main objective of this study is to examine the expected returns to a host of popular characteristics during the overnight vs. intraday periods. In particular, we focus on the following set of strategies/firm characteristics: price momentum, size, value, earnings momentum, industry momentum, time-series momentum, profitability, investment, idiosyncratic volatility, beta, turnover, equity issuance, discretionary accruals, and short-term reversals. We first decompose holding-period returns on simple value-weight long-short portfolios. Later on in the analysis, we decompose holding period returns generated by Fama-MacBeth

WLS regressions (where the WLS weights in each cross-sectional regression are proportional to market capitalization). These regressions allow us to carefully decompose partial effects. We report hypothesis tests as to whether overnight and intraday average returns are equal (both as a whole and on an hourly basis) in the context of our Fama-MacBeth analysis.

4 Results

4.1 Setting the stage

We set the stage with a plot. We first show that there is significant volume at the open by reporting dollar trading volume over 30-minute intervals throughout the trading day. In particular, each month, we sum up the number of dollars traded in each of these half-hour windows. The first half-hour window that starts at 9:30 am also includes the open auction. The last half-hour window that starts at 3:30 pm also includes the last-minute (i.e., 4 pm) trades and closing auction. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-minute interval.

Figure 1 displays the time-series average of these fractions. The percent of dollar trading volume that takes place in the first 30-minute window is 14.25%. This amount is non-trivial, though of course there is much more trading activity after the first half-hour. Consistent with previous research, trading activity dips during the day and then rises near the close. Nevertheless, we view Figure 1 as confirming that the open price is an important economic measure.

As a benchmark, we decompose the equity premium into its overnight and intraday components. Appendix Figure A1 reports this decomposition for two different market proxies, the value-weight CRSP universe and the value-weight portfolio of the top 1% of stocks by market capitalization. The red bars in Figure A1 correspond to the first market proxy, which is typically used in performance attribution. This standard proxy for the market portfolio has an average annual return of 11.22%. Of this, 4.58% is earned intraday and 6.99% is earned overnight. This breakdown lines up pretty well with one simply based on the percentage of time corresponding to each of these two periods. Specifically, the US market is open for approximately 27% of the 24-hour day and the premium earned then is roughly 40% of the total. As we shall soon see, the decomposition results for the popular trading strategies we study are all very far from this natural benchmark.

Previous work has argued that the equity premium is primarily an overnight phenomenon. Much of that research bases their conclusions on narrow market proxies like an ETF tracking the Dow 30. Appendix Figure A1 sheds some light on these findings by confirming that our TAQ-based bottom-up decomposition is quite different for the very largest stocks. This result foreshadows our finding in section 4.4 that the well-known small-stock effect is completely an intraday phenomenon. As a consequence, one has to be careful using narrow-based market proxies in such a context.

4.2 Momentum

We begin with a decomposition of the returns on a standard implementation of the classic momentum strategy, MOM, of Jegadeesh and Titman (1993), choosing this strategy as a starting point as its behaviour contrasts with that of most other characteristics. In particular, we measure momentum over a twelve-month ranking period and then skip a month before forming portfolios. Table I Panel A reports MOM's total (close-to-close) return for our sample from 1993-2013. Despite the fact that our sample period is relatively short and includes a significant momentum crash, the abnormal returns to the strategy are economically large and statistically significant. The three-factor alpha is 1.05% per month with an associated t-statistic of 2.22. A similar, though slightly weaker finding holds for CAPM-adjusted returns (0.93% per month with a t-statistic of 1.98).

Panel B of Table I presents the first major result of the paper. Essentially all of this abnormal three-factor alpha is generated overnight. Specifically, the overnight three-factor alpha is 0.95% (t-statistic of 3.65) while the intraday three-factor alpha is only 0.11% (t-statistic of 0.27).

We summarize these results in Table I Panel C. Though all of momentum profits occur from the closing price to the opening price, the overnight return on MOM is much less volatile (4.02% standard deviation) than the close-to-close return (7.85% standard deviation). Thus, the Sharpe Ratio of the overnight return on MOM is more than twice as high as the Sharpe Ratio on the close-to-close return. Interestingly, on average, more of the negative skewness observed in momentum strategies (Daniel and Moskowitz 2013) and present in MOM arrives intraday rather than overnight.

In results not shown, we measure the extent to which these overnight returns are spread evenly throughout weeknights and the weekend. Of the 89 basis points of excess return, 72 basis points accrue Monday through Thursday while 18 basis points accrue over the weekend.

Thus, in this regard, the weekend is roughly similarly to one overnight period.

Note that Table I controls for CAPM and three-factor risk by regressing monthly overnight or intraday MOM returns on the close-to-close monthly return of the factor(s) in question. Of course, since we are documenting that momentum returns occur disproportionately overnight, we must be careful to show that the risk premium implied by the CAPM or the three-factor model does not disproportionately occur overnight as well. Indeed, as mentioned above, for our sample, roughly 60% of the equity premium is earned overnight. In Appendix Table A1, we similarly decompose the market and three-factor model into overnight and intraday components and re-estimate the three-factor regression using these components. For now, we do not describe the way the properties of these factors vary from overnight to intraday; Section 4.4 will carefully decompose the size and value premiums into overnight and intraday components.

The top third of Appendix Table A1 examines the way the three-factor loadings of MOM's close-to-close return change as we split the Fama and French factors into their overnight and intraday components. We find that MOM's market loading is higher overnight than intraday, but is still negative. Moreover, MOM's SMB and HML loadings decrease and in both cases are negative. Thus, it seems unlikely that changing three-factor risks can account for the fact that momentum returns are primarily overnight.

We confirm that this is the case in the middle third of Appendix Table A1 where we explicitly regress the overnight MOM returns on the overnight Fama-French three-factor model. The three-factor loadings are negative, and the alpha remains an economically large 0.86% (t-statistic of 3.07). The lower third of Appendix Table A1 confirms that the intraday MOM three-factor alpha remains economically and statistically insignificant when the strategy and factor returns are both computed on an intraday basis.

A naturally interesting aspect of momentum returns is the extent to which they revert (Jegadeesh and Titman 2001). Appendix Figures A2 and A3 examine this question by plotting the cumulative excess returns (Appendix Figure A2) and abnormal three-factor returns (Appendix Figure A3) on MOM for up to two years after portfolio formation. These figures plot not only the close-to-close return but also the overnight and intraday components. Appendix Figure A2 shows that overnight returns are strongly positive for up to 12 months. Then, starting around month 18, these returns begin to revert and, after two years, have reverted by roughly 30%. In stark contrast, intraday returns are strongly negative for the first two years.

Of course, an aspect of momentum strategies that complicates this analysis is that winner (loser) stocks are typically growth (value) stocks; this fact is true for MOM over our sample. Thus, one must be careful when examining the long-horizon performance of a momentum strategy as growth-minus-value bets are known to strongly underperform for several years in event time. By reporting cumulative three-factor residuals, Appendix Figure A3 removes this complicating aspect and reveals that the intraday profits are essentially zero for the first seven months. Indeed the curves representing the cumulative abnormal returns overnight and close-to-close are extremely close to each other all the way to month 12. After adjusting for three-factor exposure, we still find some evidence of long-run reversal as overnight profits revert partially (about 30%) during the second year.

The fact that the negative skewness present in momentum returns tends to occur intraday raises the question of the way momentum strategies perform overnight versus intraday during momentum crashes. For insight along these lines, Appendix Figure A4 plots the components of momentum returns during 2009. In the first two months of 2009, overall momentum returns are positive. Beginning in March 2009, returns to the momentum strategy are negative for the next six months. Interestingly, March's negative return of -9.4% occurs entirely overnight (-12%) as the intraday return is positive (2.4%). The overnight crash in March is then followed by a dramatic -41% return in April, which almost entirely occurs intraday (-39%) rather than overnight (-2%). The momentum crash continues in May as returns to the momentum strategy are -18%, driven by an overnight drop that month of -26%. Though of course the March-May momentum crash coincides with many other market phenomena, it is interesting to note that the largest decline occurred intraday, but was precipitated by a smaller, but still quite large, overnight drop the month before.

4.3 Robustness Tests

To ensure the reliability of our results, we have excluded microcaps and low-price stocks from the sample and sorted stocks into value-weight portfolios based on NYSE breakpoints. Furthermore, we have made sure that overnight returns are only based on traded prices. However, to confirm those conclusions, Table II documents that our findings are robust to subsample analysis.[9]

One possibility is that our finding is driven by extremes that occur in particular subperi-

[9] For the sake of parsimony, this table simply shows the average returns on the overnight and intraday components of various subsample zero-cost momentum bets. For completeness, Appendix Table A2 reports the average returns on both the long and the short sides of these bets.

ods. Table II Panels A and B report the decomposition for the first and second halves of the sample. Of course, the 2009 crash results in very negative realized values for the momentum portfolios. As a consequence, we exclude that year from our analysis, and simply decompose momentum profits during normal markets. We find that momentum profits are entirely an overnight phenomenon in both the early subsample (1993-2002) and the late subsample (2003-2013). Specifically, we find that the three-factor alpha during the early period is 1.26% per month with a t-statistic of 3.99. The late period's three-factor alpha is 1.19 percent per month with a t-statistic of 4.26. Thus, our surprising finding is not just a historical quirk. Instead, these patterns are very much present in the recent data.

Despite using TAQ data to ensure we use only volume-weighted prices actually traded around the open, a concern might be that our findings are driven by some microstructure artifact. Table II Panels C and D report our decomposition for small- and large-cap stocks separately. Presumably, by focusing on large-cap stocks, we can eliminate concerns that any such artifact drives our results. We sort stocks each month based on median NYSE market capitalization. We find that overnight returns to the momentum strategy are actually stronger for large-cap stocks. For small-cap stocks, the overnight three-factor alpha is 0.54% (t-statistic of 4.49) while the intraday three-factor alpha is 0.39% (t-statistic of 1.59). For large-cap stocks, the overnight three-factor alpha is 1.04% (t-statistic of 5.90) while the intraday three-factor alpha is actually negative, -0.24% (t-statistic of -0.79).

A related concern is that even though we are using traded prices, perhaps these prices disproportionately reflect the ask for the winner stocks and the bid for loser stocks. Table II Panels E and F split the sample based on price as high-priced stocks presumably have much lower bid-ask spreads on a percentage basis. We again split the sample based on monthly median NYSE values and find that overnight returns to the momentum strategy are actually stronger for high-price stocks. For low-price stocks, the overnight three-factor alpha is 0.66% (t-statistic of 3.59) while the intraday three-factor alpha is 0.33% (t-statistic of 1.17). For high-price stocks, the overnight three-factor alpha is 1.14% (t-statistic of 6.63) while the intraday three-factor alpha is again negative, -0.41% (t-statistic of -1.33).

We further test this concern by replacing our VWAP open price with the midpoint of the bid-ask spread. We limit the data to NYSE stocks that have quote data updated regularly throughout the day. Recall that Table I Panel B reports that the average excess overnight return is 0.89% per month with an associated t-statistic of 3.44 and the average excess intraday return is -0.18% per month (t-statistic of -0.43) when using the VWAP price. In untabulated results, we find that these results are very similar if we instead use the midpoint of the bid-ask spread. In particular, the average excess overnight return is 0.95% per month with an associated t-statistic of 2.95, and the average excess intraday return is only 0.04% per month (t-statistic of 0.17).

Finally, to ensure that we are not picking up a temporary spike in the prices of momentum stocks that occurs when the market opens but quickly reverts during the day, Appendix Figure A5 decomposes the intraday momentum return into its hourly components. There is no evidence of anything unusual throughout the day, confirming our paper's surprising result that the vast majority of momentum profits occur overnight. Appendix Figure A5 plots both excess and three-factor adjusted returns; our conclusions are robust when using either.

In summary, our finding that momentum is an overnight phenomenon continues to hold even when we carefully examine various types of prices throughout the day, study only the largest or highest-priced stocks, or focus only on the last ten years of data.

4.4 Comparison with Size and Value

A possible economic explanation for our finding might be that the overnight premium for momentum represents compensation for periods when intermediary capital and/or collateral is most expensive. We examine two other well-known strategies that should be similar to momentum in this regard, namely strategies that capture the average returns associated with size and value (Fama and French 1992).[10] We first examine a strategy (ME) that goes long the small-stock decile and short the large-stock decile. Table III Panel A reports the overnight and intraday components of ME's excess and CAPM-adjusted returns. Essentially all of the size premium occurs intraday. Specifically, the intraday CAPM alpha is -0.43% (t-statistic of -1.85) while the overnight CAPM alpha is only -0.11% (t-statistic of -0.75).

We then decompose the returns on a strategy (BM) that goes long the high book-to-market decile and short the low book-to-market decile. We measure book-to-market-equity ratios following Fama and French (1992). Table III Panel B reports the overnight and intraday components of BM's excess and CAPM-adjusted returns. Again, we find that essentially all of the value premium occurs intraday. Specifically, the intraday CAPM alpha

[10] Fama and French (1992) argue that size and the book-to-market-equity ratio describe the cross section of average returns, subsuming many other related characteristics. Fama and French (1993) propose a three-factor model that includes not only a market factor but also a size and value factor. Fama and French (1996) argue that these factors price a variety of trading strategies except for the momentum effect of Jegadeesh and Titman (1993).

is 0.48% (t-statistic of 2.21) while the overnight CAPM alpha is actually slightly negative, though not statistically significant (-0.10% per month, t-statistic of -0.67).

As a consequence, simple stories that rely on the fact that capital and/or collateral is more expensive overnight cannot explain the reason momentum profits only accrue overnight but size and value premiums do not.

4.5 The Role of News Announcements

Macroeconomic news

Scheduled macroeconomic announcements are made both when markets are open and when they are closed, in roughly equal proportions. Of course, particular announcements may be particularly relevant in terms of cross-sectional differences in risk. We take a first step in analyzing whether exposure to macroeconomic news can explain the cross-section of overnight versus intraday returns by examining the cross-sectional response to a macroeconomic announcement that has been shown to be relevant for the market as a whole, namely the announcement from the meeting of the Federal Open Market Committee (FOMC). Lucca and Moench (2015) show the market response to macro announcements documented in Savor and Wilson (2014) exclusively comes from the FOMC announcement and occurs during the 2pm-to-2pm period prior to the scheduled FOMC announcements. Since the market response is quite strong and covers both an intraday and overnight period, this announcement has the potential to uncover differences in risk across these periods for momentum, size, and value strategies.

Table III Panel C reports the overnight and intraday components for the day of the announcement as well as the days before and after the announcement for momentum, size, and value long-short portfolios. We find no statistically significant average returns over these days for any of the three strategies.

Firm-specific news

One clear difference between the intraday and overnight periods is that a significant portion of firm-specific news tends to be released after markets close. Table III Panels D and E examine the role of news announcements. In particular, we classify months as containing news if there is either an earnings announcement or news coverage in the Dow Jones Newswire. Months without either an earnings announcement or news coverage are classified as months without news. Note that this classification is done ex post so our results should be interpreted as simply attributing whether realized overnight momentum returns are particularly large when news occurs.

Table III Panel D reports that momentum earns an overnight premium in both news months (1.02% three-factor alpha with a t-statistic of 4.30) and in no-news months (1.35% three-factor alpha with a t-statistic of 5.15). The difference in the overnight returns to momentum between months in which there is news and months without news is not statistically significant. Table III Panel E examines whether the realized intraday returns on ME and BM are particularly large during news months. We find no statistical difference across the two categories here as well.

4.6 Other Patterns in the Cross-Section of Expected Returns

We now decompose the returns on a variety of popular trading strategies to confirm and extend our results. In each case, we simply report the average returns on the overnight and intraday components of the zero-cost strategy; please see Appendix Table A3 for the average returns on both the long and the short sides of these strategies.

Earning Momentum, Industry Momentum, and Time-series Momentum

To show that our conclusion that momentum profits occur overnight is robust, we next examine three other momentum strategies. Table IV Panel A decomposes the abnormal returns on an earnings momentum strategy (SUE). Our earnings momentum characteristic is simply the difference between reported earnings and the consensus forecast; this difference is scaled by the firm's stock price. As with price momentum, we find that 100% of the returns to SUE occur overnight. In particular, the three-factor alpha of a long-short earnings momentum portfolio is 0.58% with a t-statistic of 3.23. The corresponding intraday three-factor alpha is indistinguishable from zero.

Table IV Panel B decomposes the abnormal returns on an industry momentum strategy ($INDMOM$). We follow Moskowitz and Grinblatt (1999) and measure industry momentum over a twelve-month ranking period for 20 industries based on SIC codes. Again, we find that 100% of the $INDMOM$ effect occurs overnight. In particular, the three-factor alpha of a long-short industry momentum portfolio is 1.09% with a t-statistic of 6.65. The corresponding intraday three-factor alpha is an economically large -0.56%, though (just barely) statistically indistinguishable from zero.[11]

[11] More detailed information about the time-series momentum strategy is provided in Appendix Table A10.

Table IV Panel C reports the intraday and overnight returns of Moskowitz, Ooi and Pedersen's (2012) time series momentum strategy applied to a universe of 22 of the most liquid futures on international equity indexes. Moskowitz, Ooi and Pedersen apply their strategy on 59 assets spanning all asset classes, but since equity markets are the focus of our paper, we restrict our attention only to equity indexes, which is also appropriate because "intraday" and "overnight" periods are much more well-defined for equity markets than they are for, say, USD/Yen currency futures. As with cross-sectional momentum, time series momentum occurs entirely overnight. Its four-factor monthly alpha is 1.54% with a t-statistic of 3.64. The corresponding intraday alpha is negative, economically negligible, and statistically indistinguishable from zero. Interestingly, all of this strategy's negative return skewness comes from its intraday component. In summary, for the four different momentum strategies studied in this paper, all of the abnormal profits occur overnight.

Profitability and Investment

Despite the success of the three-factor model, researchers have documented that several other characteristics generate cross-sectional variation in average returns. Chief among these characteristics are profitability – introduced by Haugen and Baker (1996) and confirmed in Vuolteenaho (2002) – and investment – introduced by Fairfield, Whisenant, and Yohn (2003) and carefully analyzed in Titman, Wei, and Xie (2004) and Polk and Sapienza (2009). Indeed, Fama and French (2014) grants that two factors based on profitability and investment help describe the cross section of average returns, even in the presence of their value factor, HML.

We examine a strategy (ROE) that goes long the high profitability decile and short the low profitability decile. Table IV Panel D reports the overnight and intraday components of ROE's excess, CAPM-adjusted, and three-factor-adjusted returns. More than 100% of the profitability premium occurs intraday as there is a very strong *negative* expected return associated with ROE overnight. Specifically, the intraday three-factor alpha is 1.43% (t-statistic of 6.44) while the overnight three-factor alpha is -0.95% (t-statistic of -6.22).

We then examine a strategy (INV) that goes long the high investment decile and short the low investment decile. Table IV Panel E reports the overnight and intraday components of INV's average excess, CAPM-adjusted, and three-factor-adjusted returns. Again, more than 100% of the negative investment premium occurs intraday as there is a statistically significant *positive* expected return associated with INV overnight. Specifically, the intraday three-factor alpha is -0.78% (t-statistic of -4.09) while the overnight three-factor alpha is 0.36% (t-statistic of 2.85).

Beta and Idiosyncratic Volatility

The next two strategies we study relate to traditional measures of risk. The fundamental measure of risk in the asset-pricing model of Sharpe (1964), Lintner (1965), and Black (1972) is market beta. However, empirical evidence indicates that the security market line is too flat on average (Black 1972 and Frazzini and Pedersen 2014).

We examine a strategy ($BETA$) that goes long the high-beta decile and short the low-beta decile. We measure beta using daily returns over the last year in a market model regression. We include one lead and one lag of the market in the regression to take nonsynchronous trading issues into account. Table IV Panel F reports the overnight and intraday components of $BETA$'s excess, CAPM-adjusted, and three-factor-adjusted returns. More than 100% of the negative beta premium occurs intraday as there is a *positive* premium associated with $BETA$ overnight. Specifically, the intraday three-factor alpha is -0.80% (t-statistic of -2.60) while the overnight three-factor alpha is 0.49% (t-statistic of 2.10).

We then analyze a strategy ($IVOL$) that goes long the high idiosyncratic volatility decile and short the low idiosyncratic volatility decile. Ang, Hodrick, Xing, and Zhang (2006) argue that high idiosyncratic stocks have abnormally low returns. We measure idiosyncratic volatility as the volatility of the residual from a daily Fama-French-Carhart four-factor regression estimated over the prior year. We include a lead and lag of each factor in the regression so that nonsynchronous trading issues are taken into account. Table IV Panel G documents that more than 100% of $IVOL$ occurs intraday. As a consequence, $IVOL$ is associated with a *positive* risk premium overnight. Specifically, the intraday three-factor alpha for $IVOL$ is -2.34% per month with an associated t-statistic of -7.82. The corresponding overnight three-factor alpha is 1.61% per month with a t-statistic of 5.81.

Equity Issuance and Discretionary Accruals

Our next group of strategies are related to firm financing and accounting decisions. Daniel and Titman (2006) show that issuance activity negatively predicts cross-sectional variation in average returns. Sloan (1996) documents a strong negative correlation between discretionary accruals and subsequent stock returns. We first examine a strategy ($ISSUE$) that goes long the high-equity-isuance decile and short the high-equity-isuance decile. Table IV Panel H reports the overnight and intraday components of $ISSUE$'s excess, CAPM-adjusted, and three-factor-adjusted returns. More than 100% of the issuance premium occurs intraday as there is a very strong *positive* expected return associated with $ISSUE$ overnight. Specifically, the intraday three-factor alpha is -1.05% (t-statistic of -6.05) while the overnight three-factor alpha is 0.52% (t-statistic of 3.35).

We then examine a strategy ($ACCRUALS$) that goes long the high discretionary accruals decile and short the low discretionary accruals decile. Table IV Panel I reports the overnight and intraday components of $ACCRUALS$'s average excess, CAPM-adjusted, and three-factor-adjusted returns. Again, more than 100% of the accruals premium occurs intraday as there is a statistically significant *positive* expected return associated with $ACCRUALS$ overnight. Specifically, the intraday three-factor alpha is -0.94% (t-statistic of -4.95) while the overnight three-factor alpha is 0.56% (t-statistic of 4.00).

Turnover and One-month Return

The final two strategies we study relate to liquidity and price impact. Datar, Naik and Radcliffe (1998) show that turnover ($TURNOVER$) is negatively related to the cross-section of average returns, and this finding is confirmed in Lee and Swaminathan (2000). Jegadeesh (1990) shows that buying (selling) short-term losers (winners) is profitable.

We first examine a strategy ($TURNOVER$) that goes long the high turnover decile and short the low turnover decile. We measure turnover following Lee and Swaminathan (2000) as the average daily volume over the last year. Table IV Panel J reports the overnight and intraday components of $TURNOVER$'s average excess, CAPM-adjusted, and three-factor-adjusted returns. Again, more than 100% of the negative turnover premium occurs intraday as there is a statistically significant *positive* expected return associated with $TURNOVER$ overnight. Specifically, the intraday three-factor alpha is -0.52% (t-statistic of -3.22) while the overnight three-factor alpha is 0.35% (t-statistic of 2.54).

We then analyze a strategy ($RET1$) that goes long the high past one-month return decile and short the low past one-month return turnover decile. Table IV Panel K reports the overnight and intraday components of $RET1$'s average excess, CAPM-adjusted, and three-factor-adjusted returns. Note that we find no short-term reversal close-to-close effect, which is perhaps not surprising given that we exclude microcaps from our sample, form value-weight portfolios, and study a relatively recent time period. However, what is surprising is that our decomposition reveals a strong overnight reversal and a slightly stronger *positive* expected return associated with $RET1$ intraday. Specifically, the intraday three-factor alpha is 1.05% (t-statistic of -3.26) while the overnight three-factor alpha is -0.88% (t-statistic of 4.01).

The interaction between momentum and idiosyncratic volatility

So far our momentum analysis has focused on the winner and loser decile portfolios. We now look more closely at how our decomposition varies across the momentum decile portfolios. This closer look in turn leads us to show that the interaction between idiosyncratic volatility and momentum plays an important role in our decomposition.

Appendix Figure A6 plots the value-weight excess returns from close-to-close, overnight, and intraday for ten value-weight momentum decile portfolios. Though the average close-to-close returns are roughly increasing as one moves from the loser decile to the winner decile, the overnight and intraday components are surprisingly U- and hump-shaped respectively.

To explain these patterns, we exploit two facts. The first fact is that both extreme winners and losers tend to be stocks with high idiosyncratic volatility. The second fact is that $IVOL$ is associated with a *positive* risk premium overnight, as our decomposition of $IVOL$ above shows. These two facts suggest an explanation for the U- and hump-shaped patterns of Figure A6; namely, extreme winner or loser stocks generally outperform overnight and underperform intraday because they tend to be high idiosyncratic volatility stocks.

As a consequence, Appendix Table A4 Panels A and B decompose the excess returns on 25 momentum- and idiosyncratic-volatility-sorted portfolios into their overnight and intraday components respectively. There are several findings worth noting. First, within all but the highest idiosyncratic volatility quintile, average excess returns are increasing with momentum. And even within the highest idiosyncratic volatility quintile, the momentum effect is much more monotonic. Second, the t-statistics on the 5-1 long-short momentum portfolios within each idiosyncratic volatility quintile are now much more statistically significant. Third, the idiosyncratic–volatility-stratified intraday return on a momentum bet is statistically insignificant from zero. Finally, both the positive overnight and the negative intraday premia associated with idiosyncratic volatility remain robust in these double sorts that control for momentum.

Appendix Table A4 Panel C presents another way to control for this interesting interaction between momentum and idiosyncratic volatility, simply excluding high idiosyncratic stocks (stocks with idiosyncratic volatility above the NYSE 80th percentile) from the sample each month. As one might expect from findings of the previous two panels in the table, we find the overnight three-factor alphas on value-weight momentum deciles using this sample are now much more monotonic. The overnight return on a portfolio that is long the winner decile and short the loser decile has a three-factor alpha of 1.25% per month with a t-statistic of 4.28.

Fama-MacBeth Regressions

Though portfolio sorts are useful as a robust, non-parametric approach to document the link between a characteristic and the cross-section of average returns, this approach has difficulty controlling for more than just a very small number of other characteristics and thus makes measuring partial effects problematic. As a consequence, we turn to Fama and MacBeth (1973) regressions to describe the cross-section of overnight versus intraday expected returns. Observations are weighted by lagged market capitalization in each cross sectional regression to be consistent with our portfolio analysis. Columns (1) through (3) of Table V report the following three regressions: a standard regression forecasting the cross-section of $r_{close-to-close}$, a regression forecasting the cross-section of $r_{overnight}$, and a regression forecasting the cross-section of $r_{intraday}$. In each regression, we include all of the characteristics studied above except for SUE, as it reduces the number of observations in each cross-section considerably.

Regression (1) shows that, for our sample, only $RET1$, INV, and $ISSUE$ are statistically significant (on a value-weighted basis). Regression (3) reveals that many of these characteristics are much stronger predictors of the cross-section of intraday returns. In fact, $SIZE$, $IVOL$, $BETA$, $TURNOVER$, ROE, INV, $ISSUE$, and $ACCRUALS$ are all statistically significant. Consistent with our portfolio sorts, the sign on $RET1$ flips to be positive and statistically significant. There are negative intraday MOM and BM effects, though the estimates are not significant at the five percent level of significance.[12]

In the cross-section of overnight returns described by regression (2), MOM is very strong. Consistent with the results in previous tables, there is a strong positive premium associated with $IVOL$ and $TURNOVER$ and a strong negative premium associated with ROE and $RET1$. The positive premium for $BETA$ is large but only marginally statistically significant. Interestingly, there is a positive premium for $SIZE$. Overall, these regressions are consistent with our main findings.

Testing for statistical differences between overnight and intraday overnight premiums for Fama-French-Carhart anomalies

Regressions (4) and (5) present the main statistical tests of our decomposition of average returns. Regression (4) tests the hypothesis that the overnight and intraday partial premiums

[12] The fact that BM does not describe cross-sectional variation in average returns after controlling for INV and ROE is consistent with Fama and French (2014b).

for a particular anomaly are equal. We easily reject a joint test of that null. Regression (5) tests the hypothesis that the overnight and intraday partial premiums for each anomaly are proportional to the corresponding percentage of the 24-hour day. We easily reject a test that this is jointly true across the anomalies in question.

Overnight premiums for Fama-French-Carhart anomalies

Table IV has the interesting result that all of the variables that are anomalous with respect to the Fama-French-Carhart model have risk premiums overnight that are opposite in sign to their intraday average returns. A closer look reveals that in every case a positive risk premium is earned overnight for the side of the trade that might naturally be deemed as riskier. In particular, firms with low return-on-equity, or firms with high investment, market beta, idiosyncratic volatility, equity issuance, discretionary accruals, or share turnover all earn a positive premium overnight. In addition to market beta, Merton (1987) argues that idiosyncratic volatility can have positive premiums in a world where investors cannot fully diversify. Relatively low profits or (excessive) investment/issuance/accruals are intuitive accounting risk factors. For example, Campbell, Polk, and Vuolteenaho (2010) link cross-sectional variation in similar accounting characteristics to cross-sectional variation in cash-flow beta.[13]

We explore whether there is a simple risk-based explanation for why the 'apparently riskier' side of the trade earns positive overnight returns. Our analysis builds on our Fama-MacBeth regressions, which allow us to isolate partial effects. Specifically, we regress the time-series of each coefficient averaged in Column (2) of Table V (the partial effect of each anomaly on overnight returns) against the time-series of overnight market returns. In each row of Column (6) in Table V we report the intercept from each of these regressions. Where this intercept is significantly smaller than the corresponding row of Column (2), the partial effect of the overnight anomaly is explainable on the basis of its exposure to market risk. However, the only anomaly which is reduced significantly is that of market beta, which is dramatically lower and no longer statistically significant. Therefore we cannot provide a simple general explanation of overnight effects based on their exposure to risks, but in future research we hope to explore this further, by linking positive overnight premiums to more

[13] At first glance, the fact that low size and high book-to-market firms do not earn positive premiums overnight as well seems inconsistent with this interpretation. However, since both size and book-to-market ratio are well-known styles that many investors follow, one could argue that there is safety in numbers for investors who invest within these styles and are evaluated relative to how the style performs. In contrast, the strategies above (ROE, INV, $BETA$, $IVOL$, $ISSUE$, $ACCRUALS$, or $TURNOVER$) are not common styles in equity markets.

general measures of overnight risk.

5 A Clientele Explanation

Since we have documented striking overnight-versus-intraday patterns in the average returns of three-factor anomalies that we cannot explain under a simple neoclassical framework, we turn to clientele explanations. We first provide a general measure of clienteles in the overnight-intraday cross-section of average returns. We then study a specific clientele effect among momentum stocks.

5.1 A General Measure of Clienteles

One potential interpretation of our findings is that some investors tend to trade certain stocks in the same direction either at the market open or during the day. In other words, there are clienteles that prefer certain types of stocks and these clienteles trade at certain times of the day. If these clienteles are persistent, then one should see persistence in overnight and intraday returns as well as a cross-period reversal. Thus, we measure intraday and overnight clienteles more generally by decomposing past returns into overnight and intraday components and looking for these continuation and reversal patterns.

In Table VI, at the end of each month, all stocks are sorted into deciles based on their lagged one-month overnight returns (Panel A) or lagged one-month intraday returns (Panel B). In each sort, we then go long the value-weight winner decile and short the value-weight loser decile. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model.

We find striking results. A hedge portfolio based on past one-month overnight returns earns on average an overnight excess return of 3.47% per month with an associated t-statistic of 16.57. This finding continues to hold regardless of the risk adjustment as the three-factor alpha is also 3.47% per month (t-statistic of 16.83). This one-month overnight return hedge portfolio earns on average an intraday excess return of -3.24% per month with an associated t-statistic of -9.34 (three-factor alpha of -3.02% per month with a t-statistic of -9.74).

Similarly, a hedge portfolio based on past one-month intraday returns earns on average an intraday excess return of 2.19% per month with an associated t-statistic of 6.72. Adjusting for three-factor exposure does not substantially reduce the effect; indeed, the three-factor alpha is higher at 2.41% per month (t-statistic of 7.70). This one-month intraday return hedge portfolio earns on average an overnight excess return of -1.81% per month with an associated t-statistic of -8.44 (three-factor alpha of -1.77% per month with a t-statistic of -7.89).[14]

As with our momentum decomposition, these results are robust to replacing the VWAP open price with the midpoint of the quoted bid-ask spread at the open. In particular, the portfolio based on past one-month overnight returns has an overnight three-factor alpha of 1.88% (t-statistic of 8.75) and an intraday three-factor alpha of -1.43% (t-statistic of -7.05). Similarly, the portfolio based on past one-month intraday returns has an intraday three-factor alpha of 1.35% (t-statistic of 4.86) and an overnight three-factor alpha of -0.85% (t-statistic of -3.31).

One interpretation is that certain clienteles persistently trade certain stocks in the same direction at market open or throughout the day, which is why we see this strong persistence in overnight and intraday returns. If so, then these patterns should persist. As a consequence, Figure 2 reports how the t-statistics associated with the four strategies analyzed in Table VI evolve in event time. Consistent with this interpretation, for each of the four strategies, t-statistics indicate statistical significance up to five years later.

Heston, Koracyzk, Sadka (2010) (henceforth HKS) document a statistically significant positive relation between a stock's return over a half-hour interval and the corresponding half-hour return occurring on each of the next 40 trading days and argue that their patterns are consistent with investors having a predictable demand for immediancy at certain times. They do not study how these half-hour intraday momentum effects aggregate or whether they persist beyond two months. Our analysis instead examines continuation effects based on the entire intraday return and documents that these effects last for five years.

Moreover, Heston, Koracyzk, Sadka (2010) do not study overnight returns at all. Our analysis in this section documents an extremely strong overnight momentum effect that lasts for five years as well as a strong cross-period reversal. Thus, in several ways, our analysis in this section is fundamentally different and conceptually distinct from Heston, Koracyzk, Sadka (2010).

Nevertheless, to confirm that our findings both here and earlier are not driven by an aggregation of the Heston, Koracyzk, Sadka (2010) half-hour effect, we reestimate the re-

[14] Table A5 shows that the result in Table VI that momentum is an overnight phenomenon continues to hold if we break the one-month return into its intraday and overnight components.

gressions in Table 5 including the most recent one-month intraday return (RET_DAY) (a simple aggregation of the HKS finding), the most recent one-month overnight return (RET_NIGHT), the exponentially weighted moving average ($EWMA\_NIGHT$) overnight return (with a half-life of 60 months and skipping the most recent month), and the exponentially weighted moving average (EWMA_DAY) intraday return (with a half-life of 60 months and skipping the most recent month). Table A6 in the Internet Appendix presents these regressions.

We find that controlling for HKS's findings has little effect on our results. We continue to find similar breakdowns into intraday and overnight components for the anomalies we decompose. Moreover, RET_NIGHT, $EWMA\_NIGHT$, and $EWMA\_DAY$ all continue to strongly predict overnight and intraday returns in the same way as the results in Figure 2. In particular, we find that $EWMA\_NIGHT$ predicts subsequent overnight and intraday returns with a coefficient of 16.8 (t-statistic of 6.00) and -21.7 (t-statistic of -5.22) respectively while $EWMA\_DAY$ forecasts subsequent intraday and overnight returns with a coefficient of 10.4 (t–statistic of 3.39) and -15.6 (t-statistic of -3.42) respectively.[15] We conclude that our empirical findings in this section and the previous one have little direct relation to those in HKS.

To confirm that these striking overnight/intraday momentum and reversal patterns are robust, we replicate our analysis in nine large non-US equity markets, again focusing on value-weight portfolios. Those markets are Canada, France, Germany, Italy, United Kingdom, Australia, Hong Kong, Japan, and South Africa. Appendix Table A6 reports our findings. Consistent with our US results, there is no short-term reversal effect in close-to-close returns. However, this hides very strong patterns within the overnight and intraday periods. In every country, we find a strong one-month overnight continuation effect. On a value-weighted basis across countries, a simple strategy that buys last-month's overnight winners and sells last-month's overnight losers earns an overnight premium of 2.31% with an associated t-statistic of 6.90. Similarly, in each of the nine countries, we find a strong one-month intraday continuation effect. Across countries, the value-weight average intraday return of buying last month's intraday winners and selling last month's intraday losers is 2.80% (t-statistic of 6.23). As in the US, we also find a strong cross-period reversal in every country that is roughly equal in magnitude.

[15] We have also estimated this regression skipping either two or three months. If we skip two months, the corresponding coefficients are 15.8 (t-statistic of 5.77), -19.0 (t-statistic of -5.33), 10.4 (t-statistic of 3.90), and -11.8 (t-statistic of -3.30). If we skip three months, the corresponding coefficients are 14.1 (t-statistic of 5.36), -17.4 (t-statistic of -5.04), 9.5 (t-statistic of 3.66), and -10.6 (t-statistic of -3.24).

5.2 Close-to-close Returns and the Overnight/Intraday Tug of War

As argued in the introduction, one way of thinking about our documented intraday/overnight spread in various return anomalies is that there are different investor clienteles: while some investors bet against the anomaly in question, others may trade in the opposite direction, thus helping create and prolong the anomalous pattern. To the extent that these different clienteles have varying degrees of trading intensities during the day vs. at night, our novel overnight/intraday return decomposition provides new insights into their collective behavior and subsequent strategy performance.

Specifically, the difference between overnight and intraday returns reveals the extent to which these two investor clienteles are effectively engaged in a tug of war over the direction of the strategy in question. All else equal, if the current tug of war is more contentious – that is, the intraday/overnight return spread is larger – the side betting to take advantage of the close-to-close pattern is more likely to be bumping up against their investment constraints in the strategy in question, and thus are more likely to leave part of the abnormal returns unexploited. Consequently, we expect these periods to be followed by higher returns to the strategy.

To take this prediction to the data, we use a smoothed measure of past overnight minus intraday returns to forecast close-to-close returns of these anomalies. Specifically, the dependent variable in our time-series regression is the monthly close-to-close return of a particular strategy, and the main independent variable is the lagged difference between the exponentially weighted moving average (EWMA) of the overnight component of the same strategy and the EWMA of the intraday component. We use a half-life of 60 months in our baseline analysis. (Our results are also robust to other half-lives.) We also include in the regression a corresponding EWMA of the lagged monthly close-to-close strategy returns and monthly daily strategy return volatility. Finally, we also include in the regressions a host of other controls including the lagged 12-month market return and market volatility, the characteristic spread between the strategy's long lag and short lag, and the difference in short interest between the strategy's long leg and short leg.[16]

[16] Cohen, Polk, and Vuolteenaho (2003) use the value spread to forecast time-series variation in expected returns on value-minus-growth strategies. Lou and Polk (2013) show that the formation spread in the momentum characteristic forecasts time-series variation in expected returns on momentum strategies. Hanson and Sunderam (2013) document how time-series and cross-sectional variation in short interest forecasts strategy returns.

Since we have shown that in the case of price momentum and short-term reversal, the clientele that tends to trade overnight captures the close-to-close abnormal return, we expect the smoothed overnight minus intraday strategy returns for these strategies to *positively* forecast future close-to-close returns. In contrast, for all other strategies, where the clientele trading intraday profits from the anomaly, we expect the sign to be *negative*.

As shown in Table VII, our measure of a strategy's tug of war forecasts subsequent close-to-close strategy returns just as predicted. All but one of the anomalies have the predicted sign for the forecasting coefficient, and seven of the eleven anomalies are statistically significant. We can easily reject the null hypothesis that these forecasting coefficients are jointly zero ($p < 0.001$). In terms of economic importance, for the average strategy in our sample, a one-standard-deviation increase in the smoothed overnight-intraday return spread forecasts a 1.01% higher close-to-close strategy return, or about 18% of its monthly return volatility.

5.3 The Role of Institutional Investors

Building on our general measure of investor clienteles, we next turn to specific examples of such clienteles to shed more light on the price momentum effect. To this end, we focus on two specific clienteles, individuals vs. institutions, who have different preferences for momentum characteristics and tend to initiate trades at different points in a day.

When do institutions trade?

We first study when institutional investors tend to trade. Figure 3 provides direct evidence that small trades occur disproportionately at market open while large trades occur disproportionately at market close. Specifically, this figure reports dollar trading volume of large vs. small orders over 30-minute intervals as a fraction of the daily volume for the period 1993-2000. Following previous research, we define small orders as those below $5,000 and large orders as those above $50,000. We end our analysis in 2001 as this link between trade size and investor type no longer holds because large institutions began splitting their orders post-2000. Since institutions tended to submit large orders while individuals tended to submit small orders, these results are consistent with the view that institutions tended to trade at market close and individuals at market open.

For broader evidence over our full sample, we link changes in institutional ownership to the components of *contemporaneous* firm-level stock returns. In Table VIII Panel A, we regress quarterly changes in institutional ownership on the overnight and intraday components of contemporaneous returns.[17] We examine this relation across institutional ownership quintiles. We find that for all but the lowest institutional ownership quintile, institutional ownership increases more with intraday rather than overnight returns.

To the extent that investors' collective trading can move prices, this evidence suggests that institutions are more likely to active trade intraday while individuals are more likely to initiate trades overnight. Of course one could argue it is hard to know how to interpret these correlations because institutional trading can both drive stock returns and react to stock returns within the quarter. Three reasons suggest that alternate interpretation of our results is unlikely. For one thing, our result is consistent with the usual understanding as to how these two classes of investors approach markets. Professional investors tend to trade during the day, and particularly near the close, taking advantage of the relatively higher liquidity at that time. Conversely, individuals may be more likely to evaluate their portfolios in the evening after work and thus may tend to make trades that execute when markets open. Our discussions with asset managers indicates that the typical manager does not trade at the open.

Second, it would be strange that institutions chase only intraday returns but not overnight returns. Finally, we replicate the analysis using high-frequency daily institutional flows from Campbell, Ramadorai, and Schwartz (2009). We find that our results continue to hold and, in fact, are statistically speaking, much stronger. Table VIII Panel B shows that for all but the lowest institutional ownership quintile, daily institutional ownership increases much more with intraday rather than overnight returns.

What types of stocks do institutions trade?

We then examine whether institutions trade with or against the momentum characteristic, both on average and conditional on key indicators. In particular, we *forecast* quarterly changes in institutional ownership using a firm's momentum characteristic.

In Table IX Panel A, we estimate both OLS and WLS (with weights tied to a firm's lagged market capitalization) cross-sectional regressions and report the resulting Fama-MacBeth estimates. We first focus on the unconditional results, reported in columns (1) and (3). When we weight firms equally, we find no relation between a stock's momentum characteristic and its subsequent change in institutional ownership. Since our analysis of returns mainly relies on value-weight portfolios, we also examine the results when we weight observations

[17] Each panel of Table VIII only shows the top and bottom quintiles. Please see Appendix Table A7 for the results for all quintiles.

by market capitalization. In this case, we find that institutions collectively trade against the momentum characteristic. The estimate is -0.260 with an associated standard error of 0.119. Of course, since a decrease in institutional ownership is an increase in individual ownership, these findings suggest that, on average, individuals, relative to institutions, are the ones trading momentum.

To better understand these patterns, we exploit two variables that arguably generate variation in momentum trading by institutions. The first variable we use is *comomentum*. Lou and Polk (2014) propose a novel approach to measuring the amount of momentum trading based on time-variation in the degree of high-frequency abnormal return comovement among momentum stocks. This idea builds on Barberis and Shleifer (2003), who argue that institutional ownership can cause returns to comove above and beyond what is implied by their fundamentals.[18] Lou and Polk confirm that their measure of the momentum crowd is a success based on three empirical findings. First, *comomentum* is significantly correlated with existing variables plausibly linked to the size of arbitrage capital. Second, *comomentum* forecasts relatively low holding-period returns, relatively high holding-period return volatility, and relatively more negative holding-period return skewness for the momentum strategy. Finally, when *comomentum* is relatively high, the long-run buy-and-hold returns to a momentum strategy are negative, consistent with times of relatively high amounts of momentum investing pushing prices further away from fundamentals.

Columns (2) and (4) in Table IX Panel A report the results from forecasting the time-series of cross-sectional regression coefficients using *comomentum*. For robustness, we simply measure *comomentum* using tertile dummies. Consistent with the interpretation that *comomentum* measures time-variation in the size of the momentum crowd, we find that institutions' tendency to trade against the momentum characteristic is decreasing in *comomentum*. The effect is statistically significant for both the OLS and WLS estimates.

Table IX Panels B and C explore the implications of this result for our decomposition of momentum profits. In particular, we partition the data into three subsamples based on the relative value of *comomentum*. Following Lou and Polk (2014), we track the buy-and-hold performance of MOM for two years following portfolio formation. When *comomentum* is low, we find that the overnight excess returns to momentum strategies are particularly strong in both Year 1 and Year 2 after classification. However, when *comomentum* is high, the

[18] Recent work by Anton and Polk (2014) uses a natural experiment to confirm that institutional ownership can cause this sort of comovement. Lou (2012) shows that mutual fund flow-induced trading could also lead to excess stock return comovement.

excess returns turn negative. The difference in the average overnight return to momentum across high and low *comomentum* states of the world is -1.56% in Year 1 and -2.26% in Year 2. Both estimates are jointly statistically significant (t-statistics of -2.22 and -4.05 respectively).

A corresponding *comomentum* effect can be seen in the average intraday returns to momentum. When *comomentum* is low, we find that the intraday excess returns to momentum strategies are particularly negative in both Year 1 and Year 2. However, when *comomentum* is high, these excess returns turn positive. The difference in the average intraday return to momentum across high and low *comomentum* states of the world is 1.11% in Year 1 and 0.86% in Year 2. Both estimates are jointly statistically significant (t-statistics of 1.79 and 2.04 respectively).

The second key indicator we use is the aggregate *active weight* in a stock. We measure *active weight* as the difference between the aggregate weight of all institutions in a stock and the weight of the stock in the value-weight market portfolio. We conjecture that a relatively large *active weight* will indicate a preference by those institutional investors to rebalance towards market weights, due to risk management, tracking error concerns. To illustrate, imagine that institutions collectively overweight stock S. If the stock goes up (down) in value relative to the market, institutions will have an even larger (smaller) weight in S, and will thus trade in a contrarian manner to keep their tracking error small. The reverse is true for an initial underweight in stock S.

Columns (2) and (4) in Table X Panel A report the results from cross-sectional regressions forecasting quarterly changes in institutional ownership using a firm's momentum characteristic, *active weight*, and the interaction between these two variables. For robustness, we simply measure *active weight* using quintile dummies.

Consistent with our conjecture that institutions with high *active weight* in a stock are reluctant to let their positions ride, we find that institutions' tendency to trade against the momentum characteristic is increasing in *active weight*. The effect is statistically significant for both the OLS and WLS estimates.

Table X Panels B and C explore the implications of this result for our decomposition of momentum profits. In particular, we independently sort stocks on momentum and *active weight* into quintiles based on NYSE breakpoints and form 25 value-weight portfolios. When *active weight* is low, we find that the overnight excess returns to momentum strategies are relatively weak the next month. However, when *active weight* is high, overnight returns become strongly positive. The difference in the average overnight return to momentum across high and low *active weight* stocks is 1.15% with an associated t-statistic of 5.39.

A corresponding effect can, again, be seen in the average intraday returns to momentum. When *active weight* is low, the average intraday excess returns to momentum strategies are close to zero. However, when *active weight* is high, these average excess returns become quite negative. The difference in the average intraday return to momentum across high and low *active weight* stocks is -0.76% with an associated t-statistic of -2.70.

Whether or not institutions are momentum traders is an important research question in finance. Despite the importance of this question, there is no clear consensus; the answer appears to depend on both the type of institution being studied and the sample in question. For our data, we find that on average, institutions tend to trade against momentum.[19] Moreover, there is interesting time-series and cross-sectional variation in institutional momentum trading that goes hand-in-hand with variation in the decomposition of momentum profits into overnight and intraday components.

Namely, in the time series, when the amount of momentum trading activity is particularly low, or in the cross-section, when the typical institution holding a stock has a particularly strong need to rebalance, we find that institutions trade more strongly against momentum and that momentum returns are even larger overnight and more strongly reverse during the day. Both cases generate variation in the spread between overnight and intraday returns on the order of two percent per month.

5.3.1 Non-US Markets

To provide further evidence of our finding that momentum profits, particularly for stocks held by institutional owners, accrue primarily overnight, we decompose profits to momentum strategies in the nine non-US equity markets studied above. A significant challenge in decomposing momentum profits in non-US markets is the availability of reliable data for open prices. We obtain that data from Thomson Reuters Tick History database, which provides complete microsecond tick data for markets around the world since 1996.[20] To construct an open price, we followed our US method and computed a VWAP price for each stock.

[19] Our results are consistent with the findings of Badrinath and Wahal (2002), who show that institutions tend to be momentum traders when they open new positions but are contrarian when they adjust existing ones.

[20] When processing the data, we also compared our accurate measures of open prices to those found on Datastream. Our analysis indicated that Datastream open prices can be quite misleading.

Appendix Table A8 Panel A reports our findings. The left-side of the Table reports results for the full sample of stocks, while the right side of the Table reports results for large-cap stocks. Of course, large-cap stocks are much more likely to be held by institutions.

For the full sample, we find that momentum in non-US markets is primarily an intraday phenomenon. For eight of the nine countries in our sample, intraday momentum profits are larger than overnight momentum profits. Indeed, only two countries, Australia and South Africa, have positive overnight momentum profits that are statistically significant. A value-weight average of the close-to-close momentum profits is 1.28% per month (t-statistic of 2.55) with 0.96% (t-statistic of 3.62) accruing intraday and only 0.23% (t-statistic of 0.58) accruing overnight.

The results change dramatically for the large-cap sample. Now, six countries have overnight momentum profits that are larger than the corresponding intraday profits. For all six of these countries, the overnight component of momentum profits is economically and statistically significant. Only one country, Germany, has momentum returns that are statistically significant. An value-weight average of the close-to-close momentum profits for the large-cap sample is 1.24% per month (t-statistic of 2.17) with a statistically-insignificant 0.44% (t-statistic of 1.24) accruing intraday and a statistically-significant 0.80% (t-statistic of 2.50) accruing overnight.

As a consequence, the change in the overnight and intraday components as one moves from the full sample to the large-cap sample goes the right way in terms of our institutional clientele interpretation and is quite statistically significant. Specifically, the overnight component increases by 0.57% (t-statistic of 3.13) and the intraday component decreases by 0.52% (t-statistic of -2.78). This difference-in-difference test is consistent with our conjecture that we should expect momentum to be more of an overnight phenomenon among stocks with a larger institutional presence.[21]

We also extend our industry momentum results to non-US markets. Our focus is on four market regions (North America, Europe, Asia, and Africa) to ensure reasonably large industry cross sections. We find strong evidence that industry momentum is an overnight phenomenon. Appendix Table A8 Panel B shows that across these four regions, the average monthly close-to-close return is 1.01% per month (t-statistic of 2.67) with 0.90% (t-statistic of 3.35) accruing overnight.

[21] Though the equal-weight average intraday component is statistically significant, this is driven entirely by one country, Germany, whose financial system is known to be idiosyncratic.

5.3.2 The Pre-1962 Evidence

Open prices are also available for a thirty-year period of 1927-1962. Of course, these prices do not have the nice feature of the VWAP approach used in the rest of our analysis in that they do not necessarily represent traded prices. Nevertheless, this sample provides a potentially useful placebo test of our hypothesis that institutional ownership is responsible for the overnight momentum pattern, as institutional ownership was very low for all but the largest stocks. Blume and Keim (2014) indicate that institutions held roughly only five percent of equity during most of this time. Consistent with that idea, Panel A of Appendix Table A9 shows that for this sample, momentum is primarily an intraday phenomenon. Momentum has a monthly three-factor alpha of 1.45% (t-statistic of 4.43). The intraday component is 1.03% (t-statistic of 3.43), while the overnight component is insignificant from zero (point estimate of 0.21% with a t-statistic of 0.97).

We also examine whether the overnight component becomes more important for large-cap stocks. Appendix Table A9 Panel B shows that this is the case. Specifically, we find that large-cap momentum has a monthly three-factor alpha of 1.39% (t-statistic of 4.74). The intraday component is still large at 0.95% (t-statistic of 3.51). However, now the overnight component is statistically significant from zero (point estimate of 0.34% with a t-statistic of 2.05). In summary, though we have less faith in the pre-1963 open price data, we do find that the results using that data are broadly consistent with the view that institutional investors play an important role in understanding why momentum is an overnight phenomenon in the 1993-2013 sample.

6 Conclusions

We provide a novel decomposition of the cross section of expected returns into overnight and intraday components. We show that essentially all of the abnormal returns on momentum and short-term reversal strategies occur overnight while the abnormal returns on other strategies occur intraday. Taken all together, our findings represent a challenge not only to traditional neoclassical models of risk and return but also to intermediary- and behavioral-based explanations of the cross section of average returns.

We argue that clienteles may explain these patterns. We first show remarkable persistence in the overnight and intraday components of firm-level returns, which is consistent with clienteles persistently trading at the open or the close certain types of stocks. Using this novel overnight/intraday clientele lens, we then document that a relatively large difference between overnight and intraday returns reveals the extent to which investor clienteles are effectively engaged in a tug of war over the direction of the strategy in question. We argue that if a strategy's current tug of war is more contentious, the clientele trading to harvest that strategy's anomalous close-to-close returns is more likely to be constrained, and thus is more likely to leave part of that strategy's abnormal returns unexploited. Our empirical results confirm this tug of war interpretation: A one-standard-deviation increase in a strategy's smoothed overnight-intraday return spread forecasts a close-to-close strategy return in the following month that is 1% higher.

We then zoom in on a specific form of investor heterogeneity that may help explain why momentum profits accrue overnight. Relative to individuals, we show that institutions as a class (on a value-weight basis) tend to trade against momentum during the day. However, the degree to which this is the case varies through time and across stocks, generating an interesting tug of war from intraday to overnight. Specifically, for those times or those stocks where the institutional holders have a relatively strong preference to trade against momentum, we find that momentum profits are higher overnight, partially revert intraday, and are larger close-to-close.

References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, "The Cross-Section of Volatility and Expected Returns", *Journal of Finance* 61:259–299.

Anton, Miguel and Christopher Polk, "Connected Stocks", *Journal of Finance* 69:1099–1127.

Badrinath, S.G. and Sunil Wahal, 2002, Momentum Trading by Institutions, *Journal of Finance* 57:2449–2478.

Bali, Turan and Nusret Cakici, 2009, "Idiosyncratic Volatility and the Cross Section of Expected Stock Returns", *Journal of Financial and Quantitative Analysis* 43:29–58.

Bandarchuk, Pavel and Jens Hilscher, 2013, "Sources of Momentum Profits: Evidence on the Irrelevance of Characteristics", *Review of Finance* 17, 809-845.

Barberis, Nicholas and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68 161-199.

Barberis, Nick, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Berkman, H., P.D. Koch, L. Tuttle, and Y. Zhang, 2009, "Dispersion of Opinions, Short Sale Constraints, and Ovemight Retums", University of Auckland Working Paper

Black, Fischer, 1972, Capital Market Equilibrium with Restricted Borrowing, *Journal of Business* 45 444-454.

Black, Fisher, 1976, "Studies of Stock Price Volatility Changes", *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section,* Washington 177–181.

Blume, Marshall E. and Donald B. Keim, 2014, "The Changing Nature of Institutional Stock Investing", working paper, University of Pennsylvania.

Branch, Ben and Aixin Ma, 2008, "The Overnight Return, One More Anomaly", working paper, University of Massachusetts.

Branch, Ben and Aixin Ma, 2012, "Overnight Return, the Invisible Hand Behind Intraday Returns", *Journal of Financial Markets* 2, 90-100.

Campbell, John Y., 1993, "Intertemporal Asset Pricing Without Consumption Data", *American Economic Review* 83:487–512.

Campbell, John Y., 1996, "Understanding Risk and Return", *Journal of Political Economy* 104:298–345.

Campbell, John Y., Stefano Giglio, and Christopher Polk, 2013, "Hard Times", *Review of Asset Pricing Studies* 3:95–132.

Campbell, John Y., Stefano Giglio, Christopher Polk, and Robert Turley, 2014, "An Intertemporal CAPM with Stochastic Volatility", London School of Economics working paper.

Campbell, John Y., Christopher Polk, and Tuomo Vuolteenaho, 2010, "Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns" *Review of Financial Studies* 23:305–344.

Campbell, John Y., Tarun Ramadorai, Allie Schwartz, "Caught on Tape: Institutional Trading, Stock Returns, and Earnings Announcements", *Journal of Financial Economics* 92: 66-91.

Campbell, John Y. and Robert J. Shiller, 1988a, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors", *Review of Financial Studies* 1:195–228.

Campbell, John Y. and Robert J. Shiller, 1988b, "Stock Prices, Earnings, and Expected Dividends", *Journal of Finance* 43:661–676.

Campbell, John Y. and Tuomo Vuolteenaho, 2004, "Bad Beta, Good Beta", *American Economic Review* 94:1249–1275.

Chen, Zhanhui and Ralitsa Petkova, 2014, "Does Idiosyncratic Volatility Proxy for Risk Exposure?", *Review of Financial Studies* 25:2745–2787.

Cieslak, Anna, Adair Morse, Annette Vissing-Jorgenson, 2015, "Stock Returns Over the FOMC Cycle", University of California at Berkeley working paper.

Cliff, Michael, Michael Cooper, Huseyin Gulen, 2008, "Return Differences between Trading and Non-trading Hours: Like Night and Day", Virginia Tech working paper.

Cohen, Randy, Paul Gompers, and Tuomo Vuolteenaho, 2002, "Who underreacts to cash-flow news? Evidence from trading between individuals and institutions", *Journal of Financial Economics* 66: 409-462.

Cohen, Randy, Christopher Polk, and Tuomo Vuolteenaho, 2003, "The Value Spread", *Journal of Finance* 58:609–671.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Investor Psychology and Security Market Under- and Over-reactions, *Journal of Finance* 53, 1839–1886.

Daniel, Kent, and Sheridan Titman. 2006, Market Reactions to Tangible and Intangible Information, *Journal of Finance* 61:1605–43.

Daniel, Kent and Tobias Moskowitz, 2013, Momentum Crashes, Columbia University working paper.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim, 2012, Tail Risk in Momentum Strategy Returns, Columbia University working paper.

Dasgupta, Amil, Andrea Prat, and Michela Verardo, 2011, Institutional Trade Persistence and Long-term Equity Returns, *Journal of Finance* 66, 635-653.

Datar, Vinay, Narayan Naik, and Robert Radcliffe, 1998, "Liquidity and asset returns: An alternative test", *Journal of Financial Markets* 1, 203-220.

Fairfield,P.M., Whisenant,S.,Yohn,T.L., 2003, "Accrued Earnings and Growth: Implications for Future Profitability and Market Mispricing", *Accounting Review* 78, 353–371.

Fama, Eugene F., 1965, "The Behavior of Stock-Market Prices", *Journal of Business*, 38, 34-105

Fama, Eugene, and James D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical tests", *Journal of Political Economy* 81, 607–636.

Fama, Eugene F. and Kenneth R. French, 1992, "The Cross-Section of Expected Stock Returns", *Journal of Finance* 47: 427-465.

Fama, Eugene F. and Kenneth R. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics* 33:3–56.

Fama, Eugene F. and Kenneth R. French, 1996, "Multifactor Explanations of Asset Pricing Anomalies", *Journal of Finance* 51:55–84.

Fama, Eugene F. and Kenneth R. French, 2014a, "A Five-factor Asset Pricing Model", *Journal of Financial Economics* forthcoming.

Fama, Eugene F. and Kenneth R. French, 2014b, "Dissecting Anomalies with a Five-factor Model", University of Chicago working paper.

Frazzini, Andrea and Lasse H. Pedersen, 2014, "Betting Against Beta", *Journal of Financial Economics* 111, 1-25.

French, Kenneth R., 1980, "Stock Returns and the Weekend Effect", *Journal of Financial Economics* 8, 55-69.

French, Kenneth R. and Richard Roll, 1986, "Stock Return Variances: The Arrival of Information of the Reaction of Traders", *Journal of Financial Economics* 17, 5-26.

French, Kenneth, G. William Schwert, and Robert F. Stambaugh, 1987, "Expected Stock Returns and Volatility", *Journal of Financial Economics* 19:3–29.

Griffen, John, Jeffry Harris, and Selim Topaloglu, 2003, "The Dynamics of Institutional and Individual Trading", *Journal of Finance* 58:2285–2320.

Hanson, Sam and Adi Sunderam, "The Growth and Limits of Arbitrage: Evidence from Short Interest", *Review of Financial Studies* 27 1238–1286.

Harvey, Campbell, Yan Liu, and Heqing Zhu, 2016, "... and the Cross-Section of Expected Returns", *Review of Financial Studies* 29 5-68.

Haugan, Robert A and Nardin L. Baker, 1996, "Commonality in the determinants of expected stock returns", *Journal of Financial Economics* 41:401–439.

Hong, Harrison and Jeremy Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *Journal of Finance* 54, 2143–2184.

Jegadeesh, Narasimhan, 1990, Evidence of Predictable Behavior of Security Returns, *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, Narasimhan and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56, 699–720.

Kelly, M. and S. Clark, 2011, "Returns in Trading Versus Non-Trading Hours: The Difference Is Day and Night," *Journal of Asset Management* 12 , 132-145.

Lee, Charles M. C. and Bhaskaran Swaminathan, 2000, Price Momentum and Trading Volume, *Journal of Finance* 55, 2017–2069.

Lettau, Martin and Jessica Wachter, 2007, Why Is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium, *Journal of Finance* 62, 55–92.

Linter, John, 1965, "The Valuation of Risk Assets on the Selection of Risky Investments in Stock Portfolios and Capital Budgets", *Review of Economics and Statistics* 47:13-37.

Lou, Dong, 2012, A Flow-Based Explanation for Return Predictability, *Review of Financial Studies*, 25, 3457-3489.

Lou, Dong and Christopher Polk, 2014, Comomentum: Inferring Arbitrage Activity from Return Correlations, London School of Economics working paper.

Lucca, David O. and Emanuel Moench, 2015, "The Pre-FOMC Announcement Drift", *Journal of Finance* 70, 329-371.

Merton, Robert C., 1973, "A Simple Model of Capital Market Equilibrium with Incomplete Information", *Journal of Finance* 42, 483-510.

Merton, Robert C., 1987, "An Intertemporal Capital Asset Pricing Model", *Econometrica* 41:867–887.

Moskowitz, Tobias and Mark Grinblatt, 1999, "Do Industries Explain Momentum", *Journal of Finance* 54, 1249-1290.

Polk, Christopher and Paola Sapienza, 2009, "The Stock Market and Corporate Investment: A Test of Catering Theory", *Review of Financial Studies* 22 187-217.

Savor, Pavel and Mungo Wilson, 2014, "Asset Pricing: A Tale of Two Days", *Journal of Financial Economics* 113, 117-201.

Sharpe, William, 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19:425-442.

Sias, Richard, 2004, Institutional Herding, *Review of Financial Studies* 17:165-206.

Sias, Richard and Laura Starks, 1997, Institutions and Individuals at the Turn-of-the-Year, *Journal of Finance* 52:1543-1562.

Sias, Richard and John Nofsinger, 1999, Herding and Feedback Trading by Institutional and Individual Investors, *Journal of Finance* 54:2263-2295.

Sloan, Richard, 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?, *The Accounting Review* 71:289–315.

Tao, Cai and Mei Qiu, 2008, "The International Evidence of the Overnight Return Anomaly", Massey University working paper.

Titman, S., Wei, K.C, and F. Xie, 2004, "Capital Investments and Stock Returns", *Journal of Financial and Quantitative Analysis* 39 677–700.

Vayanos, Dimitri and Paul Woolley, 2012, An Institutional Theory of Momentum and Reversal, *Review of Financial Studies*, forthcoming.

Vuolteenaho, Tuomo, 2002, "What Drives Firm-Level Stock Returns?", *Journal of Finance* 57, 233-264.

Table I: Overnight/Intraday Momentum Returns

This table reports returns to the momentum strategy during the day vs. at night for the period 1993-2013. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). We then go long the value-weight winner decile and short the value-weight loser decile. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Panel A reports the close-to-close momentum returns in the following month. Panel B reports the overnight and intraday momentum returns in the following month. Panel C reports some basic statistics of momentum returns during these different periods. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Close-to-Close MOM Returns			
Decile	Excess	CAPM	3-Factor
1	0.01%	-0.80%	-0.86%
	(0.02)	(-2.44)	(-2.55)
10	0.71%	0.13%	0.20%
	(1.82)	(0.58)	(0.99)
10 - 1	0.70%	**0.93%**	**1.05%**
	(1.38)	(1.98)	(2.22)

Panel B: Overnight vs. Intraday MOM Returns						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.39%	0.10%	0.15%	-0.51%	-1.05%	-1.13%
	(1.33)	(0.40)	(0.55)	(-1.09)	(-2.92)	(-3.07)
10	1.28%	1.09%	1.09%	-0.69%	-1.07%	-1.02%
	(6.35)	(6.37)	(6.33)	(-2.29)	(-4.82)	(-4.96)
10 - 1	**0.89%**	**0.98%**	**0.95%**	-0.18%	-0.02%	0.11%
	(3.44)	(3.84)	(3.65)	(-0.43)	(-0.06)	(0.27)

Panel C: Summary Statistics			
Mean	Stdev	Skew	Sharpe
Close-to-Close MOM Returns			
0.70%	7.85%	-1.16	0.31
Overnight MOM Returns			
0.89%	4.02%	-1.08	0.77
Intraday MOM Returns			
-0.18%	6.50%	-1.53	-0.10

Table II: Overnight/Intraday Momentum Returns: Subsamples

This table reports returns to the momentum strategy during the day vs. at night for the period 1993-2013. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). We then go long the value-weight winner decile and short the value-weight loser decile. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Panels A and B report overnight and intraday momentum returns in the following month in the first and second half of the sample period, respectively. Panels C and D report overnight and intraday momentum returns among small-cap and large-cap stocks, respectively. Panels E and F report overnight and intraday momentum returns among low-price and high-price stocks, respectively. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
	Overnight			Intraday		
Panel A: 1993-2002						
10 - 1	**1.28%**	**1.34%**	**1.26%**	-0.03%	0.04%	0.20%
	(3.90)	(4.16)	(3.99)	(-0.06)	(0.07)	(0.29)
Panel B: 2003-2013 (excluding 2009)						
10 - 1	**1.16%**	**1.27%**	**1.19%**	-0.23%	-0.28%	-0.25%
	(4.06)	(4.30)	(4.26)	(-0.99)	(-0.60)	(-0.55)
Panel C: Small-Cap Stocks (< NYSE Median)						
5 - 1	**0.52%**	**0.54%**	**0.54%**	0.13%	0.29%	0.39%
	(4.09)	(4.31)	(4.49)	(0.46)	(1.14)	(1.59)
Panel D: Large-Cap Stocks (>= NYSE Median)						
5 - 1	**0.93%**	**1.03%**	**1.04%**	-0.46%	-0.32%	-0.24%
	(5.13)	(5.92)	(5.90)	(-1.49)	(-1.06)	(-0.79)
Panel E: Low-Price Stocks (< NYSE Median)						
5 - 1	**0.56%**	**0.63%**	**0.66%**	0.19%	0.33%	0.33%
	(2.89)	(3.35)	(3.59)	(0.66)	(1.13)	(1.17)
Panel F: High-Price Stocks (>= NYSE Median)						
5 - 1	**1.08%**	**1.16%**	**1.14%**	-0.42%	-0.29%	-0.41%
	(6.31)	(6.77)	(6.63)	(-1.90)	(-1.56)	(-1.33)

Table III: Size and Value, and the Role of News Announcements

This table reports returns to the size and value strategies during the day vs. at night and the role of news announcements. In Panel A, at the end of each month, all stocks are sorted into deciles based on the prior month market capitalization; in Panel B, stocks are sorted based on lagged book-to-market ratio. We then go long the value-weight highest market-cap/book-to-market ratio decile and short the value-weight lowest market-cap/book-to-market ratio decile. In Panels C, D and E, we examine various strategy returns in news vs. non-news periods. In Panel C, we examine overnight and intraday returns to the momentum, size and value strategies in the three days (t-1 to t+1) around FOMC announcements. Panels D and E then examine overnight momentum returns and intraday size and value returns in months with and without firm-specific news announcements, respectively. The first row in either panel corresponds to holding months without earnings announcements or news coverage in Dow Jones Newswire, the second row corresponds to holding months with earnings announcements or news coverage, and the third row reports the difference between "news" and "no-news" months. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Overnight vs. Intraday ME Returns

	Overnight		Intraday	
Decile	Excess	CAPM	Excess	CAPM
1	0.45%	0.25%	0.55%	0.11%
	(2.27)	(1.53)	(1.61)	(0.47)
10	0.32%	0.14%	-0.01%	-0.32%
	(2.04)	(1.12)	(-0.03)	(-2.49)
10 - 1	-0.13%	-0.11%	**-0.56%**	-0.43%
	(-0.91)	(-0.75)	(-2.28)	(-1.85)

Panel B: Overnight vs. Intraday BM Returns

	Overnight		Intraday	
Decile	Excess	CAPM	Excess	CAPM
1	0.29%	0.10%	0.00%	-0.34%
	(1.77)	(0.77)	(0.01)	(-2.16)
10	0.18%	0.00%	0.41%	0.14%
	(0.99)	(0.00)	(1.71)	(0.75)
10 - 1	-0.11%	-0.10%	0.41%	**0.48%**
	(-0.77)	(-0.67)	(1.85)	(2.21)

Panel C: Returns around FOMC Announcements					
	Close-to-Close_t	Intraday_t	Overnight_t	Intraday_{t-1}	Overnight_{t+1}
MOM	0.01%	0.03%	-0.05%	0.09%	0.03%
	(0.05)	(0.48)	(-0.37)	(0.90)	(0.42)
ME	0.02%	0.00%	0.00%	0.10%	0.01%
	(0.30)	(-0.05)	(0.02)	(1.05)	(0.42)
BM	0.05%	0.00%	0.05%	-0.02%	0.01%
	(0.66)	(0.03)	(0.88)	(-0.31)	(0.23)

Panel D: Overnight Returns in News Months			
		MOM	
	Excess	CAPM	3-Factor
NoNews	**0.98%**	**1.04%**	**1.02%**
	(4.18)	(4.25)	(4.30)
News	**1.27%**	**1.37%**	**1.35%**
	(4.61)	(5.17)	(5.15)
News-NoNews	0.29%	0.33%	0.33%
	(1.07)	(1.17)	(1.17)

Panel E: Intraday Returns in News Months				
	ME		BM	
	Excess	CAPM	Excess	CAPM
NoNews	**-0.44%**	-0.41%	**0.63%**	**0.70%**
	(-1.96)	(-1.79)	(2.07)	(2.26)
News	**-0.79%**	**-0.65%**	0.53%	0.50%
	(-2.97)	(-2.50)	(1.48)	(1.40)
News-NoNews	-0.36%	-0.25%	-0.09%	-0.19%
	(-1.35)	(-0.98)	(-0.24)	(-0.45)

Table IV: Overnight/Intraday Returns – Other Firm Characteristics

This table reports returns to various strategies during the day vs. at night. In Panel A, at the end of each month, all stocks are sorted into deciles based on prior quarter earnings surprises (= actual earnings – consensus forecast); in Panel B, all industries are sorted into quintiles based on lagged 12-month cumulative industry returns. In Panel C, we examine returns to the time-series momentum strategy of Moskowitz, Ooi and Pedersen (2012) (more details in Appendix Table A10). In Panel D, stocks are sorted into deciles based on lagged return-to-equity; in Panel E, stocks are sorted into deciles based on lagged asset growth; in Panel F, stocks are sorted into deciles based on lagged 12-month market betas (using daily returns with one lead and one lag); in Panel G, stocks are sorted into deciles based on their lagged 12-month daily idiosyncratic volatilities (with regard to the Carhart four factor model, with one lead and one lag); in Panel H, stocks are sorted into deciles based on equity issuance in the prior year; in Panel I, stocks are sorted into deciles based on lagged discretionary accruals; in Panel J, stocks are sorted into deciles based on lagged 12-month share turnover; in Panel K, stocks are sorted into deciles based on lagged one month returns. We then go long the value-weight top decile (quintile) and short the value-weight bottom decile (quintile). Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
	Overnight			Intraday		
Panel A: Portfolios Sorted by SUE						
10 - 1	**0.49%**	**0.56%**	**0.58%**	0.16%	0.21%	0.34%
	(2.98)	(3.20)	(3.23)	(0.56)	(0.70)	(1.20)
Panel B: Portfolios Sorted by INDMOM						
5 - 1	**1.05%**	**1.07%**	**1.09%**	**-0.66%**	**-0.63%**	-0.56%
	(6.34)	(6.47)	(6.65)	(-2.16)	(-2.03)	(-1.92)
Panel C: Time-Series Momentum						
H - L	**1.10%**	**1.40%**	**1.42%**	-0.29%	-0.10%	-0.10%
	(2.67)	(3.24)	(3.18)	(-0.78)	(-0.24)	(-0.26)
Panel D: Portfolios Sorted by ROE						
10 - 1	**-1.00%**	**-0.95%**	**-0.95%**	**1.19%**	**1.42%**	**1.43%**
	(-6.46)	(-6.25)	(-6.22)	(4.33)	(5.58)	(6.44)
Panel E: Portfolios Sorted by INV						
10 - 1	**0.33%**	**0.28%**	**0.36%**	**-0.88%**	**-0.97%**	**-0.78%**
	(2.49)	(2.10)	(2.85)	(-4.00)	(-4.39)	(-4.09)

Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
	Overnight			Intraday		
Panel F: Portfolios Sorted by Market BETA						
10 - 1	**0.54%**	**0.49%**	**0.49%**	-0.50%	**-0.70%**	**-0.80%**
	(2.43)	(2.17)	(2.10)	(-1.63)	(-2.40)	(-2.60)
Panel G: Portfolios Sorted by IVOL						
10 - 1	**1.71%**	**1.46%**	**1.61%**	**-1.93%**	**-2.48%**	**-2.34%**
	(5.57)	(5.23)	(5.81)	(-3.86)	(-6.21)	(-7.82)
Panel H: Portfolios Sorted by Equity ISSUE						
10 - 1	**0.60%**	**0.52%**	**0.52%**	**-1.03%**	**-1.13%**	**-1.05%**
	(3.94)	(3.27)	(3.35)	(-5.41)	(-6.13)	(-6.05)
Panel I: Portfolios Sorted by Discretionary ACCRUALS						
10 - 1	**0.62%**	**0.47%**	**0.56%**	**-0.90%**	**-1.10%**	**-0.94%**
	(3.82)	(3.25)	(4.00)	(-3.75)	(-4.73)	(-4.95)
Panel J: Portfolios Sorted by TURNOVER						
10 - 1	**0.37%**	0.29%	**0.35%**	-0.40%	**-0.57%**	**-0.52%**
	(2.39)	(1.98)	(2.54)	(-1.74)	(-2.58)	(-3.22)
Panel K: Portfolios Sorted by One-Month Returns						
10 - 1	**-1.01%**	**-0.93%**	**-0.88%**	**0.86%**	**1.05%**	**1.05%**
	(-4.74)	(-4.28)	(-4.01)	(2.67)	(3.25)	(3.26)

Table V: Fama-MacBeth Return Regressions

This table reports Fama-MacBeth regressions of monthly stocks returns on lagged firm characteristics. The dependent variables in columns 1-3 are the close-to-close return, the overnight return, and the intraday return in the following month, respectively. In column 4, we report the difference between the coefficients in columns 2 and 3 (i.e., overnight-intraday). In column 5, we report the difference between the overnight coefficient *24/17.5 and intraday coefficient *24/6.5. The main independent variables include the lagged 12-month cumulative stock return (skipping the most recent month), market capitalization, book-to-market ratio, one-month stock return, 12-month daily idiosyncratic volatility (with regard to the Carhart four factor model, with one lead and one lag), 12-month market beta (using daily returns with one lead and one lag), 12-month share turnover, return-on-equity, asset growth, equity issuance, and discretionary accruals. In column 6, we regress the time series of coefficients from the analysis in the column 2 on the contemporaneous overnight market return and report the intercept from that regression. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Stock returns are expressed in percentage terms. Observations are weighted by lagged market capitalization in each cross sectional regression. Standard errors, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

X 100	Close-to-Close	Overnight	Intraday	Overnight-Intraday	Scaled Difference	Overnight Adjusted
	[1]	[2]	[3]	[4]	[5]	[6]
MOM	0.159	0.578***	-0.417*	0.996***	2.334***	0.621***
	[0.327]	[0.134]	[0.230]	[0.192]	[0.763]	[0.127]
SIZE	-0.079	0.157***	-0.246***	0.403***	1.125***	0.132***
	[0.062]	[0.034]	[0.051]	[0.059]	[0.192]	[0.032]
BM	0.037	-0.149	0.157*	-0.302**	-0.785**	-0.127**
	[0.074]	[0.092]	[0.081]	[0.124]	[0.350]	[0.065]
*RET*1	-1.743***	-2.939***	1.169**	-4.107***	-8.345***	-2.821***
	[0.609]	[0.728]	[0.595]	[1.185]	[2.908]	[0.727]
IVOL	-0.052	0.295***	-0.285***	0.580***	1.457***	0.220***
	[0.101]	[0.084]	[0.064]	[0.109]	[0.270]	[0.077]
BETA	-0.101	0.208*	-0.310***	0.519***	1.431***	0.090
	[0.172]	[0.110]	[0.119]	[0.179]	[0.480]	[0.111]
TURNOVER	0.092	0.223***	-0.161***	0.384***	0.900***	0.195***
	[0.066]	[0.054]	[0.043]	[0.073]	[0.183]	[0.048]
ROE	0.230	-0.399***	0.631***	-1.030***	-2.877***	-0.384***
	[0.250]	[0.109]	[0.267]	[0.323]	[1.051]	[0.108]
INV	-0.594**	0.077	-0.685***	0.762***	2.634***	0.111
	[0.239]	[0.111]	[0.235]	[0.276]	[0.905]	[0.112]
ISSUE	-0.780***	-0.190	-0.583**	0.394	1.893*	-0.113
	[0.276]	[0.241]	[0.229]	[0.382]	[1.002]	[0.244]
ACCRUALS	-0.462	0.224	-0.715*	0.938	2.946	-0.011
	[0.471]	[0.344]	[0.398]	[0.715]	[2.084]	[0.320]
Adj-R^2	0.118	0.083	0.119			
No. Obs.	462,070	462,070	462,070			

Table VI: Overnight/Intraday Return Predictability

This table reports returns to the short-term reversal (STR) strategy during the day vs. at night. In Panel A, at the end of each month, all stocks are sorted into deciles based on their lagged one-month overnight returns. In Panel B, stocks are sorted based on their lagged one-month intraday returns. We then go long the value-weight winner decile and short the value-weight loser decile. The first three columns show the overnight return in the subsequent month of the two short-term reversal strategies, and the next three columns show the intraday returns in the subsequent month. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. We report monthly portfolio returns in excess of the risk-free rate, adjusted by the CAPM, and by the three-factor model. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Portfolios Sorted by One-Month Overnight Returns

	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	-1.51%	-1.70%	-1.73%	1.62%	1.23%	1.06%
	(-7.76)	(-9.88)	(-9.77)	(4.76)	(4.55)	(4.15)
10	1.96%	1.73%	1.74%	-1.63%	-2.07%	-1.96%
	(8.17)	(8.60)	(8.69)	(-4.74)	(-8.58)	(-9.03)
10 - 1	**3.47%**	**3.42%**	**3.47%**	**-3.24%**	**-3.30%**	**-3.02%**
	(16.57)	(16.57)	(16.83)	(-9.34)	(-9.00)	(-9.74)

Panel B: Portfolios Sorted by One-Month Intraday Returns

	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	1.59%	1.32%	1.35%	-1.51%	-2.04%	-2.14%
	(5.51)	(5.28)	(5.04)	(-3.45)	(-6.58)	(-6.95)
10	-0.22%	-0.41%	-0.42%	0.69%	0.32%	0.27%
	(-1.20)	(-2.68)	(-2.64)	(2.51)	(1.76)	(1.57)
10 - 1	**-1.81%**	**-1.73%**	**-1.77%**	**2.19%**	**2.36%**	**2.41%**
	(-8.44)	(-8.16)	(-7.89)	(6.72)	(7.56)	(7.70)

Table VII: Forecasting Close-to-Close Factor Returns

This table reports regressions of close-to-close factor returns on lagged return differentials between the overnight and intraday components of the same factor. The dependent variable in each row is the monthly return to a factor portfolio (top decile minus bottom decile), and the independent variable of interest is the lagged difference between the exponentially weighted moving average (EWMA) of the overnight component of the same factor and the EWMA of the intraday component. We use a half-life of 60 months in the calculation. We also include in the regression a corresponding EWMA of the lagged factor return, and that of lagged monthly factor volatility. Other controls include the lagged 12-month market return and market volatility, the characteristic spread between the strategy's long leg and short leg, and the difference in short interest between the strategy's long leg and short leg. In row 1, stocks are sorted into deciles based on the lagged 12 month cumulative return; in row 2, stocks are sorted into deciles based on the lagged market capitalization; in row 3, stocks are sorted into deciles based on lagged book-to-market ratio; in row 4, stocks are sorted into deciles based on lagged profitability; in row 5 stocks are sorted into deciles based on lagged asset growth; in row 6, stocks are sorted into deciles based on lagged 12-month market betas (using daily returns with one lead and one lag); in row 7, stocks are sorted into deciles based on their lagged 12-month daily idiosyncratic volatilities (with regard to the Carhart four factor model, with one lead and one lag); in row 8, stocks are sorted into deciles based on equity issuance in the prior year; in row 9, stocks are sorted into deciles based on lagged discretionary accruals; in row 10, stocks are sorted into deciles based on lagged 12-month share turnover; in row 11, stocks are sorted into deciles based on lagged one month returns. T-statistics, shown in parentheses, are computed based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

	Depvar = Factor Return$_{t+1}$					
	Overnight-Intraday$_t$		Factor Return$_t$		Factor Vol$_t$	
MOM	**1.967**	(2.48)	0.001	(0.00)	-1.189	(-1.46)
$SIZE$	-1.027	(-1.57)	0.557	(1.01)	1.207	(1.18)
BM	0.074	(0.12)	-0.314	(-0.39)	1.212	(1.30)
ROE	**-1.100**	(-2.47)	-1.255	(-1.29)	1.279	(1.62)
INV	-1.339	(-1.93)	-1.061	(-1.32)	-0.821	(-1.04)
$BETA$	-1.340	(-1.18)	0.024	(0.03)	0.427	(0.58)
$IVOL$	**-1.207**	(-2.11)	-1.228	(-1.33)	-1.842	(-1.76)
$ISSUE$	**-2.277**	(-2.86)	**-5.258**	(-4.00)	-0.281	(-0.41)
$ACCRUALS$	-0.470	(-0.95)	-1.197	(-1.30)	**-2.045**	(-3.62)
$TURNOVER$	**-2.098**	(-3.53)	-0.901	(-0.93)	-0.858	(-0.95)
$RET1$	**1.402**	(2.39)	**-2.890**	(-2.43)	1.236	(1.83)

Table VIII: Institutional Trading and Contemporaneous Returns

This table reports Fama-MacBeth regressions of changes in institutional ownership on contemporaneous stock returns. The dependent variable is the change in the fraction of shares outstanding held by all institutional investors. The independent variable in column 1 is the cumulative overnight return measured in the contemporaneous period, and that in column 2 is the cumulative intraday return in the same period. Column 3 reports the difference between the coefficients on overnight vs. intraday cumulative returns. Panel A uses quarterly changes in institutional ownership as reported in 13-F filings. Panel B uses daily changes in institutional ownership as inferred from large trades in the TAQ database (following Campbell, Ramadorai and Schwartz, 2008). Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. We further sort stocks into five quintiles based on institutional ownership at the beginning of the quarter and conduct the same regression for each IO quintile. Standard errors, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Quarterly Change in IO			
DepVar = Contemporaneous Qtrly Change in Institutional Ownership			
IO	Overnight Return	Intraday Return	Overnight – Intraday
1	-0.003	0.030*	-0.033
	[0.007]	[0.017]	[0.022]
5	-0.008	0.070***	-0.077***
	[0.006]	[0.010]	[0.006]
5-1	-0.005	0.039*	-0.044*
	[0.008]	[0.023]	[0.027]

Panel B: Daily Change in IO			
DepVar = Contemporaneous Daily Change in Institutional Ownership			
IO	Overnight Return	Intraday Return	Overnight – Intraday
1	0.177***	0.159***	0.018
	[0.041]	[0.019]	[0.040]
5	0.130***	1.254***	-1.123***
	[0.039]	[0.116]	[0.104]
5-1	-0.047	1.095***	-1.141***
	[0.051]	[0.078]	[0.062]

Table IX: Momentum Trading

This table examines the potential role of institutions' momentum trading. Panel A reports Fama-MacBeth forecasting regressions of changes in institutional ownership on the momentum characteristic. The dependent variable is the change in the fraction of shares outstanding held by all institutional investors (as reported in 13F filings) in the subsequent quarter. The main independent variable is the lagged 12-month cumulative stock return. We estimate OLS in the first two columns and WLS (with weights proportional to lagged market capitalization) in the next two columns. We then regress the time-series coefficients on our measure of arbitrage trading in the momentum strategy, a tercile dummy constructed from comomentum, defined as the average pairwise partial return correlation in the loser decile ranked in the previous 12 months. Changes in institutional ownership are expressed in percentage terms. Panels B and C report, respectively, the overnight and intraday returns to the momentum strategy as a function of lagged comomentum. All months in our sample are classified into three groups based on comomentum. Reported in these two panels are the overnight/intraday returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in the two years after portfolio formation, following low to high comomentum. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Standard errors are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: DepVar = Subsequent Change in Institutional Ownership				
X 100	Second stage of the Fama-MacBeth regression			
	[1]	[2]	[3]	[4]
	OLS		WLS	
MOM	0.189	-0.240	-0.260**	-0.737**
	[0.117]	[0.215]	[0.119]	[0.317]
MOM X COMOM		0.199**		0.233*
		[0.088]		[0.125]
Adj-R^2	0.003	0.003	0.004	0.004
No. Obs.	181,891	181,891	181,891	181,891

Panel B: Overnight Momentum Returns					
COMOM		Year 1		Year 2	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat
1	72	1.14%	(4.76)	0.95%	(3.80)
2	72	1.04%	(4.41)	-0.03%	(-0.10)
3	72	-0.41%	(-0.61)	-1.30%	(-3.02)
3-1		**-1.56%**	(-2.22)	**-2.26%**	(-4.05)

Panel C: Intraday Momentum Returns					
COMOM		Year 1		Year 2	
Rank	No Obs.	Estimate	t-stat	Estimate	t-stat
1	72	-0.92%	(-2.95)	-0.62%	(-3.12)
2	72	-0.84%	(-2.09)	-0.70%	(-1.40)
3	72	0.19%	(0.36)	0.24%	(0.42)
3-1		1.11%	(1.79)	**0.86%**	(2.04)

Table X: Rebalancing Trades

This table examines the potential role of institutions' rebalancing trades. Panel A reports Fama-MacBeth forecasting regressions of changes in institutional ownership on the momentum characteristic. The dependent variable is the change in the fraction of shares outstanding held by all institutional investors (as reported in 13F filings) in the subsequent quarter. The main independent variable is the lagged 12-month cumulative stock return. We also include in the regression a quintile dummy constructed each quarter based on the active weight of the aggregate institutional portfolio (i.e., the aggregate weight of all institutions in a stock minus that in the market portfolio), as well as the interaction term between the quintile dummy and the lagged 12-month return. We estimate OLS in the first two columns and WLS (with weights proportional to lagged market capitalization) in the next two columns. Panels B and C report, respectively, the overnight and intraday returns to the momentum strategy as a function of institutional active weight. In particular, in each month, stocks are sorted independently into a 5X5 matrix by both institutional active weight from the most recent quarter and lagged 12-month stock returns. Reported in these two panels are the overnight/intraday returns to the momentum strategy (i.e., long the value-weight winner decile and short the value-weight loser decile) in the following month. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Standard errors are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: DepVar = Subsequent Change in Institutional Ownership				
X 100	Fama-MacBeth Regressions			
	[1]	[2]	[3]	[4]
	OLS		WLS	
MOM	0.189	0.620***	-0.260**	0.210*
	[0.117]	[0.128]	[0.119]	[0.114]
MOM X AWGHT		-0.182***		-0.143***
		[0.043]		[0.046]
AWGHT		-0.292***		-0.178***
		[0.022]		[0.015]
Adj-R^2	0.003	0.015	0.004	0.017
No. Obs.	181,891	181,891	181,891	181,891

Panel B: Overnight MOM Returns						
	Institutional Active Weight					
MOM	1	2	3	4	5	5-1
1	0.52%	0.00%	-0.07%	-0.08%	-0.27%	-0.79%
	(1.91)	(0.01)	(-0.33)	(-0.39)	(-1.21)	(-4.32)
5	0.79%	0.53%	0.44%	0.67%	1.15%	0.36%
	(4.31)	(2.60)	(2.22)	(3.64)	(6.66)	(3.37)
5 − 1	0.27%	**0.53%**	**0.51%**	**0.75%**	**1.42%**	**1.15%**
	(1.10)	(2.68)	(2.72)	(4.54)	(7.92)	(5.39)

Panel C: Intraday MOM Returns						
	Institutional Active Weight					
MOM	1	2	3	4	5	5-1
1	-0.36%	0.18%	0.71%	0.51%	0.38%	0.74%
	(-0.92)	(0.43)	(1.63)	(1.23)	(1.03)	(3.03)
5	-0.44%	0.44%	0.55%	0.24%	-0.46%	-0.02%
	(-1.71)	(1.45)	(1.81)	(0.87)	(-1.89)	(-0.14)
5 − 1	-0.09%	0.26%	-0.16%	-0.27%	**-0.84%**	**-0.76%**
	(-0.24)	(0.75)	(-0.48)	(-0.84)	(-2.62)	(-2.70)

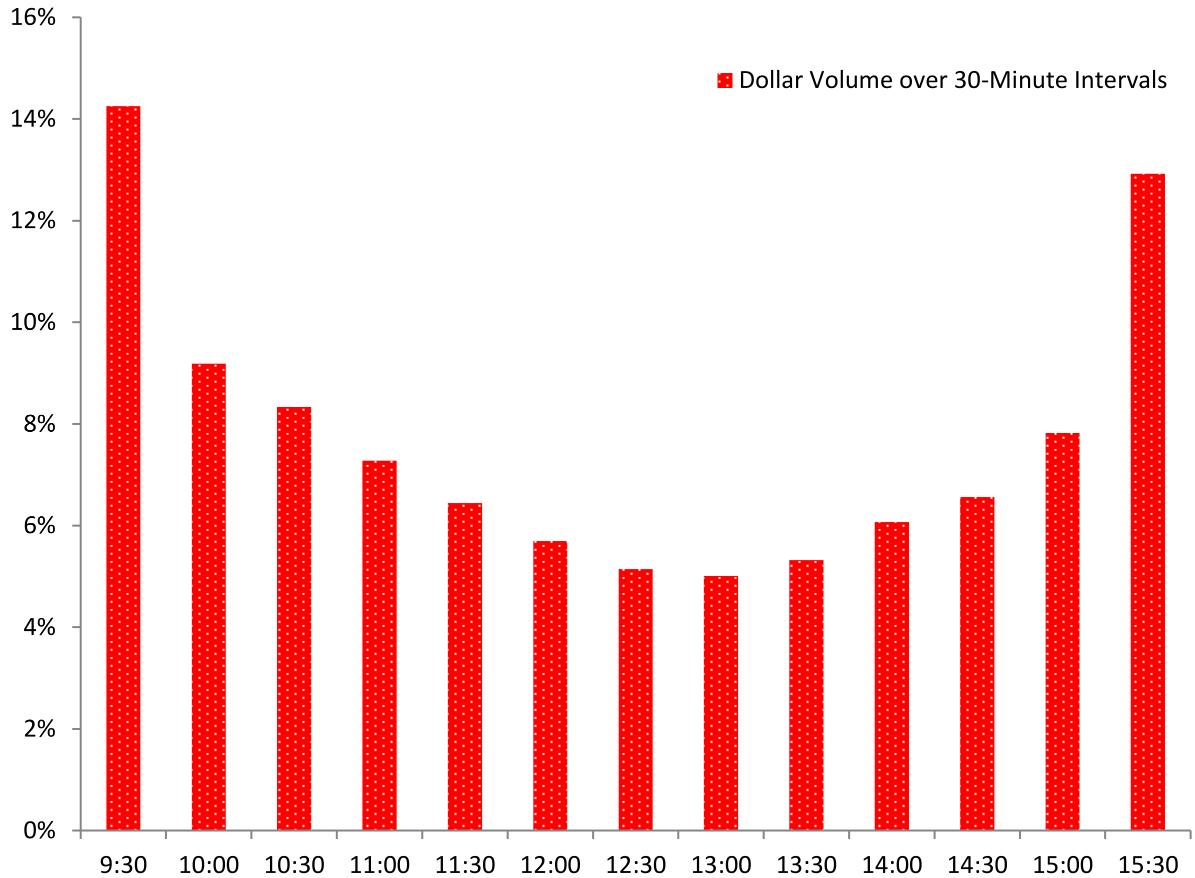

Figure 1: This figure shows dollar trading volume over 30-minute intervals throughout the trading day. In particular, we first sum up the amount of dollars traded in each of these half-hour windows. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-minute interval. In other words, these red bars sum up to 1. The first half-hour window that starts at 9:30am also includes the open auction. The last half-hour window that starts at 3:30pm also includes the last-minute (i.e., 4pm) trades and closing auction.

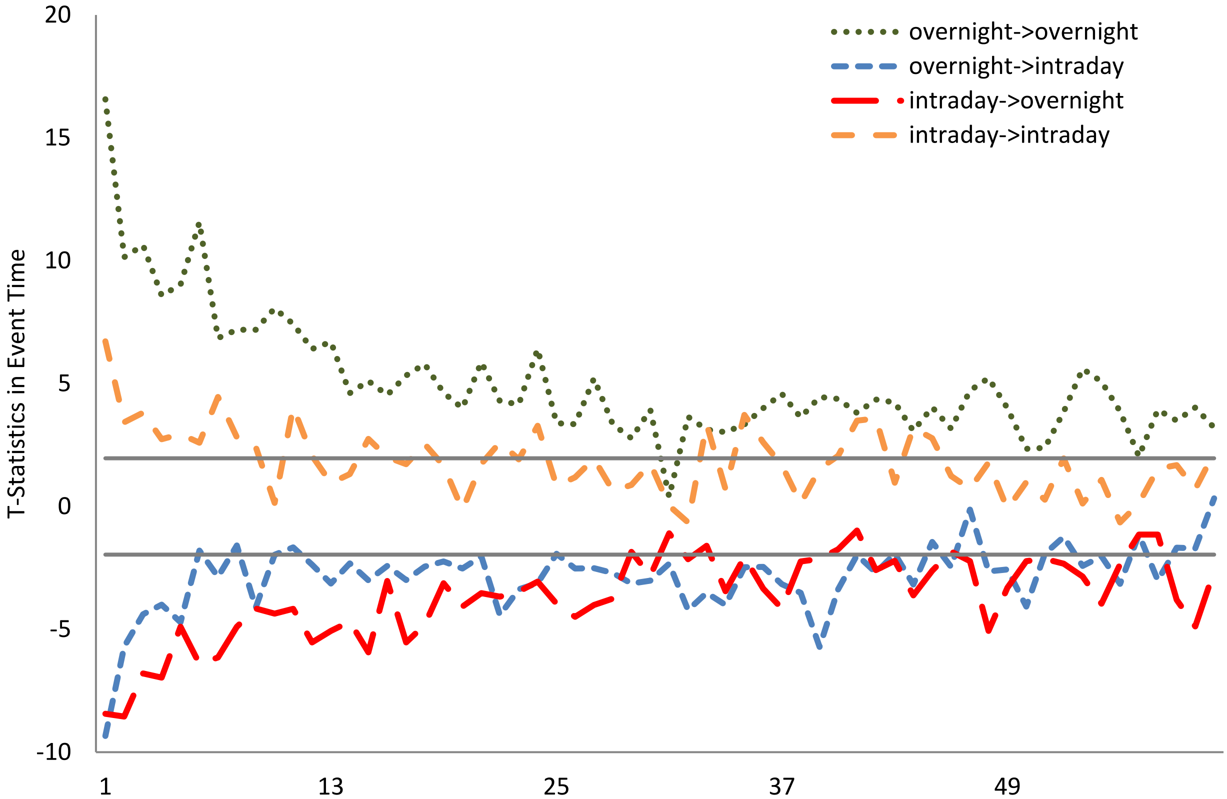

Figure 2: This figure shows the t-statistics of the overnight/intraday return persistence test, as reported in Table VI. We extend our analysis in Table VI by varying the lag between the ranking period and holding period from one month all the way to sixty months (i.e., shown by the X-axis). Stocks with prices below \$5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. The dotted green curve corresponds to using lagged overnight returns to forecast future overnight returns. The dashed orange curve corresponds to using lagged intraday returns to forecast future intraday returns. The dashed blue curve corresponds to using lagged overnight returns to forecast future intraday returns. Finally, the dashed red curve corresponds to using lagged intraday returns to forecast future overnight returns.

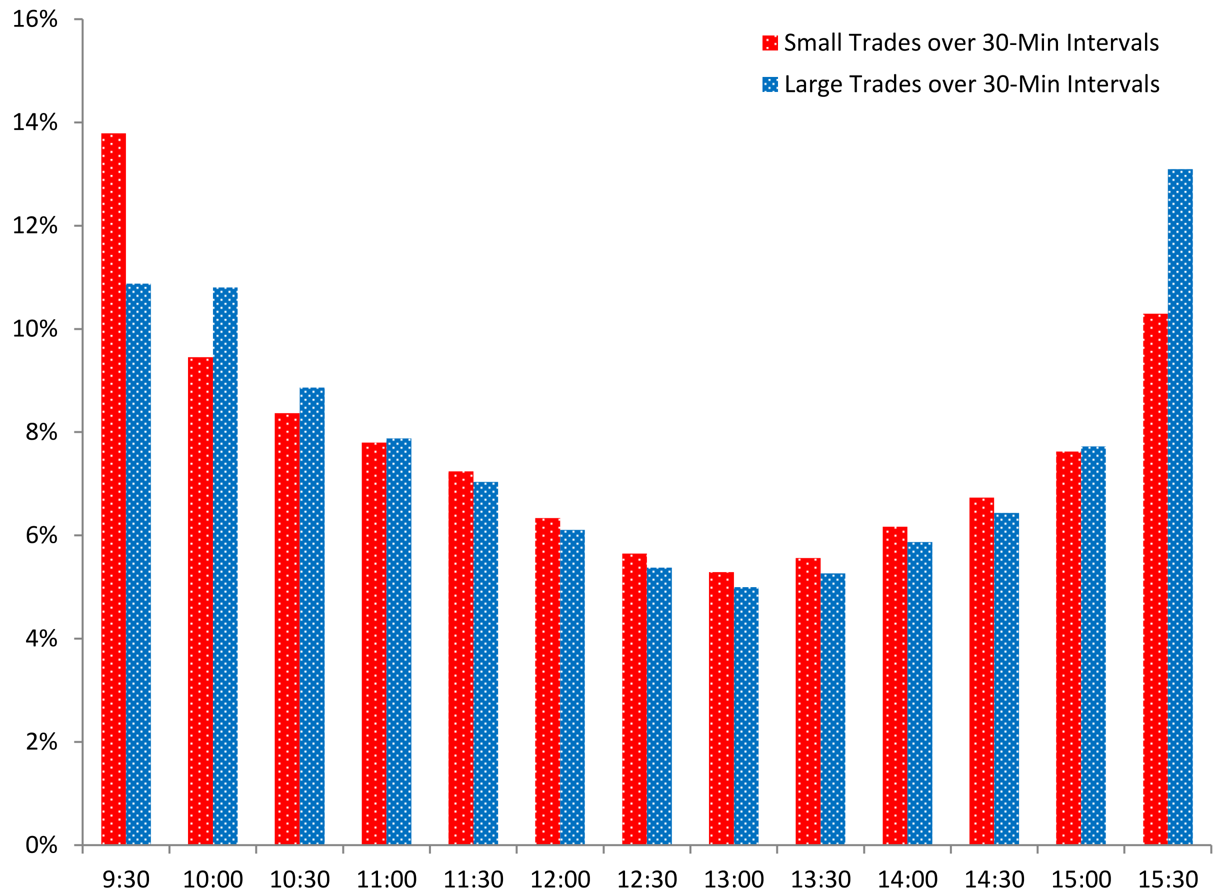

Figure 3: This figure shows dollar trading volume of large (depicted by blue bars) vs. small orders (depicted by red bars) over 30-minute intervals throughout the trading day for the period 1993-2000. We define small orders as those below \$5,000 and large orders as those above \$50,000. More specifically, we first sum up the amount of dollars traded in each of these half-hour windows. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-minute interval. In other words, both the red bars and blue bars sum up to 1. The first half-hour window that starts at 9:30am also includes the open auction. The last half-hour window that starts at 3:30pm also includes the last-minute (i.e., 4pm) trades and closing auction.