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A tug of war: Overnight versus intraday expected returns[☆]

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ABSTRACT

We link investor heterogeneity to the persistence of the overnight and intraday components of returns. We document strong overnight and intraday firm-level return continuation along with an offsetting cross-period reversal effect, all of which lasts for years. We look for a similar tug of war in the returns of 14 trading strategies, finding in all cases that profits are either earned entirely overnight (for reversal and a variety of momentum strategies) or entirely intraday, typically with profits of opposite signs across these components. We argue that this tug of war should reduce the effectiveness of clienteles pursuing the strategy. Indeed, the smoothed spread between the overnight and intraday return components of a strategy generally forecasts time variation in that strategy's close-to-close performance in a manner consistent with that interpretation. Finally, we link cross-sectional and time-series variation in the decomposition of momentum profits to a specific institutional tug of war.

1. Introduction

A textbook approach to asset pricing uses the representative investor framework in which agents are assumed to be essentially identical. Though elegant and intuitive, a large body of empirical research has documented failures of this paradigm to explain stylized market facts (Cochrane, 2004; Campbell, 2017). Based on those failures, a natural extension is to allow for investor heterogeneity.[1] However,

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[1] Harrison and Kreps (1978) study how heterogeneous beliefs can affect asset pricing. Constantinides and Duffie (1996) study the importance of heterogeneity in investor consumption in understanding key asset pricing facts. Garleanu and Panageas (2015) use heterogeneity in investor

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since heterogeneity may affect asset prices in a variety of (unobservable) ways and since the specific differences studied in the prior literature provide only a modest improvement in explanatory power, it remains challenging to understand what investor differences are particularly important and exactly why (Cochrane, 2017).

We provide new insights to these issues by introducing a novel way to measure the importance of heterogeneity in asset markets. Our starting point is that one may be able to identify the relevance of different types of agents simply through the fact that they tend to trade at different times during the day. For example, and as the primary focus in our analysis, some investors may prefer to trade at or near the morning open while others may prefer to trade during the rest of the day up to and including the market close. Since these two periods—when the market is open vs. when it is closed—differ along several key dimensions, including information flow, price impact, and borrowing costs, it seems likely that many aspects of investor heterogeneity that might be relevant for asset pricing also manifest themselves as a tendency to trade in one of these periods rather than the other. In this light, the presence of "overnight" and "intraday" clienteles seems a reasonable and perhaps even natural starting point.

We thus view the overnight and intraday components of returns as potentially reflecting the specific demand by the corresponding clientele. Under this interpretation, stocks that experience relatively strong overnight or intraday returns do so in part because of temporary demand (and thus price pressure) from the clientele in question. To the extent that clientele order flow is persistent, stocks that outperform overnight, for example, should, on average, continue to perform relatively well overnight in the future. Furthermore, that price pressure (to the extent that it is not fully informative) must eventually reverse, and is more likely to do so during subsequent intraday periods when the opposing clientele dominates market activity. In other words, any back-and-forth, or *tug of war*, across the two periods reflects and reveals the relative importance of the overnight/intraday clienteles.

We take this new way of thinking about markets to the data, providing the first study of the persistence and reversal patterns of these basic components of close-to-close returns.[2] We show that stocks with relatively high overnight returns over the last month have, on average, relatively high overnight returns as well as relatively low intraday returns in the subsequent month. Our findings are economically and statistically significant; a portfolio that buys the value-weight overnight winner decile and sells the value-weight overnight loser decile has a three-factor overnight alpha of 3.47% per month with an associated t-statistic of 16.83 and a three-factor intraday alpha of −3.02% per month (t-statistic of −9.74).

This tug of war can be identified using either component of close-to-close returns. Stocks with relatively high intraday returns have, on average, relatively high intraday returns coupled with relatively low overnight returns in the subsequent month. A portfolio that buys the value-weight intraday winner decile and sells the value-weight intraday loser decile has a three-factor intraday alpha of 2.41% per month (t-statistic of 7.70) and a three-factor overnight alpha of −1.77% per month (t-statistic of −7.89).

Though these monthly patterns are striking, more surprising is the fact that they persist even when we lag our intraday/overnight return signals by as much as 60 months. Indeed, the corresponding t-statistics for the resulting joint tests are well over 20. Of course, transaction costs will make the actual profitability of a trading strategy exploiting these overnight/intraday patterns much less attractive. But the magnitude of the t-statistics combined with the fact that consequences of the tug of war we identify still can be measured years later strongly confirm that the patterns can neither be a statistical fluke nor a manifestation of some high-frequency market microstructure effect. We argue that these novel patterns instead represent a fundamental economic phenomenon in the market and may shed insight on the importance of clienteles in driving the variation in expected returns.

Although we do not observe the fundamental drivers of these intraday/overnight investor clienteles, we conjecture that a part of this persistent investor preference/demand in these two periods can be tied to various firm characteristics. For example, some investors may be particularly averse to idiosyncratic risk overnight, and therefore (always) reduce their exposure to high-idiosyncratic-volatility stocks shortly before market close; consequently, we may observe different return patterns associated with idiosyncratic volatility during the intraday vs. overnight periods.

More specifically, we decompose the abnormal profits associated with a standard list of firm characteristics (that are known to forecast future close-to-close returns) into their intraday and overnight components. By doing so, we deliver new evidence about the cross-section of average returns through a careful examination of exactly when expected returns accrue. We find that nine of the 14 strategies we study earn their entire premia intraday (including size which is weak in our sample, yet only marginally fails to achieve intraday significance at conventional levels—see footnote 14). The five exceptions to this finding are all strategies based on past returns (or their close cousin, earnings announcements)—four momentum strategies (price, industry, earnings, and time-series momentum) and the short-term reversal effect. These five strategies all earn their premia overnight. More formally, we can easily reject the hypothesis that returns to the strategies we study are evenly distributed across these two periods. Furthermore, we show that our results are not attributable to macroeconomic or firm-specific news announcements.

In addition, we consistently find an overnight/intraday tug of war in strategy risk premia. For all strategies that earn statistically significant premia intraday (value, profitability, investment, market beta, idiosyncratic volatility, equity issuance, discretionary accruals, and share turnover), there is an economically and statistically significant overnight premium that is opposite in sign; in other

preferences to shed light on asset pricing issues. He and Krishnamurthy (2013) model the importance of investor type, specifically focusing on the role of intermediaries.

2 All our results shown below are robust to different definitions of open and close prices, as well as excluding small-cap stocks.

words, a positive risk premium is earned overnight for the side of the trade that might naturally be deemed as riskier. Our results thus reveal that these classic asset pricing anomalies are in fact primarily *intraday* anomalies in the sense that their overnight returns arguably make much more intuitive sense. Unfortunately, our tests are unable to link this cross-sectional variation in average overnight returns to a formal model of risk, but we hope that this is a promising avenue for future research.

We next exploit these strategy-specific tugs of war to reveal the relative attractiveness of these strategies going forward. We motivate this approach with intuition from a simple model of limits of arbitrage, based on Gromb and Vayanos (2010), that we provide in the Internet Appendix. As is typically the case in that class of models, since arbitrageurs are risk-averse, demand by uninformed investors has price impact and results in abnormal trading profits going forward for those arbitrageurs. In particular, the larger the uninformed demand, the larger the abnormal trading profits for arbitrageurs.

Our insight is simply that different times of the trading day will naturally have differing levels of participation by arbitrageurs and that these differences should reveal the magnitude of the uninformed trading demand, all else equal. For example, if uninformed demand is rather low, prices will move only slightly in the direction of that demand at the open and then partially revert as more arbitrage capacity enters the market. The tug of war will then be relatively small. If uninformed trading demand is instead rather high, prices will move strongly in the direction at the open. Prices will revert at the close as more arbitrage capacity comes in, but as the logic in the previous paragraph points out, will settle at a higher price than before the arrival of uninformed demand.[3] Consequently, when the relative magnitude of the demand is particularly high, we should be able to observe a large realized tug of war which should forecast larger than usual returns to betting against uninformed demand going forward.

Based on this motivation, we use the smoothed past realized overnight and intraday return components of strategies in a variable we dub *TugOfWar* (defined in Eq. (1) in Section 4.4 below) to forecast the strategies' close-to-close returns going forward. Our hypothesis is that the smoothed past overnight minus intraday return spread should positively forecast subsequent returns of strategies whose average returns accrue primarily overnight (momentum and short-term reversal) and negatively forecast returns on strategies with average returns that accrue primarily intraday (size, book-to-market, profitability, investment, beta, idiosyncratic volatility, issuance activity, accruals, and turnover).

Our results show that *TugOfWar* forecasts subsequent close-to-close returns just as hypothesized and is robust to controls for a host of popular well-known timing variables. These controls include both aggregate variables such as the lagged 12-month market return and market volatility, and strategy-specific variables such as the smoothed past close-to-close return on the strategy, the strategy's characteristic spread, and the difference in short interest between the strategy's long leg and short leg. The results are not only statistically significant but also economically important. For a typical strategy in our sample, a one-standard-deviation increase in *TugOfWar* forecasts a 1% higher close-to-close strategy return, or about 18% of its monthly return volatility.

Finally, we zoom in on one of the most widely used signals, price momentum, to provide more direct evidence of the clientele mechanism. Motivated by recent work from Lou and Polk (2018), we study the way preferences of institutions to trade momentum stocks vary through time and across stocks and whether this variation corresponds to the overnight-intraday return decomposition of this strategy. We study institutions as a source of clienteles as it is reasonable to suspect that this group may have particular preferences, not only in terms of whether they buy or sell momentum stocks but also in terms of when they prefer to trade. We therefore link institutional activity to our momentum decomposition in two steps.

We first examine when institutional investors likely initiate trades. Specifically, we link changes in institutional ownership to the components of contemporaneous firm-level stock returns and find that institutional ownership increases more with intraday than with overnight returns. To the extent that collective trading can move prices, this evidence is consistent with the notion that institutions tend to initiate trades throughout the day and particularly at the close while the opposing clientele (individuals) are more likely to initiate trades near the open. Indeed, institutions may be forced to trade intraday given the larger quantities they tend to trade and the greater liquidity present at that time. Our understanding is that many managed execution systems purposefully avoid the open given the relatively high volatility brought about from large customer orders and news from the overnight period.[4] We confirm these patterns using NYSE Trade and Quote (TAQ) data; large trades (linked to institutions) are more likely to occur near the close while small trades (linked to individuals) are more likely to occur near the open.

We next study the extent to which institutions, relative to individuals, trade momentum stocks. We find that on a value-weight basis (i.e., weights proportional to total assets), institutions as a whole trade against the momentum characteristic. Of course, this does not preclude a subset of institutions, for example, mutual funds, from following a momentum strategy (see Grinblatt et al., 1995) and particularly so for certain stocks at certain times, a point that we exploit.

We condition both our trading and decomposition results on two key variables. The first variable is a time-series measure of the degree of investment activity in momentum strategies introduced by Lou and Polk (2018). The second variable is a cross-sectional measure of the aggre-

[3] There are two opposing forces in these sorts of limits to arbitrage models. On the one hand is the magnitude of the uninformed demand. On the other hand is the risk tolerance of the arbitrageurs. Generally speaking, we are interested in how the net difference between these two opposing forces varies through time. For ease of exposition, we focus on the uninformed demand varying through time.

[4] We thank an anonymous referee for making this point.

gate 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 relatively more negative during the day (when institutions actively put on their trades) and relatively more positive overnight. Both sorting variables generate variation in the spread between overnight and intraday momentum returns on the order of 2% per month.

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. A broad set of auxiliary results and robustness checks are provided in an Internet Appendix.

2. Motivation and related literature

Though we are the first to measure the persistence of the intraday and overnight components of firm-level returns, we argue that such a decomposition is a natural one as these two periods are different along several key dimensions.

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

Second, it is reasonable to assume that the overnight return is predominantly driven by trading of investors less concerned with liquidity and price impact. Of course, after-hours trading is much thinner than trading while markets are open. Moreover, the pre-open auctions on the NYSE and Nasdaq only average anywhere from one to four percent of median daily volume, depending on the type of stock. Finally, trading in the first half hour of the day (the interval in which we measure the open price), though substantial, is still significantly less than the volume one observes intraday, particularly near or at the close.[5]

Alternatively, trading at the close 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 intraday trading may be a result of institutional capital flows. Perhaps some institutional investors' mandates effectively require capital to be invested immediately in the strategies those investors pursue, once that capital arrives.

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

3. Data and methodology

Our core Center for Research in Security Prices (CRSP)-Compustat US sample spans the period 1993–2013, constrained by the availability of TAQ data. We augment these data with information on institutional ownership from Thomson Financial. In our robustness tests, we also use international data from Thomson Reuters Tick History (TRTH).

To decompose the close-to-close return into its overnight and intraday components, we use the volume-weighted average price (VWAP) in the first half hour of trading (9:30 am–10:00 am) as reported in TAQ.[8] We rely on VWAP to ensure that our open prices are robust. To further safeguard against the possibility that our VWAP may be driven by very small orders, we exclude observations where there are fewer than 1,000 shares traded in the first half hour (we have also checked that our results are not sensitive to this restriction).

We first measure the amount of trading activity associated with our VWAP price by decomposing dollar trading volume over 30-minute intervals throughout the trading day. In particular, each month, we sum up the number of dollars traded in each of these half-hour windows. Note that the first half-hour window that starts at 9:30 am also includes the open auction and the last half-hour window that starts at 3:30 pm also includes last-minute (i.e., 4:00 pm) trades. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-min interval. Fig. 1 displays the time-series average of these fractions. Consistent with previous research, trading activity dips during the day and then rises near the close. The percent of dollar trading volume from 9:30 am–4:00 pm that takes place in the first 30-minute window is 14.25%. For each firm i, we define the intraday return, $r^i_{intraday,s}$, as the price appreciation between market open and close of the same day s, and impute the overnight return, $r^i_{overnight,s}$, based on this intraday return and the standard daily close-to-close return, $r^i_{close-to-close,s}$,

$$r^i_{intraday,s} = \frac{P^i_{close,s}}{P^i_{open,s}} - 1,$$

[5] Consistent with this idea, Barclay and Hendershott (2003) find that though prices are more efficient and more information is revealed during the day, an after-hours trade, on average, contains more information than a trade made when markets are open.

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

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

[8] We have also verified that our results are robust to using open prices from other sources: (a) open prices as reported by the Center for Research in Security Prices (CRSP) which also starts in 1993 (since their data are sourced from TAQ), (b) the first trade price from the Trade and Quote (TAQ) database, and (c) the midpoint of the quoted bid-ask spread at the open. Our findings are robust to using these alternative proxies for the open price (results available upon request).

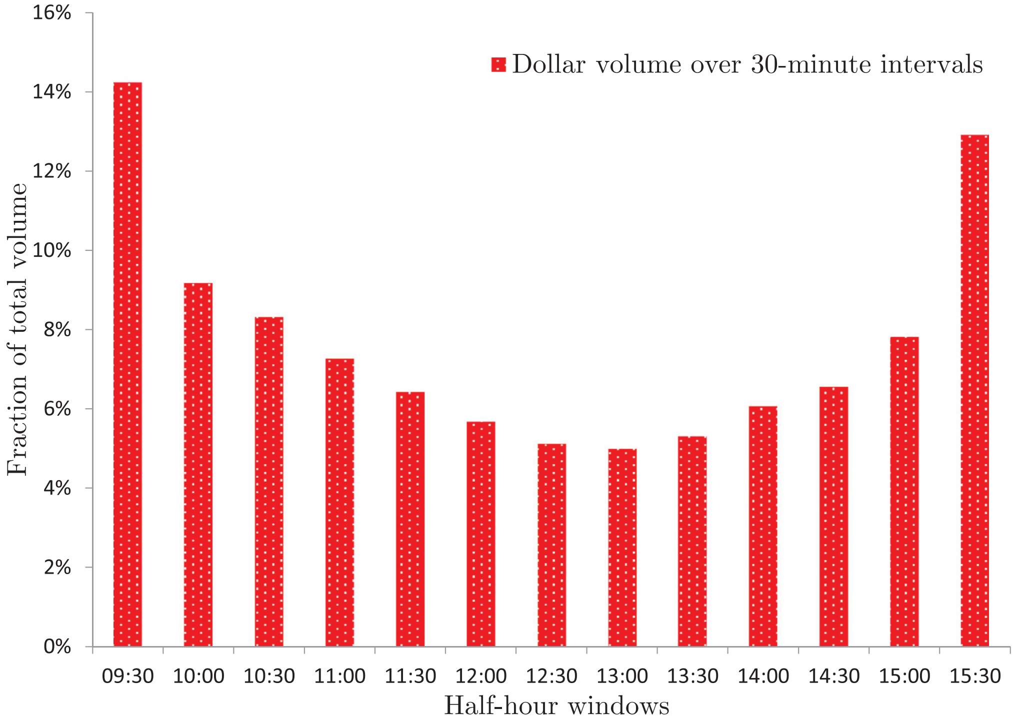

Fig. 1. This figure shows dollar trading volume over 30-min intervals throughout the trading day for the period 1993–2013. In particular, we first sum up the amount of dollars traded in each of these half-hour windows. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-min interval. In other words, these bars sum up to 1. The first half-hour window that starts at 9:30am also includes the open auction. The last half-hour window that starts at 3:30 pm also includes last-minute (i.e., 4 pm) trades and trades from the closing auction.

$$r^i_{overnight,s} = \frac{1 + r^i_{close-to-close,s}}{1 + r^i_{intraday,s}} - 1.$$

In other words, we assume that dividend adjustments, share splits, and other corporate events that could mechanically move prices take place overnight.[9] Furthermore, to ensure that the returns are actually achievable, if the open price on day s for a particular stock is missing (which happens very rarely as we exclude micro-cap stocks from our sample), we hold the overnight position from the closing of day $s - 1$ to the next available open price. Put differently, we construct our return measures such that the overnight and intraday returns aggregate up to exactly the close-to-close return. Though conceptually clean, this aspect of our methodology has no appreciable impact on our relative decomposition of average returns into their overnight and intraday components.

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

$$r^i_{intraday,t} = \prod_{s\in t}(1 + r^i_{intraday,s}) - 1,$$

$$r^i_{overnight,t} = \prod_{s\in t}(1 + r^i_{overnight,s}) - 1,$$

$$(1 + r^i_{intraday,t})(1 + r^i_{overnight,t}) = (1 + r^i_t).$$

[9] 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.

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

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

$$r^p_t = \sum_i w^i_{t-1} r^i_t,$$

$$r^p_{intraday,t} = \sum_i w^i_{t-1} r^i_{intraday,t},$$

$$r^p_{overnight,t} = \sum_i w^i_{t-1} r^i_{overnight,t}.$$

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

The main objective of this study is to examine expected returns during the overnight vs. intraday periods. In these tests, we always exclude microcap stocks—i.e., those with a price below $5 a share and those whose market capitalization is in the bottom NYSE size quintile—from the sample to mitigate microstructure issues. We decompose holding-period returns on simple value-weight long-short portfolios where breakpoints are always based on NYSE percentiles. We also decompose holding-period returns generated by Fama and MacBeth (1973) weighted least squares (WLS) regressions (where the WLS weights in each cross-

Table 1
Overnight/intraday return persistence/reversal.

This table reports overnight/intraday return persistence and reversal patterns. 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. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold. Sample period is 1993–2013.

Panel A: Portfolios sorted by one-month overnight returns

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

Panel B: Portfolios sorted by one-month intraday returns

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

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

4. Empirical results

4.1. Persistence in components of trading strategy returns

We believe it is reasonable that some investors prefer to trade more intensively around the market open, while others prefer to trade intensively later in the day. If the firm-specific order flow of such clienteles is persistent, then one should see persistence in overnight and intraday returns as well as a cross-period reversal (to the extent that the demand is not fully informative). Thus, we check for the existence of intraday and overnight clienteles by decomposing past returns into overnight and intraday components and looking for these continuation and reversal patterns.

We first look for these patterns linking one month to the next. In Table 1, 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 Capital Asset Pricing Model (CAPM), and by the three-factor model.

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

This tug of war can be identified using either component of close-to-close returns. If we instead sort stocks based on past one-month intraday returns, the resulting hedge portfolio earns an average intraday excess return of 2.19% per month with an associated t-statistic of 6.72. As before, adjusting for three-factor exposure does not substantially reduce the effect; indeed, the three-factor alpha is higher at 2.41% per month (t-statistic of 7.70). Again, we find a corresponding reversal in the overnight period as this one-month intraday return hedge portfolio earns an average overnight excess return of −1.81% per month with an associated t-statistic of −8.44 (three-factor alpha of −1.77% per month with a t-statistic of −7.89).

In untabulated results, we confirm that these results are robust to replacing the VWAP open price with the midpoint of the quoted bid-ask spread at the open. In particular, the portfolio based on past one-month overnight returns has an overnight three-factor alpha of 1.88% (t-statistic of 8.75) and an intraday three-factor alpha of −1.43% (t-statistic of −7.05). Similarly, the portfolio based on past one-month intraday returns has an intraday three-factor alpha of 1.35% (t-statistic of 4.86) and an overnight three-factor alpha of −0.85% (t-statistic of −3.31). Given these results, we feel confident that bid-ask bounce is not responsible for our findings.

Heston et al. (2010) (henceforth HKS) document a statistically significant positive relation between a stock's return over a half-hour interval and the corresponding half-hour return occurring on each of the next 40 trading days and argue that their patterns are consistent with investors having a predictable demand for immediacy at certain times. However, HKS do not study how their half-hour intraday momentum effects aggregate or whether they persist beyond two months and, more importantly, do not study overnight returns at all.

Nevertheless, to confirm that our findings are more than just a simple aggregation of the HKS half-hour effect, we include in our subsequent Fama-MacBeth regressions (discussed in the next section and presented in Table 4) the most recent one-month intraday return as a control for the HKS finding. We continue to find that both the past intraday and the past overnight returns independently forecast next month's intraday and overnight components.

Though our results are distinct from HKS, we do explore how the contribution to the intraday persistence and overnight reversal varies across the HKS half-hour intervals. Appendix Table A1 documents that returns within any half-hour interval strongly negatively forecast next month's overnight return as well as strongly positively forecast next month's intraday return. We find no obvious pattern in forecasting strength, however, across these 13 half-hours of the trading day.

With such high t-statistics, it is very unlikely that the results are spurious; nevertheless, to confirm that these striking overnight/intraday momentum and reversal patterns are robust, we replicate our analysis in nine large non-US equity markets, again focusing on value-weight portfolios. Those markets are Canada, France, Germany, Italy, United Kingdom, Australia, Hong Kong, Japan, and South Africa. Appendix Table A2 Panel A reports our findings.

For this sample, there is no short-term reversal effect in close-to-close returns. This lack of a close-to-close effect hides strong patterns within the overnight and intraday periods that are further sharpened by examined sorts on return components. Specifically, in every country, we find a strong one-month overnight continuation effect. On a value-weighted basis across countries, a simple strategy that buys last-month's overnight winners and sells last-month's overnight losers earns an overnight premium of 2.31% with an associated t-statistic of 6.90. Similarly, in each of the nine countries, we find a strong one-month intraday continuation effect. Across countries, the value-weight average intraday return of buying last-month's intraday winners and selling last-month's intraday losers is 2.80% (t-statistic of 6.23). As in the US, we also find a strong cross-period reversal in every country that is statistically significant and roughly equal in absolute magnitude.

Our interpretation of these findings is that certain clienteles persistently trade certain stocks in the same direction in the first half hour after market open, while others trade later during the day, which is why we see this strong persistence in overnight and intraday returns. If so, then these patterns should persist. As a consequence, Fig. 2 reports how the t -statistics associated with the four strategies analyzed in Table 1 evolve in event time. Consistent with this interpretation, for each of the four strategies, t-statistics indicate statistical significance up to five years later.

The international findings are similarly persistent. To highlight this fact, we compute exponentially weighted moving average overnight (*EWMA_NIGHT*) and intraday (*EWMA_DAY*) returns (with a half-life of 60 months and skipping the most recent month to ensure we are not simply repackaging the one-month result documented above) and use these variables to forecast subsequent overnight and intraday returns in each of these markets. Appendix Table A2 Panel B documents that on a value-weighted basis across countries, *EWMA_NIGHT* forecasts next month's overnight return with a t-statistic of 5.10 while *EWMA_DAY* forecasts next month's intraday return with a t-statistic of 4.60. We also find a strong cross-period reversal. On a value-weight basis across countries, *EWMA_NIGHT* forecasts next month's intraday return with a t-statistic of −3.38 while *EWMA_DAY* forecasts next month's overnight return with a t-statistic of −3.74.

Appendix Table A3 applies our EWMA approach to the half-hour returns studied in Appendix Table A1 and generally finds that the low-frequency component in each of the 13 half-hour intervals is independently informative about next month's overnight and intraday returns. The sole exceptions are that the EWMA of past 10:30 am–11:00 am returns does not independently forecast subsequent overnight returns and that the EWMA of past 1:00 pm–1:30 pm returns does not independently forecast subsequent intraday returns. Of course, since we are examining 13 half-hour intervals, we are still strongly able to reject the null hypothesis that the 13 intraday coefficients are jointly < 0 as well as the null hypothesis that the 13 overnight coefficients are jointly > 0.

4.2. The cross-section of expected return components

Given these remarkable patterns, we use our new approach to understand the importance of clienteles for expected close-to-close returns on popular trading strategies. Specifically, we decompose the abnormal profits associated with a long list of trading strategies—size, value, price momentum, earnings momentum, industry momentum, time-series momentum, profitability, investment, idiosyncratic volatility, beta, turnover, equity issuance, discretionary accruals, and short-term reversals—into their intraday and overnight components. In each case, we simply report the average CAPM alphas of the overnight and intraday components of the zero-cost strategy; please see Appendix Table A4 for the average excess returns, CAPM alphas, and, when appropriate, three-factor alphas on both the long and the short sides of these strategies. All of our conclusions are robust to these different risk adjustments.

4.2.1. The equity premium

As a benchmark, we first decompose the equity premium into its overnight and intraday components. Table 2 reports that the market portfolio (*CRSP*) as measured by the value-weight CRSP universe has an average monthly

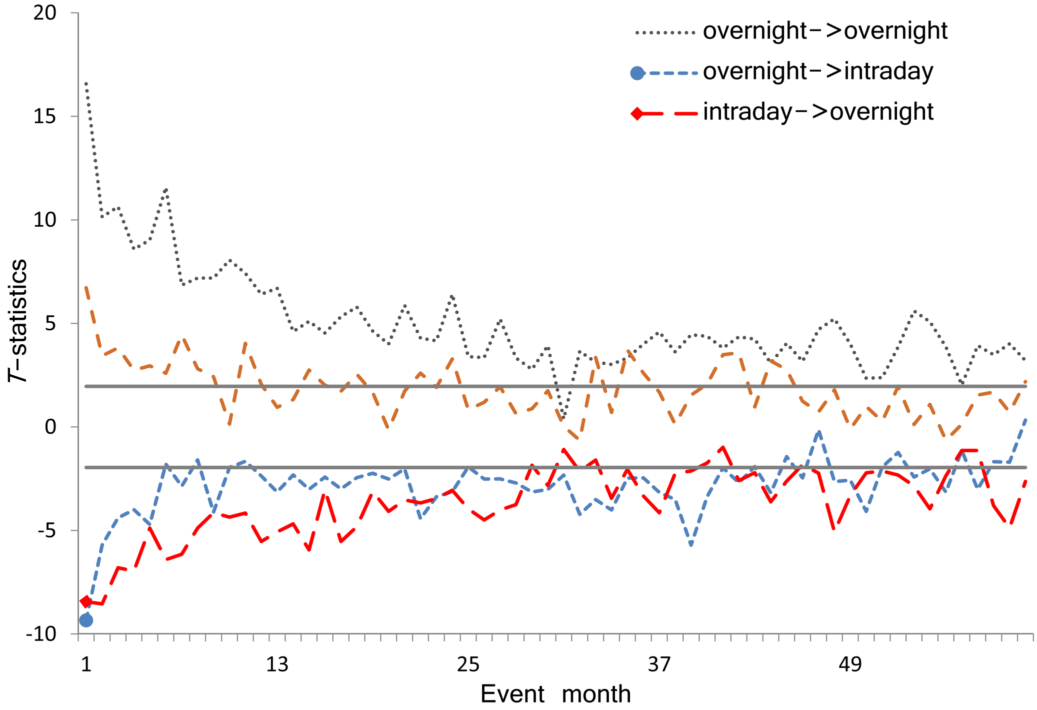

Fig. 2. This figure shows the t-statistics of the overnight/intraday return persistence test, as reported in Table 1. We extend our analysis in Table 1 by varying the lag between the ranking period and holding period from one month all the way to 60 months (i.e., as shown by the X-axis). Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. The dotted curve corresponds to using lagged overnight returns to forecast future overnight returns. The dashed curve corresponds to using lagged intraday returns to forecast future intraday returns. The dashed with dotted markers curve corresponds to using lagged overnight returns to forecast future intraday returns. Finally, the dashed curve with square markers corresponds to using lagged intraday returns to forecast future overnight returns. Sample period is 1993–2013.

intraday excess return of 0.38% and an average overnight return of 0.55%. This breakdown lines up pretty well with one simply based on the percentage of time corresponding to each of these two periods. Specifically, the US market is open for approximately 27% of the 24-h day and the premium earned then is roughly 40% of the total. As we shall soon see, the decomposition results for the popular trading strategies we study are all very far from this natural benchmark.

Our findings are, on the surface, inconsistent with previous work that has argued that the equity premium is primarily an overnight phenomenon. However, much of that research bases their conclusions on narrow market proxies like an exchange-traded fund (ETF) tracking the Dow 30. In Appendix Fig. A1, we compare an annualized version of our decomposition of the *CRSP* value-weight index against a similar decomposition of a value-weight portfolio of the top 1% stocks of the NYSE sample (similar to the Dow 30). The figure shows that for the largest stocks, essentially all of their risk premium is earned overnight. This result foreshadows our next finding that the well-known small-stock effect is entirely an intraday phenomenon.

4.2.2. Size, value, and momentum

We examine three well-known strategies that capture the average returns associated with size and value (Fama and French, 1992) and momentum (Jegadeesh and Titman, 1993).[10] We first examine a strategy (*ME*) that goes long the small-stock decile and short the large-stock decile. Table 2 reports the overnight and intraday components of *ME*'s CAPM-adjusted returns. Essentially, all of the size premium occurs intraday. Specifically, the intraday CAPM alpha is 0.43% (t-statistic of 1.85) while the overnight CAPM alpha is only 0.11% (t-statistic of 0.75).

We next decompose the returns on a strategy (*BM*) that goes long the high book-to-market decile and short the low book-to-market decile. We measure book-to-market-equity ratios following Fama and French (1992). Again, we find that essentially all of the value premium occurs intraday. Specifically, the intraday CAPM alpha is 0.48% (t-statistic of 2.21) while the overnight CAPM alpha is actually slightly negative, though not statistically significant (−0.10% per month, t-statistic of −0.67).

We then decompose the returns on a standard implementation of the classic momentum strategy, *MOM*, of Jegadeesh and Titman (1993) where we measure momen-

[10] Fama and French (1992) argue that size and the book-to-market-equity ratio describe the cross-section of average returns, subsuming many other related characteristics. Fama and French (1993) propose a three-factor model that includes not only a market factor but also a size and value factor. Fama and French (1996) argue that these factors price a variety of trading strategies except for the momentum effect of Jegadeesh and Titman (1993). See Campbell et al. (2018) for a comprehensive analysis of how these patterns and the subsequent anomalies we study can or cannot be explained by intertemporal asset pricing.

Table 2
Overnight/intraday return decomposition.

This table reports returns to the CRSP index as well as various cross-sectional strategies during the day vs. at night. In the left column of the first row, we examine the overnight/intraday returns of the value-weight CRSP index. For the rest of the table, we report returns of long-short portfolios where we go long one extreme value-weight decile (quintile) and short the other extreme value-weight decile (quintile) based on a particular firm/industry characteristic. In the right column of row 1, at the end of each month, all stocks are sorted into deciles based on the prior month market capitalization. In row 2, stocks are sorted into decile portfolios based on lagged book-to-market ratio and lagged 12-month cumulative returns (skipping the most recent month), respectively. In the left column of row 3, stocks are sorted into deciles based on prior quarter earnings surprises (=actual earnings consensus forecast); in the right column, all industries are sorted into quintiles based on lagged 12-month cumulative industry returns. In row 4, stocks are sorted into deciles based on lagged return-to-equity and lagged asset growth, respectively. In row 5, stocks are sorted into deciles based on lagged 12-month market betas (using daily returns with three lags and summing coefficients) and lagged 12-month daily idiosyncratic volatilities (with respect to the Carhart four-factor model), respectively. In row 6, stocks are sorted into deciles based on equity issuance in the prior year and lagged discretionary accruals, respectively. In row 7, stocks are sorted into deciles based on lagged 12-month share turnover and lagged one month returns, respectively. To aid in the readability of the table, the cross-sectional strategies are designed to have positive average returns based on the findings in previous research. Thus, we are long small-cap stocks, value stocks, past one-year winners, high earnings surprise stocks, past one-month industry winners, high profitability, low asset growth, low beta, low idiosyncratic volatility, low equity issuance, low accruals, low turnover, and low past one-month losers. For example, we go long small-cap stocks and short large-cap stocks. 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 adjusted by the CAPM in all instances except for the CRSP strategy, where we simply report excess returns. We compute *t*-statistics, shown in parentheses, based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold. Sample period is 1993–2013.

Overnight-intraday return decomposition					
	Overnight	Intraday		Overnight	Intraday
CRSP	**0.55%**	0.38%	ME	0.11%	0.43%
	(3.62)	(1.87)		(0.75)	(1.85)
BM	**−0.10%**	**0.48%**	MOM	**0.98%**	−0.02%
	(−0.67)	(2.21)		(3.84)	(−0.06)
SUE	**0.56%**	0.21%	INDMOM	**1.07%**	**−0.63%**
	(3.20)	(0.70)		(6.47)	(−2.03)
ROE	**−0.95%**	**1.42%**	INV	**−0.28%**	**0.97%**
	(−6.25)	(5.58)		(−2.10)	(4.39)
BETA	**−0.49%**	**0.70%**	IVOL	**−1.46%**	**2.48%**
	(−2.17)	(2.40)		(−5.23)	(6.21)
ISSUE	**−0.52%**	**1.13%**	ACCRUALS	**−0.47%**	**1.10%**
	(−3.27)	(6.13)		(−3.25)	(4.73)
TURNOVER	**−0.29%**	**0.57%**	STR	**0.93%**	**−1.05%**
	(−1.98)	(2.58)		(4.28)	(−3.25)

tum over an 11-month ranking period and then skip a month before forming portfolios. In sharp contrast to the findings for size and value, essentially all of *MOM*'s returns are generated overnight. Specifically, the overnight CAPM alpha is 0.98% (*t*-statistic of 3.84) while the intraday CAPM alpha is only −0.02% (*t*-statistic of −0.06).[11]

Although all momentum profits occur from the closing price to the opening price, the overnight return on *MOM* is much less volatile (4.02% standard deviation) than the close-to-close return (7.85% standard deviation). Thus, the Sharpe Ratio of the overnight return on *MOM* is 0.77, more than twice as high as the Sharpe Ratio of the close-to-close return (0.31). Interestingly, on average, more of the negative skewness observed in momentum strategies (Daniel and Moskowitz, 2016) and present in *MOM* arrives intraday rather than overnight.[12] Given that momentum differs dramatically from size and value as well as the other strategies we study below, the Internet Appendix provides various additional robustness tests and auxiliary analyses in Tables A10–A12.

4.2.3. Earnings momentum, industry momentum, and time-series momentum

We next examine three other momentum strategies to document whether our finding that momentum profits accrue overnight continues to hold. Table 2 decomposes the abnormal returns on an earnings momentum strategy (*SUE*). Our earnings momentum characteristic is simply the difference between reported earnings and the consensus forecast; this difference is scaled by the firm's stock price. As with price momentum, we find that 100% of the returns to *SUE* occur overnight. In particular, the CAPM alpha of a long-short earnings momentum portfolio is 0.56% with a *t*-statistic of 3.20. The corresponding intraday CAPM alpha is indistinguishable from zero.

We then decompose the abnormal returns on an industry momentum strategy (*INDMOM*). We follow Moskowitz and Grinblatt (1999) and measure industry momentum over a 12-month ranking period for 20 industries based on standard industrial classification (SIC) codes. Again, we find that 100% of the *INDMOM* effect occurs overnight. In par-

[11] We follow the standard approach in the literature by examining monthly holding periods on momentum strategies. However, our results are robust to different holding periods (see Appendix Figs. A2 and A3 and the related discussion).

[12] Overnight MOM returns have a skewness of −1.08 while the skewness of intraday MOM returns is −1.53.

Table 3
Time-series momentum returns.

This table reports returns to the time-series momentum strategy of Moskowitz et al. (2012), during the day vs. at night for the period 1996–2016, for 22 equity index futures listed in Panel B. In Panel A, returns are calculated based on TRTH data, with intraday returns for each index calculated as the returns of the front futures contract, from the 30-min VWAP centered on the "open" (defined as the minute before noon with the largest number of trades where trades are summed over all days), and the 30-min VWAP centered on the "close" (busiest minute after noon). Overnight returns are the returns between the close on day $t-1$ and the open on day t of the front contract on date t (corresponding to rolling on expiration), with any missing data handled as with our equity data. Specifically, we split monthly returns exactly into intraday and overnight components, corresponding to returns of a strategy that aims to execute intraday and overnight round-trips, without any forward-looking information about which observations are available. Where there is a missing open price at date t, but there is a close price at date $t-1$, we define the overnight returns for day t as the percent price change between the close price at date $t-1$ and the first available open or close price on day t or later, assuming such is available before contract expiration; if no such price is available, we use any one-minute VWAP that is available on the last date before expiration; if no such price is available either, we assign zero to this overnight return (though this scenario is extremely rare). Similarly, if an open price is available on date t but a close price is not, we define intraday returns so that they correspond to the return of a position opened at the open on day t. All intraday, overnight, or close-to-close drops of more than 30% are treated as missing, as are increases of more than 50%, though excluding either has no qualitative effect on our results. From daily intraday, overnight, and close-to-close returns, we aggregate to monthly returns as with our TAQ stock data used in cross-sectional momentum. The first column reports the simple monthly average return of the strategy; Column 2 reports the CAPM alpha; Column 3 reports the Fama-French 3-Factor alpha; Column 4 reports the 4-Factor alpha, which adds the up minus down (UMD) factor to the 3-Factor model. The last two columns report the standard deviation and skewness of the overnight and intraday returns of the time-series momentum strategy. We compute t-statistics, shown in parentheses, based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold.

Panel A: Time-series momentum return decomposition

	Raw	CAPM	3-Factor	4-Factor	Stdev	Skew
Close-to-close	0.81%	**1.29%**	**1.31%**	**1.50%**	7.30%	−0.491
	(1.39)	(2.04)	(2.05)	(2.42)		
Overnight	**1.10%**	**1.40%**	**1.42%**	**1.54%**	4.24%	0.178
	(2.67)	(3.24)	(3.18)	(3.64)		
Intraday	−0.29%	−0.10%	−0.10%	−0.04%	4.85%	−2.767
	(−0.78)	(−0.24)	(−0.26)	(−0.11)		

Panel B: List of futures contracts

Equity index	Start date
AEX (Netherlands)	14–Jan–2004
JSE (South Africa)	07–Jul–2005
Athens LargeCap (Greece)	26–May–2000
S&P500 MINI (U.S)	10–Sep–1997
CAC40 (France)	07–Jan–1999
DAX (Germany)	04–Nov–2008
FTSE 100 (UK)	14–Nov–2001
SMI (Switzerland)	04–Nov–2008
HANG SENG (Hong Kong)	04–Sep–2000
FTSE/MIB (Italy)	23–Mar–2004
BMFBOVESPA (Brazil)	15–Dec–2009
IPC (Mexico)	28–Jun–1999
TOPIX (Japan)	12–Jun–2001
KOPSI 200 (Korea)	13–Jan–1997
IBEX35 (Spain)	09–Jan–1996
RTS INDEX (Russia)	03–Oct–2006
CNX NIFTY (India)	11–Oct–2005
MSCI SINGAPORE	18–Jan–2005
Eurostoxx 50 (Europe)	04–Nov–2008
S&P Canada 60	10–Sep–1999
Taiwan	14–Jun–2000
SPI200 (Australia)	03–May–2000

ticular, the overnight CAPM alpha of a long-short industry momentum portfolio is 1.07% with a t-statistic of 6.47. The corresponding intraday CAPM alpha is quite negative at −0.63% (t -statistic of −2.03).

Finally, in Table 3, we examine the intraday and overnight returns of Moskowitz et al.'s (2012) time-series momentum strategy applied to a universe of 22 of the most liquid futures on international equity indexes. Note that Moskowitz, Ooi, and Pedersen study 59 future contracts spanning all asset classes, but since equity markets are the focus of our paper, we restrict our attention only to futures on equity indexes, which is also ap-

Table 4
Fama-MacBeth return regressions.
This table reports Fama-MacBeth regressions of monthly excess stock returns on lagged firm characteristics. The dependent variable in the first column is 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 the dependent variable in the third column is the intraday return in the following month. In Column 4, we report the difference between the coefficients in Columns 2 and 3 (i.e., overnight-intraday). In Column 5, we report the difference between the overnight coefficient *24/17.5 and intraday coefficient *24/6.5. The independent variables include the most recent one-month overnight return (*ret_night*), the most recent one-month intraday return (*ret_day*), the exponentially weighted moving average (*ewma_night*) overnight return (with a half-life to 60 months and skipping the most recent month), the exponentially weighted moving average (*ewma_day*) intraday return (with a half-life to 60 months and skipping the most recent month), the lagged 12-month cumulative stock return (skipping the most recent month), market capitalization, book-to-market ratio, 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 three lags), 12-month share turnover, return-on-equity, asset growth, equity issuance, and discretionary accruals. Stocks with prices below $5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Stock returns are expressed in percentage terms. Observations are weighted by lagged market capitalization in each cross-sectional regression. Standard errors, shown in brackets, are adjusted for serial-dependence with 12 lags. *, **, *** denote statistical significance at the 90%, 95%, and 99% level, respectively. Sample period is 1993–2013.

X 100	Close-to-close	Overnight	Intraday	Overnight-intraday	Scaled difference
	[1]	[2]	[3]	[4]	[5]
ret_night	−0.161	4.585***	−4.792***	9.377***	23.982***
	[0.697]	[0.480]	[0.574]	[0.802]	[2.313]
ret_day	−2.959***	−7.444***	4.484***	−11.928***	−26.766***
	[0.686]	[0.863]	[0.724]	[1.437]	[3.546]
ewma_night	−4.910	16.836***	−21.685***	38.520***	103.156***
	[4.228]	[2.804]	[4.155]	[5.639]	[16.852]
ewma_day	−2.456	−15.564***	13.583***	−29.147***	−71.499***
	[3.566]	[4.551]	[4.002]	[7.849]	[19.577]
mom	0.232	0.640***	−0.415**	1.056***	2.411***
	[0.284]	[0.143]	[0.186]	[0.176]	[0.622]
size	−0.076	0.141***	−0.227***	0.368***	1.031***
	[0.056]	[0.028]	[0.042]	[0.045]	[0.152]
bm	0.028	0.148***	−0.120*	0.268***	0.646**
	[0.074]	[0.054]	[0.071]	[0.102]	[0.295]
ivol	−0.045	0.165**	−0.149**	0.314***	0.777***
	[0.097]	[0.075]	[0.063]	[0.098]	[0.254]
beta	−0.073	0.125	−0.200*	0.325**	0.910**
	[0.171]	[0.119]	[0.111]	[0.151]	[0.419]
turnover	0.102*	0.197***	−0.124***	0.322***	0.729***
	[0.061]	[0.044]	[0.038]	[0.055]	[0.147]
roe	0.214	−0.214**	0.427*	−0.641**	−1.870**
	[0.250]	[0.105]	[0.244]	[0.280]	[0.934]
inv	−0.531**	0.001	−0.542**	0.542**	2.001***
	[0.210]	[0.100]	[0.197]	[0.229]	[0.752]
issue	−0.878***	−0.238	-0.635***	0.397	2.019**
	[0.279]	[0.217]	[0.210]	[0.327]	[0.877]
accurals	-0.403	−0.239	−0.210	-0.029	0.447
	[0.477]	[0.283]	[0.434]	[0.551]	[1.703]
Adj-R^2	0.128	0.106	0.135		
No. obs.	454,825	454,825	454,825		

propriate because "intraday" and "overnight" periods are much more well-defined for equity markets than they are for, say, USD/Yen currency futures. We list the markets we study in Panel B of the table. As with cross-sectional momentum, time-series momentum occurs entirely overnight. Table 3 Panel A documents that for our sample, the monthly overnight CAPM alpha associated with time-series momentum is 1.40% with a *t*-statistic of 3.24. The corresponding intraday alpha is negative, economically negligible, and statistically indistinguishable from zero. These conclusions are robust to controlling for the Fama-French-Carhart four-factor model. Interestingly, all of this strategy's negative return skewness comes from its intraday component.

In summary, for the four different momentum strategies studied in this paper, all of the abnormal profits occur overnight. Indeed, in the case of industry momentum, more than 100% of the close-to-close premium accrues overnight, as there is a partially offsetting negative intraday premium.

4.2.4. Profitability and investment

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), confirmed in Vuolteenaho (2002), and refined in Novy-Marx (2013), and investment—introduced by Fairfield et al. (2003) and carefully analyzed in Titman et al. (2004) and Polk and Sapienza (2009). Indeed, Fama and French (2015) grant that two factors based on profitability and investment help describe the cross-section of average returns, even in the presence of their value factor, high minus low (*HML*).

We examine a profitability or return on equity strategy (*ROE*) that goes long the high profitability decile and short the low profitability decile. Table 2 reports the overnight and intraday components of *ROE*'s CAPM alpha. More than 100% of the profitability premium occurs intraday as *ROE* has a very strong *negative* overnight CAPM alpha. Specifically, the intraday CAPM alpha is 1.42% (t-statistic of 5.58) while the overnight CAPM alpha is −0.95% (t-statistic of −6.25).

We then examine a strategy (*INV*) that goes long the low investment decile and short the high investment decile. Table 2 reports the overnight and intraday components of *INV*'s CAPM alpha. We find that more than 100% of the low investment premium occurs intraday as there is a statistically significant *negative* CAPM alpha associated with *INV* overnight. Specifically, the intraday CAPM alpha is 0.97% (t-statistic of 4.39) while the overnight three-factor alpha is −0.28% (t-statistic of −2.10).

4.2.5. 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; Frazzini and Pedersen, 2014).

We examine a strategy (*BETA*) that goes long the low-beta decile and short the high-beta decile. We measure beta using daily returns over the last year in a market model regression. We include three lags of the market in the regression and sum their coefficients to take non-synchronous trading issues into account (Dimson, 1979). Table 2 reports the overnight and intraday components of *BETA*'s CAPM alpha. More than 100% of the low-beta premium occurs intraday as there is a *negative* premium on our *BETA* strategy overnight. Specifically, the intraday CAPM alpha is 0.70% (t-statistic of 2.40) while the overnight CAPM alpha is -0.49% (t-statistic of −2.17).

We next analyze a strategy (*IVOL*) that goes long the low idiosyncratic volatility decile and short the high idiosyncratic volatility decile. Ang et al. (2006) argue that high idiosyncratic stocks have abnormally low returns. We measure idiosyncratic volatility as the volatility of the residual from a daily Fama-French-Carhart four-factor regression estimated over the prior year. Table 2 documents that more than 100% of the *IVOL* premium occurs intraday. As a consequence, *IVOL* has a *negative* risk premium overnight. Specifically, the intraday CAPM alpha for *IVOL* is 2.48% per month with an associated t-statistic of 6.21. The corresponding overnight CAPM alpha is −1.46% per month with a t-statistic of −5.23.

4.2.6. Equity issuance and discretionary accruals

Our next group of strategies is related to firm financing and accounting decisions. Daniel and Titman (2006) show that issuance activity negatively predicts cross-sectional variation in average returns. Sloan (1996) documents a strong negative correlation between discretionary accruals and subsequent stock returns. We first examine a strategy (*ISSUE*) that goes long the low-equity-issuance decile and short the high-equity-issuance decile. Table 2 reports the overnight and intraday components of *ISSUE*'s CAPM alpha. More than 100% of the issuance premium occurs intraday; *ISSUE* has a very strong *negative* overnight *CAPM* alpha. Specifically, the intraday CAPM alpha is 1.13% (t-statistic of 6.13) while the overnight CAPM alpha is −0.52% (t-statistic of −3.27).

We then examine a strategy (*ACCRUALS*) that goes long the low discretionary accruals decile and short the high discretionary accruals decile. Table 2 reports the overnight and intraday components of *ACCRUALS*'s CAPM alpha. Again, more than 100% of the accruals premium occurs intraday as there is a statistically significant *negative* overnight *CAPM* alpha associated with the *ACCRUALS* strategy. Specifically, the intraday CAPM alpha is 1.10% (t-statistic of 4.73) while the overnight CAPM alpha is −0.47% (t-statistic of −3.25).

4.2.7. Turnover and one-month return

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

We first examine a strategy (*TURNOVER*) that goes long the low turnover decile and short the high turnover decile. We measure turnover following Lee and Swaminathan (2000) as the average daily volume over the last year. Table 2 reports the overnight and intraday components of *TURNOVER*'s CAPM alpha. Again, more than 100% of the negative turnover premium occurs intraday as there is a statistically significant *negative* expected return associated with *TURNOVER* overnight. Specifically, the intraday CAPM alpha is 0.57% (t-statistic of 2.58) while the overnight CAPM alpha is −0.29% (t-statistic of −1.98).

We finally analyze a strategy (*STR*) that goes long the low past one-month return decile and short the high past one-month return turnover decile. Table 2 reports the overnight and intraday components of *STR*'s CAPM alpha. 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 *negative* expected return associated with *STR* intraday. Specifically, the intraday CAPM alpha is −1.05% (t-statistic of −3.25) while the overnight three-factor alpha is 0.93% (t-statistic of 4.28).

4.2.8. Fama-MacBeth regressions

Though portfolio sorts are useful as a robust, nonparametric approach to document the link between a characteristic and the cross-section of average returns, this approach has difficulty controlling for more than just a very small number of other characteristics and thus makes measuring partial effects problematic. As a consequence, we turn to Fama and MacBeth (1973) regressions to describe the cross-section of overnight versus intraday expected returns. Observations are weighted by lagged market capitalization in each cross-sectional regression to be consistent with our portfolio analysis. Columns 1–3 of Table 4 report the following three regressions: a standard regression forecasting the cross-section of $r_{close-to-close}$, a regression forecasting the cross-section of $r_{overnight}$, and a regression forecasting the cross-section of $r_{intraday}$. In each regression, we include all of the characteristics studied above except for earnings momentum, as it reduces the number of observations in each cross-section considerably. Also, for ease of comparison to previous results, we use the raw characteristic, distinguishing the variable from the strategies in the above analysis by the use of lowercase. Thus, for example, we expect a negative coefficient on *size* in the regressions in Table 4, just as we expected a positive CAPM alpha on the *SIZE* strategy in Table 2 that was constructed to buy small stocks and sell large stocks.

To confirm that our findings are distinct from those in Section 4.1, we include in the regressions in Table 4 the most recent one-month intraday return (*ret_day*), the most recent one-month overnight return (*ret_night*), and both *ewma_night* and *ewma_day* defined in the previous subsection.[13]

Regression (1) shows that, for our sample, only *ret_day*, *inv*, and *issue* are statistically significant (on a value-weighted basis).[14] Regression (3) reveals that many of these characteristics are much stronger predictors of the cross-section of intraday returns. In fact, *size, ivol, turnover, inv*, and *issue* are all statistically significant and *beta* and *roe* are marginally significant. Consistent with the results from our portfolio sorts, the sign on *ret_day* flips to be positive and statistically significant. There are negative intraday *mom* and *bm* effects, though the estimate on the latter is not significant at the 5% level.

In the cross-section of overnight returns described by regression (2), *mom* is very strong. Consistent with the results in previous tables, there is a strong positive premium associated with *ivol* and *turnover* and a strong negative premium associated with *roe*. The positive premium for *beta* is large but only marginally statistically significant. Interestingly, there is a positive premium for *size* and *bm*. Overall, these regressions are broadly consistent with our main findings.

It is worth emphasizing that these regressions control for the persistence finding of Section 4.1, in the sense that characteristics predict return components even though the regressions include lagged firm-level component returns (*ret_day*, *ret_night*, *ewma_night*, *ewma_day*). Moreover, *ret_night*, *ret_day*, *ewma_night*, and *ewma_day* all continue to strongly predict overnight and intraday returns in the same way as the results in Fig. 2. In particular, we find that *ewma_night* predicts subsequent overnight and intraday returns with a coefficient of 16.8 (t-statistic of 6.00) and −21.7 (t-statistic of −5.22), respectively, while *ewma_day* forecasts subsequent intraday and overnight returns with a coefficient of 13.6 (t-statistic of 3.39) and −15.6 (t-statistic of −3.42), respectively. We have also estimated this regression skipping either two or three months and the results are largely unchanged.[15]

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

Regressions (4) and (5) present the main statistical tests of our decomposition of the cross-section of average returns. Regression (4) tests the hypothesis that the overnight and intraday partial premiums for a particular anomaly are equal. We easily reject a joint test of that null. Regression (5) tests the hypothesis that the overnight and intraday partial premiums for each anomaly are proportional to the corresponding percentage of the 24-hour day. We easily reject a test that this is jointly true across the anomalies in question.

4.3. Return component patterns not explained by news announcements

4.3.1. Macroeconomic news

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

Appendix Table A6 Panel A reports the overnight and intraday components for the day of the announcement as well as the days before and after the announcement for the characteristics studied above. We find no statistically significant differences in average returns for any of the strategies. Only *BETA*, *IVOL*, and *ISSUE* have statistically significant average returns over these days, and there is no obvi-

[13] Appendix Table A5 reestimates these regressions dropping *ret_day*, *ret_night*, *ewma_night*, and *ewma_day*, and including the past one-month return, *ret*1.

[14] Several papers are consistent with our finding that the partial effects associated with size and bm are relatively weak in our post-1992 sample that focuses on relatively large stocks. In terms of size, Schwert (2003) argues that the small-firm effect disappeared shortly after the publication of Banz (1981). Moreover, Horowitz et al. (2000) argue that stocks with less than $5 million in market cap are entirely responsible for the small-firm effect. Our data filters remove those stocks from our sample so we would expect a weaker size effect. In terms of value, Fama and French (2015) state in the abstract of their paper proposing a five-factor asset pricing model that "With the addition of profitability and investment factors, the value factor of the FF three factor model becomes redundant for describing average returns in the sample we examine."

[15] If we skip two months, the corresponding coefficients are 15.8 (t-statistic of 5.77), −19.0 (t-statistic of −5.33), 10.4 (t-statistic of 3.90), and −11.8 (t-statistic of −3.30). If we skip three months, the corresponding coefficients are 14.1 (t-statistic of 5.36), −17.4 (t-statistic of −5.04), 9.5 (t-statistic of 3.66), and −10.6 (t-statistic of −3.24).

ous pattern within the intraday/overnight periods for these characteristics.

4.3.2. Firm-specific news

One clear difference between the intraday and overnight periods is that a significant portion of firm-specific news tends to be released after markets close. Appendix Table A6 Panels B and C examine the role of news announcements. Consistent with Engelberg et al. (2019), we find that there is a statistically significant abnormal return on announcement days for most of the strategies we study. However, there is no clear pattern in terms of the overnight and intraday components of these average abnormal returns. We find that *BM, MOM*, and *STR* have all of their earnings announcement premia realized intraday. In contrast, we find that *ROE, IVOL*, and *ACCRUALS* have their earnings announcement premia realized overnight. Finally, *TURNOVER* and *ISSUE* essentially have their earnings announcement premia realized evenly across the overnight and intraday periods. More broadly, Appendix Table A6 Panel C documents that there is no statistical difference between news and non-news months.

4.4. Forecasting close-to-close strategy returns with the tug of war

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

Consider modeling uninformed traders and arbitrageurs trading at the open and close. Though some arbitrageurs participate at both times of the day, there is more capacity at the close. To fix ideas, think of a positive demand shock from these uninformed traders. That shock results in overpriced assets, as arbitrageurs are risk-averse. Given the relatively light participation by arbitrageurs at the open, prices first react strongly to the uninformed demand and then revert to a lower, though still overpriced level at the close. The price does not fully return to the true value at the close as arbitrageurs must be compensated for bearing the risk.

Of course, larger demand shocks will have a larger price impact as arbitrageurs will require additional compensation for the additional liquidity they provide. Thus, both the initial back and forth from the open to the close as well as the subsequent return from the close will be higher, all else equal. We develop this model based on the work of Gromb and Vayanos (2010) and formally prove this claim in the Internet Appendix.

To take this prediction to the data, we define the variable, *TugOfWar*^{s}, for strategy s as follows:

$$
\begin{aligned}
r^{s,EWMA}_{overnight,t} &= \lambda r^{s}_{overnight,t} + (1-\lambda) r^{s,EWMA}_{overnight,t-1}, \\
r^{s,EWMA}_{intraday,t} &= \lambda r^{s}_{intraday,t} + (1-\lambda) r^{s,EWMA}_{intraday,t-1}, \\
TugOfWar^s_t &= r^{s,EWMA}_{overnight,t} - r^{s,EWMA}_{intraday,t} \\
&\quad \text{for } s \in \text{overnight strategies}, \\
TugOfWar^s_t &= r^{s,EWMA}_{intraday,t} - r^{s,EWMA}_{overnight,t} \\
&\quad \text{for } s \in \text{intraday strategies},
\end{aligned}
\tag{1}
$$

where the overnight and intraday components of returns, $r^s_{overnight,t}$ and $r^s_{intraday,t}$, are defined in Section 3. We choose a smoothing parameter λ that is consistent with a half-life of 60 months (our results are robust to other half-lives).[16]

By defining *TugOfWar* in this way, the coefficient in the regression forecasting the close-to-close returns on strategy s:

$$r^s_{t+1} = \beta TugOfWar^s_t + \varepsilon^s_{t+1},$$

is predicted to be positive regardless of whether the strategy in question is an overnight or intraday strategy.

We also include in the regression a corresponding exponentially weighted moving average (EWMA) of the lagged monthly close-to-close strategy returns and monthly daily strategy return volatility. Finally, we also include in the regressions a host of other controls including the lagged 12-month market return and market volatility, the characteristic spread between the strategy's long lag and short lag, and the difference in short interest between the strategy's long leg and short leg.[17]

As shown in Table 5, our measure of a strategy's tug of war forecasts subsequent close-to-close strategy returns just as predicted. All but one of the anomalies have the predicted sign for the forecasting coefficient, and six of the 11 anomalies are statistically significant. We can easily reject the null hypothesis that the forecasting coefficients are jointly zero ($p < 0.01$). In terms of economic importance, for the average strategy in our sample, a one-standard-deviation increase in its *TugOfWar*^{s} forecasts a 1.01% higher close-to-close strategy return, or about 18% of its monthly return volatility.

4.5. Price momentum and the institutional tug of war

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

4.5.1. Evidence from recent US data

When do institutions trade?

[16] We set the initial value of $r^{s,EWMA}_{intraday,t}$ and $r^{s,EWMA}_{overnight,t}$ to the first observation of the corresponding component of a strategy's returns.

[17] Cohen et al. (2003) use the value spread to forecast time-series variation in expected returns on value-minus-growth strategies. Lou and Polk (2018) show that the formation spread in the momentum characteristic forecasts time-series variation in expected returns on momentum strategies. Hanson and Sunderam (2014) document how time-series and cross-sectional variation in short interest forecasts strategy returns.

Table 5
Forecasting close-to-close factor returns.

This table reports regressions of close-to-close factor returns on lagged return differentials between the overnight and intraday components of the same factor. The dependent variable in each row is the monthly return to a factor portfolio (top decile minus bottom decile), and the independent variable of interest is *TugOfWar*, defined in Eq. (1) of Section 4.4. Specifically, a strategy's *TugOfWar* is the appropriately signed lagged difference between the exponentially weighted moving average (EWMA) of the intraday component and the EWMA of the overnight component of that strategy (as Eq. (1) details, for the two strategies which have their premia earned overnight, MOM and STR, we instead subtract the intraday EWMA from the overnight EWMA). We use a half-life of 60 months in the EWMA. We also include in the regression a corresponding EWMA of the lagged factor return, and that of lagged monthly factor volatility. Other controls include the lagged 12-month market return and market volatility, the characteristic spread between the strategy's long leg and short leg, and the difference in short interest between the strategy's long leg and short leg. In row 1, stocks are sorted into deciles based on the lagged 12-month cumulative return; in row 2, stocks are sorted into deciles based on the lagged market capitalization; in row 3, stocks are sorted into deciles based on lagged book-to-market ratio; in row 4, stocks are sorted into deciles based on lagged profitability; in row 5 stocks are sorted into deciles based on lagged asset growth; in row 6, stocks are sorted into deciles based on lagged 12-month market betas (using daily returns with three lags and summing coefficients); in row 7, stocks are sorted into deciles based on their lagged 12-month daily idiosyncratic volatilities (with regard to the Carhart four-factor model); in row 8, stocks are sorted into deciles based on equity issuance in the prior year; in row 9, stocks are sorted into deciles based on lagged discretionary accruals; in row 10, stocks are sorted into deciles based on lagged 12-month share turnover; in row 11, stocks are sorted into deciles based on lagged one-month returns. We compute *t*-statistics, shown in parentheses, based on standard errors corrected for serial-dependence with 12 lags. 5% statistical significance is indicated in bold. A statistical test of the null hypothesis that the forecasting coefficients on *TugOfWar* in these 11 regressions are jointly zero is easily rejected ($p < 0.01$). Sample period is 1993–2013.

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

We first study when institutional investors tend to trade. Fig. 3 provides suggestive evidence that small trades occur more near the market open while large trades occur more near the market close. Specifically, this figure reports dollar trading volume of large vs. small orders over 30-min intervals as a fraction of the daily volume for the period 1993–2000. Following previous research, we define small orders as those below $5000 and large orders as those above $50,000. We end our analysis in 2001 as this link between trade size and investor type no longer holds because large institutions began splitting their orders post-2000. Since institutions tended to submit large orders while individuals tended to submit small orders, these results are consistent with the view that institutions tended to trade at market close and individuals at market open.[18]

For broader evidence over our full sample, we link changes in institutional ownership to the components of *contemporaneous* firm-level stock returns. In Table 6 Panel A, we regress quarterly changes in institutional ownership on the overnight and intraday components of contemporaneous returns.[19] We examine this relation across institutional ownership quintiles as we expect the result to be stronger for the subset of stocks where institutions are more important. We find that for all but the lowest institutional ownership quintile, institutional ownership increases more with intraday rather than overnight returns.

[18] Though we follow the literature in assuming that institutions did not consistently break up their trades before 2001, it might be the case that institutions choose to trade smaller amounts at or near the opening, e.g., because of higher volatility or less liquidity at those times. Fig. 3 should therefore be interpreted as somewhat speculative but suggestive evidence consistent with the more detailed forthcoming evidence below.

[19] Each panel of Table 6 only shows the top and bottom quintiles. Please see Appendix Table A7 for the results for all quintiles.

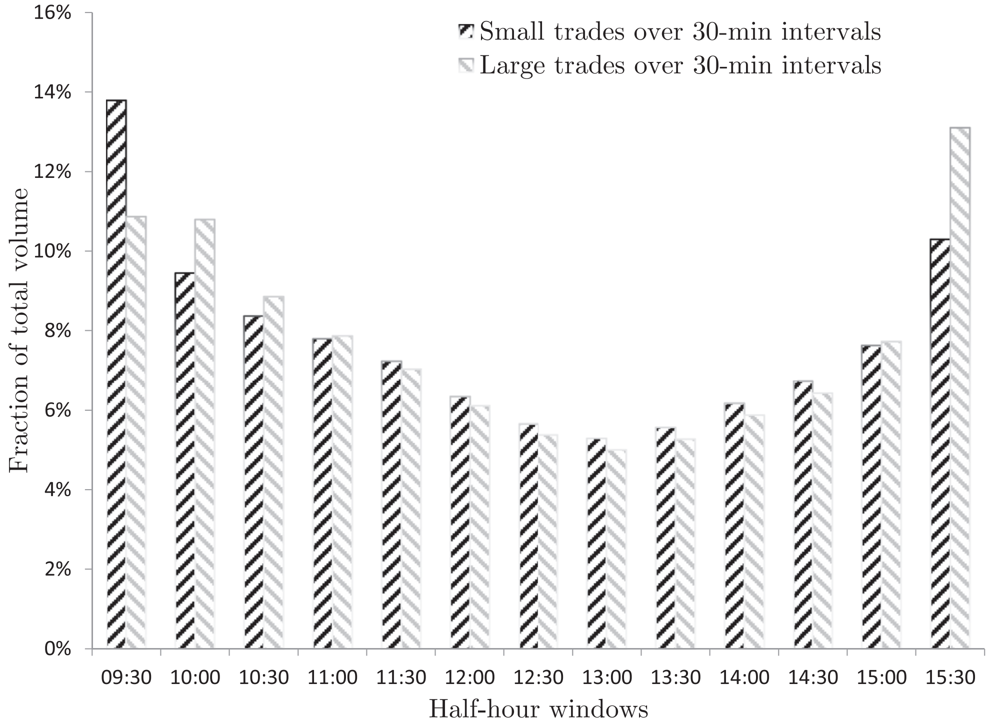

Fig. 3. This figure shows dollar trading volume of large (depicted by grey bars) vs. small orders (depicted by black bars) over 30-min intervals throughout the trading day for the period 1993–2000. We define small orders as those below $5000 and large orders as those above $50,000. More specifically, we first sum up the amount of dollars traded in each of these half-hour windows. We then compute the fraction of total daily volume (i.e., the sum over these 13 windows) that is accounted for by each 30-min interval. In other words, both the black bars and grey bars sum up to 1. The first half-hour window that starts at 9:30am also includes the open auction. The last half-hour window that starts at 3:30 pm also includes the last-minute (i.e., 4 pm) trades and closing auction.

To the extent that investors' collective trading can move prices, this evidence suggests that institutions are more likely to trade significantly after the open while individuals are more likely to initiate trades near the open. Of course, one could argue it is hard to know how to interpret these correlations because institutional trading can both drive stock returns and react to stock returns within the quarter. Three reasons suggest that alternative interpretation of our results is unlikely.

First, our result is consistent with the usual understanding as to how these two classes of investors approach markets. Professional investors tend to trade during the day, and particularly near the close, taking advantage of the relatively higher liquidity at that time. Conversely, individuals may be more likely to evaluate their portfolios in the evening after work and thus may tend to make trades that execute when markets open. Our discussions with asset managers suggest that the typical manager tends not to trade at the open.

Second, a reverse causality interpretation of our findings in Table 6 seems theoretically implausible. It would be odd that institutions chase only intraday returns but not overnight returns since the close-to-close returns are what is important in theories predicting such behavior e.g., window dressing as in Lakonishok et al. (1991).

Third, we confirm our key result in alternative data, specifically, using high-frequency daily institutional flows from Campbell et al. (2009). We find that our results continue to hold and, in fact, are statistically speaking much stronger. Table 6 Panel B shows that for all but the lowest institutional ownership quintile, daily institutional ownership increases much more with intraday rather than overnight returns.

What types of stocks do institutions trade?

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

In Table 7 Panel A, we estimate both ordinary least squares (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 sug-

Table 6
Institutional trading and contemporaneous returns.
This table reports Fama-MacBeth regressions of changes in institutional ownership on contemporaneous stock returns. The dependent variable is the change in the fraction of shares outstanding held by all institutional investors. The independent variable in Column 1 is the cumulative overnight return measured in the contemporaneous period, and the independent variable in Column 2 is the cumulative intraday return in the same period. Column 3 reports the difference between the coefficients on overnight vs. intraday cumulative returns. Panel A uses quarterly changes in institutional ownership as reported in 13-F filings. Panel B uses daily changes in institutional ownership as inferred from large trades in the TAQ database (following Campbell, Ramadorai, and Schwartz, 2009). 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 (IO) 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. Sample period is 1993–2013.

Panel A: Quarterly change in IO

DepVar = contemporaneous qtrly change in institutional ownership

IO	Overnight return	Intraday return	Overnight-intraday
1	−0.003	0.030*	−0.033
	[0.007]	[0.017]	[0.022]
5	−0.008	0.070***	−0.077***
	[0.006]	[0.010]	[0.006]
5–1	−0.005	0.039*	−0.044*
	[0.008]	[0.023]	[0.027]

Panel B: Daily change in IO

DepVar = Contemporaneous daily change in institutional ownership

IO	Overnight return	Intraday return	Overnight-intraday
1	0.177***	0.159***	0.018
	[0.041]	[0.019]	[0.040]
5	0.130***	1.254***	−1.123***
	[0.039]	[0.116]	[0.104]
5–1	−0.047	1.095***	−1.141***
	[0.051]	[0.078]	[0.062]

gest that, on average, individuals, relative to institutions, are the ones trading momentum.

These findings are consistent with Gompers and Metrick (2001) who find a strong negative cross-sectional relation between momentum and institutional ownership. Of course, a subset of institutions may follow a momentum strategy and be particularly important either at certain times or for certain stocks. Below, we exploit two variables, *comomentum* and *active weight* that arguably proxy for variation in momentum trading by institutions. We also discuss the relationship between price momentum and size, since institutions are likely more active in larger stocks.

Comomentum forecasts time-variation in price momentum component returns

Lou and Polk (2018) propose a novel approach to measuring the amount of momentum trading based on time-variation in the degree of high-frequency abnormal return comovement among momentum stocks, dubbed *comomentum*. This idea builds on Barberis and Shleifer (2003), who argue that institutional ownership can cause returns to comove above and beyond what is implied by their fundamentals.[20] Lou and Polk (2018) confirm that their measure of the momentum crowd is a success based on three empirical findings. First, *comomentum* is significantly correlated with existing variables plausibly linked to the size of arbitrage capital. Second, *comomentum* forecasts relatively low holding-period returns, relatively high holding-period return volatility, and relatively more negative holding-period return skewness for the momentum strategy. Finally, when *comomentum* is relatively high, the long-run buy-and-hold returns to a momentum strategy are negative, consistent with times of relatively high amounts of momentum investing pushing prices further away from fundamentals.

Columns 2 and 4 in Table 7 Panel A report the results from forecasting the time-series of cross-sectional regression coefficients using *comomentum*. For robustness, we simply measure *comomentum* using tercile dummies. Consistent with the interpretation that *comomentum* measures time-variation in the size of the momentum crowd, we find that institutions' tendency to trade against the momentum characteristic is decreasing in *comomentum*. The effect is statistically significant for both the OLS and WLS estimates.

Table 7 Panels B and C explore the implications of this result for our decomposition of momentum profits. In particular, we partition the data into three subsamples based on the relative value of *comomentum*. Following Lou and Polk (2018), we track the buy-and-hold performance of *MOM* for two years following portfolio formation. Our prediction is that periods when *comomentum* is low are times when institutions as a whole trade especially strongly against momentum. As a consequence, momentum profits should be stronger and the momentum tug of war (the difference between overnight and intraday average returns) should be larger.

That pattern is exactly what we find. When *comomentum* is low, we find that the overnight excess returns to momentum strategies are particularly strong in both Year 1 and Year 2 after classification. However, when *comomentum* is high, overnight excess returns turn negative. The difference in the average monthly overnight return to momentum across high and low *comomentum* states of the world is −1.02% in Year 1 and −2.14% in Year 2. Both estimates are jointly statistically significant (t-statistics of −1.82 and −5.15, respectively).

A corresponding *comomentum* effect can be seen in the average intraday returns to momentum. When *comomentum* is low, we find that the intraday excess returns to momentum strategies are particularly negative in both Year 1 and Year 2. However, when *comomentum* is high, these excess returns turn positive. The difference in the average monthly intraday return to momentum across high and low *comomentum* states of the world is 0.72% in Year 1 and 1.11% in Year 2. Both estimates are jointly statistically significant (t-statistics of 1.68 and 2.14, respectively).

[20] 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.

Table 7
Momentum trading.
This table examines the potential role of institutions' momentum trading. Panel A reports two-stage Fama-MacBeth forecasting regressions of changes in institutional ownership on the momentum characteristic. The dependent variable in the first stage is the change in the fraction of shares outstanding held by all institutional investors (as reported in 13F filings) in the subsequent quarter and the independent variable is the lagged 12-month cumulative stock return. In the second stage, we regress the time-series of first-stage momentum coefficients on a constant and on our measure of arbitrage trading in the momentum strategy, COMOM, a tercile dummy ranging from zero to two that is constructed from comomentum, defined as the average pairwise partial return correlation in both the winner and loser deciles ranked in the previous 12 months. We estimate both stages by OLS in the first two columns and by WLS (with weights proportional to lagged market capitalization) in the next two columns. 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 COMOM. Stocks with prices below \$5 a share and/or that are in the bottom NYSE size quintile are excluded from the sample. Standard errors, reported in Panel A in brackets, and *t*-statistics, reported in Panels B and C in parentheses, are adjusted for serial-dependence with 12 lags. R^2 (1st stage) is the average R^2 of all the cross-sectional regressions from the first-stage (as in other tables with Fama-MacBeth regressions) and is therefore constant across the second-stage specifications estimated with the same method. R^2 (2nd stage) is the R^2 from the forecasting regression of Fama-MacBeth coefficients on COMOM. In Panel A, *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In Panels B and C, 5% statistical significance is indicated by boldface values. Sample period is 1993–2013.

Panel A: DepVar = Subsequent change in institutional ownership

X 100	Second-stage regression forecasting the Fama-MacBeth coefficients			
	[1]	[2]	[3]	[4]
	OLS		WLS	
Constant	0.189	−0.083	−0.260**	−0.689**
	[0.117]	[0.197]	[0.119]	[0.247]
COMOM		0.146*		0.214**
		[0.085]		[0.103]
Adj-R^2 (1^s*t* stage)	0.003	0.003	0.004	0.004
Adj-R^2 (2^s*t* stage)		0.023		0.052
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	**1.20%**	(5.71)	**0.86%**	(5.57)
2	72	**1.02%**	(4.29)	0.22%	(0.83)
3	72	0.17%	(0.29)	**−1.28%**	(−3.38)
3−1		−1.02%	(−1.82)	**−2.14%**	(−5.15)

Panel C: Intraday momentum returns

COMOM		Year 1		Year 2	
Rank	No. obs.	Estimate	t-stat	Estimate	t-stat
1	72	**−0.90%**	(−2.82)	**−0.70%**	(−2.86)
2	72	**−0.88%**	(−2.00)	−0.61%	(−1.32)
3	72	−0.18%	(−0.37)	0.41%	(0.90)
3−1		0.72%	(1.68)	**1.11%**	(2.14)

Active weight forecasts the cross-section of price momentum component returns

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

Columns 2 and 4 in Table 8 Panel A report the results from cross-sectional regressions forecasting quarterly changes in institutional ownership using a firm's momentum characteristic, *active weight*, and the interaction between these two variables. For robustness, we simply measure *active weight* using quintile dummies.

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

Table 8 Panels B and C explore the implications of this result for our decomposition of momentum profits. In particular, we independently sort stocks on momentum and *active weight* into quintiles based on NYSE breakpoints and form 25 value-weight portfolios. Our prediction is that stocks with high *active weight* are stocks where institutions as a whole particularly trade against momentum. As a consequence, momentum profits should

Table 8
Rebalancing trades.

This table examines the potential role of institutions' rebalancing trades. Panel A reports Fama-MacBeth forecasting regressions of changes in institutional ownership on the momentum characteristic. The dependent variable is the change in the fraction of shares outstanding held by all institutional investors (as reported in 13F filings) in the subsequent quarter. The main independent variable is the lagged 12-month cumulative stock return. We also include in the regression AWGHT, 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 AWGHT 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 5×5 matrix by both institutional AWGHT 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, reported in Panel A in brackets, and *t*-statistics, reported in Panels B and C in parentheses, are adjusted for serial-dependence with 12 lags. In Panel A, *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In Panels B and C, 5% statistical significance is indicated by boldface values. Sample period is 1993–2013.

Panel A: DepVar = Subsequent change in institutional ownership

X 100	Fama-MacBeth regressions			
	[1]	[2]	[3]	[4]
	OLS		WLS	
MOM	0.189	0.620***	−0.260**	0.210*
	[0.117]	[0.128]	[0.119]	[0.114]
MOM X AWGHT		−0.182***		−0.143***
		[0.043]		[0.046]
AWGHT		−0.292***		−0.178***
		[0.022]		[0.015]
Adj-R^2	0.003	0.015	0.004	0.017
No. obs.	181,891	181,891	181,891	181,891

Panel B: Overnight MOM returns

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

Panel C: Intraday MOM returns

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

be stronger and the momentum tug of war should be larger.

Again, that pattern is exactly what we find. When *active weight* is low, we find that the overnight excess returns to momentum strategies are relatively weak the next month. When *active weight* is high, however, overnight returns become strongly positive. The difference in the average monthly overnight return to momentum across high and low *active weight* stocks is 1.15% with an associated *t*-statistic of 5.39.

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

Summary

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.[21] 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 2% per month.

4.5.2. Price momentum decomposition varies with size: non-US and pre-1962 evidence

In Appendix Table A10, Panels C and D we report that the spread between overnight and intraday price momentum returns is much stronger for large stocks relative to small stocks. While we believe the comomentum and active weight measures are better proxies for variation in institutional trading than market capitalization, it is worth noting that results using this measure also agree with our previous findings. This agreement is particularly important because the price momentum-capitalization relationship can be explored in data samples for which our sharper proxies are unavailable, and in this subsection we confirm that the size-momentum component relationship is stable across all samples we consider.

Evidence from non-US markets. To provide further evidence of our finding that momentum profits, particularly for stocks held by institutional owners, accrue primarily overnight, we decompose profits to momentum strategies in the nine non-US equity markets studied above. A significant challenge in decomposing momentum profits in non-US markets is the availability of reliable data for open prices. We obtain that data from Thomson Reuters Tick History database, which provides comprehensive microsecond tick data for markets around the world since 1996.[22] To construct an open price, we followed our US method and computed a VWAP price for each stock.

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

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

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

As a consequence, the change in the overnight and intraday components as one moves from the full sample to the large-cap sample goes the right way in terms of our institutional clientele interpretation and is quite statistically significant. Specifically, the overnight component increases by 0.57% (*t*-statistic of 3.13) and the intraday component decreases by 0.52% (*t*-statistic of −2.78). This difference-in-difference test is consistent with our conjecture that we should expect momentum to be more of an overnight phenomenon among stocks with a larger institutional presence.[23]

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

Evidence from pre-1962 US markets. Open prices are also available from CRSP, sourced from the *Wall Street Journal*, for the 36-year period of 1927–1962. Of course, these prices do not have the nice feature of the VWAP approach used in the rest of our analysis in that they do not necessarily represent traded prices. Nevertheless, this sample provides a potentially useful placebo test of our hypothesis that institutional ownership is responsible for the overnight momentum pattern, as institutional ownership

[21] 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.

[22] When processing the data, we also compared our accurate measures of open prices to those found on Datastream. Our analysis indicated that Datastream open prices can be quite misleading. Datastream was used to calculate total returns for the close-to-close period, after filtering the data according to the procedures of Landis and Skouras (2018).

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

was very low for all but the largest stocks. Indeed, Blume and Keim (2017) indicate that institutions, roughly speaking, held only 5% of equity during most of this time. Consistent with that observation, Panel A of Appendix Table A9 shows that for this sample, momentum is primarily an intraday phenomenon. Momentum has a monthly three-factor alpha of 1.45% (*t*-statistic of 4.43). The intraday component is 1.03% (*t*-statistic of 3.43), while the overnight component is insignificant from zero (point estimate of 0.21% with a *t*-statistic of 0.97).

In the spirit of our international tests, we also examine whether the overnight component becomes more important for large-cap stocks in the 1927–1962 sample. Appendix Table A9 Panel B shows that this is the case. Specifically, we find that large-cap momentum has a monthly three-factor alpha of 1.39% (*t*-statistic of 4.74). The intraday component is still large at 0.95% (*t*-statistic of 3.51). However, now the overnight component is statistically significant from zero (point estimate of 0.34% with a *t*-statistic of 2.05). In summary, though we have less faith in the pre-1963 open price data, we do find that the results using those data are broadly consistent with the view that institutional investors play an important role in understanding why momentum is an overnight phenomenon in the 1993–2013 sample.

5. Conclusions

We provide a novel decomposition of the cross-section of expected returns into overnight and intraday components. We first show remarkable persistence in the overnight and intraday components of firm-level returns, which is consistent with clienteles persistently trading certain types of stocks either near the open or later during the trading day. We then show that essentially all of the abnormal returns on momentum and short-term reversal strategies occur overnight while the abnormal returns on other strategies occur intraday and that this pattern is not driven by news. In general, these intraday strategies also have an economically and statistically significant overnight premium that is opposite in sign to their well-known and often-studied total effect. 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 document that a relatively large difference between overnight and intraday returns reveals the extent to which investor clienteles are effectively engaged in a tug of war over the direction of the strategy in question. We argue that if a strategy's tug of war at some point in time is particularly intense, the clientele trading to harvest that strategy's anomalous close-to-close returns is more likely to be constrained, and thus is more likely to leave part of that strategy's abnormal returns unexploited. Our empirical results confirm this tug of war interpretation: A one-standard-deviation increase in a strategy's *TugOfWar* forecasts a close-to-close strategy return in the following month that is 1% higher. Our tug of war measure thus provides a generic predictor for forecasting time-varying expected returns on anomalies.

Finally, we zoom in on a specific form of investor heterogeneity (institutions vs. individuals) and a specific strategy (price momentum) to understand its overnight/intraday return patterns in detail. Relative to individuals, we show that institutions as a class (on a value-weight basis) tend to trade against momentum during the day. The degree to which this is the case, however, varies through time and across stocks, generating a tug of war from intraday to overnight. Specifically, for those times or those stocks where the institutional holders have a relatively strong preference to trade against momentum, we find that momentum profits are higher overnight, partially revert intraday, and are larger close-to-close.

Though our findings originate from high-frequency decompositions of returns, they have important repercussions for investors. For one thing, given the large economic magnitudes of our results, it is possible that trading strategies going into and out of stocks even at this high frequency may be profitable after transaction costs for execution-savvy short-term investors. This claim seems particularly likely for trend-following strategies we have studied that invest in highly liquid equity index futures. Ignoring that possibility, and focusing on long-term investors, institutions trading the anomalies at a lower frequency can nonetheless benefit from our results by using them to optimally time their orders—at the open vs. close of trading, depending on the strategy they are pursuing. Finally, our finding that our tug of war measure can guide strategy timing should be of broad interest to long-horizon investors exploiting anomalies.

Perhaps the ultimate benefit of our decomposition exercise for long-horizon investors and researchers alike is to shed light on the causes of these anomalies—to distinguish among, for example, risk-based vs. behavioral-based vs. institutional-friction-based explanations for these well-known asset pricing patterns. We hope our strategy timing results offer a step in that direction.

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