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The cross-section of intraday and overnight returns☆

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A R T I C L E I N F O

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A B S T R A C T

I investigate cross-sectional variation in stock returns over the trading day and overnight to shed light on what drives asset pricing anomalies. Margin requirements are higher overnight, and lending fees are typically charged only on positions held overnight. Such institutional constraints and overnight risk incentivize arbitrageurs who trade on mispricing to reduce their positions before the end of the day. Consistent with this intuition, a mispricing factor earns positive returns throughout the day but performs poorly at the end of the day. This pattern strengthens in the second half of the sample and is shared by several well-known anomalies.

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 generally rely on risk, mispricing, and data mining (McLean and Pontiff, 2016).[1]

This paper studies anomaly returns over the trading day and overnight to shed light on what drives cross-sectional return predictability.[2] I argue that a study of how anomalies accrue over the day provides a useful perspective to assess their determinants. My tests build on the following intuition: a capital-constrained arbitrageur who trades on mispricing faces specific costs to hold positions overnight. First, the arbitrageur is likely subject to higher capital constraints for overnight positions than for intraday positions.[3] In addition, the arbitrageur will in general not have to pay stock lending fees and margin interest on posi-

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[1] Surveys of risk-based and behavioral theories are provided by Cochrane (2011) and Barberis (2018), respectively. The impact of data mining on the discovery of anomalies is highlighted by Fama (1991) and, more recently, by Harvey et al. (2016).

[2] The overnight return is the return outside of regular trading hours (9:30 am–4:00 pm) and is therefore defined by the change from the closing price on a given day to the opening price on the next day.

[3] In the United States, most brokers offer a higher leverage (i.e., lower margin) intraday than overnight since they generally apply the margin requirements of Regulation T at the end of the day. For instance, Vanguard's margin investing guide states that "if you become a pattern day trader, Vanguard allows you to exceed your standard margin buying power, knowingly putting yourself into a margin call, with the expectation that the position will be closed within that same trading day" (http://vanguard.com/pdf/margin.pdf ; accessed on 3/6/2020).

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tions that are held only intraday.[4] I label these effects the *institutional constraints* channel. Second, holding positions overnight, an extended period of low trading, exposes the arbitrageur to substantial illiquidity and to the risk of large price moves (e.g., Brock and Kleidon, 1992). I label this effect the *overnight risk* channel. These channels push arbitrageurs to reduce their positions towards the end of the day. As long as mispriced stocks are not perfectly liquid, this trading activity is likely to generate price pressure.

The institutional constraints and overnight risk channels make specific predictions for the intraday return patterns of anomalies driven by mispricing. Mispricing should gradually correct over the day but may actually worsen at the end of the day as arbitrageurs close or reduce their positions. This causes overpriced stocks to outperform and underpriced stocks to underperform. Hence, strategies that bet on mispricing correction should do poorly at the end of the day.

To test this prediction, I consider the mispricing factor of Stambaugh et al. (2012, 2015). I compute intraday half-hour and overnight returns on all U.S. common stocks from January 1986 to December 2015 and examine how the mispricing factor accrues over the day. To attenuate microstructure issues, I compute returns from quote midpoints and focus on value-weighted portfolios formed with NYSE breakpoints. Strikingly, the mispricing factor earns a positive average return overnight and in every half hour of the trading day except the last one. Between 3:30pm and 4:00pm, the strategy earns an alpha of −2.43 basis points (bps) with a t-statistic of −10.09. In absolute value, this is larger than for any of the other periods, including overnight.

In the second half of the sample, markets have become increasingly dominated by market participants who are concerned about holding positions overnight. For instance, high-frequency traders are often identified by their willingness not to hold positions overnight (Menkveld, 2016). A greater focus on overnight risk suggests that we could observe stronger mispricing effects at the end of the day in recent years. Consistent with this intuition, I find that the end of the day mispricing effect is twice as large in the second half of the sample than in the first half. This result contrasts with the standard limits to arbitrage argument according to which mispricing disappears as markets become more efficient (Shleifer and Vishny, 1997; McLean and Pontiff, 2016). The “high-frequency” limits to arbitrage that I consider here are likely amplified in recent years and could help explain why some mispricing persists in an era of computerized trading.

Further consistent with the explanation, a positive 1% shock to the expected overnight volatility of the mispricing factor (estimated from overnight returns in the recent past) worsens mispricing by 26 bps at the end of the day on average. This effect is not observed for other intervals of the day and supports the idea that arbitrageurs react to changes in overnight risk. The weekend represents an extended non-trading period over which interest fees accrue and with the risk of large price moves. I find that mispricing worsens roughly four times as much at the end of the day on Friday than on Monday. In the cross-section of stocks, overnight systematic variance is positively related to overnight returns and negatively related to intraday returns, in line with overnight risk theories. Returns should be high overnight and low over the trading day to compensate traders for holding risky stocks overnight (Hong and Wang, 2000). More relevant for my explanation, mispriced stocks with high overnight risk tend to display increased mispricing at the end of the day.

Price pressure at the end of the day implies a lower correlation between end-of-day mispricing returns and following returns than between returns on other successive intervals. I find statistically significant evidence of (excess) reversal between 3:30–4:00pm returns and next day’s morning returns. In contrast, there is no evidence of reversal for 3:00–3:30 pm returns. Why do arbitrageurs not trade earlier in the day? I find that changes in spread, depth, and price impact around the end of the day provide at least a partial explanation. In addition, the end-of-day increase in mispricing is smaller than the percentage effective spread of mispriced stocks and thus cannot be profitably traded on its own (at least with market orders).

Finally, I also test the explanation using order imbalance and short-selling volume for a subsample of the data. Consistent with the Stambaugh et al. (2012, 2015) measure proxying for mispricing, overpriced (underpriced) stocks exhibit significantly higher (lower) short-selling volume over the day than other stocks.[5] Overpriced (underpriced) stocks tend to experience higher (lower) order imbalance at the end of the day relative to other stocks. Overpriced stocks that are hard to borrow (as measured by low institutional ownership) are likely to have high lending fees. These stocks experience a significant decline in short-selling volume at the end of the day relative to other overpriced stocks.

Next, I apply the above insights to individual anomaly portfolios to better understand what drives anomalies. Any explanation for an anomaly has to be able to accommodate the anomaly’s intraday return pattern. I consider a set of eight well-known anomalies (e.g., Fama and French, 2008, 2016) to which I add an illiquidity characteristic. Gross profitability, idiosyncratic volatility, and net stock issues display patterns that are similar to the mispricing factor. These anomalies earn consistently positive and statistically significant returns over the trading day but perform poorly in the last half hour of trading. This pattern is again stronger in recent years. This result suggests that mispricing plays an important role for these anomalies. Moreover, the patterns are unexplained by patterns in volatility and skewness over the day, which rules out simple risk-based explanations. Regarding the profitability anomaly, which is among the most prominent asset pricing anomalies, this result supports Bouchaud et al. (2019) and chal-

[4] For instance, in the context of short selling Interactive Brokers states that “the fee is being charged for holding the stock over market close” (https://www.interactivebrokers.com/en/index.php?f=1595&p=secfinancing ; accessed on 3/6/2020). The same generally applies for buying on margin.

[5] This result also suggests that higher mispricing does not arise solely from lower trading activity by arbitrageurs, which would go against the proposed explanation.

lenges purely rational risk-based theories. Other anomalies tend to accrue in a specific period during the day (size, illiquidity, and momentum) or display no pattern at all.[6] Accruals and book-to-market do not exhibit specific intraday patterns, but these anomalies are weak over my sample period with value-weighted portfolios. Betting-against-beta performs well intraday and poorly overnight [see also Hendershott et al., 2020, discussed below]. As a robustness check, I find the "intraday mispricing pattern" for almost all of the anomalies underlying the mispricing measure that are not included in my original set of anomalies.

The results are robust across subsamples and days of the week. They also remain after: applying a volume filter to limit the impact of nonsynchronous trading, applying a $10 price filter, or using trade-based returns. Chance is also unlikely to explain the results. To provide a benchmark, I generate returns on thousands of "random strategies" using monthly returns over the sample, select the profitable ones, and examine their intraday return patterns. The average placebo anomaly earns the majority of its profits overnight. Placebo anomalies are highly unlikely to display similar intraday return patterns in a consistent manner over multiple subsamples and across days of the week. This supports the idea that intraday patterns associated with well-known characteristics have economic content, which can assist our understanding of the cross-sectional variation in stock returns. By using intraday data, I provide an "out of sample" perspective to help gauge what drives anomalies.

This paper is motivated by the work of Heston et al. (2010), who provide evidence that the cross-sectional variance in average stock returns varies over the trading day. They do not explore how this variation relates to stock-specific characteristics. Another important related paper is Lou et al. (2019), henceforth LPS. These authors show that firm-level intraday (overnight) returns positively predict future intraday (overnight) returns but negatively predict future overnight (intraday) returns, and that this predictability lasts for years. They link this "tug of war" between overnight and intraday returns to institutions trading at the end of the day and retail investors trading at the beginning of the day (i.e., clientele effects).[7] Consistent with their work, I find that clientele effects are important. Stocks that outperform other stocks in a given interval of the day over the past year tend to significantly outperform other stocks in the same interval today. My main results are, however, robust to controlling for this "long-term clientele factor." The results are therefore not simply due to (very) persistent cross-sectional differences in average returns over the day. Importantly, the return pattern of the mispricing factor does not obey a tug of war between overnight and intraday returns since its overnight alpha *and* its intraday half-hour alphas are mostly positive and statistically significant.

Furthermore, the mispricing explanation is more specific than a general clientele explanation: it makes predictions about returns and volume for certain stocks. Nowhere in LPS is it possible to distinguish, for instance, between gross profitability and size since both anomalies earn high intraday returns and low overnight returns. My analysis suggests that they differ strongly. I can make this inference because I focus on the dynamics of returns within the trading day, whereas LPS do not decompose open-to-close returns.[8] Overall, my results complement their findings: intraday and overnight returns provide valuable information to evaluate asset pricing theories.

In contemporaneous work, Hendershott et al. (2020) show that beta is positively (negatively) associated with expected overnight (intraday) returns. My findings on overnight systematic variance are consistent with this result. Whereas they focus on the cross-sectional relation between beta and average returns for intraday and overnight returns, I focus mostly on returns within the trading day across anomalies. I also test specific predictions based on overnight risk. Hence, my results complement theirs in highlighting the role of overnight risk for the cross-section of stock returns.

More generally, this paper contributes new evidence to the literature on intraday and overnight average returns.[9] There is scant empirical evidence about average returns over the trading day. Intraday average returns are examined by Wood et al. (1985), Harris (1986), and Jain and Joh (1988). These studies rely on short samples dating from before 1984. Smirlock and Starks (1986) use 21 years of hourly returns but restricted to the Dow Jones Industrial Average.

This paper is organized as follows. Section 2 presents the data and methodology. Section 3 develops the main hypotheses to be tested. Section 4 presents the main empirical results on the cross-section of intraday and overnight returns. Section 5 provides robustness checks. Section 6 concludes.

2. Data and methodology

Intraday data for U.S. common stocks listed on the NYSE, Amex, and NASDAQ are obtained from several databases. Institute for the Study of Securities Market (ISSM) and Trade and Quote (TAQ) data are used to com-

[6] Size and illiquidity tend to earn positive intraday returns once we control for other characteristics in value-weighted Fama and MacBeth (1973) regressions. Hence, one should be careful when interpreting these patterns.

[7] In a related paper, Berkman et al. (2012) argue that retail investors tend to buy stocks that attracted their attention at the open. This buying pressure results in high overnight returns followed by intraday reversals. If retail investors are most active at the open, then investor sentiment is unlikely to explain my findings about *end-of-day* returns. At the market level, Gao et al. (2018) show that the opening return positively predicts the last half-hour return.

[8] In addition, my sample period starts in 1986 whereas theirs starts in 1993. This extended sample provides new evidence. For instance, the result that momentum is only an overnight anomaly does not hold in the 1986–1992 sample. In line with their hypothesis, this could be due to a less important role of institutions over this period.

[9] Cliff et al. (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) show time-of-day effects in currencies. Muravyev and Ni (2020) find that the variance risk premium for S&P 500 and equity options is negative overnight but mildly positive intraday.

pute intraday half-hour returns and volumes for each trading day from January 1, 1986, to December 31, 2015. The ISSM data are available back to January 1, 1983, but I begin the sample on January 1, 1986, three months after the NYSE started opening at 9:30am. August 1987 is excluded from the analysis because of missing data. The TAQ data are used starting from January 1, 1993 and are stamped to the millisecond (daily TAQ) from 2004 onwards. Due to data limitations, only NYSE and Amex common stocks are included before 1993. To be included in a given month, a stock must have a price greater than \$5 and a market capitalization greater than \$100 million at the end of the previous month.[10]

I compute intraday returns based on quote midpoints at the beginning of each half-hour interval during regular trading hours (9:30 am to 4:00 pm). Intervals of 30 minutes limit the influence of microstructure effects but still capture a rich set of dynamics. The last half-hour return (3:30 pm to 4:00 pm) is computed using the last quote available during trading hours.[11]

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. To limit the scope of this issue, I consider quotes starting at 9:45 am. Hence, the first return interval goes from 9:45 am to 10:00 am. I discuss robustness checks with earlier sampling of the opening price in Section 5.2.

In addition to standard error filters (e.g., Chordia et al., 2001), quotes with a spread lower than zero or greater than \$5 are excluded. The ISSM data is filtered as in Hausman et al. (1992). I also delete any observation for which the spread is larger than 30 times the median spread during the day for a given stock. Finally, I screen the returns to discard obvious reporting mistakes.

Overnight returns are given by

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

where $r_{\text{close-to-close},t}$ is the daily midquote return and $r_{\text{intraday},t}$ is the intraday return computed using the midquote at 9:45am as described above. As a result, the overnight return includes the first 15 minutes of trading. To compute daily midquote returns, quote midpoints at the close are adjusted for stock splits and dividends using the CRSP factor to adjust prices (FACPR) and dividend amount (DIVAMT). If the absolute difference between the daily midquote return and the daily CRSP return is larger than 25%, the daily CRSP return is used instead of the midquote return. If a stock has no intraday data on a given day, the CRSP daily return, if it exists, is allocated to the overnight return. If a return is missing in the CRSP daily file and intraday trade data exists, I discard the data for this stock on this day.[12]

The main analysis uses returns computed from quote midpoints. Quotes can be updated when there is no trade, which limits the selection bias associated with the occurrence of a trade. The results are robust to using trade-based prices. I report results for arithmetic returns. The results are similar when using logarithmic returns to attenuate microstructure issues (Asparouhova et al., 2013). To compute excess returns, daily risk-free returns obtained from Kenneth French's data library are subtracted from overnight returns. As pointed out by Heston et al. (2010), the risk-free rate should not be earned intraday because transactions are settled at the end of the trading day.

Accounting data are obtained from Compustat. Institutional ownership data are obtained from the 13F filings reported in the Thomson Reuters database.

In the tests below, stock portfolios are formed as follows. At the beginning of each month, decile portfolios are formed using NYSE breakpoints based on the sorting variable under consideration at the end of the previous month. The long-short portfolio is long the high predicted return portfolio and short the low predicted return portfolio following prior literature. Portfolio returns are value-weighted to limit the influence of microstructure noise (Blume and Stambaugh, 1983). Importantly, there is no intraday rebalancing: portfolio returns are those of a buy-and-hold portfolio rebalanced at the beginning of each month.

3. Motivation and hypotheses development

Consider a capital-constrained arbitrageur who trades on mispricing. The arbitrageur goes long undervalued stocks and short overvalued stocks. Is the arbitrageur indifferent to holding the positions intraday versus overnight? Holding positions is likely more costly overnight than intraday for two reasons: institutional constraints and overnight risk.

First, institutional constraints make it costly for the arbitrageur to hold positions overnight. The arbitrageur is likely to face higher capital constraints overnight. Traders are generally allowed by brokers to take a higher leverage intraday than overnight.[13] Furthermore, interest charges

[10] The latter requirement is primarily made to exclude small stocks in the first part of the sample that are not traded actively. At the beginning of the sample (1/1986), \$100 million corresponds roughly to the 20th NYSE market capitalization percentile. The results are robust to a \$10 price filter.

[11] The results are robust to using the quote midpoint taken from the Center for Research in Security Prices (CRSP) data or the closing price if no midpoint is reported. Before 2004, end-of-day CRSP midquotes tend to be higher than TAQ midquotes for all stocks. The results of the paper are not significantly affected, however. After 2004, midquotes are close to identical.

[12] I use the TCLINK macro provided by WRDS to link the TAQ symbol to the CRSP PERMNO. In a few cases, multiple TAQ symbols are associated with a given PERMNO on the same day, which requires manual matching.

[13] "During active market hours, IB clients can take advantage of reduced intraday margin for securities—generally 25% of the long stock value. In order to hold a position overnight, margin requirement reverts to the Reg T requirement of 50% of stock value". Source: Understanding IB Margin Webinar Notes (https://www.interactivebrokers.com/en/?f=%2Fen%2Fgeneral%2Feducation%2Fpdfnotes%2FWN-UnderstandingIBMargin.php%3Fib_entity%3Din ; accessed on 3/6/2020).

such as lending fees on short positions and margin interest on levered long positions are typically charged based on whether the position is open at the market close. As a result, the arbitrageur has an incentive to reduce her positions at the end of the day to free up capital and to avoid paying lending fees and margin rates. This channel predicts that overpriced stocks that are shorted and underpriced stocks that are bought on margin by the arbitrageur could be subject to price pressure at the end of the day. In the case of short positions, the effect should be stronger for stocks with high lending fees.

In addition to institutional constraints, holding positions overnight can be especially risky for the capital-constrained arbitrageur. The low volume outside of regular trading hours impedes risk sharing. Hong and Wang (2000) solve an equilibrium model with periodic market closures and show that market closures matter for return dynamics simply as a result of investor heterogeneity. More generally, there is the risk of large overnight price moves due to new information released overnight, and the nature of risk could be substantially different overnight from intraday. The capital-constrained arbitrageur could therefore want to avoid such risk and trade with long-term investors (or other liquidity providers) at the end of the day to lower her exposure. As long as markets are not perfectly liquid, such trading is likely to create price pressure (Grossman and Miller, 1988). This is all the more so since mispriced stocks are likely to be relatively illiquid.

The idea that investors differ in their willingness to hold positions overnight goes back at least to Gerety and Mulherin (1992), who find that high expected overnight volatility leads to high trading volume at the close and at the next day's open. This is consistent with traders that unload their positions before the close and reopen them on the following day. In recent years, overnight inventory concerns are often used to identify high-frequency trading firms, which trade actively during the day but avoid carrying positions overnight (e.g., Menkveld, 2016).

Other indirect evidence is in line with the existence of significant rebalancing trades towards the end of the day. Institutional trading tends to be more one-sided at the end of the trading day (Cushing and Madhavan, 2000). Moreover, average absolute order imbalances tend to increase over the day and are highest in the last 30 minutes of trading [excluding the first five minutes of trading, which include the opening auction; see Bogousslavsky and Collin-Dufresne (2020)].

Why would the arbitrageur not close the positions earlier to lower price impact? First, if mispricing corrects gradually over the day, then it cannot be optimal for the arbitrageur to close the position too early as she would miss out on the strategy's profit. Second, the end of the trading day is a period of low spread, high volume, and high depth. The costs of trading large quantities at that time are likely lower than in the middle of the day. I discuss changes in spread, depth, and price impact around the end of the day in Section 4.1. Third, less sophisticated traders may not fully realize the price pressure generated by their (and others') trades at that time.

Based on the above channels, I test the following hypotheses.

Hypothesis 1. Overpriced stocks outperform at the end of the day, while underpriced stocks underperform at the end of the day.

The overnight risk channel applies equally to long and short positions. It further predicts that mispricing should be related to overnight risk.

Hypothesis 2. The higher is overnight risk, the more mispricing worsens at the end of the day on average.

Price pressure at the end of the day predicts some return reversal over the next day.

Hypothesis 3. End-of-day price pressure implies a lower correlation between end-of-day mispricing returns and following returns than between returns on other successive intervals.

The institutional constraints channel suggests that the increase in mispricing should be even more pronounced for overpriced stocks with high lending fees.

Hypothesis 4. Overpriced stocks with high lending fees outperform other overpriced stocks at the end of the day.

According to these hypotheses, end-of-day distortions in stock prices provide a way to identify arbitrageurs' trading activity. One may then identify mispriced stocks by examining their intraday return pattern. Similar predictions are difficult to obtain in a purely rational risk-based framework. There is no reason to think that a source of fundamental risk would vary at a specific time of the day. For instance, if value stocks earn high returns because they are exposed to distress risk, it is hard to imagine why the compensation for distress risk would vary over the trading day.

An alternative explanation could be based on fluctuations in investor sentiment and trading over the day. There is, however, no reason for sentiment traders to predominantly trade at the end of the day. If anything, retail investors appear to be most active at the beginning of the day (Berkman et al., 2012). A more general explanation is based on clientele effects (Lou et al., 2019). This explanation postulates that specific groups of investors (such as institutions) buy and sell specific stocks at specific times of the day. I discuss clientele effects in detail in Section 4.4.

4. What drives anomalies? Evidence from intraday and overnight returns

I use the cross-section of intraday and overnight returns to test the institutional constraints and overnight risk hypotheses developed in Section 3. First, I test the hypotheses by using a mispricing measure in Section 4.1. Second, I examine intraday and overnight returns of well-known asset pricing anomalies and show that several anomalies exhibit patterns consistent with mispricing (Section 4.2). These patterns are unlikely to be generated by chance (Section 4.3) and complement clientele effects documented by prior work (Section 4.4).

4.1. Mispricing

I use the mispricing measure of Stambaugh et al. (2012, 2015).[14] These authors use a sample of 11 anomaly variables to build a monthly measure of mispricing at the individual stock level. The anomaly variables are financial distress, bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investments-to-assets. Each stock is ranked according to each anomaly, with a high rank associated with higher relative overpricing. The composite mispricing rank of a stock is obtained by taking the arithmetic average of the stock's individual ranks across anomalies. As a result, stocks with a low (high) mispricing measure are the most underpriced (overpriced). The combination of multiple signals provides a more precise signal of relative mispricing in the cross-section of stocks.[15] Hence, there is a strong prior that a strategy based on this measure bets on mispricing correction. Consistent with this interpretation, I show below that overpriced stocks are significantly more shorted over the day than nonmispriced stocks, whereas underpriced stocks are significantly less shorted.

I estimate average returns and alphas of the mispricing strategy over the day. Let r_t denote the return of a portfolio in interval t (for instance, between 2:30 pm and 3:00 pm). I estimate

$$r_t = \sum_{k \in \mathcal{K}} 1_{t,k}\mu_k + \epsilon_t, \tag{2}$$

where $\mathcal{K} =$ {overnight, 9:45–10:00 am, 10:00-10:30 am, ..., 3:30–4:00 pm}. $1_{t,k}$ is a dummy variable that takes the value one if interval t belongs to period k and zero otherwise. It is important to control for heteroskedasticity in (2) since return volatility is not constant over the day. In addition, intraday returns can be serially correlated (Heston et al., 2010). Hence, I adjust standard errors for heteroskedasticity and autocorrelation using a Newey and West (1987) correction with 14 lags (one day). Simple heteroskedasticity-robust standard errors give almost identical results.

Similarly, to compute alpha in a given period, I estimate

$$r_t = \sum_{k \in \mathcal{K}} 1_{t,k}\alpha_k + \sum_{k \in \mathcal{K}} 1_{t,k} r^e_{m,t}\beta_k + \epsilon_t, \tag{3}$$

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 can 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). Regression (3) assumes that betas vary over the day but are constant over time. The main results are, however, almost unchanged if alpha is estimated using a rolling window. Furthermore, the Internet Appendix shows that nonsynchronous trading does not appear to be a major concern here. The results are qualitatively similar when I use a volume filter to restrict the sample to stocks that are actively-traded over the trading day.

Should we expect any pattern in average returns over the trading day? Fig. 1 plots the average intraday and overnight returns of the (value-weighted) market portfolio across subsamples to put things into perspective. The market portfolio earns high average returns overnight, consistent with Cliff et al. (2008), but does not display any marked pattern in average returns over the trading day.

Panel (a) of Table 1 reports intraday and overnight average returns and alphas of the mispricing strategy that buys underpriced stocks and shorts overpriced stocks. The strategy performs extremely well over the day: its (abnormal) return is positive and statistically significant in most half hours of the trading day and overnight. However, the strategy earns a significantly negative average return of −2.43 bps with a similar alpha of −2.43 bps in the last 30 minutes of trading. The t-statistic is below −10. This is consistent with Hypothesis 1. Mispricing is gradually corrected over the day but worsens at the end of the day when arbitrageurs are constrained to adjust their portfolios. Fig. IA.1 in the Internet Appendix reports mispricing end-of-day (3:30–4:00 pm) market beta and alpha estimated with a one-year rolling window. Time-variation in beta is sizable but does not explain the intraday pattern. Intuitively, the market return is generally close to zero over the day and therefore cannot account for the large mispricing return.

Mispricing returns tend to be highest in the morning. First, it could be the case that information accumulated overnight is gradually incorporated into prices, which corrects the mispricing. Competition among informed traders causes price discovery to occur mostly early in the day. Second, if arbitrageurs reopen their positions at the beginning of the day, then a similar effect is expected. Finally, it is worth pointing out that the return pattern differs from the tug of war between overnight and intraday returns highlighted by Lou et al. (2019) since the overnight alpha is positive and statistically significant, like most intraday intervals.

Panel (b) of Table 1 reports long and short legs' alphas. Consistent with Hypothesis 1, both legs perform poorly at the end of the day. The short leg end-of-day alpha is 1.67 bps higher than its intraday average alpha, whereas the long leg end-of-day alpha is 1.31 bps lower than its intraday average alpha. A small asymmetry is expected since the institutional constraints channel applies only to the part of a long position that is leveraged. However, the return difference between the two legs is not statistically significant. Hence, the two legs seem to be equally strong from a statistical perspective.

Panel (c) shows that the results are robust across subsamples. Interestingly, the end-of-day effect is stronger in the second part of the sample (2001–2015) than in the first part (1986–2000). On average, mispricing worsens by 3.19 bps at the end of the day in the second half of

[14] The measure is obtained from Robert Stambaugh's website. I thank him for making it available.

[15] Stambaugh et al. emphasize that their measure is one of relative mispricing since even the lowest ranked stock can be overpriced. This definition suits my analysis since the theory under consideration relies on arbitrageurs who trade on relative mispricing. In what follows, nonmispriced stocks is used to refer to stocks that are neither overpriced nor underpriced on a relative basis.

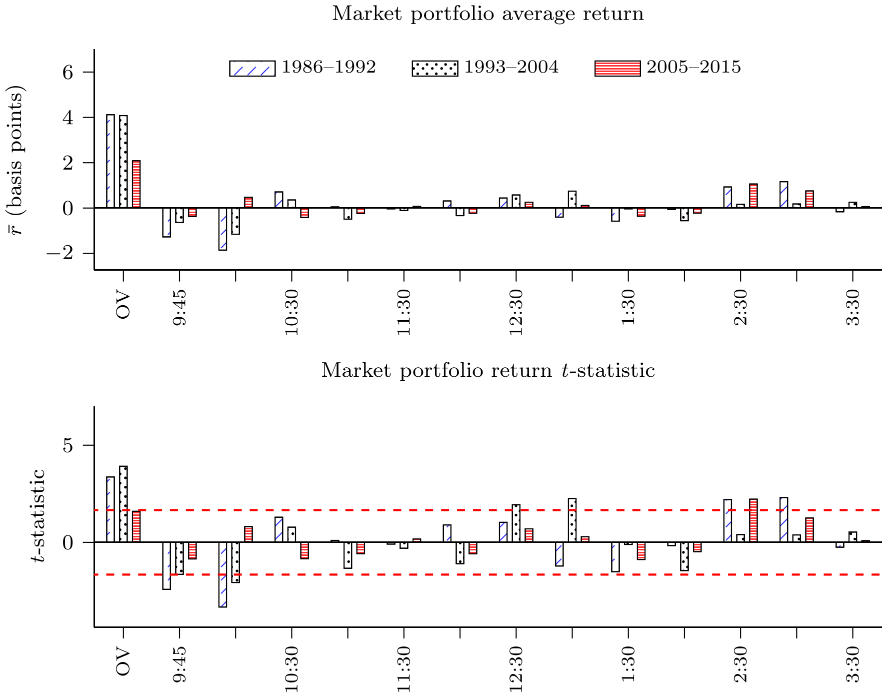

Fig. 1. Market portfolio intraday and overnight average returns (in basis points) and t-statistics across subsamples. The market return equals the value-weighted return of all stocks in the sample. The sample includes stocks with a price greater than \$5 and a market capitalization greater than \$100 million at the end of the previous month, and is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. Stock returns are computed using quote midpoints. The first interval starts at 9:45 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. OV indicates the overnight interval. Dashed lines indicate significance at the level of 10%. The t-statistics are based on Newey and West (1987) standard errors with 14 lags.

the sample. This is twice as large as in the first half of the sample. Over the second half of the sample, markets have become increasingly dominated by participants that are concerned about holding positions overnight. Hence, the overnight risk channel suggests that overnight effects should be more prevalent in recent years, consistent with the evidence in Table 1.

The previous results raise several interesting points about limits to arbitrage. According to the standard view of limits to arbitrage, mispricing should disappear as markets become more efficient (Shleifer and Vishny, 1997; McLean and Pontiff, 2016). The channels that I consider represent a form of high-frequency limits to arbitrage that may not go away as markets become more efficient. First, general shifts towards stricter overnight inventory risk management could amplify these effects. Second, institutional features such as increases in capital requirements for overnight positions represent a discontinuity in the cost of arbitrage over the day. A discontinuity generates excess volatility if investors' trading to close and reopen their positions induces price pressure. Hence, these features could help explain why some mispricing persists in an era of computerized trading.

Overnight risk predicts that mispricing at the close should worsen following shocks to overnight return volatility (Hypothesis 2). To test this prediction, I compute each month the overnight variance of the mispricing strategy return over the past 100 trading days. I then estimate a time-series regression of the value-weighted mispricing strategy return between 3:30 and 4:00 pm on changes in its log overnight variance:

$$r_{\text{MIS},3:30,t} = a + \sum_{s=0}^{S} b_s \Delta\sigma^2_{\text{MIS,OV},t-s} + \epsilon. \tag{4}$$

Table 2 reports the results. A positive overnight variance shock of 1% predicts that mispricing worsens by roughly 13 bps at the end of the day. Hence, an overnight volatility shock of 1% increases mispricing by roughly $2 \times 13 = 26$ bps on average. The effect is large but not statistically significant for same-day shocks (i.e., in the overnight period that precedes the 3:30–4:00 pm return), but it is statistically significant and of a similar magnitude for one-day lagged shocks. Moreover, a similar but much weaker effect is observed for the 3:00–3:30 pm interval (center column) and no such effect is observed for the 2:30–3:00 pm interval (right column). This is consistent with arbitrageurs who start to gradually close their positions towards the end of the day, when volatility spikes.

Both institutional constraints and overnight risk effects should be more pronounced over the weekend than over a weekday overnight period. First, lending fees and margin interest accrue over three days during the weekend as opposed to one day during a weekday overnight period. Second, the weekend represents a longer nontrading period than any weekday overnight period. In this respect, the mispricing strategy's weekend return volatility is 6.5% higher than its weekday overnight return volatility. Hypotheses 1 and 2 then predict that mispricing should

Table 1
Intraday and overnight return properties of a mispricing portfolio. This table reports the average return ($\bar{r}$) and alpha (α) in basis points of a mispricing strategy that buys underpriced stocks and shorts overpriced stocks. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the mispricing measure of Stambaugh et al. (2012, 2015). Portfolios are value-weighted and held for one month. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The t-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
(a) Long-short portfolio														
$\bar{r}$	−0.04	1.12***	1.43***	0.89***	0.87***	0.38**	0.25	0.45***	0.16	0.17	0.53***	0.38**	0.15	−2.43***
	(−0.06)	(4.41)	(4.77)	(3.75)	(4.13)	(1.99)	(1.45)	(2.61)	(0.92)	(0.98)	(2.92)	(2.00)	(0.71)	(−10.03)
α	1.25**	0.99***	1.26***	0.92***	0.83***	0.37**	0.23	0.46***	0.22	0.13	0.48***	0.47**	0.23	- 2.43***
	(2.23)	(3.95)	(4.31)	(4.00)	(3.98)	(2.02)	(1.32)	(2.91)	(1.36)	(0.73)	(2.70)	(2.55)	(1.11)	(−10.09)
(b) Long and short legs														
α_L	0.75***	0.37***	0.25*	0.21**	0.15	0.14*	0.08	0.15**	0.09	0.02	0.16**	0.20**	0.09	-1.15***
	(2.98)	(3.23)	(1.93)	(2.03)	(1.59)	(1.71)	(1.02)	(2.09)	(1.21)	(0.23)	(2.03)	(2.41)	(0.96)	(−10.43)
α_S	−0.49	−0.62***	−1.00***	−0.71***	−0.68***	−0.23*	−0.15	−0.31***	−0.13	−0.11	−0.31**	−0.27**	−0.14	1.28***
	(−1.25)	(−3.44)	(−4.84)	(−4.24)	(−4.48)	(−1.72)	(−1.19)	(−2.70)	(−1.14)	(−0.87)	(−2.42)	(−2.07)	(−0.94)	(7.59)
(c) Subsamples: (1) 1986–2000 (2) 2001–2015														
$\alpha_{(1)}$	−1.13**	0.90***	2.12***	1.50***	0.93***	0.45**	0.41**	0.61***	0.62***	0.29	0.29	0.63***	−0.12	−1.60***
	(−2.05)	(3.00)	(6.38)	(5.70)	(3.74)	(2.07)	(2.03)	(3.14)	(3.49)	(1.42)	(1.43)	(2.91)	(−0.52)	(−5.35)
$\alpha_{(2)}$	2.28**	1.37***	0.91**	−0.01	0.62**	0.45*	0.08	0.45**	−0.08	0.00	0.67***	0.26	0.50*	−3.19***
	(2.46)	(3.85)	(2.12)	(−0.02)	(2.08)	(1.66)	(0.32)	(2.03)	(−0.35)	(0.00)	(2.62)	(1.02)	(1.80)	(−9.85)

worsen most at the end of the week. Fig. 2 reports intraday and overnight mispricing alphas across days of the week. Mispricing worsens roughly four times as much at the end of the trading day on Friday than on Monday. The mispricing strategy performs particularly well on Monday. This is potentially consistent with mispricing being highest following weekends and/or arbitrageurs reopening their positions after the weekend.

Hypothesis 2 can also be tested in the cross-section by comparing mispriced stocks with high overnight risk to mispriced stocks with low overnight risk. I estimate value-weighted Fama and MacBeth (1973) regressions of intraday and overnight returns on underpricing and overpricing indicators, overnight systematic variance, and interactions between these variables. Overnight systematic variance is estimated for each stock using overnight returns in the past year. At the beginning of each month, stocks in the top (bottom) deciles of the mispricing measure are classified as overpriced (underpriced).

The results are reported in Table 3. Overnight hedging risk predicts that returns should be high overnight and low over the trading day to compensate traders for holding risky stocks overnight (Hong and Wang, 2000). Consistent with this prediction, overnight systematic variance is positively related to overnight returns and negatively related to intraday returns. The underpriced and overpriced indicators confirm the results in Table 1: underpriced (overpriced) stocks perform well (poorly) over the day and poorly (well) at the end of the day. The interaction term between underpricing and overnight risk is negative and statistically significant for the 3:30–4:00pm interval (last column). Furthermore, no such pattern is observed for other intervals of the day. The interaction term between overpricing and overnight risk is, however, close to zero. An issue with this test is that the measure of overnight risk is likely correlated with mispricing since overnight risk represents a holding cost for arbitrageurs. Stocks that are the most mispriced could actually be traded less by arbitrageurs (and therefore be the most mispriced). This is likely less of a problem with systematic risk than with idiosyncratic risk (Pontiff, 2006) but remains an issue to keep in mind for interpretation of the results in Table 3.

If arbitrageurs' trading at the end of the day moves prices for noninformational reasons, then one expects return reversal over the following periods (Hypothesis 3). Several caveats are in order. First, it is unclear over which horizon the reversal takes place. For instance, mispricing could also worsen at the open due to illiquidity and retail investor trading (discussed in Section 5.2). Second, arbitrageurs' trading could be correlated with fundamental return innovations. Setting these caveats aside, I estimate a time–series regression of the mispricing factor's returns on lagged returns (up to six lags). The regression includes interactions between the 3:30–4:00pm return on the previous day and morning half-hour indicators on the current day. Table 4 reports the results. Mispricing returns are positively autocorrelated. After accounting for this positive autocorrelation, there is statistically significant evidence of reversal between 3:30–4:00pm returns and next day's morning returns. I find no evidence of reversal for

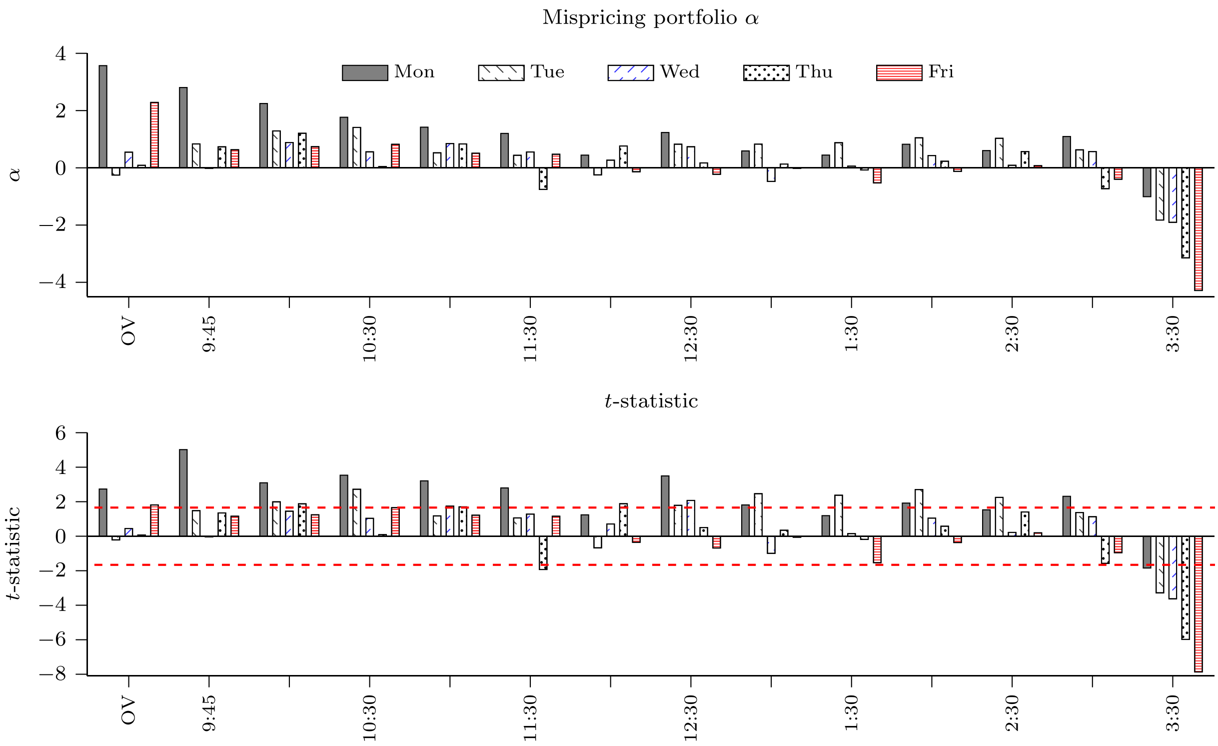

Fig. 2. Mispricing portfolio intraday and overnight alphas (in basis points) and t-statistics across days of the week. The first interval starts at 9:45 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. OV indicates the overnight interval. Portfolio construction is detailed in the caption of Table 1. Dashed lines indicate significance at the level of 10%. The t-statistics are based on heteroskedasticity-adjusted standard errors.

Table 2

Mispricing return and overnight risk. This table reports estimates of time-series regressions of a value-weighted mispricing strategy half-hour return around the end of the day on lagged changes in its overnight variance. Overnight variance is the logarithm of the overnight return variance over the past 100 trading days. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the mispricing measure of Stambaugh et al. (2012, 2015). Portfolios are value-weighted and held for one month. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45am; 10:00 indicates the half-hour interval that starts at 10:00am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The t-statistics are based on Newey-West standard errors with five lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

$$r_{\mathrm{MIS},\tau,t} = a + \sum_{s=0}^{3} b_s \Delta\sigma^2_{\mathrm{MIS,OV},t-s} + \epsilon$$

τ	3:30–4:00 pm		3:00–3:30 pm		2:30–3:00 pm	
	coeff.	t-stat.	coeff.	t-stat.	coeff.	t-stat.
a	−2.50***	−10.81	0.12	0.61	0.38**	2.08
b_0	−13.40	−1.41	−3.24	−0.36	12.14	1.40
b_1	−16.60**	−2.19	−9.51	−1.07	−6.08	−1.17
b_2	0.49	0.06	−9.47*	−1.66	5.61	0.90
b_3	−6.95	−0.89	−6.63	−0.71	1.44	0.24
Obs.	7,427		7,427		7,427	

3:00–3:30 pm returns (not reported). This result supports the price pressure hypothesis.

To further test the hypotheses, I examine intraday patterns in volume (turnover), order imbalance, and short-selling volume. Intraday order imbalances are computed for each stock using the Lee and Ready (1991) algorithm. The sample is restricted to NYSE stocks in 2005 and 2006 since I rely on intraday short-selling volume obtained from the NYSE Reg SHO data set. As before, stocks in the top (bottom) decile of the mispricing measure at the beginning of the current month are classified as overpriced (underpriced). Table 5 reports estimates of panel regressions with day fixed effects in which turnover, order imbalance, and short-selling volume are regressed on a set of interval indicators, overpricing/underpricing indicators, and their interactions.[16]

[16] The following intraday intervals are considered: 9:30 am, 10:00 am, 2:00 pm, 2:30 pm, 3:00 pm, and 3:30 pm. The results are robust to in-

Table 3
Mispricing return and overnight risk in the cross-section. This table reports estimates of value-weighted Fama-MacBeth regressions of intraday and overnight returns on underpricing and overpricing indicators based on the mispricing measure of Stambaugh et al. (2012, 2015), overnight systematic variance, and interactions between these variables. Each column reports a separate regression for a given return (measured in basis points). At the beginning of each month, stocks in the top (bottom) deciles of the mispricing measure are classified as overpriced (underpriced). The variance of overnight systematic returns (relative to the market), $\sigma^2_{OV,\text{syst}}$, is estimated for each stock over the previous year (a minimum of 100 observations is required) and multiplied by 100. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The *t*-statistics are shown in parentheses and based on Newey-West standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	10:00	2:30	3:00	3:30
$\sigma^2_{OV,\text{syst}}$	2.71***	−0.53***	−0.60***	−0.08	−0.25**	−0.41***
	(7.88)	(−3.38)	(−3.27)	(−0.72)	(−2.17)	(−3.25)
underpriced	0.07	0.15	0.47***	0.27**	0.11	−1.16***
	(0.22)	(1.04)	(2.99)	(2.45)	(1.02)	(−7.42)
overpriced	0.72*	−1.06***	−1.32***	−0.07	0.00	1.51***
	(1.84)	(−5.61)	(−6.23)	(−0.54)	(0.01)	(8.31)
underpriced*$\sigma^2_{OV,\text{syst}}$	0.97*	0.49*	0.22	0.05	0.07	−0.56**
	(1.75)	(1.90)	(0.82)	(0.31)	(0.35)	(−2.28)
overpriced*$\sigma^2_{OV,\text{syst}}$	−0.47	0.03	−0.11	−0.05	−0.01	0.01
	(−1.63)	(0.20)	(−0.72)	(−0.55)	(−0.10)	(0.05)

Table 4
Mispricing and price pressure. This table reports estimates of a time-series regression of value-weighted mispricing strategy intraday and overnight returns on lagged returns. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the mispricing measure of Stambaugh et al. (2012, 2015). Portfolios are value-weighted and held for one month. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45am; 10:00 indicates the half-hour interval that starts at 10:00am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The *t*-statistics are based on heteroskedasticity-adjusted standard errors. *, **, and *** denote significance at the 10%, 5%, and 1% level.

$r_{\text{MIS},t} = \sum_{s=1}^{6} b_s r_{\text{MIS},t-s} + \sum_{s=1}^{6} b'_s 1_{t-s\in 3:30-4:00pm} r_{\text{MIS},t-s} + \epsilon$

	coeff.	*t*-stat.
$r_{\text{MIS},t-1}$	0.0404***	5.38
$r_{\text{MIS},t-2}$	0.0456***	5.00
$r_{\text{MIS},t-3}$	0.0171***	2.58
$r_{\text{MIS},t-4}$	0.0134**	2.04
$r_{\text{MIS},t-5}$	0.0189**	2.41
$r_{\text{MIS},t-6}$	0.0217***	2.61
OV*$r_{\text{MIS},t-1}$	−0.0124	−0.19
9:45*$r_{\text{MIS},t-2}$	−0.0881***	−3.49
10:00*$r_{\text{MIS},t-3}$	0.0411	1.48
10:30*$r_{\text{MIS},t-4}$	−0.0468**	−2.26
11:00*$r_{\text{MIS},t-5}$	−0.0293	−1.48
11:30*$r_{\text{MIS},t-6}$	−0.0138	−0.74
Obs.	105,414	

Overnight risk predicts that both overpriced and underpriced stocks experience an increase in trading volume at the end of the day. This increase stems from the increased hedging activity at this time. The first column of Table 5 tests this prediction. In the first half hour of trading, overpriced stocks' turnover is 0.38 bps higher than nonmispriced stocks' turnover. The turnover of overpriced stock is consistently higher than that of nonmispriced stocks over the day, and the difference peaks in the last half hour of trading (0.58 bps). The row Test 1 shows that overpriced stocks' turnover increases in the last half hour by 0.24 bps relative to other half hours, which is strongly statistically significant. Underpriced stocks do not experience an increase in trading volume at the end of the day, however. If anything, they tend to have a lower turnover at this time relative to other intraday periods. This evidence is inconsistent with the overnight risk channel.

The second column of Table 5 examines order imbalance over the day, where order imbalance is defined as buy volume minus sell volume over total shares outstanding. Order imbalance tends to be higher (more positive) for overpriced stocks at the end of the day and peaks in the last half hour of the day. The average difference of 0.10 bps is statistically significant. Order imbalance is lowest (i.e., the most negative) for underpriced stocks at the end of the day, though the difference relative to other intraday intervals is not statistically significant with a *t*-statistic of −1.42. These results are supportive of the overnight risk channel. A trader with a position to be closed before the overnight period is expected to trade more aggressively right before the market closes. Of course, the trader will adjust her trading strategy ahead of the close to limit costly trading aggressiveness, a point that I discuss below.

Next, I use short-selling volume (computed as the total volume of shares shorted over the total share volume in the same interval) to test two additional predictions. First, if the measure developed by Stambaugh et al. (2012, 2015) correctly proxies for mispricing, then we expect overpriced (underpriced) stocks to be significantly more (less) shorted over the day than nonmispriced stocks. The last column of Table 5 confirms this prediction.

Second, overpriced stocks should experience less short selling and additional trading to cover short positions at

cluding additional intervals. To save space, the table does not report the coefficients associated with the noninteracted interval indicators.

Table 5
Intraday cross-sectional variation in turnover, order imbalance, and short-selling volume. This table reports estimates of panel regressions with day fixed effects in which turnover (in basis points; bps), order imbalance, and short-selling volume are regressed on indicator variables. Stocks in the top (bottom) decile of the mispricing measure of Stambaugh et al. (2012, 2015) are classified as overpriced (underpriced). Stocks in the bottom quintile of institutional ownership are classified as hard to borrow. The following intraday intervals are considered: 9:30 am, 10:00 am, 2:00 pm, 2:30 pm, 3:00 pm, and 3:30 pm. For instance, the 3:30 indicator takes the value one if the current interval is 3:30 pm to 4:00 pm. To save space, the table does not report the coefficients of the noninteracted interval indicators, and the 2:00pm and 2:30pm interaction terms. Turnover (order imbalance) is defined as share volume (net imbalance) over total shares outstanding. Short volume is defined as short-selling volume (in shares) over total share volume in the same interval. The last two rows report the difference between the 3:30 interval and all other intervals of the day among overpriced stocks (Test 1) and underpriced stocks (Test 2). In the last column, the difference is computed among overpriced stocks that are hard to borrow. Non-indicator variables are winsorized at 0.05%. 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 month to be included. The sample is composed of NYSE common stocks from January 1, 2005 to December 31, 2006. The *t*-statistics are shown in parentheses and based on standard errors that are double-clustered by date and firm. *, **, and *** denote significance at the 10%, 5%, and 1% level. Observations: 3,710,045.

Dependent variable:	Turnover (bps)	Order imbalance (bps)	Short volume (%)
overpriced*9:30	0.38*	0.11	6.73***
	(1.93)	(1.53)	(3.68)
overpriced*10:00	0.38**	0.12**	6.41***
	(2.15)	(2.01)	(5.86)
overpriced*3:00	0.36***	0.11**	6.46***
	(2.66)	(2.47)	(4.83)
overpriced*3:30	0.58***	0.21**	8.92***
	(2.71)	(2.40)	(5.02)
underpriced*9:30	−0.21	−0.07	−8.85***
	(−1.25)	(−1.19)	(−5.47)
underpriced*10:00	−0.17	−0.07	−4.11***
	(−1.15)	(−1.47)	(−4.25)
underpriced*3:00	−0.16	−0.06	−4.32***
	(−1.42)	(−1.58)	(−3.21)
underpriced*3:30	−0.30*	−0.11	−4.37***
	(−1.74)	(−1.63)	(−3.38)
overpriced*hard to borrow*9:30			10.16**
			(2.34)
overpriced*hard to borrow*10:00			1.33
			(0.49)
overpriced*hard to borrow*3:00			2.11
			(0.70)
overpriced*hard to borrow*3:30			−2.95
			(−0.95)
Test 1: Δ overpriced*3:30	0.24*** (3.07)	0.10** (2.35)	−5.28*** (−3.11)
Test 2: Δ underpriced*3:30	−0.13** (−2.14)	−0.05 (−1.42)	-

the end of the day. This should especially affect stocks that are expensive to borrow (Hypothesis 4). Unfortunately, I do not observe stock lending fees.[17] Instead, I classify stocks in the bottom quintile of institutional ownership at the beginning of the current quarter as hard to borrow and interact this variable with overpricing and interval indicators. Short volume is on average lower by 5.28 percentage points at the end of the day relative to other intervals for overpriced stocks that are hard to borrow. This difference is statistically significant.

To conclude this section, it is interesting to discuss why rational arbitrageurs may not want to trade earlier in the day. For a trader to be indifferent between liquidating one share at 3:30 pm instead of 4:00 pm, the half-spread must be higher at 3:30 pm by the amount by which mispricing worsens.[18]

Table 6 reports average value-weighted percentage effective and quoted spreads of stocks in the long leg and short leg of the mispricing portfolio across half-hours of the day in 2015. The change in spread can account for roughly a quarter to a third of the change in mispricing at the end of the day depending on the spread measure. Several other factors can explain, however, why a rational trader does not trade earlier. First, the above spread calculation represents the loss for the trader who trades last. An arbitrageur who exits gradually obtains a better average price. Second, the spread reflects the cost of a small liquidity-taking trade, which may not proxy well for the cost of a larger trade. To examine another dimension of liquidity, Table 6 also reports the time-weighted depth (at the best bid and ask) and a price impact measure over half hours of the day for mispriced stocks. Price impact is defined as the absolute return divided by the dollar volume in the current half hour, which is conceptually similar to the measure of Amihud (2002). Depth is 61% (50%) higher at 4:00 pm than at 3:30 pm for stocks in the short (long) leg. Price impact is 60% (59%) lower at 4:00 pm

[17] Loan fees of hard-to-borrow stocks can be above 20% (e.g., D'Avolio, 2002). In effect, per-day loan fees can be larger than effective bid-ask spreads (around 7–8 bps for overpriced stocks in 2015 as discussed below).

[18] The exact formula is $\frac{1}{2}\text{spread}_{3:30pm} = \frac{1}{2}\text{spread}_{4:00pm} + \Delta\text{mispricing} - \frac{1}{2}\text{spread}_{4:00pm}\Delta\text{mispricing}$, but the last term is negligible. From Table 1, the mispricing strategy loses on average 2.43 bps at the end of the day. Since this represents the sum of the long leg return and the short leg return, the trader is indifferent if the spread averaged across the two legs at 3:30 pm is 2.43 bps higher than that at 4:00 pm.

Table 6
Liquidity of mispriced stocks. This table reports liquidity measures of the mispricing portfolio's long and short legs in 2015. Liquidity measures are computed at the stock level and value-weighted across stocks each day. The table reports the average daily liquidity measures in 2015. Liquidity measures consist of the percentage dollar-weighted effective spread (ES), the percentage time-weighted quoted spread (QS), depth as a fraction of depth between 9:30 am and 10:00 am on the same day (Depth), and price impact. Price impact is computed as $\frac{|r_{i,k}|}{\mathrm{DVOL}_{i,k}}10^6$ for each stock i and half hour k, where $r_{i,k}$ denotes the midquote return and $\mathrm{DVOL}_{i,k}$ denotes the dollar volume. ES and QS are reported in basis points (bps). At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the mispricing measure of Stambaugh et al. (2012, 2015). 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 month to be included. The first interval starts at 9:35 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 2015 to December 31, 2015.

	ES (bps)		QS (bps)		Depth		Price impact (%)	
Time	Long	Short	Long	Short	Long	Short	Long	Short
9:30am	9.67	38.03	7.25	33.07	1.00	1.00	0.14	9.03
10:00	3.02	11.47	3.80	17.06	1.18	1.09	0.18	6.83
10:30	2.69	9.96	3.29	14.48	1.32	1.18	0.10	2.83
11:00	2.56	9.24	3.07	13.42	1.37	1.23	0.11	4.11
11:30	2.47	8.95	3.00	12.98	1.39	1.25	0.12	2.99
12:00pm	2.43	8.66	2.91	12.52	1.43	1.27	0.08	2.61
12:30	2.35	8.40	2.86	12.25	1.44	1.30	0.11	2.02
1:00	2.35	8.41	3.01	13.11	1.51	1.37	0.07	2.66
1:30	2.31	8.18	2.76	11.67	1.52	1.34	0.08	2.33
2:00	2.42	8.19	2.80	11.60	1.57	1.39	0.08	2.53
2:30	2.32	7.78	2.65	10.99	1.71	1.50	0.07	1.54
3:00	2.20	7.24	2.52	10.08	1.93	1.71	0.04	1.37
3:30	2.04	6.37	2.26	8.56	2.89	2.76	0.02	0.54

than at 3:30 pm for stocks in the short (long) leg. Hence, large trades executed at 3:30 pm are likely to have a much larger price impact than large trades executed at 4:00pm. In addition, it is possible that the higher trading volume at 4:00 pm makes it easier to trade within the spread for sophisticated traders.

Finally, why would a trader not exploit the change in mispricing between 3:30 pm and 4:00 pm? This strategy means shorting the mispricing portfolio at 3:30 pm and buying it back at 4:00 pm. This is not profitable since the change in mispricing is lower than the spread for both the long and short legs.

4.2. Anomaly returns over the day

In this section, I apply the insights developed in Section 3 and tested in Section 4.1 to a set of nine well-known asset pricing anomalies. The anomalies that I study are similar to the anomalies considered in Fama and French (2008, 2016), to which I add size, value, and illiquidity strategies.[19] This last strategy allows me to verify that the results are robust to controlling for illiquidity.

Table 7 reports average return, market alpha, volatility, skewness, and minimum return for each portfolio over the full sample. Marked differences in intraday average returns exist both within and across anomaly portfolios.[20] Contrary to what is often assumed, average returns over the trading day are often significantly different from zero. The evidence is consistent across subsamples and days of the week (Section 5.3). This variation suggests that different economic factors drive the anomalies and that a one-size-fits-all explanation is unlikely to succeed in explaining them. Intraday patterns in skewness and minimum return differ considerably across anomalies but do not seem to explain the patterns in average returns. For instance, betting-against-beta average overnight returns are large and negative but negatively skewed.

Several anomalies tend to accrue in a specific period during the day (size, illiquidity, and momentum). Size and illiquidity returns are strikingly high in the last half hour of trading. Average returns and alphas are roughly 3.5 bps with t-statistics above 10. This result is difficult to reconcile with standard theories of size and illiquidity. To the best of my knowledge, this evidence has not been highlighted before.[21]

In contrast, several anomalies tend to accrue gradually over the trading day. Idiosyncratic volatility, gross profitability, and net stock issues all tend to perform consistently well over the trading day but poorly in the last 30 minutes of trading. Going back to the hypotheses laid out in Section 3, these patterns are consistent with the overnight risk and institutional constraint channels. The long and short legs' abnormal returns of gross profitabil-

[19] The construction of the anomaly variables is described in Table A.2 in the Appendix. Cross-sectional correlations are reported in Table A.3, and cross-sectional correlations within five-year subsamples are reported in the Internet Appendix.

[20] Market alphas display similar intraday patterns to average returns. This is not surprising since 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. Like the mispricing strategy, the anomalies' intraday alpha patterns are robust to using a rolling window methodology to account for time-variation in beta.

[21] Using transaction data on NYSE stocks over December 1981 to January 1983, Harris (1986) finds 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. Additionally, I do not find evidence of a shift in the end-of-day pattern of small and illiquid stocks around the time when decimalization was implemented in 2001. Moreover, Harris (1989) does not focus on the cross-sectional difference between large and small stocks.

Table 7

Intraday and overnight return properties of long-short decile portfolios. This table reports the average return ($\bar{r}$) and alpha (α) in basis points, the volatility (σ), the skewness (skew), and the minimum return (min) of long-short portfolios. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the characteristics defined in Table A.2. Portfolios are value-weighted and held for one month. 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 month to be included. Financial firms are excluded from portfolios based on accounting variables. Stock returns are computed using quote midpoints. The half-hour interval that starts at 10:00 am and ends before 10:30 am appears as 10:00. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The t-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	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 (low minus high)														
$\bar{r}$	0.75	0.80***	0.28	0.10	−0.43**	−0.05	0.18	0.31**	−0.00	−0.34**	0.02	−0.08	−0.27	−0.37*
	(1.52)	(3.28)	(1.13)	(0.47)	(−2.38)	(−0.27)	(1.15)	(2.03)	(−0.02)	(−2.38)	(0.11)	(−0.49)	(−1.61)	(−1.83)
α	0.59	0.91***	0.35	0.09	−0.39**	−0.04	0.19	0.25*	−0.02	−0.30**	0.04	−0.15	−0.32*	−0.38*
	(1.21)	(3.68)	(1.41)	(0.41)	(−2.23)	(−0.26)	(1.26)	(1.69)	(−0.18)	(−2.18)	(0.29)	(−1.00)	(−1.93)	(−1.91)
σ (%)	0.43	0.21	0.22	0.18	0.15	0.15	0.13	0.13	0.12	0.12	0.13	0.14	0.14	0.18
skew	1.23	2.45	0.83	1.49	0.01	−0.63	−0.22	1.70	−0.02	−0.49	0.25	0.01	−0.31	0.25
min (%)	−4.15	−1.23	−1.56	−1.66	−1.13	−2.23	−1.64	−1.07	−1.10	−1.53	−0.97	−1.07	−1.23	−1.80
Beta (low minus high)														
$\bar{r}$	−7.44***	1.79***	1.80***	0.17	0.60	0.49	0.43	−0.30	0.15	0.51	0.92***	−0.48	−0.01	0.25
	(−6.55)	(4.21)	(3.38)	(0.38)	(1.62)	(1.51)	(1.47)	(−0.99)	(0.49)	(1.63)	(2.71)	(−1.35)	(−0.03)	(0.60)
α	−3.06***	0.93***	0.90***	0.36	0.26	0.46**	0.27	0.21	0.45***	0.18	0.55***	0.29	0.60***	0.33
	(−4.48)	(3.31)	(2.76)	(1.36)	(1.19)	(2.28)	(1.47)	(1.24)	(2.69)	(1.00)	(2.90)	(1.50)	(2.93)	(1.32)
σ (%)	0.99	0.37	0.46	0.38	0.32	0.28	0.26	0.26	0.27	0.27	0.29	0.31	0.33	0.36
skew	−0.77	0.02	−0.11	−0.21	−0.20	0.08	0.01	−5.99	−4.23	−1.76	−0.22	−0.85	−0.91	−0.24
min (%)	−15.26	−5.50	−4.44	−4.56	−6.06	−2.50	−3.32	−9.41	−7.32	−5.62	−2.83	−3.94	−5.16	−4.40
Book-to-market (high minus low)														
$\bar{r}$	−2.93***	0.77***	0.58**	−0.32	−0.09	0.13	0.08	−0.08	0.35**	0.01	0.19	−0.10	0.15	0.97***
	(−5.36)	(2.94)	(1.97)	(−1.31)	(−0.44)	(0.69)	(0.48)	(−0.45)	(1.99)	(0.05)	(1.03)	(−0.51)	(0.69)	(4.00)
α	−2.40***	0.58**	0.39	−0.28	−0.17	0.13	0.05	0.05	0.43***	−0.06	0.11	0.10	0.28	0.99***
	(−4.41)	(2.32)	(1.39)	(−1.19)	(−0.82)	(0.69)	(0.27)	(0.31)	(2.62)	(−0.35)	(0.61)	(0.58)	(1.42)	(4.40)
σ (%)	0.48	0.23	0.25	0.22	0.18	0.17	0.15	0.15	0.15	0.15	0.16	0.17	0.18	0.21
skew	0.08	0.90	0.17	−0.52	−0.43	0.76	0.19	−2.33	−3.90	−0.37	−0.46	−0.25	−0.20	1.14
min (%)	−3.84	−1.75	−3.41	−2.12	−2.23	−1.20	−1.54	−3.74	−4.78	−1.82	−1.83	−2.53	−2.11	−1.86
Gross profitability (high minus low)														
$\bar{r}$	−0.50	0.11	0.48*	0.71***	0.52***	0.37**	0.35**	0.29*	0.21	0.19	0.02	0.50***	0.11	−1.23***
	(−1.05)	(0.51)	(1.91)	(3.40)	(2.87)	(2.24)	(2.28)	(1.83)	(1.51)	(1.28)	(0.15)	(3.32)	(0.63)	(−6.56)
α	−0.25	0.13	0.50**	0.71***	0.53***	0.37**	0.35**	0.24*	0.22	0.20	0.02	0.50***	0.11	−1.23***
	(−0.52)	(0.59)	(1.98)	(3.38)	(2.91)	(2.25)	(2.29)	(1.66)	(1.57)	(1.34)	(0.14)	(3.30)	(0.69)	(−6.63)
σ (%)	0.41	0.19	0.22	0.18	0.16	0.14	0.13	0.14	0.12	0.13	0.13	0.13	0.15	0.16
skew	0.18	−0.04	0.13	−0.15	−0.02	0.04	−1.02	8.28	−0.91	0.57	0.04	0.18	−1.45	−0.45
min (%)	−3.93	−1.66	−1.97	−2.01	−1.56	−1.23	−2.83	−1.00	−2.24	−1.60	−0.89	−1.26	−3.17	−1.68
Illiquidity (high minus low)														
$\bar{r}$	−2.76***	−0.21	−0.10	−0.45*	−0.06	−0.01	0.03	−0.36*	0.07	0.27	0.36*	−0.15	0.17	3.70***
	(−6.14)	(−0.85)	(−0.38)	(−1.91)	(−0.30)	(−0.06)	(0.18)	(−1.83)	(0.42)	(1.48)	(1.84)	(−0.69)	(0.72)	(11.82)
α	−1.50***	−0.57***	−0.41*	−0.38**	−0.20	−0.02	−0.04	−0.09	0.21	0.12	0.19	0.21	0.45**	3.73***
	(−4.11)	(−2.66)	(−1.78)	(−1.99)	(−1.24)	(−0.15)	(−0.29)	(−0.69)	(1.58)	(0.85)	(1.30)	(1.35)	(2.56)	(13.08)
σ (%)	0.39	0.21	0.23	0.21	0.18	0.16	0.15	0.17	0.15	0.16	0.17	0.18	0.20	0.27
skew	−0.75	−2.76	−0.32	−0.98	−1.08	−0.21	0.03	−15.98	−2.97	1.32	−0.67	−0.78	0.13	0.94
min (%)	−6.50	−5.61	−3.05	−4.11	−4.21	−1.47	−1.40	−8.29	−4.16	−1.51	−2.06	−3.19	−1.67	−2.38

(*continued on next page*)

Table 7 (*continued*)

	OV	9:45	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Idiosyncratic volatility (low minus high)														
$\bar{r}$	−7.62***	2.07***	2.92***	1.16***	1.44***	0.45*	0.50**	−0.01	0.41*	0.28	0.33	0.40	0.64**	−1.28***
	(−8.87)	(5.82)	(6.83)	(3.40)	(5.22)	(1.75)	(2.26)	(−0.06)	(1.75)	(1.19)	(1.25)	(1.51)	(2.22)	(−3.95)
α	−5.06***	1.57***	2.40***	1.25***	1.29***	0.45**	0.42**	0.20	0.58***	0.12	0.16	0.73***	0.96***	−1.26***
	(−7.32)	(4.97)	(6.77)	(4.42)	(5.43)	(2.07)	(2.23)	(1.05)	(3.06)	(0.58)	(0.73)	(3.26)	(4.05)	(−4.26)
σ (%)	0.75	0.31	0.37	0.30	0.24	0.22	0.19	0.18	0.20	0.21	0.23	0.23	0.25	0.28
skew	−0.66	0.39	0.01	−0.01	0.54	0.81	0.36	0.70	−6.56	−3.32	0.25	−0.13	−1.01	−0.00
min (%)	−9.94	−2.23	−3.59	−3.04	−2.14	−2.14	−1.64	−1.71	−7.52	−5.73	−4.35	−2.23	−3.47	−3.09
Momentum (high minus low)														
$\bar{r}$	5.12***	0.30	−0.18	0.08	0.60*	0.33	−0.04	−0.24	−0.04	−0.00	0.10	−0.02	−0.13	−0.69**
	(5.83)	(0.86)	(−0.43)	(0.21)	(1.93)	(1.19)	(−0.15)	(−1.06)	(−0.19)	(−0.00)	(0.36)	(−0.07)	(−0.46)	(−2.25)
α	5.64***	0.32	−0.19	0.08	0.62**	0.33	−0.04	−0.27	−0.02	−0.01	0.08	−0.01	−0.12	−0.69**
	(6.53)	(0.89)	(−0.45)	(0.22)	(1.97)	(1.20)	(−0.16)	(−1.21)	(−0.08)	(−0.06)	(0.32)	(−0.05)	(−0.41)	(−2.27)
σ (%)	0.76	0.31	0.37	0.32	0.27	0.24	0.21	0.20	0.20	0.21	0.23	0.22	0.24	0.27
skew	−0.91	0.34	−1.00	−0.68	−0.40	−0.42	−0.13	0.82	−0.47	−0.01	1.04	−0.29	−0.32	−0.35
min (%)	−11.16	−2.20	−4.68	−3.85	−3.61	−3.67	−2.28	−1.94	−2.47	−3.75	−2.15	−2.62	−3.30	−3.04
Net stock issues (low minus high)														
$\bar{r}$	−1.82***	0.75***	1.32***	0.97***	0.33**	0.52***	0.03	0.41**	−0.10	0.41***	0.28**	0.47***	−0.30*	−1.71***
	(−4.20)	(3.38)	(5.76)	(5.11)	(2.01)	(3.47)	(0.23)	(2.55)	(−0.76)	(3.01)	(2.08)	(3.24)	(−1.85)	(−9.00)
α	−1.41***	0.68***	1.24***	0.97***	0.32*	0.52***	0.02	0.39***	−0.08	0.38***	0.26*	0.52***	−0.24	−1.70***
	(−3.33)	(3.12)	(5.50)	(5.18)	(1.92)	(3.48)	(0.16)	(2.80)	(−0.63)	(2.83)	(1.92)	(3.57)	(−1.56)	(−9.01)
σ (%)	0.38	0.19	0.20	0.16	0.14	0.13	0.12	0.14	0.11	0.12	0.12	0.13	0.14	0.16
skew	0.29	0.52	−0.58	0.53	0.01	0.66	−0.40	15.74	−0.61	−1.07	0.01	0.47	−1.33	−0.16
min (%)	−3.46	−2.85	−3.09	−1.44	−1.62	−1.35	−1.30	−0.78	−1.23	−2.39	−1.04	−1.12	−2.11	−1.73
Size (small minus large)														
$\bar{r}$	−1.05**	−0.22	−0.57**	−0.68***	−0.27	−0.03	−0.00	−0.38**	−0.14	0.07	0.09	−0.33	0.02	3.46***
	(−2.54)	(−0.92)	(−2.13)	(−2.91)	(−1.32)	(−0.19)	(−0.01)	(−2.09)	(−0.80)	(0.38)	(0.46)	(−1.58)	(0.07)	(11.24)
α	0.00	−0.56**	−0.85***	−0.61***	−0.40**	−0.05	−0.07	−0.14	−0.01	−0.07	−0.06	0.01	0.28	3.49***
	(0.00)	(−2.56)	(−3.59)	(−3.16)	(−2.35)	(−0.31)	(−0.47)	(−1.07)	(−0.10)	(−0.51)	(−0.43)	(0.05)	(1.53)	(12.48)
σ (%)	0.36	0.21	0.23	0.20	0.18	0.16	0.15	0.16	0.15	0.15	0.17	0.18	0.20	0.27
skew	−0.73	−2.75	−0.12	−0.65	−1.49	−0.12	−0.04	−11.26	−2.10	1.05	−0.87	−0.88	0.04	0.75
min (%)	−5.92	−5.57	−2.69	−3.77	−4.04	−1.42	−1.34	−6.98	−3.47	−1.42	−2.13	−3.37	−2.05	−2.25

ity, net stock issues, and idiosyncratic volatility portfolios are reported in the Internet Appendix. The short leg performs particularly poorly at the end of the day, but the long leg also tends to perform poorly. This evidence supports the idea that gross profitability, idiosyncratic volatility, and net stock issues are driven by mispricing. Regarding the profitability anomaly, this result supports Bouchaud et al. (2019) and challenges purely rational risk-based theories.[22]

Four of the above anomalies overlap with the 11 anomalies used to construct the Stambaugh et al. (2012, 2015) mispricing measure (momentum, accruals, net stock issues, and profitability). I show in Section 5.1 that almost all of the other anomalies underlying the mispricing measure display an intraday "mispricing pattern," in line with my explanation.

Table 7 shows how intraday average returns vary with a specific characteristic. I next estimate value-weighted Fama-MacBeth regressions. Similar results are obtained from panel regressions with day fixed effects and standard errors double-clustered by date and stock. The regression setup allows for an examination of how characteristics jointly predict intraday returns. For example, a short exposure to size or illiquidity could drive the negative returns at the end of the day of the "gradual" anomalies. If this is the case, then it is not obvious that the overnight risk and institutional constraints channels hypotheses can explain the patterns.

The value-weighted cross-sectional regressions employ as explanatory variables the characteristics used to construct the anomaly portfolios: accruals, market beta, log book-to-market, log gross profitability, idiosyncratic volatility, past 12-month return skipping the last month, log illiquidity, log of net stock issues growth rate, and log of market capitalization. They are measured at the end of the previous month. All the variables are winsorized at 0.05% each year. Explanatory variables are standardized to have a zero mean and a unit standard deviation. Full sample estimates and standard errors are then computed using the approach of Fama and MacBeth (1973) with Newey and West (1987) correction.

Table 8 reports the estimation results for each intraday interval and the overnight period. The results for gross profitability, idiosyncratic volatility, and net stock issues are in line with those in Table 7. Even after controlling for the other characteristics, these characteristics tends to consistently predict returns over the trading day and returns with the opposite sign in the last half hour. Hence, the results are not driven by exposure to size or illiquidity.[23] Similarly, the mispricing pattern in Table 1 is robust to controlling for illiquidity (reported in the Internet Appendix).

4.3. Placebo anomalies

The lack of strong theoretical guidance relative to intraday and overnight returns could cause a critical reader to be skeptical of the previous evidence. I now show that the above patterns are unlikely to be the outcome of chance.

I generate placebo anomalies using monthly returns and examine their average intraday returns. 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.

Among all random strategies, 1057 earn average monthly returns that are statistically significant at the level of 10%. I refer to these strategies as spurious anomalies. The "best" spurious anomaly has a t-statistic of 3.97. Market returns do not explain the returns of spurious anomalies. For each spurious anomaly, I compute intraday half-hour and overnight alphas with associated t-statistics. Most spurious anomalies earn the bulk of their return overnight. Overnight alpha is negative for less than 20% of spurious anomalies.

First, I evaluate whether a spurious anomaly earns a statistically significant alpha in a given period across all subsamples and days of the week (like size and illiquidity, as shown in Section 5.3). Only one spurious anomaly passes this test. Like momentum, this strategy has a positive overnight alpha. This evidence suggests that concentrated patterns similar to those of size and illiquidity are not replicated by simple random strategies.

Second, The histogram in Fig. 3 reports the number of spurious anomalies that have a given number of positive and significant half-hour alphas (at the level of 10%). Spurious anomalies do not appear to earn positive and statistically significant returns consistently across the trading day. This contrasts with many anomalies identified above, for which the same statistic is indicated in the histogram.[24] This result supports the idea that intraday return patterns have economic content that can help to understand cross-sectional variation in stock returns.

[22] Table 7 is retabulated using a price filter of \$10 instead of \$5. The results are not substantially affected (reported in the Internet Appendix). Intraday return statistics computed from trade prices give similar results to returns computed from quote midpoints (reported in the Internet Appendix).

[23] Illiquidity tends to earn positive intraday returns after controlling for size, and size has an insignificant end-of-day average return after controlling for illiquidity. Table A.3 shows that size and illiquidity are highly correlated, which raises concerns about multicollinearity. Importantly, the results in Table 8 for other anomalies are not sensitive to excluding size, illiquidity, or both.

[24] Since 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. To address this concern, I repeat the exercise with the following adjustment: the portfolios are formed using a randomly generated characteristic for each stock that follows an autoregressive process with a persistence parameter equal to 90% and normally distributed shocks. The results are similar. Three strategies earn a statistically significant alpha in a given period across all subsamples and days of the week, which represents 0.28% of all spurious anomalies.

Table 8

Intraday and overnight cross-sectional average return variation. This table reports estimates of value-weighted Fama-MacBeth regressions of intraday and overnight returns on characteristics. Each column represents a separate regression where stock returns are regressed on a set of characteristics. The characteristics are measured at the end of the previous month and are: accruals (AC), market beta (BE), log book-to-market (BM), log gross profitability (GP), log illiquidity (IL), idiosyncratic volatility (IV), past 12-month return skipping the last month (MO), log of net stock issues growth rate (NI), and log of market capitalization (SI). Details on the characteristics' construction are provided in Table A.2. All the variables are winsorized at 0.05% each year. Explanatory variables are standardized to have a zero mean and a unit standard deviation. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45am; 10:00 indicates the half-hour interval that starts at 10:00am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The *t*-statistics are shown in parentheses and based on Newey-West standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	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	−0.24**	−0.11*	−0.09	0.03	0.13***	0.02	−0.13***	−0.03	−0.02	0.09**	0.00	0.03	−0.00	−0.13**
	(−1.97)	(−1.88)	(−1.34)	(0.52)	(2.85)	(0.36)	(−3.27)	(−0.86)	(−0.68)	(2.46)	(0.06)	(0.75)	(−0.11)	(−2.45)
BE	2.64***	−0.36**	−0.49***	−0.20	−0.23**	−0.14	−0.26***	0.05	−0.19**	−0.17*	−0.22**	0.01	−0.12	−0.34***
	(8.17)	(−2.48)	(−2.85)	(−1.42)	(−2.09)	(−1.36)	(−2.68)	(0.54)	(−2.14)	(−1.81)	(−2.12)	(0.07)	(−1.09)	(−2.86)
BM	0.41***	0.09	0.20***	0.10*	0.06	−0.01	−0.04	0.02	0.06	−0.03	−0.03	−0.02	−0.19***	−0.30***
	(2.69)	(1.28)	(2.86)	(1.71)	(1.14)	(−0.25)	(−0.81)	(0.56)	(1.33)	(−0.60)	(−0.67)	(−0.54)	(−3.84)	(−4.84)
GP	−0.19	0.09	0.31***	0.26***	0.14***	0.11**	0.10**	0.06	0.09**	0.03	0.05	0.10**	0.10*	−0.40***
	(−1.37)	(1.30)	(4.19)	(4.14)	(2.72)	(2.29)	(2.21)	(1.46)	(2.45)	(0.83)	(1.06)	(2.38)	(1.86)	(−7.31)
IL	−5.05***	0.84***	0.84***	−0.10	0.05	−0.18	−0.05	0.31**	0.22*	0.35***	0.07	0.02	0.62***	0.99***
	(−11.02)	(4.14)	(3.48)	(−0.52)	(0.28)	(−1.27)	(−0.38)	(2.39)	(1.80)	(2.73)	(0.58)	(0.17)	(4.31)	(5.15)
IV	1.90***	−0.44***	−0.72***	−0.25***	−0.35***	−0.14**	−0.09	−0.07	−0.11**	−0.21***	−0.10*	−0.18***	−0.29***	0.04
	(10.94)	(−5.15)	(−7.47)	(−3.13)	(−5.03)	(−2.28)	(−1.55)	(−1.40)	(−2.25)	(−4.13)	(−1.90)	(−3.36)	(−4.76)	(0.53)
MO	2.57***	−0.29***	−0.24**	−0.07	−0.05	−0.01	−0.06	−0.06	−0.00	−0.05	−0.12**	−0.03	−0.25***	−0.12
	(11.88)	(−2.74)	(−2.20)	(−0.80)	(−0.64)	(−0.13)	(−0.97)	(−1.10)	(−0.05)	(−0.82)	(−2.09)	(−0.42)	(−3.97)	(−1.29)
NI	0.18*	−0.14***	−0.13***	−0.08**	−0.03	−0.04	0.00	−0.04	0.03	−0.07**	−0.04	−0.01	0.02	0.20***
	(1.94)	(−3.45)	(−3.02)	(−2.13)	(−0.98)	(−1.29)	(0.01)	(−1.61)	(1.34)	(−2.45)	(−1.31)	(−0.45)	(0.51)	(5.23)
SI	−2.66***	0.65***	0.69***	0.13	0.02	−0.24**	−0.19*	0.23**	0.05	0.14	−0.05	−0.06	0.24**	−0.16
	(−7.54)	(4.03)	(3.56)	(0.94)	(0.18)	(−2.10)	(−1.78)	(2.27)	(0.50)	(1.38)	(−0.47)	(−0.52)	(2.05)	(−0.95)

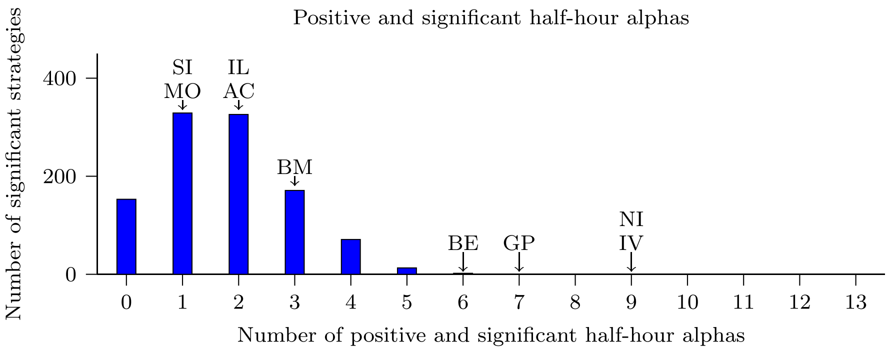

Fig. 3. Placebo anomaly portfolios. At the beginning of each year, stocks with a price greater than $5 and a market capitalization greater than $100 million are allocated randomly into decile portfolios. Two of the decile portfolios are selected randomly to compute monthly value-weighted returns on a 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 1057 strategies that have an average monthly return significant at the level of 10% are labeled as significant strategies. The figure reports a histogram of the number of significant strategies with a given number of positive and significant (at the level of 10%) intraday half-hour alphas. The same statistic is indicated for 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).

4.4. Clientele effects and alternative explanations

Clientele effects denote the idea that investors could self-select into holding different assets or trading at different times. Several papers consider such effects in the context of overnight and intraday stock returns. Berkman et al. (2012) argue that retail investors tend to buy stocks that attracted their attention at the open. This buying pressure results in high overnight returns followed by intraday reversals. Lou et al. (2019) show that firm-level intraday (overnight) returns positively predict future intraday (overnight) returns but negatively predict future overnight (intraday) returns. They link this tug of war between overnight and intraday returns to clientele effects: institutions trading at the end of the day and retail investors trading at the beginning of the day.

In a broad sense, my explanation falls under clientele effects since it features arbitrageurs averse to holding positions in stocks with high overnight risk or/and high capital costs. But the explanation makes specific predictions to shed light on the sources of anomalies. In particular, the results should not be driven by long-term clientele effects; that is, by a specific group of investors that trade repeatedly the same set of stocks at the same time of the day.

As shown in Fig. 2 of LPS, intraday returns forecast future intraday returns in a statistically significant way up to a horizon of around one year. To assess the role of these long-term clientele effects, I compute for each stock its average return in a given intraday interval and overnight over the past year and control for this variable in my tests. For instance, when the return between 10:00am and 10:30am is the dependent variable in the Fama-MacBeth regressions, the regression includes the average return between 10:00am and 10:30am over the previous year as an explanatory variable.

Panel (a) of Table 9 reports the estimates of value-weighted Fama-MacBeth regressions with the Stambaugh et al. (2012, 2015) mispricing measure and the average same-interval return. Consistent with Table 1, higher overpricing is associated with lower return over the trading day except in the last half hour of trading. Hence, the results are robust to the inclusion of the prior-year average return in the same interval. The coefficient on the prior-year average returns is positive and statistically significant for every interval of the day. Stocks that outperformed other stocks over the past year in a specific interval tend to outperform other stocks in the same interval again (Heston et al., 2010). In summary, past average returns are strong cross-sectional predictors of future returns but do not explain the mispricing pattern.

As shown in Panel (b) of Table 9, the results with the full set of characteristics reported in Table 8 are robust to including the prior-year average return, though the end-of-day coefficients are reduced to some extent.[25] For instance, the gross profitability coefficient changes from a value of −0.40 (with a *t*-statistic of −7.31) to a value of −0.25 (with a *t*-statistic of −4.72). This suggests that long-term stock-specific effects matter but explain only part of the patterns. The drop is most pronounced for the end-of-day illiquidity effect, where the 3:30pm coefficient drops from 0.99 in Table 8 to 0.37 in Table 9, which is only significant at the level of 10%. This suggests that clientele effects could explain in large part why illiquid stocks tend to do well at the end of the day.

It is intuitive that closing prices could be subject to pressure induced by institutions. Shares in open-end mutual funds trade at net asset values that are computed once a day based on closing prices. Hence, mutual fund managers could concentrate their trades towards the end of the day, when there is less uncertainty about net daily flows. In line with this idea, Goetzmann and Massa (2003) show that, for a sample of index funds, daily net flows are correlated with afternoon index returns but not with morning returns. For such institutional trading to explain the pattern in Table 1, institutions must sell stocks that have performed well over the afternoon (and the rest of the day),

[25] To save space, I do not report the coefficients on all of the characteristics. The full set of results is reported in the Internet Appendix.

Table 9

Intraday and overnight cross-sectional average return variation and return persistence. This table reports estimates of value-weighted Fama-MacBeth regressions of intraday and overnight returns on a return seasonality variable. A stock's return seasonality variable ($\bar{r}^h_{1y}$) is the stock's average return over the past year in the same interval as the dependent variable return. For instance, when the return between 10:00am and 10:30am is the dependent variable, the regression includes the average return between 10:00am and 10:30am over the previous year as an explanatory variable. Panel (a) includes the mispricing measure (MIS) of Stambaugh et al. (2012, 2015). Panel (b) includes the following set of characteristics: accruals (AC), market beta (BE), log book-to-market (BM), log gross profitability (GP), log illiquidity (IL), idiosyncratic volatility (IV), past 12-month return skipping the last month (MO), log of net stock issues growth rate (NI), and log of market capitalization (SI). Details on the characteristics' construction are provided in Table A.2. All the variables except the mispricing variable are winsorized at 0.05% each year. Explanatory variables are standardized to have a zero mean and a unit standard deviation. 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 month to be included. Stock returns are computed using quote midpoints. The first interval starts at 9:45am; 10:00 indicates the half-hour interval that starts at 10:00am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The *t*-statistics are shown in parentheses and based on Newey-West standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
(a) Mispricing measure														
MIS	0.14	−0.25***	−0.44***	−0.25***	−0.20***	−0.09*	−0.05	−0.04	−0.03	−0.08	−0.08	−0.10**	−0.07	0.54***
	(0.87)	(−3.92)	(−4.85)	(−3.64)	(−3.64)	(−1.84)	(−0.98)	(−0.97)	(−0.76)	(−1.62)	(−1.53)	(−2.03)	(−1.25)	(7.74)
$\bar{r}^h_{1y}$	5.61***	1.01***	0.88***	0.42***	0.28***	0.15**	0.37***	0.24***	0.17***	0.14**	0.24***	0.37***	0.74***	2.47***
	(20.41)	(9.96)	(9.00)	(4.24)	(3.25)	(2.24)	(6.41)	(4.56)	(3.23)	(2.56)	(3.95)	(5.91)	(12.50)	(23.70)
(b) Full set of characteristics														
BM	0.34**	0.08	0.17**	0.08	0.06	−0.01	−0.04	0.02	0.05	−0.02	−0.03	−0.02	−0.15***	−0.24***
	(2.35)	(1.10)	(2.41)	(1.35)	(1.11)	(−0.19)	(−0.84)	(0.40)	(1.31)	(−0.58)	(−0.77)	(−0.49)	(−3.04)	(−3.95)
GP	−0.03	0.08	0.27***	0.22***	0.13**	0.10**	0.09*	0.05	0.10***	0.03	0.04	0.09**	0.08	−0.25***
	(−0.19)	(1.16)	(3.51)	(3.64)	(2.48)	(2.23)	(1.92)	(1.22)	(2.61)	(0.75)	(0.84)	(2.19)	(1.51)	(−4.72)
IL	−3.32***	0.67***	0.67***	−0.12	0.05	−0.19	−0.07	0.27**	0.19	0.33**	0.06	0.00	0.42***	0.37*
	(−7.50)	(3.38)	(2.80)	(−0.65)	(0.27)	(−1.33)	(−0.59)	(2.12)	(1.61)	(2.52)	(0.45)	(0.00)	(2.92)	(1.95)
IV	1.37***	−0.35***	−0.61***	−0.21***	−0.31***	−0.13**	−0.07	−0.07	−0.10**	−0.19***	−0.10**	−0.15***	−0.25***	−0.08
	(8.29)	(−4.26)	(−6.62)	(−2.81)	(−4.71)	(−2.14)	(−1.31)	(−1.51)	(−2.10)	(−3.81)	(−1.99)	(−2.87)	(−4.21)	(−1.19)
NI	0.16*	−0.12***	−0.11**	−0.07**	−0.02	−0.04	0.01	−0.05*	0.03	−0.06**	−0.02	−0.01	0.01	0.08**
	(1.79)	(−2.92)	(−2.44)	(−2.00)	(−0.73)	(−1.25)	(0.18)	(−1.85)	(1.32)	(−2.38)	(−0.87)	(−0.43)	(0.35)	(2.13)
SI	−1.79***	0.52***	0.57***	0.12	0.03	−0.23**	−0.20*	0.21**	0.03	0.14	−0.06	−0.07	0.13	−0.27
	(−5.14)	(3.24)	(2.90)	(0.80)	(0.25)	(−2.00)	(−1.79)	(2.03)	(0.32)	(1.37)	(−0.53)	(−0.59)	(1.10)	(−1.62)
$\bar{r}^h_{1y}$	4.79***	0.95***	0.92***	0.41***	0.20***	0.15***	0.28***	0.24***	0.13***	0.15***	0.25***	0.34***	0.75***	2.46***
	(24.33)	(14.24)	(12.08)	(3.34)	(3.15)	(6.15)	(5.63)	(3.31)	(3.77)	(5.69)	(5.89)	(8.17)	(15.27)	(29.41)

Table 10
Intraday and overnight alphas in basis points of long-short portfolios (extended set of anomalies). At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of different variables. The construction of these variables is similar to Stambaugh et al. (2012, 2015) except that accounting variables are computed once a year at the end of June using data for the previous fiscal year. The only exception is for return on assets, which uses quarterly income data. This variable is assumed to be available at the beginning of the month that follows the Compustat reporting date (item RDQ). Portfolios are value-weighted and held for one month. A stock is required to have a price greater than $5 at the end of the previous month and a market capitalization greater than $100 million at the end of the previous month to be included. Financial firms are excluded from portfolios based on accounting variables. Stock returns are computed using quote midpoints. The first interval starts at 9:45am; 10:00 indicates the half-hour interval that starts at 10:00am and ends before 10:30am. OV indicates the overnight interval. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1986 to December 31, 2015. NASDAQ stocks are included since 1993. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	OV	9:45	10:00	10:30	11:00	11:30	12:00	12:30	1:00	1:30	2:00	2:30	3:00	3:30
Asset growth														
α	−1.44***	0.74***	0.98***	0.19	−0.02	0.46***	0.12	0.10	0.16	0.23	0.14	0.17	0.26	0.03
	(−2.96)	(3.06)	(3.94)	(0.91)	(−0.09)	(2.84)	(0.78)	(0.74)	(1.07)	(1.60)	(0.89)	(1.03)	(1.45)	(0.12)
Composite equity issues														
α	−0.92**	0.91***	0.94***	0.96***	0.47***	0.44***	0.18	0.33**	0.32**	0.24*	0.38***	0.40***	0.23	−1.87***
	(−2.10)	(3.99)	(4.22)	(5.08)	(2.91)	(2.99)	(1.34)	(2.46)	(2.44)	(1.73)	(2.71)	(2.70)	(1.40)	(−8.57)
Distress (O −score)														
α	−1.43***	1.01***	1.56***	0.77***	0.64***	0.28*	0.26*	0.21	−0.01	0.05	0.07	0.30*	−0.07	−2.91***
	(−3.15)	(4.11)	(5.77)	(3.57)	(3.47)	(1.65)	(1.68)	(1.41)	(−0.06)	(0.37)	(0.46)	(1.79)	(−0.37)	(−12.05)
Investments-to-assets														
α	1.70***	0.05	0.45	0.34	0.08	−0.18	−0.56***	−0.48***	−0.23	0.22	−0.04	−0.01	0.30	−1.50***
	(2.62)	(0.17)	(1.46)	(1.21)	(0.32)	(−0.84)	(−2.94)	(−2.63)	(−1.25)	(1.17)	(−0.20)	(−0.03)	(1.41)	(−5.80)
Net operating assets														
α	1.50***	1.03***	0.99***	0.58***	0.46**	0.23	0.09	−0.11	−0.04	0.29**	0.13	−0.23	−0.15	−1.43***
	(3.06)	(4.39)	(4.03)	(2.83)	(2.51)	(1.44)	(0.58)	(−0.80)	(−0.30)	(1.99)	(0.84)	(−1.45)	(−0.91)	(−6.91)
Return on assets														
α	0.09	0.58**	1.22***	0.77***	0.85***	0.36**	0.38***	0.16	−0.04	0.02	0.20	0.46***	0.44***	−1.81***
	(0.18)	(2.30)	(4.81)	(3.69)	(4.61)	(2.26)	(2.66)	(1.11)	(−0.29)	(0.12)	(1.25)	(2.98)	(2.61)	(−8.73)

Table 11
Opening price and overnight return. This table reports overnight and opening average logarithmic returns in basis points of long-short portfolios computed using midquotes at 9:35 am, 9:40 am, and 9:45 am, and the volume-weighted average price in the first half-hour of trading (VWAP). For instance, with the opening midquote at 9:35 am, the overnight return is computed between 4:00pm on the previous close and 9:35 am on the current day, while the opening return is computed from 9:35am until 10:00am on the current day. At the end of each month, stocks are split into decile portfolios based on the NYSE breakpoints of the mispricing measure (MIS) of Stambaugh et al. (2012, 2015) and the characteristics defined in Table A.2: accruals (AC), market beta (BE), book-to-market (BM), gross profitability (GP), illiquidity (IL), idiosyncratic volatility (IV), past 12-month return skipping the last month (MO), net stock issues growth rate (NI), and market capitalization (SI). Portfolios are value-weighted and held for one month. 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 month to be included. Financial firms are excluded from portfolios based on accounting variables. The sample is composed of NYSE, Amex, and NASDAQ common stocks from January 1, 1993 to December 31, 2015. The *t*-statistics are shown in parentheses and based on Newey and West (1987) standard errors with 14 lags. *, **, and *** denote significance at the 10%, 5%, and 1% level.

	Overnight return				Opening return			
	9:35	9:40	9:45	VWAP	9:35	9:40	9:45	VWAP
MIS	−0.15	0.16	0.16	1.57*	1.49***	1.19**	1.19***	−0.22
	(−0.18)	(0.19)	(0.20)	(1.92)	(2.73)	(2.38)	(3.90)	(−0.39)
AC	1.48	1.89**	0.68	0.79	−0.26	−0.66	0.54**	0.44
	(1.42)	(2.14)	(1.13)	(1.45)	(−0.27)	(−0.91)	(2.04)	(1.55)
BE	−7.33***	−7.39***	−6.68***	−6.06***	2.43***	2.49***	1.78***	1.16*
	(−5.38)	(−5.43)	(−4.83)	(−4.80)	(3.18)	(4.04)	(3.47)	(1.91)
BM	−3.25***	−3.46***	−3.09***	−1.64	0.80*	1.01**	0.63**	−0.82
	(−5.15)	(−5.01)	(−4.59)	(−1.61)	(1.84)	(2.42)	(2.06)	(−0.91)
GP	−2.36***	−1.42**	−1.10*	−1.54***	1.67***	0.73**	0.41	0.85***
	(−4.16)	(−2.49)	(−1.89)	(−2.89)	(3.67)	(2.14)	(1.60)	(3.11)
IL	2.18	−1.94***	−2.61***	−3.80***	−5.45***	−1.32***	−0.65**	0.53
	(1.17)	(−3.61)	(−5.38)	(−7.95)	(−2.99)	(−3.61)	(−2.50)	(1.56)
IV	−8.31***	−9.56***	−7.82***	−7.15***	3.01***	4.26***	2.51***	1.85
	(−7.32)	(−7.76)	(−7.18)	(−4.46)	(3.82)	(5.20)	(5.72)	(1.33)
MO	6.93***	6.65***	6.33***	7.52***	−0.42	−0.14	0.18	−1.01
	(6.69)	(6.17)	(5.70)	(7.38)	(−0.62)	(−0.25)	(0.42)	(−1.61)
NI	−2.16***	−2.78***	−2.30***	−0.48	0.43	1.05***	0.58**	−1.25**
	(−3.62)	(−5.15)	(−4.33)	(−0.68)	(0.87)	(3.10)	(2.24)	(−2.25)
SI	1.53***	−0.11	−0.92**	−2.03***	−3.09***	−1.44***	−0.64**	0.47
	(2.83)	(−0.21)	(−2.02)	(−4.21)	(−6.85)	(−3.79)	(−2.46)	(1.18)

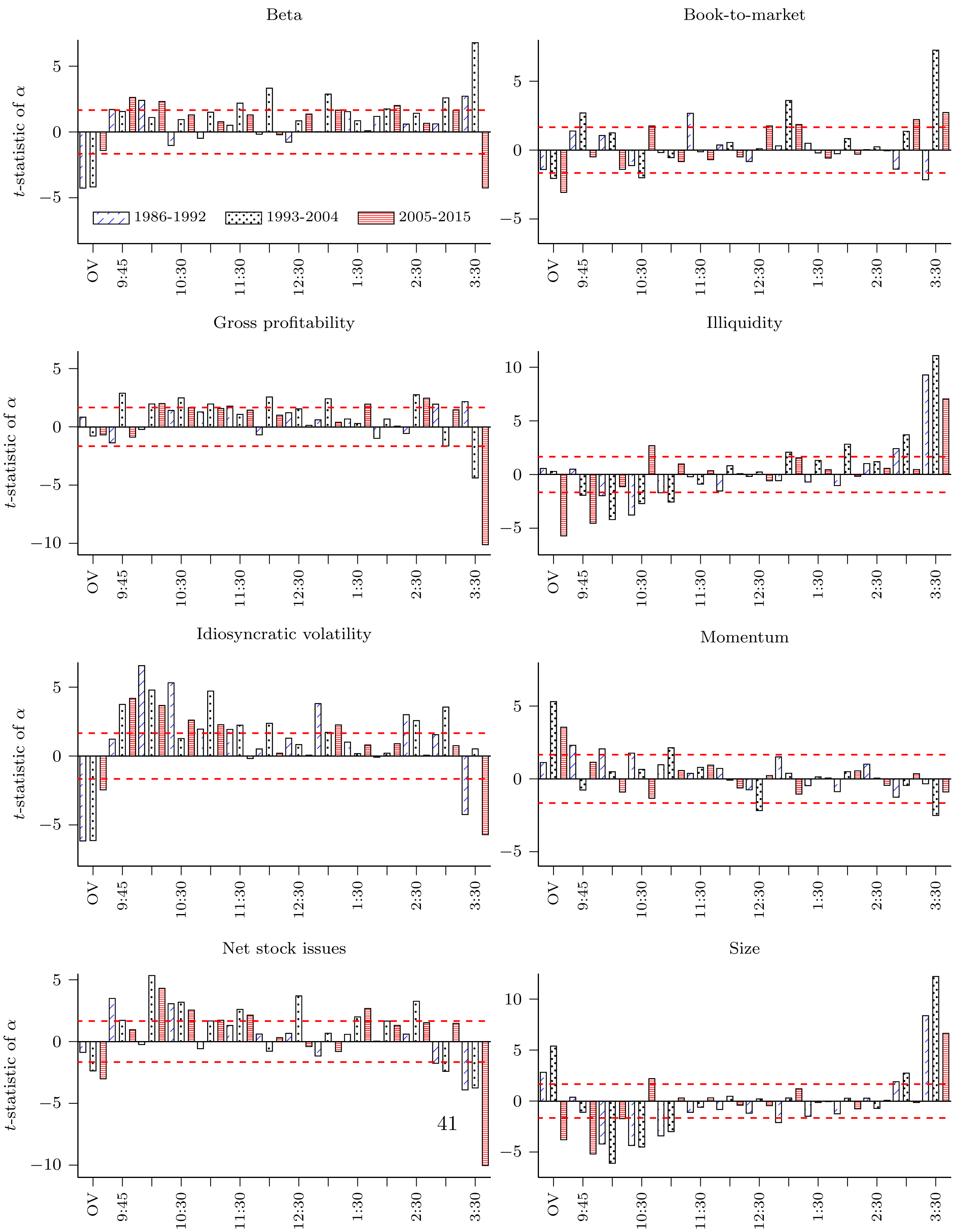

Fig. 4. Intraday and overnight *t*-statistics of market alphas of long-short portfolios across subsamples. The first interval starts at 9:45 am; 10:00 indicates the half-hour interval that starts at 10:00 am and ends before 10:30 am. OV indicates the overnight interval. Portfolio construction is detailed in the caption of Table 7. Dashed lines indicate significance at the level of 10%. The *t*-statistics are based on Newey and West (1987) standard errors with 14 lags.

inconsistent with the evidence in Goetzmann and Massa (2003).

To further assess the role of clientele effects, I include quarterly institutional ownership (measured at the beginning of each quarter) as an additional explanatory variable. Even controlling for the full set of characteristics, institutional ownership is a strong predictor of intraday and overnight returns (reported in the Internet Appendix). Institutional ownership negatively predicts overnight returns and early morning returns but positively predicts afternoon returns. The negative coefficient for overnight returns and the subsequent positive morning coefficients are consistent with Berkman et al. (2012) and LPS. However, the coefficients on the other characteristics (Table 8) remain similar.

In summary, long-term clientele effects are important but do not explain my results.

5. Robustness checks

This section provides several robustness checks mentioned in the analysis.

5.1. Additional set of anomalies

This paper focuses on a set of major anomalies (Fama and French, 2008; 2016). To provide an additional test, this section examines all of the anomalies underlying the construction of the Stambaugh et al. (2012, 2015) mispricing measure. Relative to the mispricing measure, the set of anomalies considered in Table 7 misses financial distress, composite equity issues, net operating assets, asset growth, return on assets, and investments-to-assets. For simplicity, I focus on a single measure of financial distress, the O-score.

Table 10 reports intraday and overnight alphas for these anomalies. Five out of six anomalies have a negative and statistically significant end-of-day alpha, and most of these anomalies tend to perform well during the trading day. Hence, Table 10 supports the proposed explanation: the variables underlying the mispricing measure were selected to proxy for mispricing, and it turns out that most of them display the intraday "mispricing pattern."

5.2. Opening price

The above analysis uses the midquote at 9:45am to compute overnight returns. This section examines whether earlier sampling of the opening price affects the results.[26]

On the one hand, sampling earlier avoids contamination with price movements in the first half hour of trading that are unrelated to overnight information. This should help measure overnight returns more precisely. Also, if the return accrues linearly over time, then sampling earlier should simply spread the return between the overnight and opening periods. On the other hand, spreads are highest and depth is lowest at the open (Lee et al., 1993). High illiquidity could lead arbitrageurs to delay their trades. Moreover, uninformed price pressure could worsen mispricing at the open (Berkman et al., 2012). This channel predicts that sampling earlier should lead to lower overnight mispricing return.

Table 11 reports anomaly overnight and opening average returns using midquotes sampled at 9:35 am, 9:40 am, and 9:45 am. The table also reports overnight and opening average returns using the volume-weighted average price in the first half hour of trading as opening price. To ease comparisons between sampling times, the table reports average logarithmic raw returns. Due to data limitations, the table focuses on the TAQ part of the sample (1993–2015).

For the mispricing strategy, sampling at 9:35 am decreases overnight average return (and therefore increases opening average return). This result is consistent with the idea that high illiquidity prevents arbitrageurs from trading immediately at the open. This is also consistent with potential price pressure from uninformed trading that worsens mispricing right at the open. Sampling at 9:40 am yields identical but noisier estimates to sampling at 9:45 am.

Results for other anomalies show, however, that this result is anomaly-specific. Intuitively, the timing should depend on the underlying stocks' liquidity, which likely varies across anomalies. Indeed, size and illiquidity portfolios' overnight (opening) average return increases (decreases) monotonically as we sample earlier. These two portfolios highlight the importance of the opening price for overnight and intraday return patterns in the cross-section of stocks. A tug of war between overnight and intraday alphas appears only with the 9:35 midquote. Hence, the open should be given special consideration in any analysis of overnight and intraday returns.

5.3. Subsamples and days of the week

The return patterns in Table 7 are robust across subsamples and days of the week.

The sample is split into three parts. The first part spans the ISSM data and goes from 1986 to 1992 (included). The second part covers 1993 to 2004. Finally, the last part covers 2005 to 2015. Fig. 4 shows that the patterns are robust across subsamples, though statistical significance tends to be lower because of the smaller number of observations.

Harris (1986), Smirlock and Starks (1986), and Jain and Joh (1988) show a strong day-of-the-week effect in intraday index returns. More recently, Birru (2018) finds day-of-the-week effects for anomalies in a sample that goes from 1995 to 2013. The Internet Appendix reports *t*-statistics of intraday and overnight anomaly alphas across days of the week. The cross-sectional variation is robust across days of the week. Size returns tend to be particularly low early in the week (Birru, 2018) but remain high at the end of the day across all days of the week.

[26] I thank the referee for suggesting this analysis.

6. Conclusion

Intraday average returns are often assumed to be negligible or constant over the day. I show that asset pricing anomalies accrue over the trading day in markedly different ways. This evidence helps understand the economic drivers of cross-sectional variation in stock returns. Several anomalies perform well over most of the day but poorly in the last 30 minutes of trading. This evidence is consistent with mispricing. Mispricing gradually corrects over the day but worsens at the end of the day due to price pressure induced by capital-constrained arbitrageurs. These arbitrageurs close or reduce their positions because of overnight risk and institutional effects. I find support for this explanation using the mispricing factor of Stambaugh et al. (2012, 2015). The results suggest that mispricing plays an important role for gross profitability, idiosyncratic volatility, and net stock issues anomalies, as well as most of the other anomalies underlying the mispricing factor. The paper highlights a form of high-frequency limits to arbitrage, which arise due to market closures and could be even more relevant in an era of computerized trading.

Appendix A

Spurious reversals at the open plague midquote returns computed from TAQ. These reversals are especially prevalent across small stocks in the second part of the sample. Table A.1 illustrates the problem for a randomly selected stock by showing the first and last available intraday quotes on several dates.

On both October 12, and 13, 2012, a high ask price at the open generates a large overnight return and a negative first half-hour return (i.e., spurious reversal). Even the second and third quoted ask prices can be 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 taking the first valid quote with nonzero trade size (e.g., Berkman et al., 2012) does not seem to be sufficient. Numerous similar examples can be found for stocks that display more frequent quote updates.

Table A.1.
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

Table A.2.
List of anomalies. 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 (AC)	Change in working capital (excluding cash) minus depreciation, scaled by average total assets over the previous two years (Sloan, 1996).
Beta (BE)	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.
Book-to-market (BM)	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 (GP)	Revenue minus cost of good sold, divided by total assets (Novy-Marx, 2013).
Idiosyncratic volatility (IV)	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.
Illiquidity (IL)	Average ILLIQ over the past 250 trading days (Amihud, 2002). More precisely, $\mathrm{ILLIQ}_{i,t} = \frac{1}{N_{i,t}} \sum_{d \in D_{i,t}} \frac{\lvert r_{i,d} \rvert}{\mathrm{DVOL}_{i,d}} 10^6$, 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. NASDAQ volume is adjusted as in Gao and Ritter (2010) to take into account double counting from interdealer trading.
Momentum (MO)	Return over the past 12 months skipping the last month (Jegadeesh and Titman, 1993).
Net stock issues (NI)	Growth rate of the split-adjusted shares outstanding at fiscal year end as in Fama and French (2008).
Size (SI)	Market capitalization in the previous month.

To deal with these spurious reversals, I use the following criteria. First, I only consider quotes after 9:45am. Empirically, I find that most quotes seem to have normalized by 9:45am. 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 9:45am. Third, I delete any observation for which the spread is larger than 30 times the median spread during the day. Finally, I screen the data to eliminate large outliers, in particular, large return reversals that are not accompanied by any trading volume.

Table A.3.
Average cross-sectional correlation between characteristics. The characteristics are accruals (AC), market beta (BE), log book-to-market (BM), log illiquidity (IL), idiosyncratic volatility (IV), past 12-month return skipping the last month (MO), log of net stock issues growth rate (NI), log of market capitalization (SI), and mispricing factor of Stambaugh et al. (2012, 2015) (MIS). Details on the characteristics' construction are provided in Table A.2.

	AC	BE	BM	GP	IL	IV	MO	NI	SI	MIS
AC	1.00	0.01	−0.04	0.04	0.04	0.03	−0.03	0.06	−0.06	0.25
BE	0.01	1.00	−0.20	0.03	−0.18	0.28	0.05	0.08	0.10	0.12
BM	−0.04	−0.20	1.00	−0.27	0.15	−0.12	−0.17	−0.03	−0.18	0.07
GP	0.04	0.03	−0.27	1.00	−0.00	0.02	0.02	−0.13	−0.01	−0.39
IL	0.04	−0.18	0.15	−0.00	1.00	0.29	0.10	0.06	−0.91	0.15
IV	0.03	0.28	−0.12	0.02	0.29	1.00	0.08	0.11	−0.32	0.22
MO	−0.03	0.05	−0.17	0.02	0.10	0.08	1.00	0.03	0.02	−0.23
NI	0.06	0.08	−0.03	−0.13	0.06	0.11	0.03	1.00	−0.07	0.36
SI	−0.06	0.10	−0.18	−0.01	−0.91	−0.32	0.02	−0.07	1.00	−0.23
MIS	0.25	0.12	0.07	−0.39	0.15	0.22	−0.23	0.36	−0.23	1.00

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