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Abstract

We decompose the abnormal profits associated with well-known patterns in the cross-section of expected returns into their overnight and intraday components. We show that, on average, all of the abnormal returns on momentum strategies remarkably occur overnight while the abnormal profits on the other trading strategies we consider occur intraday. These patterns are extremely robust across subsamples and indeed are stronger for large-cap and high-price stocks. Furthermore, we find that all of the variables that are anomalous with respect to the Fama-French-Carhart model have risk premiums overnight that partially offset their much larger intraday average returns. Indeed, 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 fact, we show that an overnight CAPM explains much of the cross-sectional variation in average overnight returns we document. Finally, we argue that investor heterogeneity may explain why momentum profits tend to accrue overnight. We first provide evidence that, relative to individuals, institutions prefer to trade during the day and against the momentum characteristic. We then highlight conditional patterns that reveal a striking tug of war. 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 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 2 percent per month.

JEL classification: G12, N22

1 Introduction

Understanding cross-sectional variation in average returns is crucial for testing models of market equilibrium. Indeed, over the last two decades, researchers have documented a rich set of characteristics that describe cross-sectional variation in average returns, thus providing a tough test to our standard models of risk and expected return.[2]

We deliver remarkable new evidence about the cross-section of expected returns through a careful examination of exactly when expected returns accrue. In particular, we decompose the abnormal profits associated with these characteristics into their overnight and intraday components.[3] We find that 1003 of the abnormal returns on momentum strategies occur overnight; in stark contrast, the average intraday component of momentum profits is economically and statistically insignificant. This finding is robust to a variety of controls and risk-adjustments, is stronger among large-cap stocks and stocks with relatively high prices, and is true not only for a standard price momentum strategy but also for earnings and industry momentum strategies. 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.

It is possible that variation in risk drives why momentum profits accrue overnight while size and value premiums instead accrue intraday. However, we find no evidence that this is the case. Second, since the momentum phenomenon is often viewed as underreaction to news, and since a significant amount of news is released after markets close, another possi-

[2]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 (2014).

[3]A more precise explanation 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. We thank Mike Hertzel for suggesting we confirm that the weekend isn t special in this regard.

bility is that news drives the differences we find. However, we find no statistical difference in our decomposition across news and no-news months, defined as months with and without an earnings announcement or news coverage in Dow Jones Newswire, respectively. As a consequence, we exploit a key difference between these two periods linked to investor heterogeneity, namely, the degree of institutional activity. Though there are certainly many types of investors, this heterogeneity is perhaps the most fundamental and relevant during our sample period. We link institutional activity to our effect in two ways.

We first examine when institutional investors likely trade. 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 by institutions can move prices, this evidence is consistent with the notion that institutions tend to trade intraday while individuals are more likely to trade overnight. Such a result is also 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 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.

We then examine the extent to which institutions, relative to individuals, trade momentum stocks. We find that on average, for the value-weight portfolios we consider, institutions trade against the momentum characteristic. We build on this finding by refining our understanding of why this intraday/overnight tug of war occurs by conditioning 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 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 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.

Our analysis ends by studying patterns in the cross-section not captured by the four-factor 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 stronger than that from close to close. Thus, these results imply, which we then confirm, the striking finding that these characteristics have overnight premiums that are opposite in sign to their well-known and often-studied total effects.

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.[4] Consistent with this interpretation, we show that once we control for a strategy s overnight market exposure, the positive overnight risk premiums associated with idiosyncratic volatility and market beta are dramatically lower and no longer statistically significant.

We also include the one-month past return in our analysis. Interestingly, we find that

[4] 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 similar accounting risk measures to cash-flow beta.

the negative premium that previous research has documented from close to close turns out to be realized entirely overnight. Thus, momentum and short-term reversal are alike in this regard. 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.

As our tug of war documents an interesting link between intraday and overnight returns conditional on the intensity of momentum trading and rebalancing needs, we decompose the standard one-month past return characteristic into overnight and intraday components. This analysis reveals striking results. We show that stocks with relatively-high lagged overnight returns have relatively-high average overnight returns the next month; these stocks also have average intraday returns the next month that are relatively low. In particular, 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 3.473 per month with an associated t-statistic of 16.83 and a three-factor intraday alpha of -3.023 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 2.413 per month (t-statistic of 7.70) and a three-factor intraday alpha of -1.773 per month (t-statistic of -7.89).

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. 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 volume-weighted prices during the first half-hour the market is open as well as the midpoint of the quoted bid-ask spread. The former measure ensures that our open price is tradable while the later ensures that bid-ask bounce is not responsible for any of our findings. We also show that our findings are robust to examining subsequent prices during the day. We further show that our finding continues to hold even in the most recent 10-year subperiod and, as mentioned above, is particularly strong in large-cap as well as high-price stocks.

Taken all together, our findings further challenge theories of the risk-return tradeoff 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.

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 concludes.

2 Motivation and Previous Literature

Though we are the first to decompose the cross section of average returns in this way, 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 information surprises. The United States stock market is open from 9:30 am to 4:00 pm but the vast majority of earnings announcements occur outside of these times. Of these overnight announcements, roughly a quarter occur in the half hour after the market has closed with most of the remaining announcements taking place in the morning before the market opens. 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 the trading of investors less concerned with liquidity and price impact, as the after-hours markets are much thinner than when the exchanges 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.[5] Recent work by Kelly and Clark (2011) suggests that stock returns on average are higher overnight than intraday.[6] To our knowledge, there is no paper decomposing the returns on popular trading strategies 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

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

[6] 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).

regularities.

Many papers have linked investor heterogeneity 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).

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 the VWAP price 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 price is not driven by very small orders, we exclude observations where there are fewer than 100 shares traded in the first half an hour. (Our results are not sensitive to this restriction.)

We define the intraday return, [illegible], as the price appreciation between market open and close of the same day, and impute the overnight return, [illegible], based on this intraday return and the standard daily close-to-close return, [illegible], taken directly from CRSP,

$$[illegible] = \frac{[illegible]}{[illegible]} - 1$$

$$[illegible] = \frac{1 + [illegible]}{1 + [illegible]} - 1.$$

In other words, we assume that dividend adjustments, share splits, and other corporate events that could mechanically move prices take place overnight.[7] Furthermore, to ensure that the returns are actually achievable, if the open price on day t 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 $t-1$ 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. We then accumulate these overnight and intraday returns over each month. Thus, all of our analysis examines the intraday and overnight components of the standard CRSP monthly return.

Our final sample is from 1993-2013, constrained by the availability of the TAQ data. We exclude microcap stocks-i.e., those with a price below $5 a share and 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 holding-period returns to a host of popular arbitrage strategies 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, profitability, investment, idiosyncratic volatility, beta, turnover, equity issuance, discretionary accruals, and short-term reversals.

[7] 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.

4 Results

4.1 Momentum

We first decompose the returns on a standard implementation of the classic momentum strategy, □□□, of Jegadeesh and Titman (1993). In particular, we measure momentum over a twelve-month ranking period and then skip a month before forming portfolios. Table I Panel A reports □□□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 1.053 per month with an associated □-statistic of 2.22. A similar, though slightly weaker finding holds for CAPM-adjusted returns (0.933 per month with a □-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 0.953 (□-statistic of 3.65) while the intraday three-factor alpha is only 0.113 (□- 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 □□□□is much less volatile (4.023 standard deviation) than the close-to-close return (7.853 standard deviation). Thus, the Sharpe Ratio of the overnight return on □□□□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 □□□□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 accrues 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 □□□□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, for our sample, roughly 603 of the equity premium is earned overnight. In Table II, 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 how the properties of these factors vary from overnight to intraday; Section 4.3 will carefully decompose the size and value premiums into overnight and intraday components.

The top third of Table II examines how the three-factor loadings of □□□s close-to-close return change as we split the Fama and French factors into their overnight and intraday components. We find that □□□s market loading is higher overnight than intraday, but is still negative. Moreover, □□□s □□□□and □□□□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 Table II where we explicitly regress the overnight □□□□returns on the overnight Fama-French three-factor model. The three-factor loadings are negative, and the alpha remains an economically large 0.863 (□-statistic of 3.07). The lower third of Table II confirms that the intraday □□□□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). Figures 1 and 2 examine this question by plotting the cumulative excess returns (Figure 1) and abnormal three-factor returns (Figure 2) on □□□□ 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. Figure 1 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 303. 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 □□□□ 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, Figure 2 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 303) during the second year.

The fact that the negative skewness present in momentum returns tends to occur intraday raises the question of how momentum strategies perform overnight versus intraday during momentum crashes. Figure 3 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 -9.43 occurs entirely overnight (-123) as the intraday return is positive (2.43). The overnight crash in March is then followed by a dramatic -413 return in April, which almost entirely occurs intraday (-393) rather than overnight (-23). The momentum crash continues in May as returns to the momentum strategy are -183, driven by an overnight drop that month of -263. Though of course the March-May momentum crash coincides with many other market phenomena, it is interesting to see that the largest decline occurred intraday, but was precipitated by a smaller, but still quite large, overnight drop the month before.

4.2 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 III documents that our findings are robust to subsample analysis.

One possibility is that our finding is driven by extremes that occur in particular subperiods. Table III 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 1.263 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 our care in using only volume-weighted traded prices, a concern might be that our findings are driven by some microstructure artifact. Table III 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 0.543 (t-statistic of 4.49) while the intraday three-factor alpha is 0.393 (t-statistic of 1.59). For large-cap stocks, the overnight three-factor alpha is 1.043 (t-statistic of 5.90) while the intraday three-factor alpha is actually negative, -0.243 (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 III 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 0.663 (t-statistic of 3.59) while the intraday three-factor alpha is 0.333 (t-statistic of 1.17). For high-price stocks, the overnight three-factor alpha is 1.143 (t-statistic of 6.63) while the intraday three-factor alpha is again negative, -0.413 (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. Table I Panel B reports that the average excess overnight return is 0.893 per month with an associated t-statistic of 3.44 and the average excess intraday return is -0.183 per month (t-statistic of -0.43) when using the VWAP price. In results not reported, 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 0.953 per month with an associated t- statistic of 2.95, and the average excess intraday return is only 0.043 per month (t-statistic of 0.17).

Finally, to ensure that we are not picking up an unusual spike in the prices of momentum stocks when the market opens, Figure 4 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. Figure 4 plots both excess and three-factor adjusted returns; our conclusions are robust to using either.

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

4.3 Comparison with Size and Value

A possible economic explanation for our finding might be that the overnight premium for momentum represents compensation for 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).[8] We first examine a strategy (□□) that goes long the small-stock decile and short the large-stock decile. Table IV Panel A reports the overnight and intraday components of □□s excess and CAPM-adjusted returns. Essentially all of the size premium occurs intraday. Specifically, the intraday CAPM alpha is -0.433 (□-statistic of -1.85) while the overnight CAPM alpha is only -0.113 (□-statistic of -0.75).

We then decompose the returns on a strategy (□□) that goes long the high book-to-market decile and short the low book-to-market decile. We measure book-to-market-equity

[8] 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).

ratios following Fama and French (1992). Table IV Panel B reports the overnight and intraday components of □□s excess and CAPM-adjusted returns. Again, we find that essentially all of the value premium occurs intraday. Specifically, the intraday CAPM alpha is 0.483 (t-statistic of 2.21) while the overnight CAPM alpha is actually slightly negative, though not statistically significant (-0.103 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 why momentum profits only accrue overnight but size and value premiums do not.

4.4 The Role of News Announcements

One clear difference between the intraday and overnight periods is that certain types of news may tend to be released after markets close. Table IV Panels C and D 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 IV Panel C reports that momentum earns an overnight premium in both news months (1.023 three-factor alpha with a t-statistic of 4.30) and in no-news months (1.353 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 IV Panel D 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.

4.5 The Role of Institutional Investors

Though it is possible that variation in risk from overnight to intraday explains these striking patterns in expected returns, we are unable to find such variation, at least in terms of standard measures such as CAPM and three-factor risks. Though risks may be different from intraday to overnight, other aspects of the market are clearly different, including, but not limited to, the types of investors that tend to trade intraday versus overnight. We pursue this avenue to understand our findings.

When do institutions trade?

We first study when institutional investors tend to trade. Specifically, we link changes in institutional ownership to the components of *contemporaneous* firm-level stock returns. In Table V, we regress quarterly changes in institutional ownership on the overnight and intraday components of contemporaneous returns. 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 trade intraday while individuals are more likely to trade overnight. Such a 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.

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 VI 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 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, if anything, 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 □□□□□□□□□□ Lou and Polk (2014) propose a novel approach to measuring the amount of momentum trad- ing 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 that implied by their fundamentals.[9] Lou and Polk confirm that their measure of the momentum crowd is a suc- cess based on three empirical findings. First, □□□□□□□□□□□s significantly correlated with existing variables plausibly linked to the size of momentum trading. Second, □□□□□□□□□□ forecasts relatively low holding-period returns, relatively high holding-period return volatil-

[9]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.

ity, and relatively more negative holding-period return skewness for the momentum strategy. Finally, when [illegible]s relatively high, the long-run buy-and-hold returns to a mo- mentum 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 VI Panel A report the results from forecasting the time-series of cross-sectional regression coefficients using [illegible] For robustness, we sim- ply measure [illegible]using tritile dummies. Consistent with the interpretation that [illegible]measures time-variation in the size of the momentum crowd, we find that insti- tutions tendency to trade against the momentum characteristic is decreasing in [illegible] The effect is statistically significant for both the OLS and WLS estimates.

Table VI 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 [illegible] Following Lou and Polk (2014), we track the buy-and-hold performance of [illegible]for two years following portfolio formation. When [illegible]s 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 [illegible]s high, the excess returns turn negative. The difference in the average overnight return to momentum across high and low [illegible]states of the world is -1.563 in Year 1 and -2.263 in Year 2. Both estimates are jointly statistically significant ([illegible]-statistics of -2.22 and -4.05 respectively).

A corresponding [illegible]effect can be seen in the average intraday returns to mo- mentum. When [illegible]s low, we find that the intraday excess returns to momentum strategies are particularly negative in both Year 1 and Year 2. However, when [illegible] is high, these excess returns turn positive. The difference in the average intraday return to momentum across high and low [illegible]states of the world is 1.113 in Year 1 and

0.863 in Year 2. Both estimates are jointly statistically significant ([illegible]-statistics of 1.79 and 2.04 respectively).

The second key indicator we use is the aggregate [illegible] in a stock. We measure [illegible] 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 [illegible] will indicate a preference by those institutional investors to rebalance towards market weights, due to risk management concerns such as tracking error.

Columns (2) and (4) in Table VII Panel A report the results from cross-sectional regressions forecasting quarterly changes in institutional ownership using a firm s momentum characteristic, [illegible], and the interaction between these two variables. For robust- ness, we simply measure [illegible] using quintile dummies.

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

Table VII 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 [illegible] into quintiles and form 25 value-weight portfolios.[10] When [illegible] is low, we find that the overnight excess returns to momentum strategies are relatively weak the next month. However, when [illegible] is high, overnight returns become strongly positive. The difference in the average overnight return to momentum across high and low [illegible] stocks is 1.153 with an associated [illegible]-statistic of 5.39.

A corresponding effect can, again, be seen in the average intraday returns to momentum.

[10] As throughout the paper, these sorts are based on NYSE breakpoints.

When [illegible] is low, the average intraday excess returns to momentum strategies are close to zero. However, when [illegible] is high, these average excess returns become quite negative. The difference in the average intraday return to momentum across high and low [illegible] stocks is -0.763 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.[11] 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.

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.

Earning Momentum and Industry Momentum

[11] 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.

To show that our conclusion that momentum profits occur overnight is robust, we next examine two other momentum strategies. Table VIII Panel A decomposes the abnormal returns on an earnings momentum strategy (□□□). 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 1003 of the returns to □□□□occur overnight. In particular, the three-factor alpha of a long-short earnings momentum portfolio is 0.583 with a □-statistic of 3.23. The corresponding intraday three- factor alpha is indistinguishable from zero.

Table VIII Panel B decomposes the abnormal returns on an industry momentum strategy (□□□□□□). 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 1003 of the □□□□□□□effect occurs overnight. In particular, the three-factor alpha of a long-short industry momentum portfolio is 1.093 with a □-statistic of 6.65. The corresponding intraday three-factor alpha is an economically large -0.563, though (just barely) statistically indistinguishable from zero. In summary, for the three 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, □□□

We examine a strategy (□□□) that goes long the high profitability decile and short the low profitability decile. Table VIII Panel C reports the overnight and intraday components of □□□s excess, CAPM-adjusted, and three-factor-adjusted returns. More than 1003 of the profitability premium occurs intraday as there is a very strong *negative* expected return associated with □□□□overnight. Specifically, the intraday three-factor alpha is 1.433 (□-statistic of 6.44) while the overnight three-factor alpha is -0.953 (□-statistic of -6.22).

We then examine a strategy (□□□□) that goes long the high investment decile and short the low investment decile. Table VIII Panel D reports the overnight and intraday components of □□□□s average excess, CAPM-adjusted, and three-factor-adjusted returns. Again, more than 1003 of the negative investment premium occurs intraday as there is a statistically significant *positive* expected return associated with □□□□overnight. Specifically, the intraday three-factor alpha is -0.783 (□-statistic of -4.09) while the overnight three-factor alpha is
0.363 (□-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 (□□□□□) 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 nonsyn- chronous trading issues into account. Table VIII Panel E reports the overnight and intraday components of □□□□□s excess, CAPM-adjusted, and three-factor-adjusted returns. More than 1003 of the negative beta premium occurs intraday as there is a *positive* premium associated with □□□□□□overnight. Specifically, the intraday three-factor alpha is -0.803 (t-statistic of -2.60) while the overnight three-factor alpha is 0.493 (t-statistic of 2.10).

We then analyze a strategy (□□□□□) 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 re- gression 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 VIII Panel F documents that more than 1003 of □□□□□□occurs intraday. As a consequence, □□□□□□is as- sociated with a *positive* risk premium overnight. Specifically, the intraday three-factor alpha for □□□□□□is -2.343 per month with an associated □-statistic of -7.82. The corresponding overnight three-factor alpha is 1.613 per month with a □-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 (□□□□□) that goes long the high-equity-isuance decile and short the high-equity-isuance decile. Table VIII Panel G reports the overnight and intraday components of □□□□□s excess, CAPM-adjusted, and three-factor-adjusted returns. More than 1003 of the issuance premium occurs intraday as there is a very strong *positive* expected return associated with □□□□□□overnight. Specifically, the intraday three-factor alpha is -1.053 (□-statistic of -6.05) while the overnight three-factor alpha is 0.523 (□-statistic of 3.35).

We then examine a strategy (□□□□□□□□) that goes long the high discretionary ac- cruals decile and short the low discretionary accruals decile. Table VIII Panel H reports the overnight and intraday components of □□□□□□□s average excess, CAPM-adjusted, and three-factor-adjusted returns. Again, more than 1003 of the accruals premium occurs intraday as there is a statistically significant *positive* expected return associated with □□□□□□□□□□overnight. Specifically, the intraday three-factor alpha is -0.943 (□-statistic of -4.95) while the overnight three-factor alpha is 0.563 (□-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 (□□□□□□□□□□□□) 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 (□□□□□□□□□□□□) 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 VIII Panel I reports the overnight and intraday components of □□□□□□□□□□□□s average excess, CAPM-adjusted, and three-factor- adjusted returns. Again, more than 1003 of the negative turnover premium occurs intraday as there is a statistically significant *positive* expected return associated with □□□□□□□□□□□□ overnight. Specifically, the intraday three-factor alpha is -0.523 (□-statistic of -3.22) while the overnight three-factor alpha is 0.353 (□-statistic of 2.54).

We then analyze a strategy (□□□□□) that goes long the high past one-month return decile and short the low past one-month return turnover decile. Table VIII Panel J reports the overnight and intraday components of □□□□□ 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 □□□□□ intraday. Specifically, the intraday three-factor alpha is 1.053 (□-statistic of -3.26) while the overnight three-factor alpha is -0.883 (□-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.

Figure 5 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 extreme momentum stocks tend to be stocks with high idiosyncratic volatility. The second fact is that □□□□□ is associated with a *positive* risk premium overnight, as our decomposition of □□□□□□ above shows. These two facts suggest an explanation for the U- and hump-shaped patterns of Figure 5; namely, extreme winner or loser stocks generally outperform overnight and underperform intraday because they tend to be high idiosyncratic volatility stocks.

As a consequence, Table IX 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 when controlling for momentum.

Table IX 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 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 1.253 per month with a [illegible]-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, it is difficult to control for other characteristics to measure carefully the partial effect with this method. As a consequence, we turn to Fama and MacBeth (1973) regressions to describe the cross-section of overnight versus intraday expected returns. Table X reports three regressions, a standard regression forecasting the cross-section of [illegible], a regression forecasting the cross-section of [illegible], and a regression forecasting the cross-section of [illegible]. In each regression, we include all of the characteristics studied above except for [illegible], as it reduces the number of observations in each cross-section considerably.

Regression (1) shows that, for our sample, only [illegible], [illegible], [illegible], and [illegible] are statistically significant. Regression (3) reveals that many of these characteristics are much stronger predictors of the cross-section of intraday returns. In fact, [illegible], [illegible], [illegible], [illegible], [illegible], [illegible], and [illegible] are all statistically significant. In- terestingly, the sign on [illegible] flips to be positive and statistically significant. There is no intraday [illegible] effect; indeed, the point estimate is negative. [illegible] and [illegible] also remain statistically insignificant.[12]

In the cross-section of overnight returns described by regression (2), [illegible] is very strong. Consistent with the results in previous table, there is a strong positive premium associated with [illegible] and [illegible] and a strong negative premium associated with [illegible]. The positive premium for [illegible] is large but only marginally statistically significant. Interest- ingly, there is a positive premium for [illegible] and a weak negative premium for [illegible]. Overall, these regressions are consistent with our main findings.

Overnight premiums for Fama-French-Carhart anomalies

Table VIII 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.

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

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

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 (□□□, □□□□, □□□□□, □□□□□, □□□□□, □□□□□□□□, or □□□□□□□□□□□) are not common styles in equity markets.

We explore this possibility in the setting of Fama-MacBeth regressions, which help us isolate partial effects. Column (4) in Table X takes a first step in explaining these overnight premiums. We regress each of the time series of cross-sectional regression coefficients behind the estimates in regression (2) of the table on the contemporaneous overnight market return and report the resulting intercept. Doing so, we are able to control directly for a strategy s overnight market exposures. An obvious future step is to control for other overnight measures of risk.

We find results consistent with the above conjecture. The positive overnight risk premiums associated with idiosyncratic volatility and market beta are dramatically lower and no longer statistically significant. Our work-in-progress hopes to continue to link the positive overnight premiums on low return-on-equity and high share turnover to more general measures of overnight risk.

Overnight/Intraday Short-term Reversal

Since we have documented a striking tug of war tied to momentum linking cross-sectional variation in intraday and overnight returns over the next month, our final analysis examines the relation between intraday and overnight short-run returns more generally by decomposing the short-term reversal signal into overnight and intraday components. Specifically, in Table XI, 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 3.473 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 3.473 per month (t-statistic of 16.83). This one-month overnight return hedge portfolio earns on average an intraday excess return of -3.243 per month with an associated t-statistic of -9.34 (three-factor alpha of -3.023 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 2.193 per month with an associated t-statistic of 6.72. This finding continues to hold regardless of the risk adjustment as the three-factor alpha is also 2.413 per month (t-statistic of 7.70). This one-month intraday return hedge portfolio earns on average an overnight excess return of -1.813 per month with an associated t-statistic of -8.44 (three-factor alpha of -1.773 per month with a t-statistic of -7.89).

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 1.883 (t-statistic of 8.75) and an intraday three-factor alpha of -1.433 (t-statistic of - 7.05). Similarly, the portfolio based on past one-month intraday returns has an intraday three-factor alpha of 1.353 (t-statistic of 4.86) and an overnight three-factor alpha of -0.853 (t-statistic of -3.31).

5 Conclusions

We provide a novel decomposition of the cross section of expected returns into its overnight and intraday components. We show that essentially all of the abnormal return on momentum strategies occurs overnight while the abnormal returns on other strategies primarily 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 investor heterogeneity 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 not only higher overnight, but also partially revert intraday.

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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: Factor Betas

This table reports factor betas of momentum returns. 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. The first two rows report factor exposures of close-to-close momentum returns, the middle two rows report the exposures of overnight momentum returns, and the last two rows report the exposures of intraday momentum returns. In the first two columns, we include in the time-series regression monthly Fama-French factors; in the next four columns, we include in the regression the overnight and intraday versions of the Fama-French factors. 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.

	FF Factors		Overnight Factors		Intraday Factors	
			Close-to-Close MOM Returns			
Alpha	**1.05%**	(2.22)	0.56%	(1.17)	**1.04%**	(2.01)
Mktrf	**-0.55**	(-3.22)	-0.20	(-0.78)	**-0.87**	(-3.36)
SMB	0.19	(0.72)	-0.31	(-0.61)	0.17	(0.64)
HML	-0.36	(-1.06)	-1.02	(-1.25)	-0.68	(-1.23)
			Overnight MOM Returns			
Alpha	**0.95%**	(3.65)	**0.86%**	(3.07)	**0.74%**	(2.36)
Mktrf	**-0.20**	(-2.38)	**-0.35**	(-2.34)	-0.13	(-1.73)
SMB	0.18	(2.28)	-0.04	(-0.18)	0.13	(1.67)
HML	0.03	(0.29)	-0.84	(-1.51)	0.30	(1.48)
			Intraday MOM Returns			
Alpha	0.11%	(0.27)	-0.26%	(-0.69)	0.30%	(0.68)
Mktrf	**-0.36**	(-2.86)	0.15	(0.74)	**-0.74**	(-3.21)
SMB	0.00	(0.01)	-0.27	(-0.65)	0.03	(0.10)
HML	-0.35	(-1.32)	-0.07	(-0.09)	-0.90	(-1.80)

Table III: Robustness Checks

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.

Panel A: 1993-2002						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.20%	-0.05%	0.01%	-0.79%	-1.19%	-1.17%
	(0.50)	(-0.16)	(0.04)	(-1.22)	(-2.29)	(-1.95)
10	1.48%	1.29%	1.27%	-0.82%	-1.15%	-0.98%
	(4.95)	(5.35)	(4.92)	(-1.84)	(-3.40)	(-3.04)
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)						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.15%	-0.21%	-0.14%	-0.26%	-0.89%	-0.95%
	(0.43)	(-0.73)	(-0.52)	(-0.51)	(-2.25)	(-2.56)
10	1.30%	1.06%	1.05%	-0.49%	-1.17%	-1.20%
	(5.01)	(4.58)	(4.56)	(-1.79)	(-4.21)	(-4.56)
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)						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	-0.17%	-0.45%	-0.47%	0.66%	0.02%	-0.21%
	(-0.84)	(-2.86)	(-2.94)	(1.55)	(0.05)	(-0.86)
5	0.35%	0.08%	0.07%	0.78%	0.30%	0.18%
	(1.76)	(0.53)	(0.49)	(2.59)	(1.38)	(1.12)
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)						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.08%	-0.24%	-0.25%	0.07%	-0.47%	-0.53%
	(0.34)	(-1.28)	(-1.29)	(0.20)	(-1.82)	(-2.01)
5	1.00%	0.79%	0.79%	-0.39%	-0.79%	-0.77%
	(6.01)	(5.72)	(5.57)	(-1.60)	(-4.69)	(-4.60)
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)						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.33%	-0.03%	-0.09%	-0.12%	-0.75%	-0.86%
	(1.31)	(-0.14)	(-0.40)	(-0.30)	(-2.63)	(-3.02)
5	0.89%	0.60%	0.57%	0.07%	-0.43%	-0.53%
	(4.03)	(3.30)	(3.20)	(0.22)	(-1.82)	(-2.65)
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)						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	-0.14%	-0.42%	-0.40%	0.20%	-0.13%	-0.29%
	(-0.63)	(-2.30)	(-2.15)	(0.80)	(-0.85)	(-1.07)
5	0.95%	0.74%	0.74%	-0.22%	-0.42%	-0.70%
	(5.78)	(5.43)	(5.30)	(-1.36)	(-2.36)	(-4.28)
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 IV: 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 and D, we examine various strategy returns in news vs. non-news months. In Panel C, stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). In Panel D, stocks are sorted based on prior month market capitalization in the first two columns and lagged book-to-market ratio in the next two columns. 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: Overnight Returns			
	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 D: Intraday Returns 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 V: 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 (as reported in 13F filings). The independent variable in column 1 is the cumulative overnight return measured in the contemporaneous quarter, and that in column 2 is the cumulative intraday return in the same quarter. Column 3 reports the difference between the coefficients on overnight vs. intraday cumulative returns. 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.

DepVar = Contemporaneous Change in Institutional Ownership			
IO	Overnight Return	Intraday Return	Overnight - Intraday
1	-0.003	0.030*	-0.033
	[0.007]	[0.017]	[0.022]
2	-0.001	0.055***	-0.056***
	[0.005]	[0.003]	[0.005]
3	0.000	0.073***	-0.073***
	[0.003]	[0.004]	[0.005]
4	-0.005	0.071***	-0.077***
	[0.003]	[0.009]	[0.007]
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]

Table VI: Momentum Trading

This table examines the potential role of 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 VII: Rebalancing Trades

This table examines the potential role of 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 MOM	0.189	0.620***	-0.260**	0.210*
	[0.117]	[0.128]	[0.119]	[0.114]
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)

Table VIII: 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, stocks are sorted into deciles based on lagged return-to-equity; in Panel D, stocks are sorted into deciles based on lagged asset growth; in Panel E, stocks are sorted into deciles based on lagged 12-month market betas (using daily returns with one lead and one lag); in Panel F, 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 G, stocks are sorted into deciles based on equity issuance in the prior year; in Panel H, stocks are sorted into deciles based on lagged discretionary accruals; in Panel I, stocks are sorted into deciles based on lagged 12-month share turnover; in Panel J, 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.

Panel A: Overnight vs. Intraday SUE Returns

	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.30%	0.04%	0.02%	-0.20%	-0.70%	-0.93%
	(1.16)	(0.17)	(0.10)	(-0.47)	(-2.10)	(-3.22)
10	0.80%	0.60%	0.60%	-0.04%	-0.49%	-0.58%
	(4.08)	(3.72)	(3.74)	(-0.12)	(-2.26)	(-2.69)
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: Overnight vs. Intraday INDMOM Returns

	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	-0.12%	-0.31%	-0.34%	0.52%	0.16%	0.05%
	(-0.62)	(-1.86)	(-2.05)	(1.62)	(0.66)	(0.22)
5	0.93%	0.77%	0.75%	-0.14%	-0.47%	-0.51%
	(5.08)	(4.79)	(4.73)	(-0.51)	(-2.41)	(-2.68)
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: Portfolios Sorted by ROE						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	1.09%	0.86%	0.88%	-0.84%	-1.36%	-1.30%
	(4.67)	(4.42)	(4.52)	(-2.24)	(-5.39)	(-5.44)
10	0.09%	-0.10%	-0.07%	0.35%	0.06%	0.13%
	(0.55)	(-0.78)	(-0.53)	(1.63)	(0.43)	(0.93)
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 D: Portfolios Sorted by INVSTMNT						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.36%	0.19%	0.16%	0.25%	-0.09%	-0.19%
	(2.09)	(1.26)	(1.06)	(0.98)	(-0.53)	(-1.05)
10	0.69%	0.47%	0.52%	-0.64%	-1.06%	-0.97%
	(3.33)	(2.78)	(3.01)	(-2.04)	(-5.07)	(-4.71)
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)

Panel E: Portfolios Sorted by Market BETA						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.38%	0.17%	0.19%	-0.08%	-0.41%	-0.36%
	(1.60)	(0.80)	(0.87)	(-0.27)	(-1.74)	(-1.54)
10	0.92%	0.66%	0.68%	-0.58%	-1.11%	-1.16%
	(3.66)	(3.17)	(3.18)	(-1.53)	(-4.68)	(-4.87)
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 F: Portfolios Sorted by IVOL						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	-0.23%	-0.32%	-0.38%	0.72%	0.62%	0.53%
	(-1.75)	(-2.48)	(-3.16)	(3.67)	(3.10)	(2.83)
10	1.49%	1.15%	1.22%	-1.21%	-1.86%	-1.81%
	(4.67)	(4.48)	(4.65)	(-2.49)	(-5.79)	(-6.95)
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 G: Portfolios Sorted by Equity ISSUE						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.08%	-0.11%	-0.12%	0.56%	0.15%	0.07%
	(0.43)	(-0.72)	(-0.75)	(2.08)	(0.75)	(0.35)
10	0.67%	0.40%	0.40%	-0.48%	-0.98%	-0.98%
	(3.41)	(2.49)	(2.34)	(-1.63)	(-5.23)	(-5.13)
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 H: Portfolios Sorted by Discretionary ACCRUALS						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.11%	-0.05%	-0.10%	0.35%	-0.03%	-0.03%
	(0.78)	(-0.40)	(-0.71)	(1.55)	(-0.17)	(-0.18)
10	0.73%	0.41%	0.47%	-0.56%	-1.12%	-0.96%
	(3.19)	(2.30)	(2.52)	(-1.59)	(-4.50)	(-4.32)
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 I: Portfolios Sorted by TURNOVER						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	0.24%	0.08%	0.07%	0.16%	-0.11%	-0.07%
	(1.68)	(0.69)	(0.61)	(0.84)	(-0.88)	(-0.56)
10	0.61%	0.37%	0.42%	-0.23%	-0.68%	-0.59%
	(2.65)	(1.97)	(2.21)	(-0.72)	(-3.00)	(-3.19)
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 J: Portfolios Sorted by One-Month Returns						
	Overnight			Intraday		
Decile	Excess	CAPM	3-Factor	Excess	CAPM	3-Factor
1	1.39%	1.06%	1.04%	-1.03%	-1.65%	-1.67%
	(5.54)	(4.95)	(4.76)	(-2.73)	(-6.15)	(-6.18)
10	0.38%	0.14%	0.16%	-0.17%	-0.60%	-0.63%
	(1.83)	(0.78)	(0.86)	(-0.60)	(-2.75)	(-2.97)
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 IX: Controlling for IVOL

This table reports returns to the momentum strategy during the day vs. at night after controlling for idiosyncratic volatility. In Panels A and B, at the end of each month, all stocks are independently sorted into a 5 by 5 matrix based on lagged 12-month daily idiosyncratic volatilities (with regard to the Carhart four factor model, with one lead and one lag to incorporate non-synchronous trading) and lagged 12-month cumulative returns (skipping the most recent month). Panel A reports the value-weight overnight returns to these 25 portfolios in the following month. Panel B reports the value-weight intraday returns to these portfolios 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. In Panel C, we further exclude stocks whose lagged 12-month idiosyncratic volatility (IVOL) is in the top NYSE IVOL quintile; the remaining stocks are then sorted into deciles based on their lagged 12-month cumulative returns. Reported below are the monthly portfolio returns in excess of the risk-free rate. 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 Returns

	IVOL				
MOM	1	2	3	4	5
1	-0.65%	-0.33%	-0.11%	-0.08%	0.63%
	(-2.19)	(-1.29)	(-0.42)	(-0.29)	(2.29)
5	-0.03%	0.58%	0.74%	1.19%	1.52%
	(-0.13)	(3.66)	(3.95)	(5.80)	(5.12)
5 - 1	**0.78%**	**0.92%**	**0.85%**	**1.27%**	**0.89%**
	(2.16)	(3.84)	(3.37)	(5.52)	(4.09)

Panel B: Intraday Returns

	IVOL				
MOM	1	2	3	4	5
1	0.63%	1.11%	0.38%	0.14%	-0.87%
	(1.89)	(2.42)	(0.94)	(0.36)	(-1.73)
5	0.84%	0.09%	-0.22%	-0.50%	-0.67%
	(2.59)	(0.38)	(-0.82)	(-1.62)	(-1.65)
5 - 1	0.19%	**-1.02%**	-0.60%	-0.64%	0.19%
	(0.43)	(-2.38)	(-1.68)	(-1.84)	(0.56)

Panel C: Excluding stocks with high IVOL			
Overnight MOM Returns			
Decile	Excess	CAPM	3-Factor
1	-0.05%	-0.30%	-0.29%
	(-0.15)	(-1.05)	(-0.99)
2	-0.16%	-0.36%	-0.40%
	(-0.74)	(-1.89)	(-1.91)
3	-0.23%	-0.41%	-0.47%
	(-1.23)	(-2.51)	(-2.99)
4	-0.13%	-0.29%	-0.32%
	(-0.79)	(-2.10)	(-2.38)
5	-0.25%	-0.39%	-0.41%
	(-1.60)	(-2.85)	(-3.11)
6	-0.07%	-0.20%	-0.27%
	(-0.44)	(-1.43)	(-1.98)
7	0.00%	-0.14%	-0.18%
	(0.02)	(-1.11)	(-1.42)
8	0.12%	-0.04%	-0.08%
	(0.80)	(-0.30)	(-0.58)
9	0.37%	0.23%	0.19%
	(2.43)	(1.74)	(1.47)
10	1.14%	0.97%	0.96%
	(6.38)	(6.28)	(6.18)
10 - 1	**1.19%**	**1.26%**	**1.25%**
	(4.04)	(4.37)	(4.28)

Table X: Fama-MacBeth Return Regressions

This table reports Fama-MacBeth regressions of monthly stocks returns on lagged firm characteristics. The dependent variable in the first column in the close-to-close return in the following month; the dependent variable in the second column is the overnight return in the following month, and that in the last column is the intraday return in the following month. 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. For the fourth column, we regress the time series of coefficients from the analysis in the second column 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. 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 Adjusted
	[1]	[2]	[3]	[4]
MOM	0.116	0.290***	-0.209	0.322***
	[0.292]	[0.106]	[0.203]	[0.094]
ME	-0.080	0.172***	-0.253***	0.146***
	[0.049]	[0.035]	[0.036]	[0.031]
BM	0.053	0.049	0.020	0.041
	[0.076]	[0.048]	[0.079]	[0.049]
STR	-1.836***	-3.061***	1.072**	-2.782***
	[0.515]	[0.562]	[0.498]	[0.513]
IVOL	0.027	0.217**	-0.050	0.093
	[0.104]	[0.087]	[0.093]	[0.077]
BETA	-0.050	0.179*	-0.232**	0.085
	[0.145]	[0.104]	[0.107]	[0.096]
TURNOVER	-0.012	0.311***	-0.379***	0.277***
	[0.046]	[0.049]	[0.056]	[0.040]
ROE	0.156	-0.798***	0.972***	-0.683***
	[0.223]	[0.133]	[0.196]	[0.127]
INVSTMNT	-0.708***	0.010	-0.820***	0.038
	[0.215]	[0.121]	[0.213]	[0.124]
ISSUE	-1.209***	-0.333*	-0.578**	-0.326
	[0.247]	[0.206]	[0.247]	[0.212]
DISCACC	-0.859**	0.184	-1.052**	-0.069
	[0.344]	[0.285]	[0.407]	[0.289]
Adj-R^2	0.079	0.051	0.079	0.051
No. Obs.	462,070	462,070	462,070	462,070

Table XI: Overnight/Intraday Short Term Reversal

This table reports returns to the short-term reversal 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: 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: 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)

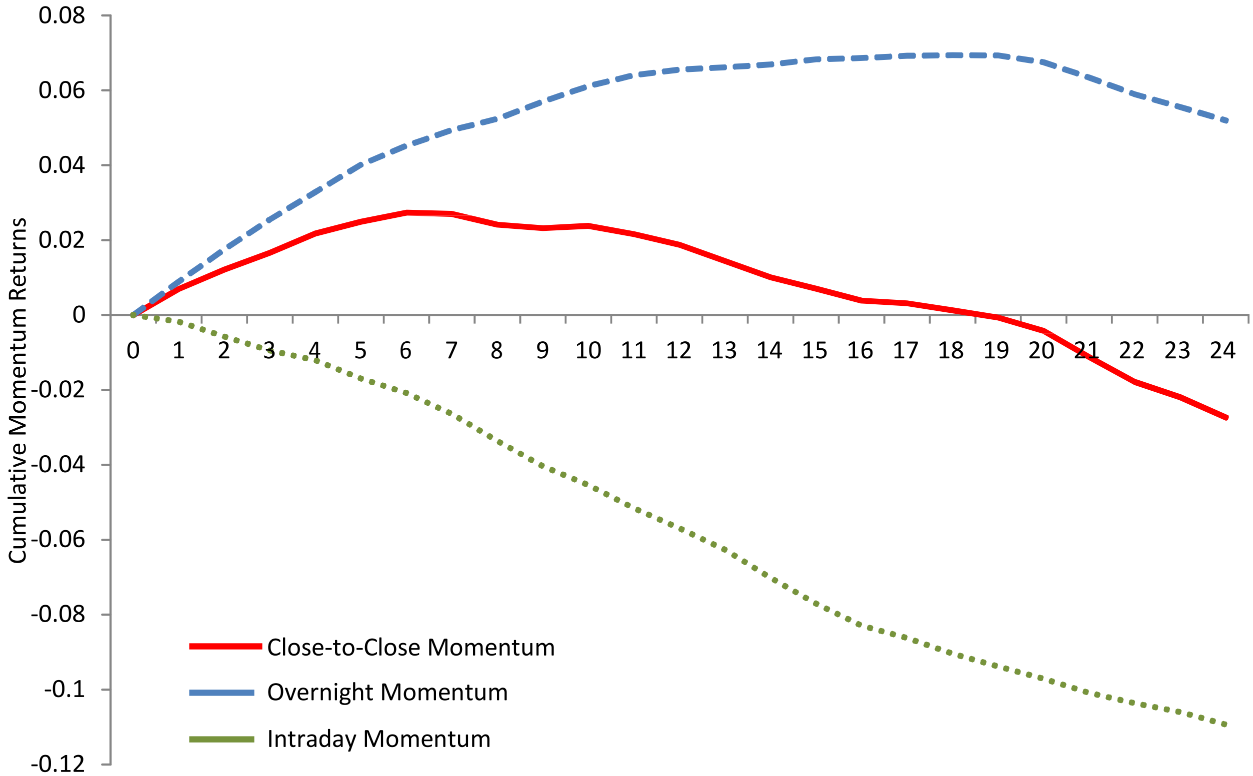

Figure 1: This figure plots cumulative returns to the momentum strategy during the day vs. at night in the 24 months following portfolio formation. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). We then 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. The red solid curve shows the cumulative close-to-close momentum returns in the 24 months following portfolio formation. The blue dashed curve shows the cumulative overnight momentum returns in the 24 months following portfolio formation. The green dotted curve shows the cumulative intraday momentum returns in the 24 months following portfolio formation.

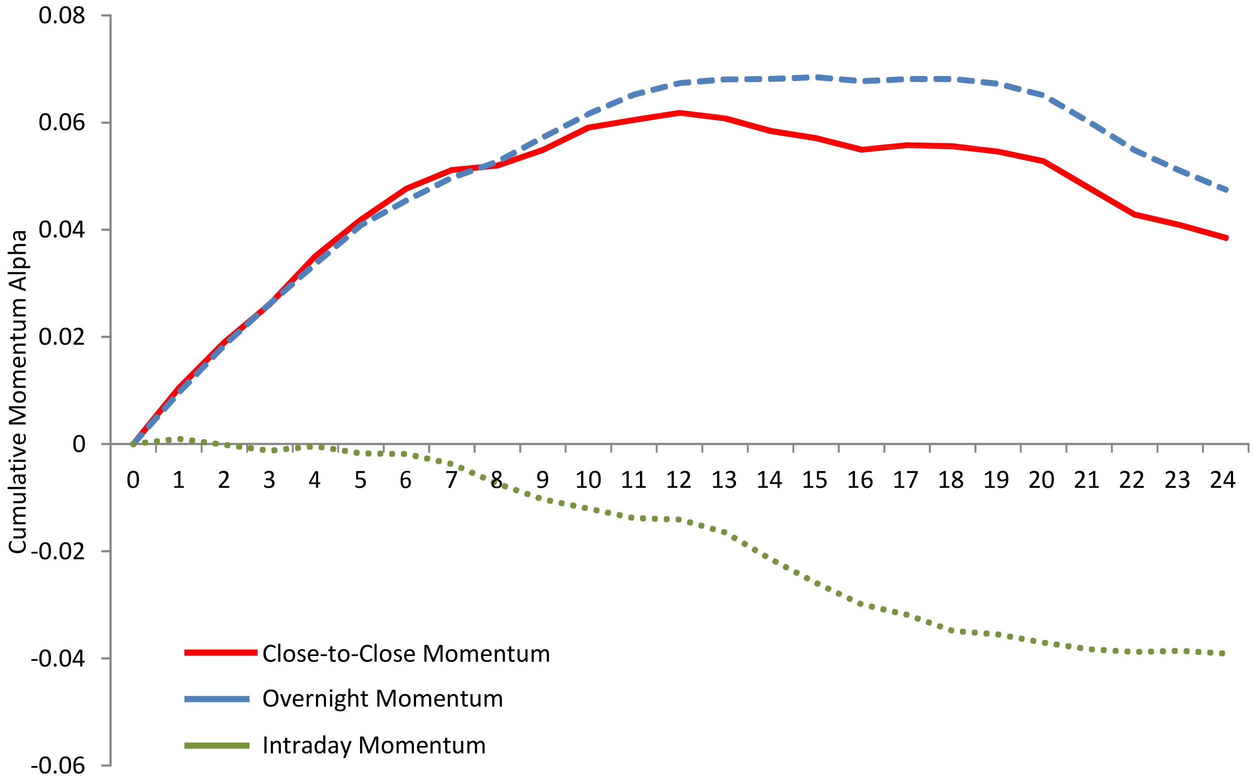

Figure 2: This figure shows cumulative three-factor alpha to the momentum strategy during the day vs. at night in the 24 months following portfolio formation. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). 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. The red solid curve shows the cumulative close-to-close momentum returns in the 24 months following portfolio formation. The blue dashed curve shows the buy-and-hold overnight momentum returns in the 24 months following portfolio formation. The green dotted curve shows the buy-and-hold intraday momentum returns in the 24 months following portfolio formation.

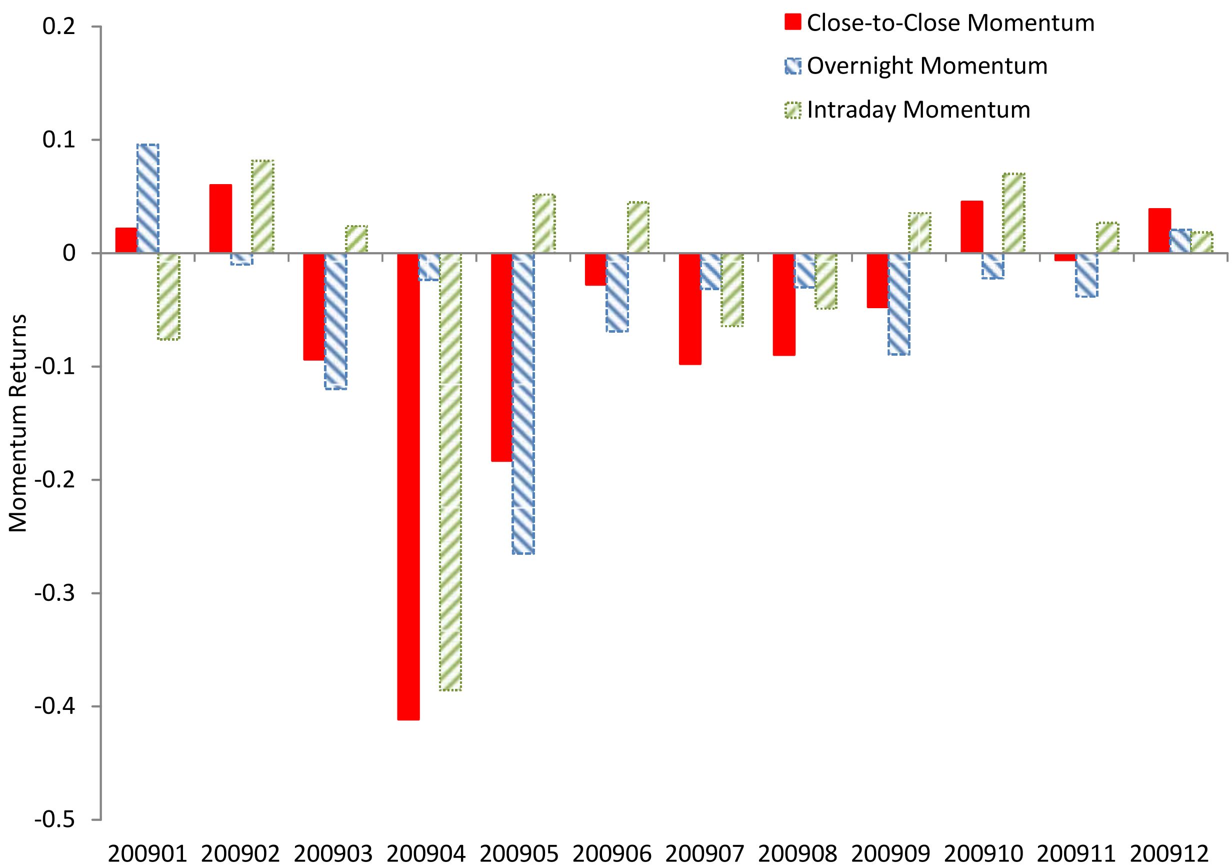

Figure 3: This figure shows monthly returns to the momentum strategy during the day vs. at night in the year 2009. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). We then go long the value-weight winner decile 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. The red solid bars show the value-weight close-to-close momentum return in each month of 2009. The blue shaded bars show the value-weight overnight momentum return in each month, and the green shaded bars show the value-weight intraday momentum return in each month.

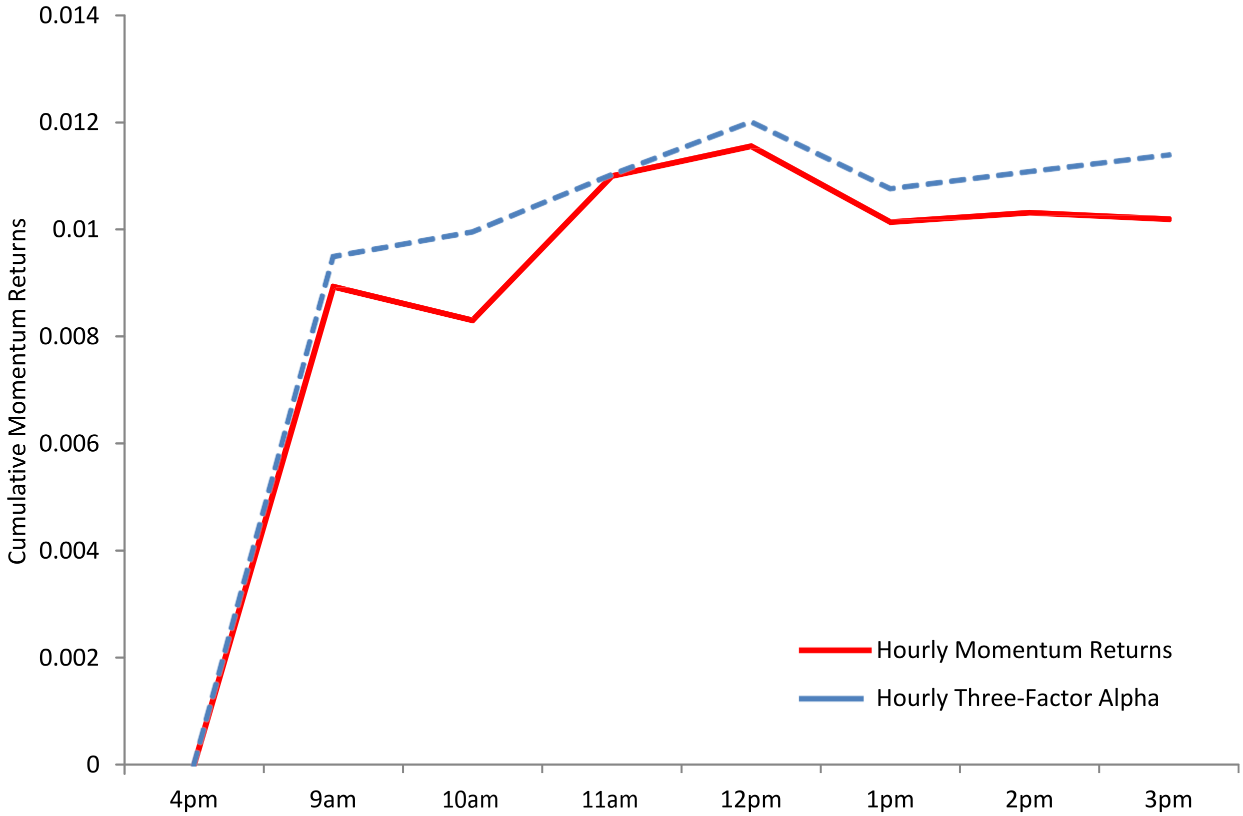

Figure 4: This figure shows the cumulative hourly (abnormal) returns to the momentum strategy from the previous close to the next close, aggregated to the monthly level. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent 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. The red solid curve shows the cumulative hourly returns to the momentum strategy. The blue dashed curve shows the cumulative three-factor alpha to the momentum strategy.

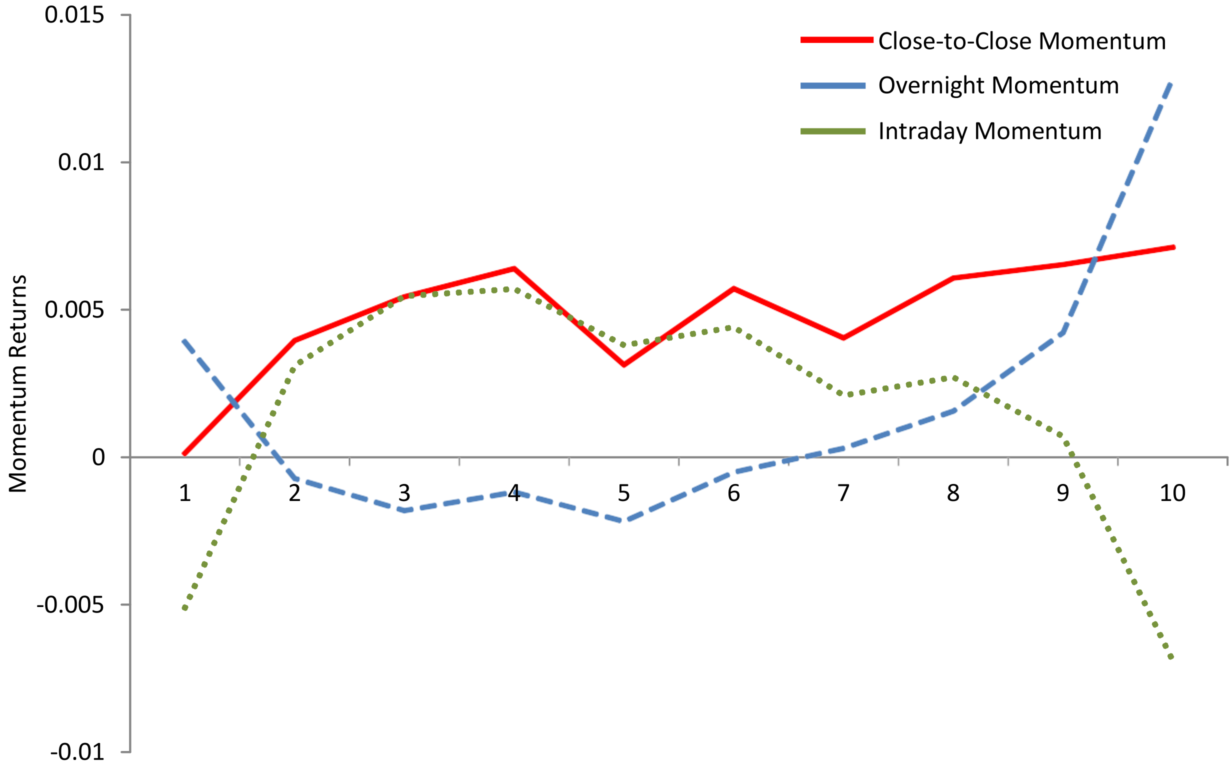

Figure 5: This figure shows value-weight portfolio returns of the ten momentum deciles during the day vs. at night. At the end of each month, all stocks are sorted into deciles based on their lagged 12-month cumulative returns (skipping the most recent month). Stocks with prices below \$5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. The red solid curve shows the value-weight close-to-close returns of the ten momentum deciles in the following month. The blue dashed curve shows the value-weight overnight returns of the ten momentum deciles in the following month. The green dotted curve shows the value-weight intraday returns of the ten momentum deciles in the following month. Table IX Panel C documents that the U-shaped overnight momentum pattern of this graph becomes much more monotonic once we exclude the 20% of stocks with high idiosyncratic volatility.