The Cross-Section of Intraday and Overnight Returns

Vincent Bogousslavsky*

December 21, 2016

JOB MARKET PAPER

Abstract

Using a thirty-year sample of intraday returns on U.S. stocks, I show that asset pricing anomalies accrue over the day in radically different ways. Size and illiquidity premia are realized in the last thirty minutes of trading. Furthermore, the turnover of small stocks relative to that of large stocks spikes around the close. This evidence can be explained by a model in which liquidity deteriorates before the close. Other anomalies, such as profitability and idiosyncratic volatility, accrue gradually throughout the trading day but incur large negative returns overnight. The evidence is consistent with mispricing at the open.

1 Introduction

Over the past decades, research in finance has reported many variables that predict the cross-section of stock returns and are not explained by standard finance theory. These anomalies are the focus of a large literature, but there is little consensus about their sources. Proposed explanations rely on risk, mispricing, microstructure effects, and data mining.[1] Relatedly, since anomalies often

*EPFL and Swiss Finance Institute. E-mail: vincent.bogousslavsky@epfl.ch. www.vincentbogousslavsky.com.
I am grateful to Pierre Collin-Dufresne for his advice and to Kent Daniel for detailed suggestions. I also thank Rüdiger Fahlenbrach, Christoph Herpfer, Andrew Hertzberg, Jiacui Li, Erwan Morellec, Paul Tetlock, and seminar participants at EPFL-UNIL brown bag, SFI PhD Workshop, SFI Research Days, University of Geneva, and University of Zürich brown bag for helpful comments. The latest version of this paper is available on my website.

[1]Surveys of risk-based and behavioral theories are provided by Cochrane (2011) and Barberis and Thaler (2003), respectively. Notable examples of microstructure biases to mean returns of portfolios are given by Blume and Stambaugh (1983) and Asparouhova, Bessembinder, and Kalcheva (2013). The impact of data mining on the discovery of anomalies is highlighted by Fama (1991) and, more recently, by Harvey, Liu, and Zhu (2016).

seem to have little in common with each other, it is not clear which variables provide independent information about average returns and which are subsumed by others (Cochrane (2011)).

This paper studies anomaly returns over the trading day and overnight to shed light on what drives cross-sectional return predictability. A study of how anomalies accrue over the day provides a useful perspective to assess their determinants. Fundamentally different factors drive an anomaly that earns returns solely between 2 p.m. and 3 p.m. relative to an anomaly that earns returns evenly over the day. For the first anomaly, specific factors linked to this time interval, such as announcements, must play a key role.

Following on this intuition, I compute anomaly returns over the trading day and overnight using intraday half-hour and overnight returns on all U.S. common stocks from October 1985 to December 2015. The overnight return is the return outside of regular trading hours and is therefore defined by the change from the closing price on a given day to the opening price on the next day. I am not aware of any related paper using such an extensive data set to examine intraday average returns.[2]

Using a set of nine well-known anomalies, I show that intraday returns provide valuable information about cross-sectional variation in stock returns: Substantial differences in intraday average returns exist *both within and across* anomalies. Anomalies fall into three groups: Anomalies that accrue in a specific period during the day (size, illiquidity, and momentum), referred to as "period-specific" anomalies; anomalies that accrue gradually over the trading day (betting-against-beta, gross profitability, idiosyncratic volatility, and net stock issues), referred to as "gradual" anomalies; and anomalies that display no clear pattern (accruals and book-to-market).

I document the novel finding that, strikingly, size and illiquidity premia are earned in the last half hour of trading. This result is not driven by nonsynchronous trading or bid-ask bounce and holds across subsamples and days of the week. Size and illiquidity tend to earn negative returns in the first hour of trading, but this pattern is only marked on Mondays. Outside of the opening and closing hours, size and illiquidity returns appear like noise.

[2]There is scant empirical evidence about intraday average returns. Wood, McInish, and Ord (1985), Harris (1986), and Jain and Joh (1988) document patterns in intraday average returns, but they rely on short samples dating from before 1984. Smirlock and Starks (1986) use a longer sample—twenty-one years of hourly returns—but only for the Dow Jones Industrial Average. On the contrary, patterns in return volatility and volume over the trading day are well-documented, robust, and appear in different markets; see, for instance, Wood, McInish, and Ord (1985), Amihud and Mendelson (1987), Jain and Joh (1988), Gerety and Mulherin (1994), and Andersen and Bollerslev (1997).

This result is difficult to reconcile with standard theories of size and illiquidity. For instance, if size proxies for distress risk, then it is not clear why small stocks should only earn large returns at the end of the day. Furthermore, market closures do not matter in a standard representative agent economy absent any specific assumption about the volatility of news (Hong and Wang (2000)).

An equilibrium model as in Bogousslavsky (2016) can explain why cross-sectional variation in average returns is larger in specific periods of the day. In a nutshell, traders require a larger premium to hold risky assets when they expect liquidity to be lower in the next period. The large size returns at the end of the day can then be explained if liquidity deteriorates at the end of the day for small stocks.

Following on this idea, I show in this paper that the end-of-day size returns can be explained by a model in which traders subject to endowment shocks rebalance their holdings of small stocks around the close. In line with this explanation, I document that the turnover of small stocks relative to that of large stocks spikes in the last half hour of trading. The model also predicts that the price impact of transitory shocks increases at the close, in line with extant empirical evidence (Madhavan, Richardson, and Roomans (1997), Cushing and Madhavan (2000)). Alternative explanations based on increased risk aversion or more volatile liquidity shocks around the close cannot explain the combined evidence.

The other period-specific anomaly is momentum. Consistent with the prior work of Lou, Polk, and Skouras (2016), I find that momentum returns accrue overnight. Intraday, momentum returns do not exhibit any clear pattern except at the end of the day, when returns tend to be negative. This evidence is potentially consistent with overnight liquidity risk. I document that past winners are traded much more actively than past losers at the open, which may help explain the overnight pattern. Trading around market closures appears to play a key role for period-specific anomalies.

Turning to the second group of anomalies, gradual anomalies (i.e., betting-against-beta, gross profitability, net stock issues, and idiosyncratic volatility) earn consistently positive and statistically significant returns over most of the trading day. Models of risk and mispricing do not make clear predictions about intraday and overnight returns. Absent any theoretical guidance, one may expect returns to accrue gradually over the day (French (1980)). But the gradual anomalies also tend to have large negative returns in the last half hour of trading and overnight.

Exposure to size partly explains the negative returns of the gradual anomalies in the last half hour of trading, which highlights a commonality among anomalies. However, negative overnight returns seem difficult to explain with a risk-based theory. The evidence rejects overnight liquidity risk and is difficult to reconcile with asymmetric information theories (reviewed in Section 2). Furthermore, noise at the open does not drive the negative overnight returns: The evidence is robust to using volume-weighted average prices in the first half hour of trading.

The short leg of the gradual anomalies drives their negative overnight returns. Hence, an explanation based on time-varying mispricing over the day may better accommodate the evidence than a risk-based explanation. Mispricing increases at the open—for instance, due to systematic retail buying pressure at this time (Berkman et al. (2012)). Evidence from intraday turnover is in line with this explanation: For most gradual anomalies, the difference in turnover between the short leg and the long leg is highest at the open.

Period-specific anomalies earn higher returns during earnings announcement months than non-announcement months. For instance, the average overnight momentum return in non-announcement months is almost double that in announcement months. Hence, mispricing correction that is associated with the disclosure of earnings does not appear to drive the period-specific anomalies, which are distinct from the gradual anomalies (Engelberg, McLean, and Pontiff (2016)).

The last two anomalies—accruals and book-to-market—are not statistically significant over my sample period. Accruals is indistinguishable from noise over the day. Book-to-market tends to earn negative overnight returns and positive returns at the beginning and end of the trading day, but the pattern is noisy across subsamples.

To benchmark the results, I simulate random strategies using monthly returns and examine their intraday return patterns. The anomalies that I study appear unlikely to be spurious. Profitable random strategies are highly unlikely to accrue intraday in a consistent manner over multiple subsamples and days of the week, contrary to the period-specific anomalies. Similarly, none of the random strategies is able to reproduce the consistently positive *and* statistically significant intraday average returns of the gradual anomalies.

The results are robust across subsamples and days of the week and remain after applying a volume filter to limit the impact of nonsynchronous trading. Furthermore, microstructure effects are unlikely to explain the findings: Portfolios are value-weighted and returns computed from quote midpoints.

In summary, the results emphasize the role of trading around market closures for anomalies—in particular, period-specific anomalies. Any explanation that rejects the role of market closures should be able to provide an alternative as to why size returns accrue in the last half hour of trading and momentum returns accrue overnight. While well-known factor models often include size and momentum, this choice is generally made without any clear justification. My analysis provides a step in the direction of better understanding these factors. Several anomalies incur large negative returns in the last half hour of trading and overnight. Negative overnight returns seem in line with mispricing explanations.

Striking patterns in intraday and overnight stock returns have been documented by previous research. Heston, Korajczyk, and Sadka (2010) provide evidence that some stocks tend to perform systematically better than others during specific half hours of the trading day. Lou, Polk, and Skouras (2016) show that momentum profits accrue solely overnight for U.S. stocks over 1993 to 2013. They also report the intraday return and the overnight return of several other anomalies but focus their analysis on momentum and do not decompose the intraday return as I do. My paper contributes more broadly to studies of intraday and overnight returns: Overnight returns on aggregate portfolios are large, but their magnitude is sensitive to the definition of the opening price. Overnight returns are lower when they include the first five minutes of trading or are computed using volume-weighted average prices.[3]

In addition, my research relates to a few recent papers that attempt to distinguish among competing explanations of anomalies. Studies investigate the sources of anomalies by examining investor sentiment (Stambaugh, Yu, and Yuan (2012)), financial distress (Avramov et al. (2013)), out-of-sample and post-publication returns (McLean and Pontiff (2016)), and cash flow and discount rate shocks (Lochstoer and Tetlock (2016)).

The paper is organized as follows. Section 2 discusses theoretical determinants of intraday and overnight returns and lay out the intuition behind the analysis. Section 3 presents the data and methodology. Section 4 examines the cross-section of intraday and overnight returns. Section 5 provides robustness checks. Section 6 concludes.

[3] Cliff, Cooper, and Gulen (2008), Kelly and Clark (2011) and Berkman et al. (2012) find that overnight returns account for a sizable fraction of the U.S. equity premium. Marked intraday and overnight patterns in average returns exist in other asset classes. Breedon and Ranaldo (2013) document time-of-day effects in currencies. Muravyev and Ni (2016) find that the variance risk premium for S&P 500 and equity options is earned overnight and is, puzzlingly, negative intraday.

2 Theories of Intraday and Overnight Average Returns

Studies that examine average returns over trading and non-trading periods go back to French (1980). French tests a *calendar time hypothesis* and a *trading time hypothesis* by comparing returns on different days of the week. The calendar time hypothesis predicts that the Monday average return is three times the average return on the other days of the week. The trading time hypothesis predicts that the Monday average return is the same as for the other days of the week. French (1980) strongly rejects both hypotheses in light of the large negative Monday average return over his sample.

Few models make predictions about intraday and overnight patterns in average returns. A notable exception is Hong and Wang (2000), who solve a general equilibrium model with periodic market closures.[4] More precisely, they model a competitive setup with informed and uninformed traders. Both groups hedge returns from a private investment opportunity, but informed traders receive a private signal about mean dividend growth. The interaction of two effects can generate a rich set of dynamics in average returns. First, investors cannot use the stock as a hedge overnight. This absence of trading opportunities makes the stock more risky to hold overnight, and investors want to reduce their hedging demand in the stock before the market closes. As a result, the stock price decreases over the day. Second, the level of information asymmetry tends to decrease over the trading day since uninformed investors cannot learn from the stock price overnight. Indeed, information asymmetry decreases as more information is incorporated into prices through trading. Uninformed investors then require a lower discount to hold the stock. This effect makes the stock price increase over the day. The model is, however, a competitive setup in which informed investors cannot time their trades.

In line with the hedging channel modeled by Hong and Wang (2000), Gerety and Mulherin (1992) find evidence that high expected overnight volatility leads to high trading volume at the close and at the next day's open. This evidence is consistent with traders that unload their positions before the close and reopen them on the following day. Though Gerety and Mulherin (1992) do not explore implications for average returns, risk-averse liquidity providers require a price discount to

[4] Slezak (1994) also develops an equilibrium model to study market closures. He models a single closure as a pure information event; i.e., the variance of private news increases in the period after the closure, but the variance of liquidity trading remains the same.

absorb temporary order imbalances (Grossman and Miller (1988)). Previous research documents evidence consistent with liquidity provision being compensated at the open (Stoll and Whaley (1990)) but has not investigated liquidity provision at the close. This effect should be important if overnight crash risk is a concern for investors.

Institutional features may also lead to temporary price pressure at specific times of the day. For instance, S&P500 futures and options settle based on the opening prices of the constituents, which generates large liquidity shocks at the open (Barclay, Hendershott, and Jones (2008)). Relatedly, Berkman et al. (2012) argue that buying by attention-constrained investors drives up the opening price of stocks with large fluctuations in the previous day (i.e., stocks who caught investors' attention). In theory, order imbalances that are perfectly anticipated generate gradual patterns in prices, as illustrated by Duffie (2010).

2.1 Link with Theories of Cross-Sectional Return Predictability

Most models of risk and mispricing do not make direct predictions about intraday anomaly returns. But an analysis of when and how returns accrue intraday remains relevant to understand what drives anomalies. I detail the reasoning assuming that the anomalies are not spurious. In the empirical analysis, I acknowledge this issue and benchmark the results by simulating random anomalies.

Patterns in the intraday average returns of anomalies can fit into two broad categories. For some anomalies, returns accrue evenly over the day. This case is the natural benchmark considered by French (1980) with his calendar time hypothesis. If agents require a risk premium to hold an asset, the premium required over a half hour in the morning should not differ substantially from the premium required over a half hour in the afternoon. When agents are homogeneous in the model of Hong and Wang (2000), there is no trade and market closures do not matter. While the risk premium can vary over the day, shifts in its sign across intervals of the day seem difficult to rationalize with a risk-based theory. Mispricing may also be gradually corrected over the day. For instance, if news that help traders correct mispricing are spread out over the day.

The second possibility is that returns accrue only during specific intervals of the day. An economic effect linked to these intervals must be at play once mechanical effects such as nonsynchronous trading are ruled out. On the one hand, if returns accrue overnight, at the open, or at the close, then trading linked to market closures, such as hedging, may explain the evidence. Similarly, the mix of traders active in the market may vary over the day; I discuss this possibility below using a model of infrequent rebalancing. On the other hand, if returns accrue in the middle of the day, scheduled macroeconomic announcements are likely at play.

When an anomaly accrues sheds light on its economic drivers. Furthermore, how an anomaly accrues can help to distinguish among competing explanations. Any theory that purports to explain an anomaly should also be able to accommodate the observed intraday pattern. In addition, I test the theories of intraday and overnight return patterns reviewed in the previous section since they can overlay more general theories with specific effects linked to market closures.

3 Data and Methodology

The data used in this paper come from several databases. Institute for the Study of Securities Market (ISSM) and Trade and Quote (TAQ) data are used to compute intraday half-hour returns and volumes for each trading day from October 1, 1985, to December 31, 2015. ISSM data is available back to January 1, 1983, but I begin the sample on October 1, 1985, one day after the NYSE starts opening at 9:30 a.m. TAQ data is used starting from January 1, 1993, and is stamped to the millisecond (daily TAQ) from 2004 onwards. At the beginning of each quarter, I select all NYSE, Amex, and NASDAQ common stocks with a price higher than \$5 and a market capitalization larger than 100 million. Before 1993, I use only NYSE and Amex stocks.

I compute intraday returns based on quote midpoints at the beginning of the trading day and end of each half-hour interval during regular trading hours (9:30 a.m. to 4:00 p.m.). I use half-hour returns to limit the influence of microstructure issues but still capture a rich set of dynamics. In addition to standard error filters (e.g., Chordia, Roll, and Subrahmanyam (2001)), quotes with a spread lower than zero or greater than \$5 are excluded. The ISSM data is filtered as in Hausman, Lo, and MacKinlay (1992).

I focus on returns computed from quote midpoints and provide robustness checks using trade prices as well as volume-weighted average prices (VWAP) in the first half hour of trading. Trade-based returns are computed using the last available transaction price in each half-hour interval and the opening price. A return is set to zero if there are no transactions during the interval. To remove abnormal data, I exclude transactions at prices that are greater than the ask plus the spread and lower than the bid minus the spread (Barndorff-Nielsen et al. (2009)). Bid and ask quotes are matched to trades with a five-second lag before 1999 and no lag afterwards. To compute VWAP, I keep only stocks that have a sufficient amount of trading in the first half hour. A stock is required to have a share volume greater than 1,000 in the first half hour of the trading day on at least 95% of the days over which the stock is traded in a given quarter.

While nonsynchronous trading is likely less of an issue for midquote returns than for trade-based returns, inaccurate quotes at the open generate spurious reversals in midquote returns. For instance, an abnormally high ask price at the open biases the quote midpoint upward and results in a high overnight return, but this return is immediately reversed in the first half hour when quotes are updated. This problem is marked for small stocks in the recent part of the sample. The Appendix provides a specific example and additional details. In addition to the standard filters mentioned above, I only consider quotes after 9:35 a.m. and delete the first quote available during the day since it is often biased. Last, I delete any observation for which the spread is larger than 30 times the median spread during the day for a given stock.

Overnight returns are computed using daily data from the Center for Research in Security Prices (CRSP). Following Lou, Polk, and Skouras (2016),

$$r_{\text{overnight},t} = \frac{1 + r_{\text{close-to-close},t}}{1 + r_{\text{intraday},t}} - 1, \tag{1}$$

where $r_{\text{close-to-close},t}$ is the daily CRSP midquote return and $r_{\text{intraday},t}$ is the intraday return computed using the opening midquote as described above. To compute daily CRSP midquote returns, quote midpoints at the close are adjusted for stock splits and dividends using CRSP factor to adjust prices (FACPR) and CRSP dividend amount (DIVAMT). If the absolute difference between the daily CRSP midquote return and the daily CRSP return is larger than 20%, the daily CRSP return is used instead of the midquote return. Overnight trade-based returns are computed using the the first transaction price and the daily CRSP return adjusted for delisting returns.

Whenever a stock has no intraday trade data on a given day, the CRSP daily return, if it exists, is allocated to the overnight return. On the other hand, when a return is missing in the CRSP daily file and intraday trade data exists, I discard the data for this stock on this day.[5]

[5] I use the TCLINK macro provided by WRDS to link TAQ symbol to CRSP PERMNO. In a few cases, there are more than one TAQ symbol associated with a given PERMNO on the same day. Among these overlapping

In the analysis, I use value-weighted portfolios returns to limit the influence of microstructure noise (Blume and Stambaugh (1983)). The weights are updated at each interval, which is crucial given that I study returns at a high frequency. The portfolio returns are therefore similar to those of a buy-and-hold portfolio that is rebalanced whenever a stock is delisted. Importantly, I verify that no discernible difference exists between the average monthly portfolio return computed by compounding intraday half-hour and overnight returns and the average monthly value-weighted portfolio return computed using CRSP monthly returns.

To compute excess returns, I subtract daily risk-free returns obtained from Kenneth French's data library from overnight returns. As pointed out by Heston, Korajczyk, and Sadka (2010), the risk-free rate should not be earned intraday because transactions are settled at the end of the trading day. My focus on long-short portfolios makes this choice unsubstantial.

I obtain accounting data from Compustat to compute accruals, book equity, gross profitability, and net stock issues. The accounting variables are computed once a year at the end of June using data for the previous fiscal year. Table A2 in the Appendix provides additional details about the construction of each variable.

4 Intraday and Overnight Average Returns

I first examine intraday and overnight returns on portfolios of large, small, and micro stocks in Section 4.1 to provide a point of comparison for the cross-sectional analysis in Section 4.2.

The day is split into $k = 1, \ldots, K$ periods, where 1 indicates the overnight period and K indicates the last half hour of trading. Let r_t denote the return of a portfolio in interval t. The following regression is then estimated:

$$\frac{r_t}{\hat{\sigma}_t} = \sum_{k=1}^{K} \frac{1_{t,k}}{\hat{\sigma}_k} \mu_k + \epsilon_t, \tag{2}$$

where $\hat{\sigma}_k$ denotes the standard deviation of returns in period k, $1_{t,k}$ is a dummy variable that takes the value one if interval t belongs to period k and zero otherwise, and $\hat{\sigma}_t = \sum_{k=1}^{K} 1_{t,k} \hat{\sigma}_k$. Estimating this regression is equivalent to computing average returns and standard deviations

observations, I keep the TAQ symbol with the most observations over the current quarter and discard the others.

separately for each period of the day. This is important to control for heteroskedasticity given that return volatility is well-known not to be constant over the day. In addition, standard errors are adjusted for heteroskedasticity and autocorrelation using a Newey and West (1987) correction with 14 lags (1 day). Similarly, to compute alpha in a given period, I estimate

$$\frac{r_t}{\hat{\sigma}_t} = \sum_{k=1}^{K} \frac{1_{t,k}}{\hat{\sigma}_k} \alpha_k + \sum_{k=1}^{K} \frac{1_{t,k}}{\hat{\sigma}_k} r^e_{m,t} \beta_k + \epsilon_t, \tag{3}$$

where $r^e_{m,t}$ is the market (excess) return in interval t. Alpha in a given half hour is estimated using returns in the same half hour. This methodology recognizes that beta may vary over the day. Theoretically, such variation can occur if, for instance, the proportion of traders active in the market is not constant across the day (Bogousslavsky (2016)). The results are robust to including lagged market returns in equation (3).

4.1 Aggregate Evidence

The comprehensive sample used in this paper allows me to revisit several stylized facts documented by previous studies. In addition, market structure and technology have experienced dramatic changes over the sample period, which makes it worthwhile to examine the evolution of intraday average returns over time.

Following Fama and French (2008), I divide stocks into large, small, and micro stocks based on the 20^{th} and 50^{th} percentiles of NYSE market capitalization at the end of June each year. On average, there are 833 large stocks that represent 91.2% of total market capitalization over the sample, 727 small stocks that represent 6.4%, and 913 micro stocks that represent 2.4%. The large (small) stocks portfolio earns an average monthly excess return of 0.68% (0.75%) with a t-statistic of 2.96 (2.54).

In par with a decrease in trading costs, trading activity has skyrocketed over the sample period. This surge in trading likely affects intraday price dynamics. For instance, Chordia, Roll, and Subrahmanyam (2011) document that intraday volatility has decreased over 1993 to 2008. As a result, I split the sample into three parts. The first part spans the ISSM data and goes from October 1, 1985, to December 31, 1992. The second part covers 1993 to 2004 included. Finally, the last part covers 2005 to 2015.

Table 1 reports intraday and overnight average returns with associated t-statistics for each portfolio across the different subsamples (equation 2). Average returns vary within the day, with most of this variation concentrated overnight, at the open, and at the close. During the middle of the trading day, average returns do not appear to follow a specific pattern and are often close to zero. For the large and small portfolios, F-tests of return equality across intraday half hours are rejected at the level of 5% in the first and second samples but cannot be rejected in the most recent sample.[6]

[Place Table 1 about here]

Overnight returns are positive and statistically significant in each sample for all but one portfolio. They also tend to be economically large relative to intraday returns. As shown in Section 5.1, the magnitude of overnight returns is, however, sensitive to the definition of the opening price. Overnight returns tend to be lower in the most recent sample, but there is no discernible trend when comparing the three samples. The small and micro stocks portfolios do not have larger overnight returns than the large stocks portfolio.

Average returns tend to be negative in the first hour of trading. These returns are large for the small and micro portfolios. For these portfolios, negative average returns become solely concentrated in the first half hour of trading in the most recent part of the sample. The large portfolio does not exhibit a statistically significant beginning-of-day reversal in the recent part of the sample. These results are in line with the analysis of Chordia, Roll, and Subrahmanyam (2011), who link the rise in trading activity to increased market efficiency.

Strikingly, average returns on the small and micro portfolios are positive and statistically significant in the last hour of trading. The magnitude of this end-of-the-day returns is large relative to other intraday returns. I analyze this evidence in Section 4.2 when I examine returns on a long-short size portfolio.

Wood, McInish, and Ord (1985) document an intraday U-shaped pattern in the average return of an equal-weighted index of NYSE-listed stocks for the year 1982. This evidence is taken as a stylized fact in the model of Hong and Wang (2000). Yet, a similar pattern does not appear in Table 1.

[6] Controlling for heteroskedasticity as in Smirlock and Starks (1986) does not change this conclusion.

4.2 Cross-Sectional Evidence

I now examine cross-sectional patterns in intraday and overnight average returns to shed light on what drives cross-sectional return predictability, as explained in Section 2.1. This analysis is also valuable to understand the impact of market closures on the return process.

The anomalies literature documents a large number of characteristics associated with abnormal returns relative to the market. My analysis focuses on a range of well-known sorting variables based on accounting data, market capitalization, past returns, and trading volume. These variables are described in Table A2 in the Appendix. The anomalies that I study are similar to the anomalies considered in Fama and French (2016), to which I add an illiquidity variable.

At the beginning of each month, decile portfolios are formed using NYSE breakpoints based on the values of the sorting variable under consideration at the end of the previous month. Portfolios are value-weighted. I focus on strategies that are long the highest decile portfolio and short the lowest decile portfolio. To exclude highly illiquid stocks and attenuate microstructure effects, each stock is required to have at least ten days with non-zero volume in the previous month and a price greater than \$10 at the end of the previous month to be included.

Table 2 reports monthly average returns and market alphas over the sample period (363 monthly observations). Most of the anomalies earn statistically significant alpha. The relation between beta and unconditional returns is flat, but the betting-against-beta portfolio earns positive and significant alpha (Black, Jensen, and Scholes (1972)). Shorting high idiosyncratic volatility stocks also yields high alpha. Gross profitability, momentum, and net stock issues stand out as the strongest anomalies.

[Place Table 2 about here]

Accruals, illiquidity, and size earn positive but statistically insignificant premia. Size monthly return, however, jumps to 0.36% with a t-statistic of 1.72 when NASDAQ stocks are excluded (other anomalies' returns are mostly left unchanged). Furthermore, as discussed below, there is a strong day-of-the-week effect in size returns. Book-to-market average return and alpha have the wrong sign and are insignificant.[7] In general, anomalies tend to be stronger among smaller stocks (Fama

[7] The book-to-market long-short decile portfolio obtained from Kenneth French's data library earns an average monthly return of 0.18% with a t-statistic of 0.72 over my sample period. The difference with my results is reduced

and French (2008)) and weaker after their have been publicized (McLean and Pontiff (2016)). In this respect, Hou, Xue, and Zhang (2015) document that simply using value-weighted portfolios with NYSE breakpoints makes many anomalies statistically insignificant.

I now examine intraday and overnight returns. Table 3 reports average returns, market alphas, and several other statistics for each anomaly over the full sample. Average returns and alphas are estimated using equation (3). Table 3 shows that marked differences in intraday average returns exist *both within and across* anomalies. This variation is the building block of my analysis. Indeed, I aim to show that useful information about the source of anomalies can be extracted from intraday returns.

[Place Table 3 about here]

Anomalies fall into three groups: Anomalies that accrue in a specific period during the day (size, illiquidity, and momentum), referred to as "period-specific" anomalies; anomalies that accrue gradually over the trading day (betting-against-beta, gross profitability, idiosyncratic volatility, and net stock issues), referred to as "gradual" anomalies; and anomalies that display no clear pattern (accruals and book-to-market). These patterns are robust across subsamples (Figure 1) and days of the week (Figure 2), though statistical significance tends to be lower because of the smaller number of observations.[8] To benchmark these results, Section 4.6 shows that spurious anomalies are highly unlikely to display similar overnight and intraday patterns.

Market alphas display quite similar intraday patterns as average returns. This is not surprising because the average market return is small throughout most of the trading day. Furthermore, anomaly betas are small and often close to zero. For most anomalies, I find that betas are relatively stable across the trading day and leave a detailed investigation of exposures across the day for future research. The discrepancy between monthly average return and alpha for betting-against-beta and idiosyncratic volatility in Table 2 seems mainly driven by overnight returns. Overnight,

to 0.2% per month when I lower the price screen to $5, include financial firms, and exclude the ISSM period. The remaining difference may be due to the price screen and market capitalization filters described in Section 3.

[8] Monthly returns mask systematic variation in average return across days of the week. Harris (1986), Smirlock and Starks (1986), and Jain and Joh (1988) all document a strong day-of-the-week effect in intraday index returns. In particular, returns tend to be markedly negative over the first hours of trading on Mondays. This evidence follows from the "weekend effect," i.e., returns tend to be particularly low on Mondays for the U.S. stock market (see, for instance, French (1980)). While the weekend effect does not appear in recent data, Birru (2016) finds day-of-the-week effects for anomalies in a sample that goes from 1995 to 2013.

risk-adjusted returns are higher than raw returns for these strategies. Betting-against-beta is the only anomaly for which intraday returns and alphas show non-negligible differences. Given that nonsynchronous trading can bias beta, it is reassuring that the results are similar for average returns and alphas.[9]

Anomalies differ on other dimensions than average returns. While several anomalies exhibit a marked U-shaped pattern in volatility across the trading day, other anomalies exhibit a L-shaped pattern. Intraday patterns in skewness and minimum return also seem to differ considerably across anomalies.[10] All in all, these findings support the idea that there is marked cross-sectional variation in intraday and overnight return patterns.

[**Place Figure 1 and Figure 2 about here**]

4.3 Size and Illiquidity

The core of my analysis focuses on size and illiquidity returns. In particular, I propose an explanation based on deteriorating liquidity around the close to explain size and illiquidity returns.

Table 3 and the top two charts of Figure 1 show that size and illiquidity have similar intraday and overnight patterns, even though NASDAQ stocks are excluded from the illiquidity portfolio. Overnight alpha is positive and, in the case of illiquidity, significant at the level of 10%. Overnight size alpha and returns are positive and significant when NASDAQ stocks are excluded.

Strikingly, the bulk of size and illiquidity average returns (alpha) is earned in the last half hour of trading. This result is statistically significant across all subsamples and days of the week (Figures 1 and 2), robust to excluding all January observations, and not limited to extreme deciles. Overnight returns show no marked relation to firm size. But last half-hour returns increase monotonically with size, while first half-hour returns decrease monotonically with size (not reported). The last half hour return is also robust to excluding NASDAQ stocks or forming a (size) portfolio using only NASDAQ stocks. The spike in small and illiquid stock returns at the end of the day is also apparent in Table 1 for the small and micro portfolios. There appears to be partial reversal as both

[9]Since I focus on portfolios, I do not adjust the regressions for nonsynchronous trading. On average over all stocks in the market, measured betas and alphas are equal to true alphas and betas (Scholes and Williams (1977)). Section 5.3 shows that nonsynchronous trading and thin trading do not appear to be a major concern for my results.

[10]Before computing skewness, returns are winsorized at 0.1% separately for each half hour and the overnight period.

strategies have negative returns early in the trading day. Average returns remain then close to zero until the last half hour of trading. In addition, size is the only characteristic for which volatility at the close is as high as volatility at the open in Table 3.

To the best of my knowledge, this evidence has not been highlighted before. Using transaction data on NYSE stocks over December 1981 to January 1983, Harris (1986) documents that prices rise on the last trade of the day. This rise is in large part due to the tendency of the last transaction to be at the ask (Harris (1989)). This effect cannot be at play in my sample of midquote returns. Moreover, Harris (1989) does not find any link between trading volume and the end-of-day return. Below, I document a specific pattern in the turnover of small stocks relative to that of large stocks at the end of the day.

The high end-of-the-day return of size and illiquidity is not a mechanical side effect of non-synchronous trading. Table 1 shows that small stocks earn a positive and statistically significant average excess return over the sample period. If small stocks trade mostly around the close or, equivalently, their quotes are updated mostly around the close, then positive returns should be concentrated at this time. In Section 5.3, I apply a volume filter to evaluate the impact of nonsynchronous trading. This filter keeps only stocks that have several trades in the first hour of trading and the last hour of trading on most days. The end-of-the-day effect remains large and highly statistically significant. In addition, both size and illiquidity earn much higher overnight returns and alphas after applying the volume filter.

The previous result is difficult to reconcile with standard theories of size and illiquidity. For instance, if size proxies for distress risk, then it is not clear why small stocks should only earn large returns at the end of the day. In addition, the large average return of small stocks (the long leg) over the last half hour of trading does not appear to be consistent with overnight liquidity risk being compensated. Prices should go down for liquidity providers to hold risky stocks overnight (see Section 2). Moreover, evidence from extreme negative returns does not support a crash risk story: Among all anomalies, size and illiquidity have the smallest number of overnight returns among their 20 worst realized returns.

As explained in Section 2, a decline in the degree of information asymmetry may lead to a price increase over the day. This story is in line with small stocks being subject to a higher degree of information asymmetry than large stocks. However, the size pattern implies an abrupt shift in the degree of information asymmetry in the last half hour of trading. Such a shift seems difficult to reconcile with the competitive model of Hong and Wang (2000) but may be consistent with strategic models such as Admati and Pfleiderer (1988) in which informed investors time their information production.[11] Next, I document that the turnover of small stocks behaves in a particular way before the close. I then show that an explanation based on trading around market closures can explain the evidence.

4.3.1 Trading Around Market Closures

Pronounced return patterns around market closures call for an investigation of trading at the open and close. While trading volume is well-known to have a U-shaped pattern over the day, it is not clear which leg of a long-short anomaly portfolio is traded more actively across the day. To answer this question, I compute for each stock share turnover in each half hour of the trading day over the sample. For each anomaly portfolio, Figure 2 reports the difference between the value-weighted turnover of the long leg and the value-weighted turnover of the short leg (in percent) averaged over each half-hour. This difference indicates to which extent the long leg of a portfolio is traded more actively than the short leg.

[Place Figure 2 about here]

The turnover of small stocks is markedly larger than the turnover of large stocks in the last half hour of trading. The evidence in Figure 2 is particularly striking because the difference in turnover between small and large stocks does not exhibit a U-shaped pattern over the day. This turnover pattern also contrast with the patterns of other anomalies. This evidence points towards an important role of trading before the close to explain the large contemporaneous size returns.[12] Relatedly, Cushing and Madhavan (2000) document a common factor in stock returns at the end of the day and link their finding to institutional trading at this time. I now discuss a potential explanation for the size pattern based on trading around market closures.

[11] See Collin-Dufresne and Fos (2016) for a strategic model in which informed investors have *long-lived* information and time their trades. The asset price follows a martingale in this type of model.

[12] Illiquidity does not display a similar pattern. Illiquidity is, however, computed using dollar volume, which may make the turnover pattern less informative than for size (i.e., holding market capitalization fixed, a lower turnover increases illiquidity). The turnover evidence for size is robust to applying a volume filter (Section 5.3). In this case, the turnover of small stocks relative to that of large stocks displays a slightly U-shaped pattern over the day with a large spike in the last half hour.

4.3.2 A Model of Infrequent Rebalancing

A model of infrequent rebalancing can help explain why cross-sectional variation in average returns is larger in some periods than others. Building on the model of Duffie (2010), Bogousslavsky (2016) shows that cross-sectional variation in average returns increases in periods when more traders rebalance. A model in which traders subject to endowment shocks rebalance around the close predicts that *realized* returns and trading volume are high around the close, in line with the evidence. The model is detailed in Section A.2 in the Appendix.

The intuition can be summarized as follows. Traders who are present all the time in the market require a larger return to hold an asset when they expect liquidity—here, proxied by the inverse of price impact—to be lower in the next period. When traders subject to endowment shocks readjust their portfolios, price impact is high. As a result, market makers require a large return to hold the asset right before the close. The price of risk is also higher at the close. Note that an alternative model in which market makers are more risk-averse at the close predicts a low return at the close, in stark contrast to the evidence.

Assets for which there is a larger proportion of rebalancing traders (or for which traders have more volatile endowment shocks) are more affected. Hence, this effect increases the cross-sectional variation in realized returns in the period during which more traders rebalance. Also consistent with the model, volatility is particularly high in the last half hour of trading for the size portfolio (Table 3).

Importantly, the previous model is not equivalent to a setup in which a trader is subject to endowment shocks that are more volatile at the close (see the Appendix for details). This model predicts higher realized returns at the close but also a *smaller* price impact of endowment shocks at the close. This is the case because the trader's position is more likely to reverse in the following period.[13] Hence, the trader requires a smaller discount to absorb an incremental endowment shock. This result is opposite to that of the infrequent rebalancing economy, in which it is more difficult for market makers to reverse their positions since infrequent traders are out of the market (i.e.,

[13]To get more intuition, consider an extreme case with highly volatile endowment shocks in one period and endowment shocks with close to zero volatility in the following period. A trader in the period subject to highly volatile shocks is almost guaranteed that her position reverses in the next period. Hence, the price impact of endowment shocks is smaller in the period with more volatile liquidity shocks. In this setup, the endowment shocks can also be interpreted as the exogenous supplies of liquidity traders.

liquidity shocks do not reverse in the next period). A smaller price impact at the close is inconsistent with the evidence in Madhavan, Richardson, and Roomans (1997), who show that temporary price impact increases over the day, and with the evidence in Cushing and Madhavan (2000), who show that the return sensitivity to order flow is higher in the last half hour of trading than during the rest of the day. As explained in the appendix, this last setup also fails on the volume side.

To summarize, the large size returns at the end of the day can be explained if liquidity deteriorates at the end of the day for small stocks. This is the case in a model in which a fraction of traders subject to endowment shocks rebalance their portfolio around the close. In the model, large positive returns are *realized* at the close when trading volume is high. In addition, the model predicts that the price impact of transitory shocks is higher at the end of the day, in line with extant empirical evidence.

The infrequent rebalancing model does not explain why size returns are negative in the morning. However, these negative returns are concentrated in the first hours of trading on Mondays, as can be seen in Figure 2. As a result, it is not clear that the two phenomena are linked. Birru (2016) draws on the psychology literature to explain the negative size returns early in the week. In any case, a simple reversal story appears incomplete.

Since a similar effect is not observed for large stocks, the model requires that a different mix of investors trade in large and small stocks. This assumption is potentially in line with the lower proportion of institutional investors trading in small stocks than large stocks. The appendix further discusses the model as well as potential extensions.

As an alternative and potentially complementary explanation, exogenous buy imbalances—for instance due to institutional features as described in Section 2—may cause an increase in the price of small and illiquid stocks at the end of the day. Since prices do not appear to reverse overnight in Table 3, this story requires the opening price to be biased upwards as well, which is consistent with the evidence in Berkman et al. (2012). Still, this explanation does not predict that the price impact of transitory shocks is higher around the close.

To further illustrate the importance of trading around market closures for size returns, I separately examine a portfolio of small stocks that are required to be actively traded after the open and before the close during the previous month. More precisely, I require stocks to have trades in the first, second, second-to-last, and last half hours of trading on at least 90% of the business days in the previous month. The size portfolio earns large and significant overnight returns that reverse in the first hour of trading, which is consistent with buying pressure at the open (not reported).

4.4 Momentum

Using U.S. stocks over 1993 to 2013, Lou, Polk, and Skouras (2016) find that momentum returns are earned overnight. Figure 1 confirms this result. Over my sample period, the momentum portfolio earns on average close to 7bp overnight. Over the 1985-1992 period, the overnight average return is, however, not statistically significant. In all subsamples, momentum returns appear to behave like noise intraday.

Still, the negative and significant (at the level of 10%) momentum returns over the last hour of trading are consistent with a compensation for overnight crash risk. Overnight momentum returns are negatively skewed. Momentum experiences large negative returns overnight and over the first half hour of trading. Only betting-against-beta experiences a worse overnight return.[14]

Figure 2 shows that past winners are traded much more actively than past losers at the open. Lou, Polk, and Skouras (2016) suggest a clientele-based explanation for the overnight momentum return where retail investors drive momentum returns by trading at the open. Retail investors are especially likely to buy stocks at the open (Berkman et al. (2012)). Hence, my evidence is consistent with their explanation if retail investors tend to buy past winners. The puzzle here is that, contrary to the turnover of past winners relative to past losers, the overnight momentum return does not reverse over the trading day.[15]

4.5 Gradual Anomalies

The gradual anomalies—betting-against-beta, gross profitability, idiosyncratic volatility, and net stock issues—earn consistently positive and statistically significant average returns over the trading day. This evidence is robust across subsamples and days of the week. Hence, these anomalies may be in line with all the theories for which returns should not differ significantly across the day (see Section 2.1).

[14] In my sample, momentum and beta experience their worst return in the overnight period on September 19, 2008, when the market sharply rebounds after the Troubled Asset Relief Program is announced. Following a downturn, the momentum portfolio tends to have a large negative exposure to market beta (Daniel and Moskowitz (2016)).

[15] Intraday returns of past winners and losers are quite similar. The large overnight return of past winners relative to past losers drives momentum returns.

These anomalies realize, however, large negative returns overnight and in the last half hour of trading. Such returns are puzzling and difficult to reconcile with risk-based explanations. Since the overnight returns of gradual anomalies are negatively skewed, overnight crash risk does not seem to explain the low overnight returns.[16]

Another potential explanation for the large overnight returns is that the quote midpoints of stocks in these portfolios tend to be associated with low liquidity at 9:35 a.m. Hence, even small trades could easily bias the quotes, which would reverse shortly afterwards. In this respect, Section 5.1 shows that the definition of the opening price has a large impact on the magnitude of overnight returns of aggregate portfolios. Such reversal at the open is not economically meaningful for an understanding of anomalies over longer horizons.

To test this explanation, I compute overnight returns using volume-weighted average prices (VWAP) in the first half hour of trading. As detailed in Section 3, I use only stocks that have a sufficient number of shares traded over this interval. Panel (a) of Table 4 reports market alphas in the overnight period, the first half hour of trading (using the VWAP opening price as described above and the current midquote at 10:00 a.m.), the second half hour (10:00 to 10:30 a.m.), and the last half hour (3:30 to 4:00 p.m.).[17] Overnight alphas remain large and negative for all gradual anomalies except gross profitability.

[Place Table 4 about here]

To assess whether exposure to size can explain the negative returns, I include a size factor in the regression to compute alpha, where the size factor is simply the return on the size portfolio. As shown in Panel (b) of Table 4, the size factor does not help explain the negative overnight returns of anomalies, and intraday alphas are, for the most part, left unchanged. The size factor, however, explains fully the negative last half-hour returns of beta and idiosyncratic volatility and partly that of net stock issues. Since the exposure of these strategies to size is roughly constant across the day (not reported), it is enough to understand why the size premium is large in the last half hour of trading to explain contemporaneous returns of beta and idiosyncratic volatility.

[16] Moreover, even though a series of positive returns over the day is in line with information asymmetry being gradually resolved with trading (Section 2), there is no reason to expect that stocks in the long leg of these portfolios are subject to more information asymmetry than stocks in the short leg.

[17] Alphas are relative to market returns computed in a similar way as the anomalies. The results for all intervals are reported in the Internet Appendix available at www.vincentbogousslavsky.com.

Mispricing theories generally predict an asymmetry between an anomaly long leg return and short leg return because buying stocks is easier than shorting them (e.g., Stambaugh, Yu, and Yuan (2012)). Table 5 reports the long and short legs of the four gradual anomalies. While both legs contribute to the intraday profits of the anomalies, the short leg drives the low overnight return and—to a large extent—the low return at the end of the day. According to mispricing theories, this evidence means that mispricing worsens at the open and in the last half hour of trading because the short leg becomes more overvalued.

[Place Table 5 about here]

There is evidence that mispricing can worsen at the open. Neal (1996) documents that the degree of mispricing associated with stock index arbitrage is highest at the open. Bid-ask spreads tend to be especially high at the open (McInish and Wood (1992)), which may hinder arbitrage. Furthermore, systematic buying pressure by retail investors at the open may increase mispricing, as suggested by the analysis of Berkman et al. (2012).

Intuitively, mispricing may also increase around the close. One potential explanation is that arbitrageurs tend to close their short positions at the end of the day; for example, they may not want to carry short positions overnight.[18] This theory predicts a low return on the short leg of anomalies portfolios in the last half hour of trading. This explanation could be tested using intraday data on short sales.

Gradual anomalies (except for profitability) tend to have a short leg that is traded more actively relative to the long leg at the open and close (Figure 2). This evidence is consistent with an explanation based on trading around market closures for the negative overnight and last half-hour returns.

Even though the negative overnight returns are most consistent with mispricing, the gradual returns over the trading day may still represent a compensation for risk, mispricing that gradually resolves over the day, or a combination of both. In this respect, Kozak, Nagel, and Santosh (2016) argue that only sentiment demands that are aligned with common risk factors should survive in equilibrium.

[18]The initial margin requirements of Regulation T in the U.S. are typically applied at the end of the day; see for instance https://gdcdyn.interactivebrokers.com/en/index.php?f=marginnew&p=overview1.

4.5.1 Other Anomalies

Not all of the anomalies that I examine display specific intraday patterns. Accruals is indistinguishable from noise over the day. Book-to-market performs poorly overnight and exhibits a U-shaped pattern in intraday returns: Average returns (alphas) are close to zero over most of the trading day but positive and statistically significant in the first and last half hours of trading. The pattern is, however, not robust across subsamples. In addition, both of these anomalies are statistically insignificant at the monthly level (Table 2).

4.6 A Benchmark: Random Anomaly Strategies

Is the previous intraday evidence in line with the returns of spurious anomalies? Both gradual anomalies and period-specific anomalies may be spurious. To shed some light on the role of data mining, I generate random anomaly strategies *at the monthly level* with the following objectives in mind. First, I assess whether random strategies are able to generate consistently positive and significant profits over the trading day (test of gradual anomalies). Second, I assess whether profitable random strategies earn consistent average returns in specific intervals over multiple subsamples and days of the week (test of period-specific anomalies). These two measures provide benchmarks to which I can contrast the "real" anomalies. Of course, an anomaly whose intraday returns are not stable across periods may not be spurious.

At the beginning of each year, stocks are allocated randomly into decile portfolios. I impose the same filters as for the anomaly portfolios. Two of the decile portfolios are selected randomly to compute monthly value-weighted returns on a long-short decile portfolio over the following year. The long and short legs are determined ex post to obtain a positive average monthly return over the sample period (1986-2015). This procedure is repeated 10,000 times.

Two remarks are in order. First, I assume annual rebalancing to simplify the computations. Second, given that there is no persistence in the sorts over a period greater than a year, the unconditional persistence in the composition of the random portfolios may not match the persistence in the composition of the anomaly portfolios.[19] While the first point is unlikely to be a concern,

[19] The average rank correlation of the characteristics from one year to the next ranges from 0.04 for momentum to 0.97 for illiquidity. Net stock issues (0.40), beta (0.63), idiosyncratic volatility (0.65), and gross profitability (0.93) lie in between.

the second point may make the random strategies not fully comparable to the anomalies. Still, these random strategies provide a neat benchmark to evaluate intraday and overnight returns of anomalies.

Among all random strategies, 1,065 earn average monthly returns that are statistically significant at the level of 10%. In what follows, I refer to these strategies as "significant strategies." The best significant strategy has a t-statistic of 3.98. Unsurprisingly, market returns do not explain the simulated strategies' returns, and average returns and alphas are highly similar. For each significant strategy, I compute intraday half-hour and overnight alphas with associated t-statistics.

The top chart in Figure 3 plots the first quartile, median, and third quartile of t-statistics across all significant strategies in each interval. These statistics help to understand the average alpha profile over the day of a significant strategy. The overnight period drives the profitability of most random strategies. This result is expected given that the overnight period spans a much longer time than any intraday interval. In fact, there are only 203 significant strategies with a negative overnight alpha (19.06%). In the aggregate, returns on random strategies do not accrue in a perfectly gradual manner intraday. Returns from the beginning of the day appear to contribute slightly more to the profitability of random strategies than returns from the end of the day.

[Place Figure 3 about here]

To benchmark the gradual anomalies, I examine intraday half-hour alphas of significant strategies. The two histograms at the bottom of Figure 3 report the number of strategies that have a given number of positive half-hour alphas (left histogram) and that have a given number of positive *and* significant half-hour alphas (right histogram). The histograms indicate where the anomalies considered in the paper would fit. Many random strategies have as many positive half-hour alphas as some of the gradual anomalies. But not a single random strategy has more than six statistically significant intraday intervals (and only two attain this threshold). Simple random strategies do not appear to earn positive and statistically significant returns consistently across the trading day. From this point of view, the return pattern of the gradual anomalies stands out and does not appear to reflect randomness. In particular, returns around market closures tend to be less extreme for random strategies than for anomalies. The minimum overnight average return across all significant random strategies is only -1.23 basis points. This contrasts to the large negative overnight returns observed for beta, idiosyncratic volatility, and net stock issues.

To benchmark period-specific anomalies, I evaluate whether a significant strategy can earn statistically significant alpha in a given period across all subsamples. The probability for the random anomalies is close to zero for all periods except overnight (1.22%) and, to a lesser extent, in the last half hour (0.47%). Among the 10,000 original strategies, only one strategy earns significant alpha in a given period in all subsamples and across all days of the weeks. Like momentum, this strategy has a positive overnight alpha. Overall, this evidence suggests that concentrated patterns similar to that of the period-specific anomalies are highly unlikely to be generated by chance. While a large literature provides strong evidence that momentum is a pervasive phenomenon, this methodology can be useful to examine the robustness of other, less well-known, anomalies.

4.7 Summary and Discussion

Gradual anomalies (i.e., beta, gross profitability, net stock issues, and idiosyncratic volatility) earn consistently positive and statistically significant returns over most of the trading day, while period-specific anomalies (momentum, size, and illiquidity) earn their returns only during specific periods of the day. These patterns are unlikely to be spurious.

Notably, the large and positive size returns in the last half hour of trading are associated with a high turnover of small stocks relative to large stocks. A model of infrequent rebalancing can help explain this evidence. Exposure to size can explain the negative last half-hour returns of several gradual anomalies, which highlights a commonality among anomalies. But the negative overnight returns of gradual anomalies seem difficult to explain with risk-based theories. The short legs of the portfolios drive the patterns. Hence, an explanation based on mispricing that increases at the open—for instance, due to systematic retail buying pressure—may better accommodate the evidence. Evidence from intraday turnover is also in line with this explanation.

The results strongly highlight the role of trading around market closures for anomalies—in particular, period-specific anomalies. Any explanation that rejects the role of market closures should be able to provide an alternative explanation as to why size returns accrue in the last half hour of trading and momentum returns accrue overnight. The analysis indicates that size and momentum are important factors that should be separately included in a factor model. While well-known factor models often include size and momentum, this choice is generally made without any clear justification.

4.8 The Impact of Public Announcements

This section discusses the role of earnings announcements and FOMC announcements on the intraday and overnight return patterns of anomalies.

4.8.1 Earnings Announcements

Using a sample of 97 anomalies, Engelberg, McLean, and Pontiff (2016) find that anomalies tend to earn higher returns on earnings announcement days. They argue that, in line with behavioral theories, the arrival of information helps correct mispricing. There is, however, no reason to expect that earnings announcements generate the return of period-specific anomalies if these anomalies are linked to general trading patterns around market closures.

I separate months in which few companies make earnings announcements—that is, March, June, September, and December—from others months. For each anomaly, the following regression is then estimated

$$\hat{e}_t = \sum_k \delta_k 1_{k,t} + \sum_k \delta_{\mathrm{EA},k} 1_{k,t} 1_{\mathrm{EA},t} + u_t, \tag{4}$$

where $\hat{e}_t$ is the anomaly's market residual in interval t, $1_{k,t}$ is a dummy variable that equals one in interval k, and $1_{\mathrm{EA},t}$ is a dummy variable that equals one during earnings announcement months. All the variables are normalized by the volatility of residuals in interval t to control for heteroskedasticity. Market residuals are estimated separately for each interval of the day.

Table 6 reports the coefficients $\delta_{\mathrm{EA},k}$ and their associated t-statistics. Gradual anomalies do not differ significantly between announcement and non-announcement months. Betting-against-beta (net stock issues) tends to be weaker (stronger) in announcement months, but statistical significance is weak.

[Place Table 6 about here]

Period-specific anomalies, however, differ: Momentum, size, and illiquidity tend to have lower returns in announcement months. In particular, the momentum overnight return is markedly lower.

During non-announcement months, intraday momentum returns are positive and often statistically significant in the morning (the detailed results are reported in the Internet Appendix). During non-announcement months, size and illiquidity earn higher overnight returns as well as higher intraday returns over almost all half-hour intervals. The return over the last half hour of trading is more than one basis point higher than in announcements months.

Months with few announcements correspond to the end of quarters. As shown by Carhart et al. (2002), portfolio pumping by fund managers may take place on the last day of each quarter. This aggressive trading can affect the cross-section of stock returns and, in particular, the size and illiquidity portfolios.[20] The evidence is therefore consistent with portfolio pumping at the end of the quarter (the end-of-the-day effect remains, however, large and statistically significant in other months). Moreover, the large negative morning returns of size and illiquidity are specific to announcement months.

The arrival of information, as proxied by earnings announcements, does not appear to drive period-specific anomalies. In fact, the evidence goes in the other direction, which further differentiates these anomalies from gradual anomalies. Most other anomalies do not appear to differ much between earnings announcement and non-announcement months. The difference with respect to the results of Engelberg, McLean, and Pontiff (2016) may stem from the crude classification scheme employed here and the fact that they do not individually examine anomalies.

4.8.2 FOMC Announcements

I focus on scheduled Federal Open Market Committee (FOMC) announcements since Lucca and Moench (2015) document that, from January 1994 to March 2011, about 80% of annual realized market excess returns accrue in the 24 hours before scheduled FOMC announcements.

I estimate a regression similar to (4) using dummies for FOMC announcement days. The sample starts in 1994, when the decisions of scheduled FOMC meetings have been made available to the public around 2:15 p.m. There are 176 announcements in the sample (eight announcements per year over 22 years). The first row in Table 7 shows that market returns tend to be markedly larger on FOMC announcement days until the afternoon—i.e., the pre-FOMC announcement drift. The

[20] Bogousslavsky (2015) shows that small stocks earn large returns on the last day of each quarter that partly reverse on the following day.

difference is statistically significant for the overnight return and most half-hour returns. Investors may not want to carry stocks ahead of such announcements, but returns do not appear to reverse following the announcements.

[Place Table 7 about here]

Most anomalies tend not to perform well on FOMC announcement days.[21] But apart from beta and idiosyncratic volatility, which incur large negative overnight returns and continue to lose value over the day, intraday and overnight average returns on other anomalies are not significantly different at the level of 10%. This evidence shows that long-short anomalies portfolios are not exposed to FOMC announcements to the same extent as the market portfolio. The short leg eliminates most of the exposure.

Contrary to several anomalies, the return on a portfolio of large stocks does not accrue gradually over the day (Table 1). This is surprising because one would expect an aggregate portfolio to earn returns smoothly over the day. After excluding scheduled FOMC announcements days, the market portfolio does not earn positive and significant return in any half-hour interval of the trading day, which further deepens the puzzle. Overnight returns remain large and highly significant (not reported).

5 Robustness

This section examines the robustness of overnight returns to the measure of the opening price (Section 5.1), the robustness of the results to the use of trade-based returns (Section 5.2), and the impact of nonsynchronous trading and thin trading (Section 5.3).

5.1 Do Stocks Earn High Overnight Returns?

As shown in the main analysis, anomaly overnight returns are robust to the choice of the opening price. Overnight returns on long-only portfolios are, however, more sensitive to this choice. Table 8 reports intraday and overnight average returns for each of the aggregate portfolio of Section 4.1 using three measures of the opening price: quote midpoints, trade prices, and VWAP as described

[21] For completeness, intraday and overnight anomaly returns on FOMC announcement days are reported in the Internet Appendix.

in Section 3. To make an exact comparison, each portfolio in Table 8 has the same composition as the VWAP portfolio.[22] The table reports raw returns.

[Place Table 8 about here]

The choice of the opening price matters. Overnight returns are lowest using VWAP. The differences are particularly marked in the first part of the sample and for the small and micro stocks portfolios. Midquote and trade prices yield negative intraday returns for the large stocks portfolio between 1993 and 2004, while VWAP yield positive intraday returns.

Cliff, Cooper, and Gulen (2008) claim that the U.S. equity premium over 1993 to 2006 is entirely earned overnight. Table 8 shows that this statement depends on the definition of the opening price. A substantial fraction of overnight returns computed from trades and quote midpoints can be explained by short-term price movements in the first half hour of trading. This evidence indicates abnormally high prices at the open that revert over the following half hour of trading.

These results have implications for empirical studies. The first transaction price of the day is likely subject to temporary price pressures (Section 2) and may therefore not be the right measure of the opening price to examine average returns over long horizons. At the same time, the volume-weighted average price may give up interesting information about the first half hour of trading.[23]

5.2 Trade-Based Returns

Intraday and overnight average trade-based returns on the large, small, and micro portfolios of Section 4.1 and anomalies are reported in the Internet Appendix. In general, returns computed from trade prices give similar results than returns computed from quote midpoints. As hinted by the evidence in Section 5.1, most differences occur in the old part of the sample and are due to the inclusion of the first five minutes of trading when computing trade-based returns. Intraday returns on anomalies do not differ much. The results in the main analysis are therefore robust. In fact, return patterns around market closures tend to be more pronounced with trade-based returns.

[22] The results for the micro portfolio over the 1985-1992 period should be taken with a grain of salt since this portfolio holds on average only 50 stocks during this period.

[23] Consider a recent example: The largest exchange traded fund in the world—the SPDR S&P 500 ETF—opened 5% below its previous close on August 24, 2015, and lost an additional 3% in the first five minutes of trading before recovering past its opening value over the next five minutes (Securities and Exchange Commission (2015)). This sudden price move took place without any news. In such a case, the VWAP return underestimates return variation and may therefore not be appropriate to measure liquidity, market efficiency, or intraday portfolio risk.

5.3 Nonsynchronous Trading and Thin Trading

Nonsynchronous trading is an important issue to consider when studying returns over short horizons. Nonsynchronous trading smoothes portfolio returns, which generates positive portfolio return autocorrelation (e.g., Fisher (1966)) and lowers a portfolio's volatility below its true economic volatility. The use of midquote returns, which are not necessarily associated with trades, and the filters described in Section 3 should limit the problem. Still, quotes may not be revised actively, especially during the old part of the sample.

To assess the impact of nonsynchronous trading and thin trading, I apply the following volume filter: Each year, a stock is required to have trades in the first, second, second to last, and last half hours of the trading day on at least 90% of the days for which the stock has a valid CRSP daily return.[24] In addition to excluding stocks that trade particularly infrequently, this restriction ensures that the overnight and opening half-hour returns are associated with actual transactions.

Table 9 reports intraday and overnight alphas of anomalies portfolios after applying the volume filter. The patterns documented in Section 4.2 are robust. Alphas tend, however, to be slightly smaller over the trading day, and a few large differences arise for overnight and first-hour returns. In particular, both size and illiquidity now earn positive and statistically significant overnight alpha, but idiosyncratic volatility earns lower overnight alpha. Hence, monthly alphas tend to be lower except for size and illiquidity (alphas and average returns are reported in the right columns of Table 2). This evidence further indicates that trading plays an important role for size returns.

[Place Table 9 about here]

6 Conclusion

Asset pricing anomalies accrue over the trading day in radically different ways. This evidence is novel and helps understand the economic drivers of cross-sectional variation in stock returns. The patterns that I document are robust and, as shown by a comparison with random strategies, unlikely to be spurious.

[24] The ISSM data set misses volume data in 1987. I use as a benchmark the maximum number of days for which a stock has ISSM volume data in this year (210).

The evidence in this paper strongly suggests an important role for trading around market closures in determining size, illiquidity, and momentum returns. Size and illiquidity premia accrue only in the last half hour of trading. The evidence is most consistent with liquidity that deteriorates around the close due to traders' rebalancing. Small stocks appear to be subject to large liquidity shocks around the close, as suggested by their high turnover relative to that of large stocks at this time of the day.

Recently, Stambaugh and Yuan (2016) document that the size premium increases when controlling for two mispricing factors. An interesting extension for future work would be to document which components of daily returns drive this increase and understand why.

Anomalies that earn their returns gradually over the day (gross profitability, net stock issues, betting-against-beta, and idiosyncratic volatility) may be consistent with risk-based or mispricing explanations at lower frequencies. But these anomalies also earn large and robust negative returns in the last half hour of trading and overnight. Negative returns in the last half hour of trading are partly explained by exposure to size. Negative overnight returns are difficult to reconcile with risk-based theories. One possibility is that mispricing increases at the open, which is consistent with evidence of retail buying pressure at this time. In line with this explanation, the short leg drives the pattern and has a high turnover relative to the long leg at the open.

References

Admati, Anat R., and Paul Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies* 1, 3–40. [17, 55]

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5, 31–56. [56]

Amihud, Yakov, and Haim Mendelson, 1987, Trading Mechanisms and Stock Returns: An Empirical Investigation, *Journal of Finance* 42, 533–553. [2]

Andersen, Torben G., and Tim Bollerslev, 1997, Intraday Periodicity and Volatility Persistence in Financial Markets, *Journal of Empirical Finance* 4, 115–158. [2]

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance* 61, 259–299. [56]

Asparouhova, Elena, Hendrik Bessembinder, and Ivalina Kalcheva, 2013, Noisy Prices and Inference Regarding Returns, *Journal of Finance* 68, 665–714. [1]

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2013, Anomalies and Financial Distress, *Journal of Financial Economics* 108, 139–159. [5]

Barberis, Nicholas, and Richard Thaler, 2003, A Survey of Behavioral Finance, in G.M. Constantinides, M. Harris, and R. Stulz, eds., *Handbook of the Economics of Finance*, 1051–1120. [1]

Barclay, Michael J., Terrence Hendershott, and Charles M. Jones, 2008, Order Consolidation, Price Efficiency, and Extreme Liquidity Shocks, *Journal of Financial and Quantitative Analysis* 43, 93. [7]

Barndorff-Nielsen, O. E., P. Reinhard Hansen, A. Lunde, and N. Shephard, 2009, Realized Kernels in Practice: Trades and Quotes, *Econometrics Journal* 12, C1–C32. [9]

Berkman, Henk, Paul D. Koch, Laura Tuttle, and Ying Jenny Zhang, 2012, Paying Attention: Overnight Returns and the Hidden Cost of Buying at the Open, *Journal of Financial and Quantitative Analysis* 47, 715–741. [4, 5, 7, 19, 20, 22, 51]

Birru, Justin, 2016, Day of the Week and the Cross-Section of Returns, Fisher College of Business Working Paper No. 2016-03-01. [14, 19]

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, *The Capital Asset Pricing Model: Some Empirical Tests* (Praeger, New York). [13]

Blume, Lawrence, and Robert F. Stambaugh, 1983, Biases in Computed Returns, *Journal of Financial Economics* 12, 387–404. [1, 10]

Bogousslavsky, Vincent, 2015, Seasonalities in Anomalies, EPFL Working paper. [27]

Bogousslavsky, Vincent, 2016, Infrequent Rebalancing, Return Autocorrelation, and Seasonality, *Journal of Finance* (forthcoming). [3, 11, 18, 52, 53]

Breedon, Francis, and Angelo Ranaldo, 2013, Intraday patterns in FX returns and order flow, *Journal of Money, Credit and Banking* 45, 953–965. [5]

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed, 2002, Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds, *Journal of Finance* 57, 661–693. [27]

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001, Market Liquidity and Trading Activity, *Journal of Finance* 56, 501–530. [8]

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2011, Recent Trends in Trading Activity and Market Quality, *Journal of Financial Economics* 101, 243–263. [11, 12]

Cliff, Michael, Michael J. Cooper, and Huseyin Gulen, 2008, Return Differences between Trading and Non-trading Hours: Like Night and Day, Working Paper. [5, 29]

Cochrane, John H., 2011, Presidential Address: Discount Rates, *Journal of Finance* 66, 1047–1108. [1, 2]

Collin-Dufresne, Pierre, and Vyacheslav Fos, 2016, Insider Trading, Stochastic Liquidity and Equilibrium Prices, *Econometrica* 84, 1441–1475. [17]

Cushing, David, and Ananth Madhavan, 2000, Stock Returns and Trading at the Close, *Journal of Financial Markets* 3, 45–67. [3, 17, 19]

Daniel, Kent, and Tobias J. Moskowitz, 2016, Momentum Crashes, *Journal of Financial Economics* . [20]

Duffie, Darrell, 2010, Presidential Address: Asset Price Dynamics with Slow-Moving Capital, *Journal of Finance* 65, 1237–1267. [7, 18]

Engelberg, Joseph, R. David McLean, and Jeffrey Pontiff, 2016, Anomalies and News, Working paper. [4, 26, 27]

Fama, Eugene F., 1991, Efficient Capital Markets: II, *Journal of Finance* 46, 1575–1617. [1]

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63, 1653–1678. [11, 13, 56]

Fama, Eugene F., and Kenneth R. French, 2016, Dissecting Anomalies with a Five-Factor Model, *Review of Financial Studies* 29, 69–103. [13]

Fisher, Lawrence, 1966, Some New Stock-Market Indexes, *The Journal of Business* 39, 191–225. [30]

French, Kenneth R., 1980, Stock Returns and the Weekend Effect, *Journal of Financial Economics* 8, 55–69. [3, 6, 7, 14]

Gerety, Mason S., and Harold J. Mulherin, 1992, Trading Halts and Market Activity: An Analysis of Volume at the Open and the Close, *Journal of Finance* 47, 1765–1784. [6]

Gerety, Mason S., and Harold J. Mulherin, 1994, Price Formation on Stock Exchanges: The Evolution of Trading within the Day, *Review of Financial Studies* 7, 609–629. [2]

Grossman, Sanford J., and Merton H. Miller, 1988, Liquidity and Market Structure, *Journal of Finance* 43, 617–633. [7]

Harris, Lawrence, 1986, A Transaction Data Study of Weekly and Intradaily Patterns in Stock Returns, *Journal of Financial Economics* 16, 99–117. [2, 14, 16]

Harris, Lawrence, 1989, A Day-End Transaction Price Anomaly, *Journal of Financial and Quantitative Analysis* 24, 29–45. [16]

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, ... and the Cross-Section of Expected Returns, *Review of Financial Studies* 29, 5–68. [1]

Hausman, Jerry A., Andrew W. Lo, and A. Craig MacKinlay, 1992, An Ordered Probit Analysis of Transaction Stock Prices, *Journal of Financial Economics* 31, 319–379. [8]

Heston, Steven L., Robert A. Korajczyk, and Ronnie Sadka, 2010, Intraday Patterns in the Cross-section of Stock Returns, *Journal of Finance* 65, 1369–1407. [5, 10]

Hong, Harrison, and Jiang Wang, 2000, Trading and Returns under Periodic Market Closures, *Journal of Finance* 55, 297–354. [3, 6, 7, 12, 17, 55]

Hou, Kewei, Chen Xue, and Lu Zhang, 2015, Digesting Anomalies: An Investment Approach, *Review of Financial Studies* 28, 650–705. [14]

Jain, Prem C., and Gun-Ho Joh, 1988, The Dependence between Hourly Prices and Trading Volume, *Journal of Financial and Quantitative Analysis* 23, 269–283. [2, 14]

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65–91. [56]

Kelly, Michael A., and Steven P. Clark, 2011, Returns in Trading versus Non-Trading Hours: The Difference is Day and Night, *Journal of Asset Management* 12, 132–145. [5]

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh, 2016, Interpreting Factor Models, Working paper, University of Michigan and University of Maryland. [22]

Lochstoer, Lars A., and Paul C. Tetlock, 2016, What Drives Anomaly Returns?, Columbia Business School Working Paper. [5]

Lou, Dong, Christopher Polk, and Spyros Skouras, 2016, A Tug of War: Overnight Versus Intraday Expected Returns, London School of Economics Working Paper. [3, 5, 9, 20]

Lucca, David O., and Emanuel Moench, 2015, The Pre-FOMC Announcement Drift, *Journal of Finance* 70, 329–371. [27]

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why Do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks, *Review of Financial Studies* 10, 1035–1064. [3, 19]

McInish, Thomas H., and Robert A. Wood, 1992, An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks, *Journal of Finance* 47, 753–764. [22]

McLean, R. David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5–32. [5, 14]

Muravyev, Dmitriy, and Xuechuan Ni, 2016, Why Do Option Returns Change Sign from Day to Night?, Boston College Working Paper. [5]

Neal, Robert, 1996, Direct Tests of Index Arbitrage Models, *Journal of Financial and Quantitative Analysis* 31, 541–562. [22]

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708. [11, 41, 43]

Novy-Marx, Robert, 2013, The Other Side of Value: The Gross Profitability Premium, *Journal of Financial Economics* 108, 1–28. [56]

Scholes, Myron, and Joseph Williams, 1977, Estimating Betas From Nonsynchronous Data, *Journal of Financial Economics* 5, 309–327. [15]

Securities and Exchange Commission, 2015, Equity Market Volatility on August 24, 2015, Research Note. [29]

Slezak, Steve L., 1994, A Theory of the Dynamics of Security Returns around Market Closures, *Journal of Finance* 49, 1163–1211. [6, 55]

Sloan, Richard G., 1996, Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?, *Accounting Review* 71, 289–315. [56]

Smirlock, Michael, and Laura Starks, 1986, Day-of-the-Week and Intraday Effects in Stock Returns, *Journal of Financial Economics* 17, 197–210. [2, 12, 14]

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The Short of It: Investor Sentiment and Anomalies, *Journal of Financial Economics* 104, 288–302. [5, 22]

Stambaugh, Robert F., and Yu Yuan, 2016, Mispricing Factors, *Review of Financial Studies* (forthcoming). [31]

Stoll, Hans R., and Robert E. Whaley, 1990, Stock Market Structure and Volatility, *Review of Financial Studies* 3, 37–71. [7]

Wood, Robert A., Thomas H. McInish, and J. Keith Ord, 1985, An Investigation of Transactions Data for NYSE Stocks, *The Journal of Finance* 40, 723–739. [2, 12]

Figure 1. Intraday and overnight t-statistics of market alphas of long-short portfolios for different subsamples. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight return. Details about the formation of the portfolios are provided in the caption of Table 3. Dashed red lines indicate significance at the level of 10%.

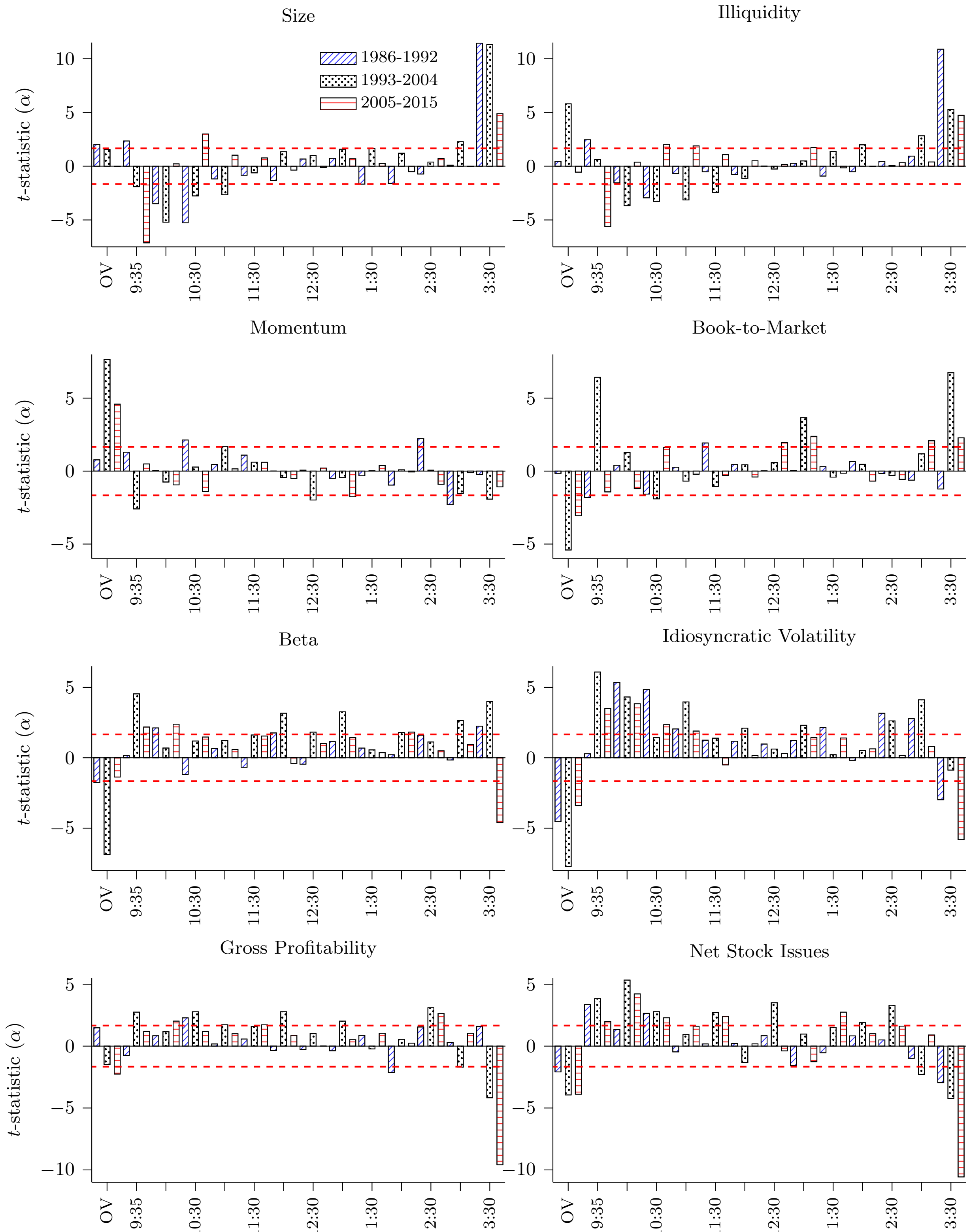
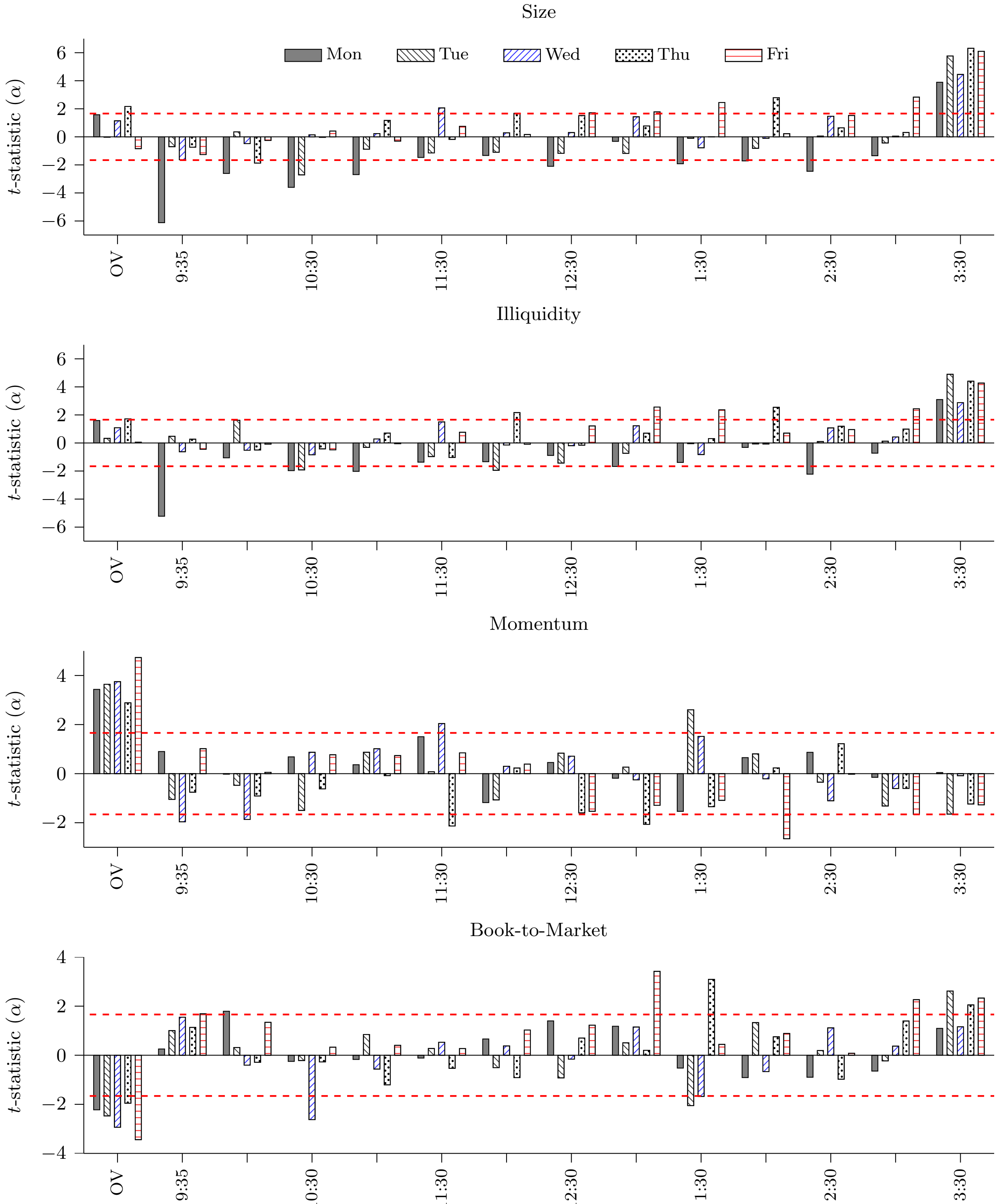


Figure 2. Intraday and overnight t-statistics of market alphas of long-short portfolios across days of the week. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight return. Details about the formation of the portfolios are provided in the caption of Table 3. Dashed red lines indicate significance at the level of 10%.



(Figure 2 continued.)

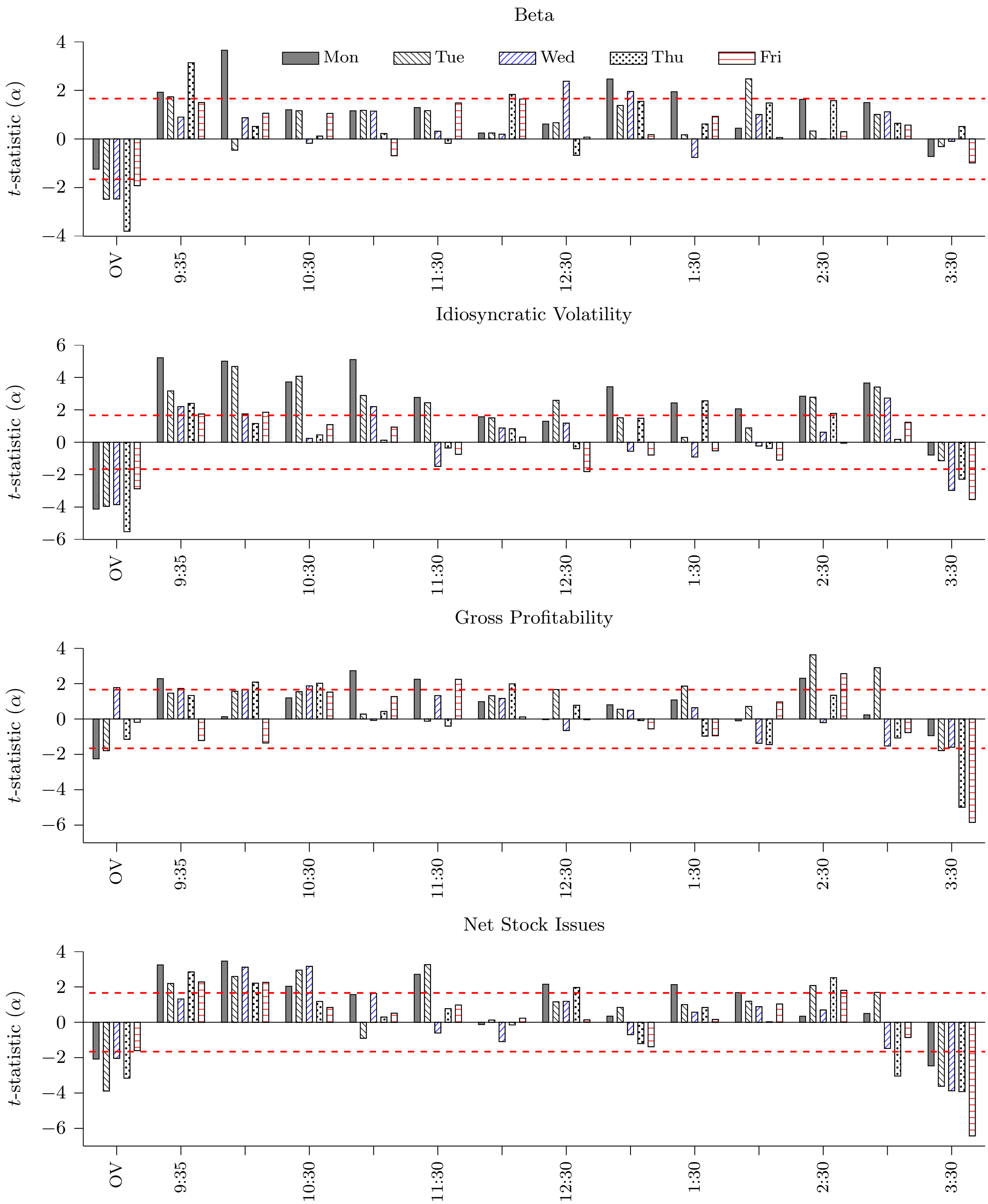


Figure 2. Intraday turnover of long-short portfolios. This figure reports the difference between the value-weighted turnover of the long leg and the value-weighted turnover of the short leg (in percent) averaged over each interval of the trading day. 9:30 indicates the half-hour interval that starts at 9:30 a.m. and ends before 10:00 a.m. Details about the formation of the portfolios are provided in the caption of Table 3.

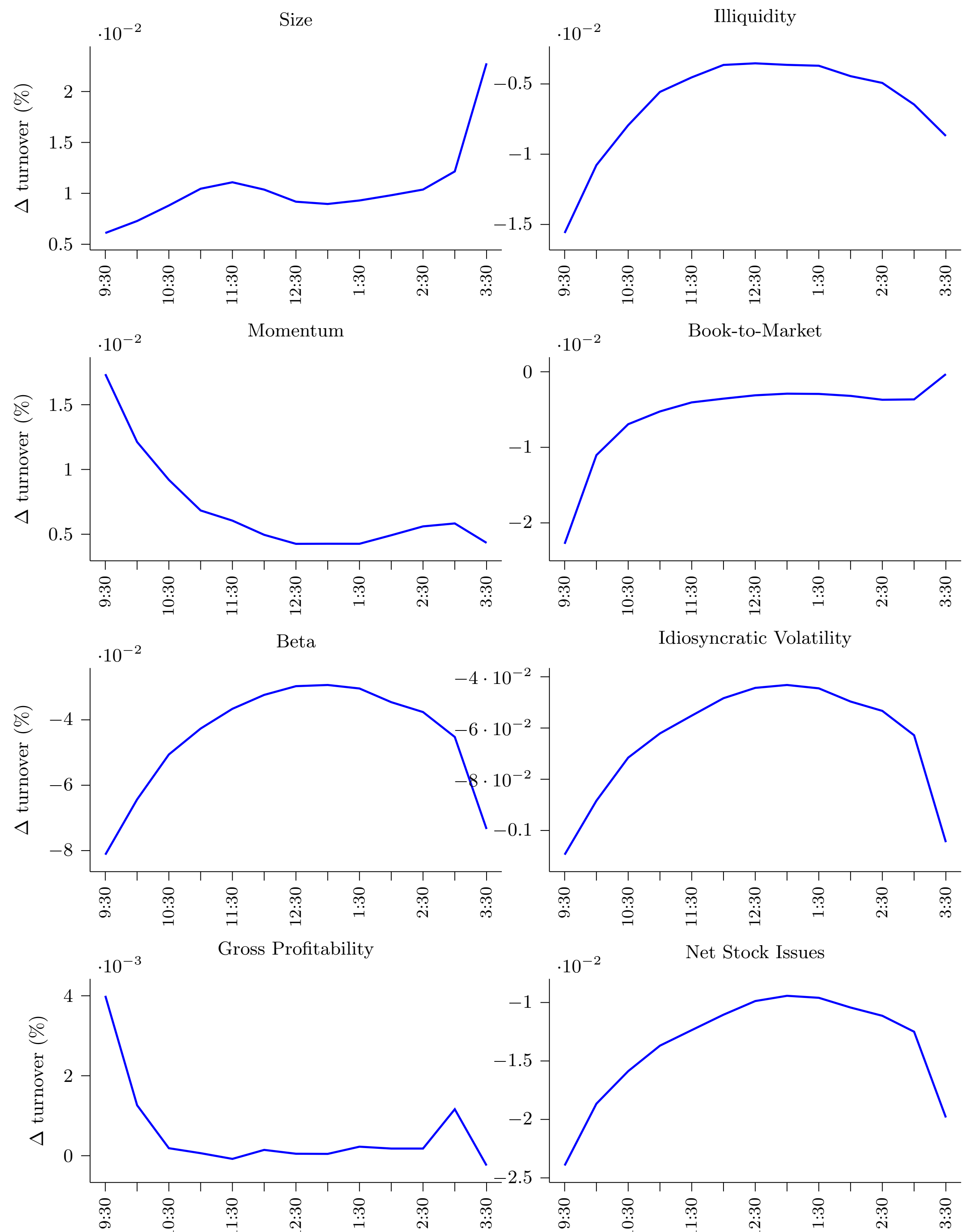


Figure 3. Random anomaly strategies. At the beginning of each year, stocks with a price larger than \$10 and at least ten days of nonzero volume over the previous month are allocated randomly into decile portfolios. Two of the decile portfolios are selected randomly to compute monthly value-weighted returns on a long-short decile portfolio over the following year. The long and short legs are determined ex post to obtain a positive average monthly return over the full sample period (1986-2015). This procedure is repeated 10,000 times. The 1,065 strategies that have an average monthly return significant at the level of 10% are labeled as significant strategies. The top figure reports the first quartile, median, and third quartile of alpha's t-statistics across all significant strategies in each interval of the day. The bottom histograms report the number of significant strategies with a given number of positive intraday half-hour alphas (left chart) and a given number of positive and significant intraday half-hour alphas (right chart). The two histograms also indicate where accruals (AC), beta (BE), book-to-market (BM), gross profitability (GP), idiosyncratic volatility (IV), illiquidity (IL), momentum (MO), net stock issues (NI), and size (SI) fit.

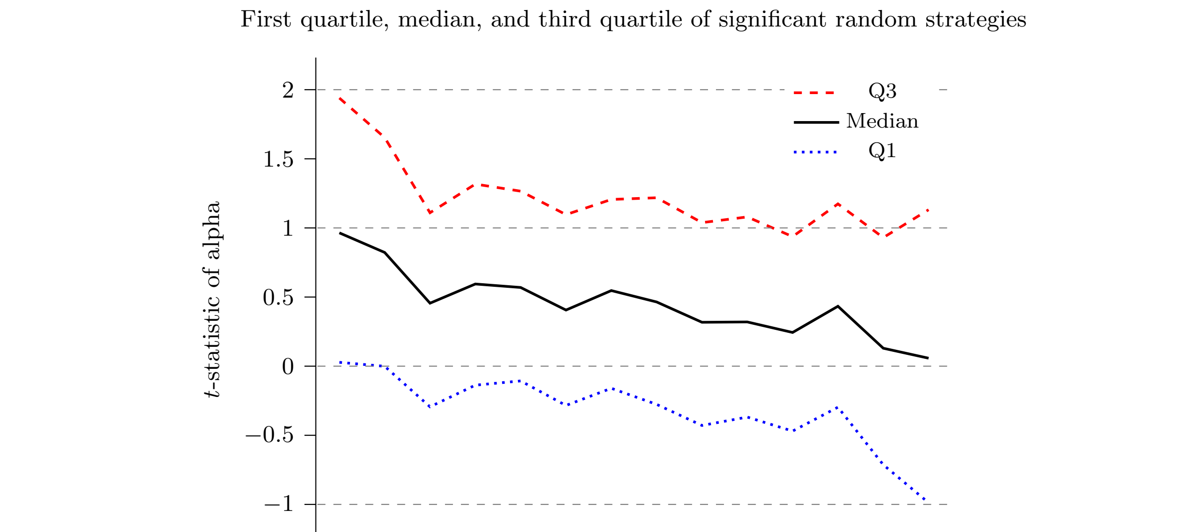


Table 1. Intraday and overnight average returns in basis points of aggregate portfolios for different subsamples. Stocks are allocated into micro, small, and large value-weighted portfolios based on the 20$^{\text{th}}$ and 50$^{\text{th}}$ percentiles of NYSE market capitalization each year at the end of June. Stock returns are computed using quote midpoints. Overnight returns (OV) are in excess of the daily risk-free rate. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. A stock is required to have a price greater than \$5 and a market capitalization greater than \$100 million at the end of the previous quarter to be included. All t-statistics are based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Large stocks portfolio														
1985-1992	2.99**	0.18	-1.74***	0.86	0.08	0.06	0.46	0.55	-0.42	-0.44	-0.37	0.76*	1.33***	-0.20
	(2.10)	(0.39)	(-3.50)	(1.61)	(0.16)	(0.15)	(1.31)	(1.32)	(-1.31)	(-1.17)	(-1.05)	(1.78)	(2.63)	(-0.34)
1993-2004	4.00***	-0.91**	-1.10*	0.53	-0.40	-0.06	-0.36	0.59*	0.70**	-0.02	-0.65*	0.17	0.18	0.39
	(3.91)	(-2.00)	(-1.95)	(1.14)	(-1.08)	(-0.16)	(-1.17)	(1.93)	(2.16)	(-0.07)	(-1.67)	(0.42)	(0.37)	(0.78)
2005-2015	2.30*	-0.42	0.40	-0.45	-0.24	0.11	-0.21	0.25	0.07	-0.32	-0.23	1.06**	0.70	-0.03
	(1.74)	(-0.70)	(0.71)	(-0.93)	(-0.57)	(0.26)	(-0.56)	(0.68)	(0.18)	(-0.80)	(-0.50)	(2.26)	(1.19)	(-0.04)
Small stocks portfolio														
1985-1992	2.83***	0.32	-1.56***	-0.48	0.06	-0.18	0.05	0.12	-0.40**	-0.19	-0.18	0.15	0.49**	2.04***
	(2.83)	(1.05)	(-5.29)	(-1.64)	(0.24)	(-0.71)	(0.20)	(0.68)	(-2.20)	(-1.00)	(-0.98)	(0.77)	(1.96)	(6.53)
1993-2004	4.70***	-1.57***	-2.23***	-0.32	-0.80**	-0.32	-0.21	0.57**	0.69***	0.14	-0.09	0.08	0.12	2.36***
	(5.23)	(-3.35)	(-4.26)	(-0.82)	(-2.47)	(-1.08)	(-0.84)	(2.33)	(2.83)	(0.55)	(-0.31)	(0.28)	(0.36)	(5.24)
2005-2015	2.01	-2.07**	0.74	0.15	0.01	-0.03	-0.26	0.16	0.17	-0.41	-0.28	1.31**	0.95	0.99
	(1.35)	(-2.37)	(0.94)	(0.23)	(0.01)	(-0.06)	(-0.53)	(0.36)	(0.37)	(-0.83)	(-0.52)	(2.33)	(1.42)	(1.31)
Micro stocks portfolio														
1985-1992	2.31**	0.74	-1.15***	-0.78***	0.38	-0.83	-0.05	0.28	-0.35**	-0.46**	-0.29	0.22	0.66***	2.71***
	(2.27)	(1.65)	(-3.67)	(-3.17)	(0.56)	(-1.39)	(-0.21)	(1.25)	(-2.17)	(-1.99)	(-1.62)	(1.27)	(3.00)	(9.29)
1993-2004	4.89***	-1.69***	-2.26***	-0.42	-0.82***	-0.32	-0.17	0.21	0.49**	0.22	-0.06	0.09	0.32	3.75***
	(5.62)	(-4.16)	(-5.30)	(-1.30)	(-3.05)	(-1.23)	(-0.80)	(1.00)	(2.31)	(0.97)	(-0.25)	(0.34)	(1.08)	(9.16)
2005-2015	3.09**	-3.59***	0.13	0.26	-0.10	-0.04	-0.39	0.11	0.10	-0.43	-0.44	0.98*	0.55	2.13**
	(2.32)	(-4.52)	(0.17)	(0.43)	(-0.19)	(-0.09)	(-0.86)	(0.25)	(0.24)	(-0.95)	(-0.87)	(1.89)	(0.84)	(2.48)

Table 2. Monthly average return and alpha in percent of long-short portfolios formed on different characteristics. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2. The table reports returns of strategies that are long the highest decile portfolio and short the lowest decile portfolio. The portfolios are value-weighted and held for one month. A stock is required to have a price greater than $10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolios. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1985 to December 2015 (363 monthly observations). NASDAQ stocks are included since 1993. #L (#S) indicates the average number of stocks in the long (short) portfolio. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	return	alpha	#L/#S
Accruals	0.13	0.18	164/194
	(0.79)	(1.05)	
Beta	-0.13	0.56**	230/363
	(-0.38)	(2.25)	
Book-to-market	-0.19	-0.03	125/233
	(-0.84)	(-0.14)	
Gross profitability	0.42**	0.44**	335/256
	(2.36)	(2.47)	
Idiosyncratic volatility	0.34	0.86***	146/410
	(1.00)	(2.93)	
Illiquidity	0.26	0.21	138/116
	(1.38)	(1.09)	
Momentum	0.92***	1.02***	335/256
	(2.60)	(2.86)	
Net Stock Issues	0.26	0.34**	130/204
	(1.63)	(2.11)	
Size	0.22	0.11	530/127
	(1.09)	(0.54)	

Table 3. Intraday and overnight return properties of long-short decile portfolios. This table reports average returns ($\bar{r}$) and alpha in basis points (α), volatility in percent (σ), skewness (skew), and minimum return (min) in percent. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2. Portfolios are value-weighted and held for one month. A stock is required to have a price greater than \$10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolio. Stock returns are computed using quote midpoints. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight return. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. All t-statistics are based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Accruals														
$\bar{r}$	0.52	1.01***	0.21	0.11	-0.46**	-0.06	0.19	0.50***	-0.19	-0.21	0.10	0.05	-0.35*	-0.54***
	(1.09)	(3.22)	(0.87)	(0.51)	(-2.52)	(-0.34)	(1.16)	(3.02)	(-1.32)	(-1.41)	(0.64)	(0.34)	(-1.95)	(-2.69)
α	0.33	1.05***	0.28	0.08	-0.44**	-0.06	0.20	0.44***	-0.21	-0.18	0.13	0.00	-0.40**	-0.56***
	(0.70)	(3.37)	(1.15)	(0.40)	(-2.43)	(-0.35)	(1.24)	(2.77)	(-1.45)	(-1.26)	(0.85)	(0.00)	(-2.28)	(-2.83)
σ	0.41	0.27	0.21	0.18	0.16	0.16	0.14	0.14	0.13	0.13	0.13	0.14	0.16	0.17
skew	0.31	0.10	0.13	0.09	-0.26	-0.20	0.08	0.36	-0.08	-0.05	0.23	0.11	-0.20	-0.21
min	-3.51	-1.71	-2.53	-1.83	-2.29	-2.26	-2.55	-1.04	-1.11	-1.64	-1.05	-0.92	-4.78	-2.40
Beta														
$\bar{r}$	-7.24***	2.46***	1.71***	0.12	0.56	0.35	0.49*	-0.24	0.31	0.41	0.93***	-0.38	-0.14	-0.34
	(-6.66)	(4.28)	(3.32)	(0.27)	(1.57)	(1.08)	(1.71)	(-0.83)	(1.06)	(1.33)	(2.85)	(-1.11)	(-0.39)	(-0.86)
α	-3.31***	1.74***	0.80**	0.41	0.30	0.37*	0.37**	0.26	0.55***	0.16	0.48**	0.32	0.47**	-0.16
	(-5.28)	(4.14)	(2.47)	(1.54)	(1.35)	(1.80)	(2.00)	(1.46)	(3.24)	(0.81)	(2.50)	(1.63)	(2.27)	(-0.65)
σ	0.95	0.50	0.45	0.37	0.31	0.28	0.25	0.26	0.25	0.27	0.29	0.30	0.32	0.35
skew	-0.12	0.08	-0.01	-0.07	0.06	-0.04	0.10	0.03	0.07	-0.25	-0.50	-0.32	-0.26	-0.26
min	-17.72	-7.92	-4.04	-3.63	-4.88	-2.22	-3.39	-7.96	-5.40	-5.41	-2.80	-3.97	-5.14	-4.57
Book-to-market														
$\bar{r}$	-3.60***	0.95***	0.52*	-0.39	-0.01	0.03	0.08	0.02	0.42**	0.00	0.22	-0.20	0.14	0.84***
	(-6.93)	(2.80)	(1.78)	(-1.61)	(-0.04)	(0.17)	(0.44)	(0.15)	(2.40)	(0.01)	(1.22)	(-1.02)	(0.67)	(3.56)
α	-2.81***	0.83**	0.32	-0.32	-0.07	0.04	0.05	0.15	0.48***	-0.06	0.11	-0.00	0.28	0.89***
	(-5.72)	(2.48)	(1.15)	(-1.40)	(-0.36)	(0.21)	(0.28)	(0.97)	(2.94)	(-0.35)	(0.65)	(-0.02)	(1.49)	(4.06)
σ	0.45	0.30	0.25	0.21	0.18	0.17	0.16	0.15	0.15	0.15	0.16	0.17	0.18	0.21
skew	-0.15	0.18	-0.03	-0.22	-0.14	-0.07	0.22	-0.17	0.06	-0.13	-0.27	0.19	0.31	0.68
min	-4.03	-6.85	-3.45	-2.15	-2.49	-3.74	-1.49	-3.83	-2.95	-2.14	-2.44	-2.31	-2.13	-1.90
Gross Profitability														
$\bar{r}$	-0.86*	0.74**	0.46*	0.80***	0.36*	0.40**	0.40**	0.16	0.11	0.10	-0.09	0.71***	-0.02	-1.23***
	(-1.93)	(2.36)	(1.80)	(3.68)	(1.91)	(2.31)	(2.55)	(0.86)	(0.66)	(0.63)	(-0.60)	(4.45)	(-0.12)	(-6.72)
α	-0.76*	0.79**	0.48*	0.79***	0.38**	0.40**	0.40**	0.10	0.11	0.11	-0.09	0.70***	-0.02	-1.24***
	(-1.68)	(2.50)	(1.87)	(3.64)	(1.97)	(2.31)	(2.57)	(0.58)	(0.66)	(0.68)	(-0.58)	(4.41)	(-0.13)	(-6.85)
σ	0.39	0.27	0.22	0.19	0.17	0.15	0.14	0.16	0.15	0.14	0.13	0.14	0.15	0.16
skew	-0.33	0.10	0.18	0.19	0.03	0.04	0.14	0.10	-0.22	0.03	-0.06	0.02	-0.13	-0.14

	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
min	-4.05	-4.62	-1.99	-2.19	-1.79	-2.03	-1.96	-4.47	-6.76	-2.69	-0.91	-1.28	-3.13	-1.57
Idiosyncratic Volatility														
$\bar{r}$	-8.14***	3.18***	2.69***	1.05***	1.23***	0.23	0.50**	-0.01	0.29	0.42*	0.33	0.47*	0.83***	-1.35***
	(-10.05)	(6.70)	(6.56)	(3.17)	(4.55)	(0.90)	(2.30)	(-0.04)	(1.32)	(1.77)	(1.31)	(1.83)	(2.99)	(-4.46)
α	-5.89***	2.73***	2.16***	1.19***	1.12***	0.25	0.44**	0.20	0.42**	0.29	0.12	0.78***	1.16***	-1.29***
	(-9.09)	(6.68)	(6.32)	(4.27)	(4.77)	(1.17)	(2.36)	(1.07)	(2.28)	(1.40)	(0.55)	(3.48)	(5.03)	(-4.63)
σ	0.71	0.41	0.36	0.29	0.24	0.22	0.19	0.18	0.19	0.21	0.22	0.23	0.24	0.27
skew	-0.64	0.61	-0.01	0.19	0.53	-0.14	0.37	0.19	0.09	0.04	-0.54	0.03	-0.12	-0.01
min	-7.24	-5.84	-3.02	-2.90	-1.95	-2.16	-1.57	-1.42	-4.48	-5.77	-4.67	-2.18	-3.36	-2.92
Illiquidity														
$\bar{r}$	-0.15	-0.69**	0.13	-0.67***	-0.04	-0.10	-0.08	-0.32	0.10	0.11	0.36*	-0.12	0.04	2.24***
	(-0.32)	(-2.19)	(0.46)	(-2.70)	(-0.19)	(-0.53)	(-0.46)	(-1.53)	(0.58)	(0.60)	(1.89)	(-0.57)	(0.19)	(8.02)
α	0.79*	-0.83***	-0.06	-0.58**	-0.12	-0.10	-0.12	-0.09	0.18	0.03	0.22	0.13	0.27	2.30***
	(1.92)	(-2.70)	(-0.21)	(-2.58)	(-0.63)	(-0.54)	(-0.72)	(-0.57)	(1.20)	(0.15)	(1.27)	(0.70)	(1.40)	(8.77)
σ	0.41	0.28	0.25	0.22	0.19	0.16	0.15	0.18	0.15	0.16	0.17	0.18	0.20	0.24
skew	-0.13	-0.30	-0.18	-0.41	-0.07	-0.22	-0.08	-0.22	-0.10	-0.18	-0.22	0.03	-0.14	0.42
min	-11.15	-3.90	-2.92	-4.35	-4.13	-1.44	-1.64	-8.72	-3.01	-3.94	-1.94	-3.19	-1.42	-2.25
Momentum														
$\bar{r}$	6.41***	-0.35	-0.60	0.06	0.36	0.30	-0.12	-0.12	-0.38*	0.04	-0.12	0.06	-0.50*	-0.53*
	(8.04)	(-0.72)	(-1.48)	(0.17)	(1.22)	(1.11)	(-0.51)	(-0.52)	(-1.72)	(0.18)	(-0.49)	(0.23)	(-1.83)	(-1.79)
α	6.58***	-0.39	-0.60	0.05	0.38	0.30	-0.12	-0.17	-0.36*	0.04	-0.13	0.05	-0.50*	-0.54*
	(8.31)	(-0.81)	(-1.47)	(0.15)	(1.27)	(1.11)	(-0.51)	(-0.76)	(-1.66)	(0.17)	(-0.49)	(0.18)	(-1.83)	(-1.82)
σ	0.70	0.43	0.35	0.31	0.26	0.24	0.21	0.20	0.19	0.20	0.22	0.23	0.24	0.26
skew	-0.27	-0.32	-0.38	-0.32	-0.49	-0.30	-0.10	-0.27	-0.36	-0.17	-0.16	0.19	-0.58	-0.71
min	-12.40	-5.95	-3.43	-3.58	-2.63	-3.80	-2.43	-2.51	-2.15	-3.57	-2.91	-2.79	-3.51	-2.99
Net Stock Issues														
$\bar{r}$	-2.75***	1.52***	1.47***	0.89***	0.24	0.49***	-0.06	0.40***	-0.14	0.31**	0.34**	0.47***	-0.27	-1.66***
	(-6.39)	(5.48)	(6.42)	(4.54)	(1.44)	(3.16)	(-0.39)	(2.62)	(-1.02)	(2.13)	(2.34)	(3.04)	(-1.64)	(-9.03)
α	-2.35***	1.44***	1.38***	0.90***	0.23	0.49***	-0.06	0.40***	-0.12	0.28**	0.31**	0.52***	-0.21	-1.66***
	(-5.56)	(5.25)	(6.14)	(4.64)	(1.36)	(3.19)	(-0.45)	(2.78)	(-0.90)	(1.98)	(2.15)	(3.36)	(-1.34)	(-9.02)
σ	0.38	0.24	0.20	0.17	0.15	0.14	0.12	0.13	0.12	0.13	0.13	0.13	0.14	0.16
skew	-0.01	0.05	0.05	0.20	0.13	0.27	-0.06	0.21	-0.34	0.10	0.07	0.30	-0.56	-0.19
min	-3.04	-2.77	-1.89	-1.53	-1.35	-1.06	-1.39	-1.49	-1.17	-3.69	-1.75	-1.02	-1.93	-1.71
Size														
$\bar{r}$	-0.35	-1.21***	-0.28	-0.67***	-0.11	-0.01	-0.01	-0.18	0.09	0.06	0.20	-0.16	-0.11	3.13***
	(-0.83)	(-4.13)	(-1.07)	(-2.82)	(-0.56)	(-0.08)	(-0.04)	(-0.86)	(0.53)	(0.30)	(1.05)	(-0.78)	(-0.49)	(10.85)
α	0.52	-1.37***	-0.51**	-0.57***	-0.20	-0.01	-0.05	0.05	0.18	-0.04	0.03	0.13	0.13	3.20***
	(1.45)	(-4.91)	(-2.07)	(-2.75)	(-1.13)	(-0.04)	(-0.32)	(0.29)	(1.25)	(-0.23)	(0.19)	(0.76)	(0.72)	(11.92)
σ	0.37	0.25	0.23	0.21	0.18	0.16	0.15	0.18	0.15	0.17	0.16	0.18	0.20	0.25
skew	-0.27	-0.26	-0.26	-0.45	-0.21	-0.05	-0.19	-0.35	-0.19	-0.41	-0.29	-0.12	-0.07	0.48
min	-11.55	-3.47	-2.49	-3.85	-3.55	-1.33	-1.98	-7.26	-2.44	-6.59	-1.65	-3.32	-1.92	-2.16

Table 4. Intraday and overnight alphas in basis points of long-short portfolios using volume-weighted average prices at the open. Overnight returns (OV) are computed using the volume-weighted average price (VWAP) for each stock in the first half-hour of trading. To be included, a stock is required to have a share volume greater than 1,000 in the first half-hour of trading on at least 95% of the days in a given quarter (using days for which the stock has a valid CRSP daily return). 9:30 indicates the return on the first interval, which is computed using the VWAP opening price as described above and the current midquote at 10:00 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. 3:30 indicates the half-hour interval that starts at 3:00 p.m. and ends before 4:00 p.m. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2: accruals (AC), beta (BE), book-to-market (BM), gross profitability (GP), idiosyncratic volatility (IV), illiquidity (IL), momentum (MO), net stock issues (NI), and size (SI). Portfolios are value-weighted and held for one month. A stock is required to have a price greater than $10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolio. Stock returns are computed using quote midpoints. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Alphas relative to the market

	AC	BE	BM	GP	IV	IL	MO	NI	SI
OV	0.63	-5.43***	-2.92***	-0.16	-5.48***	0.71	6.81***	-2.96***	2.28***
	(1.24)	(-7.17)	(-4.62)	(-0.31)	(-7.78)	(1.23)	(8.01)	(-5.19)	(3.86)
9:30	0.51*	2.47***	0.96**	-0.35	1.21***	2.58***	-0.38	1.26***	1.05**
	(1.73)	(6.26)	(2.15)	(-1.36)	(3.60)	(5.77)	(-1.03)	(2.96)	(2.39)
10:00	0.09	0.95***	0.32	0.42	2.39***	-0.85***	-0.79*	1.49***	-1.98***
	(0.33)	(3.03)	(1.07)	(1.49)	(6.48)	(-2.85)	(-1.88)	(6.02)	(-6.35)
3:30	-0.26	-0.65**	0.57*	-1.12***	-1.05***	2.15***	-0.67**	-1.42***	2.50***
	(-1.08)	(-2.18)	(1.94)	(-5.39)	(-3.40)	(8.01)	(-2.10)	(-6.81)	(8.80)

(b) Alphas relative to the market and a size factor

	AC	BE	BM	GP	IV	IL	MO	NI
OV	0.74	-5.05***	-2.76***	-0.13	-4.99***	0.02	6.79***	-2.88***
	(1.46)	(-7.02)	(-4.43)	(-0.26)	(-7.79)	(0.05)	(7.99)	(-5.07)
9:30	0.54*	2.79***	1.02**	-0.35	1.51***	1.66***	-0.33	1.29***
	(1.80)	(7.52)	(2.27)	(-1.38)	(4.84)	(7.46)	(-0.89)	(3.03)
10:00	-0.04	0.31	0.40	0.35	1.41***	0.52**	-0.76*	1.20***
	(-0.15)	(0.88)	(1.33)	(1.24)	(4.20)	(2.54)	(-1.78)	(4.93)
3:30	-0.10	-0.11	0.45	-1.06***	0.13	0.27*	-0.65**	-0.99***
	(-0.42)	(-0.36)	(1.52)	(-5.08)	(0.47)	(1.67)	(-2.03)	(-4.84)

Table 5. Intraday and overnight alphas in basis points of long (α_L) and short (α_S) portfolios. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2. Portfolios are value-weighted and held for one month. A stock is required to have a price greater than $10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolios. Stock returns are computed using quote midpoints. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight return. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Beta														
α_L	0.35	0.89***	0.45***	-0.03	0.09	0.08	0.04	0.07	0.17**	-0.03	0.19*	-0.02	0.10	0.26**
	(1.26)	(4.91)	(2.93)	(-0.25)	(0.86)	(0.84)	(0.50)	(0.82)	(2.00)	(-0.28)	(1.89)	(-0.22)	(0.99)	(2.24)
α_S	3.66***	-0.84***	-0.36	-0.44**	-0.21	-0.29*	-0.32**	-0.19	-0.39***	-0.18	-0.30**	-0.34**	-0.37**	0.42**
	(7.73)	(-2.69)	(-1.50)	(-2.20)	(-1.28)	(-1.85)	(-2.36)	(-1.38)	(-2.95)	(-1.26)	(-2.10)	(-2.32)	(-2.24)	(2.25)
Gross Profitability														
α_L	1.46***	-0.07	-0.00	0.37***	0.22*	0.13	0.23**	0.03	0.08	0.00	-0.05	0.47***	0.17	-0.12
	(4.66)	(-0.37)	(-0.00)	(2.67)	(1.82)	(1.21)	(2.32)	(0.26)	(0.61)	(0.03)	(-0.53)	(4.50)	(1.52)	(-1.05)
α_S	2.22***	-0.86***	-0.48***	-0.42***	-0.16	-0.27**	-0.17	-0.07	-0.04	-0.10	0.04	-0.23**	0.19	1.11***
	(8.04)	(-3.91)	(-2.78)	(-2.95)	(-1.25)	(-2.23)	(-1.54)	(-0.60)	(-0.38)	(-1.00)	(0.36)	(-2.16)	(1.62)	(8.71)
Idiosyncratic Volatility														
α_L	-0.21	0.83***	0.65***	0.23**	0.43***	-0.01	0.05	0.03	0.20***	0.07	0.07	0.18**	0.34***	-0.25**
	(-0.92)	(5.15)	(4.90)	(2.08)	(4.52)	(-0.11)	(0.58)	(0.45)	(2.67)	(0.87)	(0.85)	(1.98)	(3.56)	(-2.23)
α_S	5.68***	-1.90***	-1.51***	-0.96***	-0.69***	-0.26	-0.40***	-0.16	-0.22	-0.22	-0.05	-0.60***	-0.82***	1.04***
	(11.27)	(-6.22)	(-5.97)	(-4.60)	(-3.92)	(-1.63)	(-2.79)	(-1.17)	(-1.58)	(-1.44)	(-0.29)	(-3.62)	(-4.77)	(5.01)
Net Stock Issues														
α_L	0.87***	0.63***	0.28*	0.26**	0.05	0.29***	-0.16*	0.26**	-0.08	0.14	0.16*	0.22**	-0.33***	-0.74***
	(2.91)	(3.18)	(1.78)	(1.98)	(0.47)	(2.66)	(-1.72)	(2.57)	(-0.85)	(1.35)	(1.67)	(2.07)	(-2.95)	(-5.52)
α_S	3.22***	-0.81***	-1.11***	-0.64***	-0.17	-0.20*	-0.10	-0.14	0.04	-0.15	-0.14	-0.29**	-0.11	0.92***
	(10.66)	(-4.08)	(-6.74)	(-4.58)	(-1.43)	(-1.77)	(-0.94)	(-1.34)	(0.43)	(-1.37)	(-1.36)	(-2.55)	(-0.94)	(6.63)

Table 6. Earnings announcement months versus non-announcements months. For each portfolio, the following regression is estimated: $\hat{e}_t = \sum_k \delta_k 1_{k,t} + \sum_k \delta_{\mathrm{EA},k} 1_{k,t} 1_{\mathrm{EA},t} + u_t$, where $\hat{e}_t$ is the portfolio's market residual in interval t (in basis points), $1_{k,t}$ is a dummy variable that equals one in interval k, and $1_{\mathrm{EA},t}$ is a dummy variable that equals one during earnings announcement months (January, February, April, May, July, August, October, and November). All the variables are normalized by the volatility of residuals in interval t. Market residuals are estimated separately for each interval of the day. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2: accruals (AC), beta (BE), book-to-market (BM), gross profitability (GP), idiosyncratic volatility (IV), illiquidity (IL), momentum (MO), net stock issues (NI), and size (SI). Portfolios are value-weighted and held for one month. A stock is required to have a price greater than $10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolio. Stock returns are computed using quote midpoints. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight period. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

							$\delta_{\mathrm{EA},k}$							
k	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
AC	-0.89	0.55	-0.13	-0.25	0.21	0.46	0.07	-0.22	0.26	0.15	0.18	0.74**	-0.84**	0.54
	(-0.89)	(0.84)	(-0.25)	(-0.57)	(0.54)	(1.23)	(0.22)	(-0.65)	(0.84)	(0.49)	(0.55)	(2.19)	(-2.25)	(1.29)
BE	-0.81	0.75	0.35	-0.98*	-0.43	-0.31	-0.61	-0.63	-0.28	-0.33	-0.83**	-0.11	0.57	0.21
	(-0.62)	(0.85)	(0.51)	(-1.76)	(-0.92)	(-0.72)	(-1.55)	(-1.64)	(-0.76)	(-0.83)	(-2.03)	(-0.26)	(1.25)	(0.41)
BM	-0.46	0.41	-0.04	-0.04	-0.10	-0.20	-0.15	-0.50	0.25	0.41	-0.20	-0.13	-0.21	0.45
	(-0.45)	(0.58)	(-0.07)	(-0.08)	(-0.24)	(-0.50)	(-0.41)	(-1.49)	(0.73)	(1.21)	(-0.55)	(-0.35)	(-0.53)	(0.97)
GP	0.30	0.69	0.80	-0.32	-0.43	0.69*	-0.24	0.08	-0.68*	-0.01	0.16	0.55	0.10	0.12
	(0.32)	(1.04)	(1.49)	(-0.70)	(-1.07)	(1.89)	(-0.71)	(0.22)	(-1.86)	(-0.02)	(0.48)	(1.64)	(0.27)	(0.31)
IV	-0.87	0.07	0.77	0.20	-0.33	-0.07	-0.35	0.52	0.20	-0.57	-0.51	-0.42	0.60	-0.03
	(-0.64)	(0.08)	(1.07)	(0.34)	(-0.67)	(-0.16)	(-0.87)	(1.33)	(0.51)	(-1.32)	(-1.12)	(-0.89)	(1.22)	(-0.05)
IL	-1.69*	-1.60**	-0.28	-1.35***	0.02	-0.06	-0.24	-0.75**	0.01	0.26	0.07	-0.47	-0.15	-1.05*
	(-1.90)	(-2.45)	(-0.49)	(-2.82)	(0.05)	(-0.17)	(-0.69)	(-1.97)	(0.03)	(0.74)	(0.20)	(-1.22)	(-0.35)	(-1.89)
MO	-3.45**	-0.18	-1.61*	-1.30*	-1.23*	-1.36**	-0.14	-0.40	-0.46	-0.45	-0.63	0.25	-0.06	0.01
	(-2.05)	(-0.17)	(-1.88)	(-1.72)	(-1.95)	(-2.37)	(-0.28)	(-0.82)	(-0.98)	(-0.92)	(-1.17)	(0.46)	(-0.10)	(0.01)
NI	-1.34	0.23	0.05	0.66	0.48	0.40	-0.03	0.58*	-0.21	0.29	0.50*	0.93***	0.35	0.05
	(-1.51)	(0.40)	(0.10)	(1.61)	(1.36)	(1.22)	(-0.12)	(1.78)	(-0.74)	(0.96)	(1.67)	(2.88)	(1.03)	(0.12)
SI	-1.12	-1.49**	-0.27	-0.75*	0.00	-0.11	-0.15	-0.74*	-0.08	0.25	-0.01	-0.35	-0.04	-1.12**
	(-1.42)	(-2.53)	(-0.51)	(-1.70)	(0.01)	(-0.33)	(-0.46)	(-1.95)	(-0.25)	(0.70)	(-0.02)	(-0.99)	(-0.11)	(-1.96)

Table 7. Scheduled FOMC announcement days versus non-announcements days. For each portfolio, the following regression is estimated: $r_t = \sum_k \delta_k 1_{k,t} + \sum_k \delta_{\text{FOMC},k} 1_{k,t} 1_{\text{FOMC},t} + u_t$, where r_t is the portfolio return in interval t (in basis points), $1_{k,t}$ is a dummy variable that equals one in interval k, and $1_{\text{FOMC},t}$ is a dummy variable that equals one on scheduled FOMC announcement days. All the variables are normalized by return volatility in interval t. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2: accruals (AC), beta (BE), book-to-market (BM), gross profitability (GP), idiosyncratic volatility (IV), illiquidity (IL), momentum (MO), net stock issues (NI), and size (SI), plus the market (MK). Portfolios are value-weighted and held for one month. A stock is required to have a price greater than $10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolio. Stock returns are computed using quote midpoints. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight period. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1994, to December 31, 2015. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

$\delta_{\text{FOMC},k}$

k	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
MK	6.02***	2.76*	1.23	2.09*	-0.11	2.40**	1.88*	0.98	-0.18	5.67***	-0.65	-1.11	4.43	0.98
	(3.49)	(1.84)	(0.97)	(1.76)	(-0.10)	(2.22)	(1.76)	(0.86)	(-0.14)	(4.14)	(-0.39)	(-0.60)	(1.17)	(0.57)
AC	3.71	-1.25	1.24	-0.29	1.18	0.55	-0.61	1.03	1.08	-0.34	0.98	0.00	-2.87**	-1.73
	(1.14)	(-0.57)	(0.74)	(-0.21)	(0.98)	(0.47)	(-0.61)	(1.09)	(1.17)	(-0.36)	(1.02)	(0.00)	(-2.45)	(-1.33)
BE	-12.72	-6.01	-10.29***	-8.80***	-1.03	-5.93**	-0.87	-2.73	-4.73**	-2.73	7.65***	-7.90***	4.60*	-1.47
	(-1.61)	(-1.40)	(-2.68)	(-2.84)	(-0.40)	(-2.54)	(-0.42)	(-1.40)	(-2.25)	(-1.21)	(3.20)	(-3.18)	(1.71)	(-0.51)
BM	-1.11	-2.59	-1.47	0.10	-1.27	-2.09	0.72	-1.04	0.77	0.09	0.14	1.27	0.94	-0.49
	(-0.31)	(-1.10)	(-0.71)	(0.06)	(-0.90)	(-1.59)	(0.60)	(-0.95)	(0.67)	(0.07)	(0.11)	(0.96)	(0.66)	(-0.31)
GP	-1.03	2.31	0.02	-0.56	-0.47	-1.73	-0.38	0.54	0.11	-0.31	-0.79	-3.19***	1.24	1.03
	(-0.34)	(1.02)	(0.01)	(-0.37)	(-0.36)	(-1.46)	(-0.36)	(0.52)	(0.11)	(-0.30)	(-0.77)	(-2.97)	(1.05)	(0.85)
IV	-5.39	-0.81	-7.11**	-5.76**	-1.71	-3.10*	0.14	-0.39	-1.74	0.34	3.21*	-2.36	0.28	-0.03
	(-0.89)	(-0.23)	(-2.30)	(-2.34)	(-0.86)	(-1.67)	(0.09)	(-0.27)	(-1.10)	(0.19)	(1.74)	(-1.25)	(0.14)	(-0.02)
IL	4.39	0.73	-0.18	0.87	-0.24	-0.74	1.47	-1.10	-1.35	-0.30	1.19	-1.34	0.65	2.12
	(1.52)	(0.33)	(-0.10)	(0.56)	(-0.18)	(-0.59)	(1.25)	(-1.00)	(-1.19)	(-0.27)	(0.94)	(-0.99)	(0.44)	(1.13)
MO	0.16	-2.03	-1.90	-3.19	-0.28	1.55	-2.82	0.95	-0.26	1.27	3.67*	-0.62	2.36	3.46
	(0.03)	(-0.56)	(-0.63)	(-1.21)	(-0.13)	(0.77)	(-1.62)	(0.61)	(-0.16)	(0.75)	(1.96)	(-0.33)	(1.17)	(1.61)
NI	-2.25	-1.19	-2.26	-0.85	-0.34	0.68	0.90	-0.23	-0.39	0.79	0.20	-0.87	-2.16*	-1.73
	(-0.73)	(-0.60)	(-1.42)	(-0.64)	(-0.30)	(0.64)	(0.98)	(-0.24)	(-0.44)	(0.80)	(0.21)	(-0.86)	(-1.96)	(-1.37)
SI	0.49	0.38	-1.04	1.39	-0.73	-0.74	1.61	-1.46	-1.55	-0.74	1.53	-2.39*	1.07	3.17
	(0.20)	(0.19)	(-0.59)	(0.91)	(-0.56)	(-0.61)	(1.41)	(-1.36)	(-1.37)	(-0.65)	(1.23)	(-1.76)	(0.72)	(1.59)

Table 8. Intraday (IN) and overnight (OV) average returns in basis points of aggregate portfolios for different measures of the opening price. The table also reports the correlation (corr) between overnight and intraday returns. Stocks are allocated into micro, small, and large value-weighted portfolios based on the 20^{th} and 50^{th} percentiles of NYSE market capitalization each year at the end of June. Opening prices are computed using the first trade of the day (trade), the first quote of the day after 9:35 (quote), and the volume-weighted average price in the first half-hour of trading (VWAP). Each stock is required to have a share volume greater than 1,000 in the first half-hour of trading on at least 95% of the days in a given quarter (using days for which the stock has a valid CRSP daily return). The sample is composed of NYSE, Amex, and NASDAQ common stocks. NASDAQ stocks are included since 1993. A stock is required to have a price greater than $5 and a market capitalization greater than $100 million at the end of the previous quarter to be included. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	10/1985-1992			1993-2004			2005-2015		
	OV	IN	corr	OV	IN	corr	OV	IN	corr
Large									
trade	3.30**	3.43*	0.06	5.83***	-1.07	-0.02	2.90**	0.68	0.05
	(2.18)	(1.66)		(5.74)	(-0.62)		(2.20)	(0.36)	
quote	5.03***	1.69	-0.02	5.47***	-0.76	-0.02	2.82**	0.74	0.05
	(3.19)	(0.84)		(5.22)	(-0.45)		(2.12)	(0.40)	
VWAP	0.69	6.12***	-0.06	3.25***	1.59	0.03	2.02	1.45	0.13
	(0.42)	(2.89)		(3.11)	(0.94)		(1.55)	(0.81)	
Small									
trade	5.08***	1.08	0.12	8.75***	-3.26*	0.12	2.81**	1.61	0.08
	(3.89)	(0.54)		(10.17)	(-1.77)		(2.07)	(0.69)	
quote	6.47***	-0.30	0.12	7.71***	-2.26	0.08	2.30	2.11	0.03
	(4.49)	(-0.15)		(7.79)	(-1.27)		(1.55)	(0.93)	
VWAP	1.65	4.27**	0.06	4.78***	0.40	0.07	0.21	3.94*	0.12
	(1.06)	(2.09)		(4.41)	(0.22)		(0.14)	(1.79)	
Micro									
trade	8.26***	-2.62	0.06	11.99***	-3.59	0.06	4.70***	1.00	0.10
	(4.94)	(-1.06)		(10.76)	(-1.55)		(3.34)	(0.38)	
quote	8.98***	-3.33	0.06	11.51***	-3.25	0.03	4.53***	1.13	0.07
	(4.97)	(-1.38)		(9.01)	(-1.46)		(3.05)	(0.44)	
VWAP	3.12	2.83	-0.00	8.66***	-1.99	0.02	0.83	3.28	0.13
	(1.58)	(1.18)		(5.74)	(-0.82)		(0.55)	(1.32)	

Table 9. Intraday and overnight alphas (α) in basis points of long-short portfolios with volume filter. Each year, a stock is required to have trades in the first, second, second to last, and last half-hours of the trading day on at least 90% of the days for which it has a valid CRSP daily return. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A2. Portfolios are value-weighted and held for one month. A stock is required to have a price greater than \$10 at the end of the previous month and at least ten days with non-zero volume in the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. NASDAQ stocks are excluded from the illiquidity portfolio. Stock returns are computed using quote midpoints. The first interval starts at 9:35 a.m. 10:00 indicates the half-hour interval that starts at 10:00 a.m. and ends before 10:30 a.m. OV indicates the overnight return. The sample is composed of NYSE, Amex, and NASDAQ common stocks from October 1, 1985, to December 31, 2015. NASDAQ stocks are included since 1993. Standard t-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:35	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Accruals														
α	0.02	1.22***	0.13	0.04	-0.47**	0.14	0.19	0.30*	-0.18	-0.20	0.18	0.11	-0.42**	-0.36*
	(0.03)	(3.76)	(0.52)	(0.17)	(-2.44)	(0.72)	(1.15)	(1.86)	(-1.16)	(-1.24)	(1.11)	(0.66)	(-2.21)	(-1.72)
Beta														
α	-4.65***	1.48***	0.80**	0.57**	0.11	0.25	0.35*	0.24	0.67***	0.17	0.41*	0.48**	0.39	-0.32
	(-7.27)	(3.42)	(2.30)	(1.99)	(0.47)	(1.12)	(1.75)	(1.27)	(3.57)	(0.83)	(1.88)	(2.17)	(1.64)	(-1.15)
Book-to-market														
α	-2.89***	0.89***	0.39	-0.31	-0.20	0.10	0.00	0.24	0.51***	0.01	0.05	-0.03	0.18	0.77***
	(-5.74)	(2.66)	(1.37)	(-1.31)	(-1.00)	(0.52)	(0.00)	(1.44)	(2.75)	(0.06)	(0.27)	(-0.14)	(0.88)	(3.09)
Gross Profitability														
α	-1.10**	0.68**	0.37	0.73***	0.38*	0.36*	0.35**	0.18	0.11	0.09	-0.12	0.80***	-0.13	-1.15***
	(-2.30)	(2.03)	(1.34)	(3.13)	(1.83)	(1.89)	(2.03)	(0.92)	(0.52)	(0.54)	(-0.74)	(4.43)	(-0.68)	(-5.71)
Idiosyncratic Volatility														
α	-6.72***	2.12***	1.86***	0.71**	0.90***	0.05	0.20	0.20	0.30	0.22	0.04	0.78***	0.95***	-0.83***
	(-10.72)	(5.17)	(5.38)	(2.53)	(3.73)	(0.23)	(1.02)	(1.03)	(1.60)	(1.10)	(0.20)	(3.46)	(4.05)	(-2.92)
Illiquidity														
α	1.48***	-0.27	-0.31	-0.63***	-0.04	0.08	0.05	-0.04	0.23	-0.07	0.18	0.01	0.15	2.09***
	(3.56)	(-0.82)	(-1.12)	(-2.64)	(-0.18)	(0.38)	(0.29)	(-0.25)	(1.36)	(-0.42)	(0.94)	(0.04)	(0.75)	(7.88)
Momentum														
α	6.55***	-0.90*	-0.94**	-0.03	0.27	0.19	-0.30	-0.13	-0.40*	0.02	-0.17	0.05	-0.63**	-0.67**
	(8.44)	(-1.83)	(-2.33)	(-0.09)	(0.90)	(0.70)	(-1.25)	(-0.58)	(-1.77)	(0.09)	(-0.64)	(0.17)	(-2.23)	(-2.21)
Net Stock Issues														
α	-2.59***	1.63***	1.43***	0.75***	0.31*	0.48***	-0.09	0.38**	-0.18	0.21	0.28*	0.54***	-0.17	-1.48***
	(-5.73)	(5.51)	(5.88)	(3.55)	(1.74)	(2.84)	(-0.59)	(2.32)	(-1.21)	(1.34)	(1.79)	(3.23)	(-0.98)	(-7.37)
Size														
α	3.03***	-1.53***	-0.88***	-0.25	0.04	0.31	0.25	0.05	0.29*	0.10	0.20	-0.10	0.04	2.61***
	(7.52)	(-4.79)	(-3.21)	(-1.08)	(0.17)	(1.61)	(1.39)	(0.28)	(1.70)	(0.57)	(1.02)	(-0.47)	(0.19)	(9.41)

Appendix

Reversals in Midquote Returns

Spurious reversals plague midquote returns computed from TAQ. These reversals are especially prevalent across small stocks in the second part of the sample. Table A1 illustrates the problem for a randomly selected stock by showing the first and last available intraday quotes on several dates.

Table A1. First and last available intraday quotes for symbol IT on several dates extracted from the TAQ database.

Date	Time	Bid	Ask	Bid Size	Ask Size
2005-10-11	15:59:50.0	11.38	11.39	5	5
2005-10-12	9:30:54.0	11.03	16.03	1	1
	9:34:57.0	11.3	11.36	1	1
	⋮				
2005-10-12	15:59:42.0	11.3	11.31	2	23
2005-10-13	9:30:31	10.35	13.67	30	1
	9:30:32	10.35	14.38	30	1
	9:30:33	10.35	15.09	30	1
	9:32:19	11.24	11.25	2	1

As can be seen in the table, the best ask at the open can be biased. A high ask generates a large overnight return and a negative first half-hour return (i.e., spurious reversal). Furthermore, even the second and third quoted ask prices can be too high. The best bid is subject to similar problems. It takes a few minutes for the quotes to stabilize to what appears to be their normal level. Note that there is a nonzero trade size at both bid and ask quotes. The criterion of Berkman et al. (2012) of taking the first valid quote (i.e., with nonzero trade size on both bid and ask) does not seem sufficient. Numerous similar examples can be found for stocks that display more frequent quote updates. At the same time, genuine reversals also take place over the first half hour of trading.

To deal with these spurious reversals, I use the following criteria. First, I only consider quotes after 9:35. This threshold is based on an empirical investigation of many spurious reversals. For all stocks that have quote updated on a regular basis, I find that quotes seem to have normalized by 9:35. Second, I always delete the first quote available during the day. It is often the case that this quote is biased. This restriction is important for stocks whose first available quote is released after 9:35. Third, I delete any observation for which the spread is larger than 30 times the median spread during the day. This restriction helps exclude outliers that may have passed the other filters.

A Model of Infrequent Rebalancing

This section details a variant of the model in Bogousslavsky (2016). Consider a discrete time infinite horizon economy. N assets pay at every time t a vector of dividends $D_t \sim \mathcal{N}(0, \Sigma_D)$, where Σ_D is the variance-covariance matrix. A risk-free asset that pays a gross return R_f at every time t is available in perfectly elastic supply.

There are two groups of traders in the economy. First, frequent traders are present in the market every period and maximize their exponential utility over total wealth at the end of their investment horizon h. Second, infrequent traders rebalance their portfolio every k period. When they rebalance, these traders maximize their exponential utility over total wealth in k periods. Dividends received when infrequent traders are out of the market are reinvested at the risk-free rate. When they rebalance at time t, these traders are subject to endowment shocks that are proportional to the cumulative payoff over their rebalancing horizon:

$$\theta_t' \left(P_{t+k} + \sum_{i=1}^{k} R^{k-i} D_{t+i} \right), \tag{A1}$$

where $\theta_t \sim \mathcal{N}(0, \Sigma_\theta)$. This structure of endowment shocks is chosen for simplicity. Both groups of traders are assumed to have a coefficient of absolute risk aversion equal to γ.

Let $h - j$ be the remaining horizon of a frequent trader ($0 \leq j \leq h-1$). Her optimization problem is then given by

$$\begin{aligned} &\max_{X_{t,j}^F} \mathbb{E}_t \left[-e^{-\gamma_F W_{t+h-j}^F} \right], \\ \text{s.t.} \quad & W_{t+1}^F = (X_{t,j}^F)' \left(P_{t+1} + D_{t+1} - RP_t \right) + RW_t^F, \end{aligned}$$

where X_t^F is the vector of asset demands, P_t is the vector of asset prices at time t, and W_t^F is the initial wealth. The expectation is taken with respect to an information set that is common to all traders and includes the current and past levels of all variables. Infrequent traders optimize the following problem:

$$\begin{aligned} &\max_{X_t^I} \mathbb{E}_t \left[-e^{-\gamma_I W_{t+k}^I} \right], \\ \text{s.t.} \quad & W_{t+k}^I = (X_t^I + \theta_t)' \left(P_{t+k} + \sum_{j=1}^{k} R^{k-j} D_{t+j} \right) + R^k (W_t^I - (X_t^I)' P_t), \end{aligned}$$

where W_t^I is initial wealth.

Let a calendar cycle be composed of C calendar periods. For example, if time t is calendar period 1, then time $t+1$ is calendar period 2, and so on. In the context of this paper, a calendar period should be interpreted as a specific period of the day (for instance, the close). Let the function $c(t)$ denote the calendar period at time t.

In what follows, I assume that infrequent traders rebalance once per calendar cycle; hence, $k = C$ and the mass of infrequent traders rebalancing is constant in a given calendar period. This assumption is not strictly necessary but simplifies the exposition. A mass q_j of infrequent traders rebalance their portfolio in calendar period $j = 1, \ldots, C$. The mass of frequent traders is fixed and equals $1 - q$, where $q = \sum_{j=1}^{C} q_j$. Let $R_t = P_t + D_t - R_f P_{t-1}$ denote the vector of (dollar) excess returns at time t.

The market-clearing condition at time t is

$$\left(\frac{1-\sum_{j=1}^{C} q_j}{h}\right)\sum_{j=0}^{h-1} X_{j,t}^F + q_{c(t)} X_t^I = \bar{S} - \sum_{i=1}^{C-1} q_{c(t-i)} X_{t-i}^I, \tag{A2}$$

where X_t^I is the demand vector of infrequent traders rebalancing at time t, and $\bar{S}$ is the vector of share supplies. Crucially, the demands of infrequent traders at time $t-i$, X_{t-i}^I $(i = 1, \dots, k)$, are subtracted from the available supplies at time t since these traders are out of the market.

In a linear stationary rational expectations equilibrium, if it exists, the vector of prices is

$$P_t = \bar{P}_{c(t)} + P_{\theta,c(t)}\theta_t + \sum_{i=1}^{C-1} P_{X_i,c(t)} X_{t-i}^I.$$

where the coefficient matrices are solutions to a system of nonlinear equations. The price impact matrix of endowment shocks, $P_{\theta,c}$, varies with the calendar period $c = 1, \dots, C$. The equilibrium coefficients can be computed in a similar way as in Bogousslavsky (2016) (see the proof of Proposition 3) with an adjustment to account for the fact that infrequent traders are subject to endowment shocks. In general, multiple equilibria exist. I focus on the "low volatility" equilibrium (see Bogousslavsky (2016) for a discussion).

The demand vector of myopic frequent traders at time t is

$$X_t^F = \frac{1}{\gamma}\Sigma_{c(t)}^{-1}\mathbb{E}_t[R_{t+1}], \tag{A3}$$

where γ is the coefficient of risk aversion, and Σ_j is the variance-covariance matrix of one-period ahead returns as of calendar period j, which is constant given the calendar period. One has that $\Sigma_j = P_{\theta,j'}\Sigma_\theta P_{\theta,j'}' + \Sigma_D$, where $P_{\theta,j'}$ is the price impact of supply shocks in the next calendar period (j'). From this expression and the previous equation it is clear that, all else equal, (myopic) frequent traders demand less of an asset the higher the price impact of supply shocks is in the next period. Assuming that $h = 1$ and using the previous expressions, the vector of expected excess returns in calendar period j, $\mathbb{E}[R_{t+1}|c(t) = j]$, is given by

$$\mathbb{E}[R_{t+1}|c(t) = j] = \frac{\gamma}{(1-q)}\left(P_{\theta,j'}\Sigma_\theta P_{\theta,j'}' + \Sigma_D\right)\bar{S}_q, \tag{A4}$$

where j' is the calendar period following j, and $\bar{S}_q =$ is the vector of average supplies available in the market, which is independent of the calendar period (because $k + 1 = C$). The expected excess return in a given calendar period is high when price impact in the next period is high. Equation (A4) also implies that the price of risk increases with price impact in the next period.

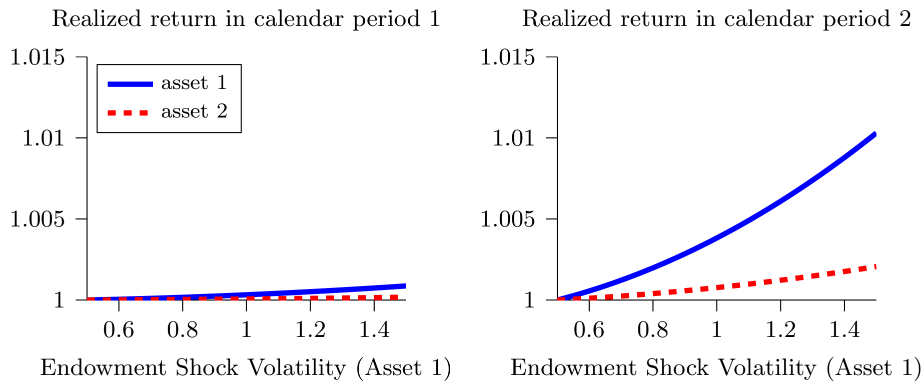
Conditional on the calendar period (and assuming $h = 1$), the CAPM holds:

$$\mathbb{E}[R_{i,t+1}|c(t) = j] = \beta_{i,j}\mathbb{E}[R_{m,t+1}|c(t) = j], \tag{A5}$$

where $R_{m,t+1}$ is the market excess return. Assuming that market betas do not vary substantially across calendar periods, the spread in expected return across assets is proportional to the expected excess return on the single factor. From the previous result, the factor realized excess return is larger when more traders rebalance.

As an example, consider two assets that only differ with respect to the volatility of the endowment shocks. Assume that there are two calendar periods and that infrequent traders rebalance every two periods (i.e., $k = C = 2$). Further assume that $q_2 > q_1$; that is, more traders rebalance in period 2 than in period 1. Figure A1 plots the realized excess return for each asset in both calendar periods as a function of the first asset's endowment shock volatility. Excess returns are normalized to one when both assets have the same endowment shock volatility (0.5) and are therefore identical. Since $q_1 > q_2$, the cross-sectional variance in realized returns is larger in calendar period 2 than calendar period 1. Turnover is also higher in the period during which more traders rebalance. Here, calendar period 2 can be interpreted as being around the close of the market.

Figure A1. Impact of infrequent rebalancing on realized returns. A larger proportion of traders rebalance their portfolio at the close, which leads to a larger cross-sectional variance in average returns at that time. Calibration: $R = 1.0001$, $\sigma_D = 0.2$, $\rho_D = 0.3$, $\sigma_\theta = 0.5$, $\bar{S} = 10$, $\gamma = 1$, $q_1 = 0.05$, $q_2 = 0.2$.



The previous model is not equivalent to a setup in which a frequent trader is subject to endowment shocks that are more volatile at the close (i.e., the diagonal elements of Σ_θ are higher at the close). In this setup, the vector of prices is given by $P_t = \bar{P}_{c(t)} + P_{\theta,c(t)}\theta_t$. Here, the endowment shocks can be equivalently interpreted as the exogenous supplies of liquidity traders. Assuming a myopic market maker, market-clearing requires $X_t^F = \bar{S} + \theta_t$, where X_t^F solves the same optimization problem as above (with $h = 1$). The following two conditions hold in equilibrium:

$$-RP_{\theta,j} = \gamma(P_{\theta,j'}\Sigma_{\theta,j'}P'_{\theta,j'} + \Sigma_D), \quad \text{and} \tag{A6}$$
$$\bar{P}_{j'} - R\bar{P}_j = \gamma(P_{\theta,j'}\Sigma_{\theta,j'}P'_{\theta,j'} + \Sigma_D)\bar{S}, \tag{A7}$$

where j' is the calendar period that follows j. Expected returns in calendar period j are then given by

$$\mathbb{E}[R_{i,t+1}|c(t) = j] = -RP_{\theta,j}\bar{S}. \tag{A8}$$

In the case of two calendar periods, it is direct to show that realized returns are higher in the period during which noise trading volatility is higher.

Proposition 1: *Consider a single-asset economy with a trader subject to endowment shocks $\theta_t \sim \mathcal{N}(0, \sigma_{\theta,c(t)})$, $c(t) = j, j'$. If $\sigma_{\theta,j'} > \sigma_{\theta,j}$, then*

1. $\mathbb{E}[R_{i,t+1}|c(t+1) = j'] > \mathbb{E}[R_{i,t+1}|c(t+1) = j]$.
2. $|P_{\theta,j}| < |P_{\theta,j'}|$.

This setup implies, however, that the price impact of endowment shocks is *lower* (in absolute value) in this period than in the other period. In the period with more volatile shocks, frequent traders know that the price is likely to reverse in the following period. This result is opposite to that in the infrequent rebalancing economy, in which it is more difficult for market makers to reverse their positions since infrequent traders are out of the market (and contrary to extant empirical evidence, as shown in Section 4.3.1).

The previous setup makes no prediction about trading volume with only two calendar periods. Since $V_t = |\theta_t - \theta_{t-1}|$, average volume is the same in both periods. Trading volume would be abnormally high at *both* the open and close even with multiple calendar periods, which is not consistent with the evidence from the intraday turnover of small stock relative to that of large stocks. Again, this is not the case in the infrequent rebalancing economy: Trading volume is higher when more traders rebalance, even with only two calendar periods.

Several caveats should be pointed out with respect to the empirical analysis in this paper. First, this setup does not explicitly model market closures (contrary to Hong and Wang (2000) and similarly to Slezak (1994)). Second, the rebalancing frequency is an exogenous parameter. More theoretical work is needed to solve for an equilibrium model along these lines with an endogenous rebalancing frequency. Relatedly, traders are competitive and perfectly informed. In this sense, this type of model is complementary to strategic models such as Admati and Pfleiderer (1988), which do not make predictions about average returns. Third, the model features a single risk factor. This seems in contrast with the anomalies studied in the paper. Hence, one has to assume, for instance, that a different mix of investors trade in large and small stocks. This assumption is consistent with available empirical evidence. It would be interesting for future work to consider how the infrequent rebalancing effect plays out in a model with multiple sources of risk (for example, with hedging demands arising from additional state variables).

Table A2. Description of the anomalies used in the paper. All the accounting variables are computed once a year at the end of June using data for the previous fiscal year.

Name	Sorting variable
Accruals	Change in working capital (excluding cash) minus depreciation, scaled by average total assets over the previous two years (Sloan, 1996). The strategy shorts stocks with high accruals.
Beta	Market beta for each stock estimated using daily returns over the past year. The market return is the value-weighted return of all stocks in the sample excluding stocks with a price below $5 and is rebalanced once a month. The strategy shorts stocks with high beta.
Book-to-market	Book equity over market value, where market value is the market capitalization of the firm six months ago. Stockholders' equity is computed as in Novy-Marx (2013) and negative BE firms are excluded from the portfolios.
Gross profitability	Revenue minus cost of good sold, divided by total assets (Novy-Marx, 2013). The strategy is long stocks with high gross prof.
Idiosyncratic volatility	Standard deviation of the residuals from regressing the stock's daily excess returns on Fama-French's three factors (Ang et al., 2006). A stock is required to have at least 17 valid returns in a month to be included. The strategy shorts stocks with high idiosyncratic volatility.
Illiquidity	Average ILLIQ over the past 250 trading days (Amihud, 2002). More precisely, $\text{ILLIQ}_{i,t} = \frac{1}{N_{i,t}} \sum_{d \in D_{i,t}} \frac{\lvert r_{i,d} \rvert}{\text{DVOL}_{i,d}} 10^6$, where $D_{i,t}$ is the set of trading days with trading volume for stock i in the past 250 business days before day t, and $N_{i,t}$ is their total number. DVOL is the dollar volume. A stock is required to have at least 100 trading days to be included. The strategy is long stocks with high ILLIQ.
Momentum	Return over the past twelve months skipping the last month (Jegadeesh and Titman, 1993).
Net stock issues	Growth rate of the split-adjusted shares outstanding at fiscal year end as in Fama and French (2008). The strategy shorts stocks with high net stock issues.
Size	Market capitalization in the previous month.