Intraday Residual Reversal in the U.S. Stock Market

Jonathan Brogaard, Jaehee Han, and Hanjun Kim[*]

ABSTRACT

Li et al. (2023) show that intraday risk factor exposure leads to predictable returns. In this paper, we focus on the unexplained price movements from the factor-based intraday model. We document an economically large and statistically significant return reversal based on the previous period's residual return. This residual reversal strategy, which buys stocks with negative residuals and sells stocks with positive residuals, earns an annualized return of 162.3%. The strategy captures the returns to liquidity provision to the transitory component of stock returns.

Keywords: Residual Reversal, Market Efficiency, Intraday Market, Trading Strategy

JEL classification: G11, G12, G14

---

[*] Jonathan Brogaard, Jaehee Han, and Hanjun Kim are with the Eccles David School of Business, The University of Utah.
E-mail addresses: brogaardj@eccles.utah.edu (J. Brogaard), jaehee.han@eccles.utah.edu (J. Han), hanjun.kim@eccles.utah.edu (H. Kim)

I. Introduction

A growing body of literature has studied stock return predictability in various settings using risk and residual of stock prices. Recently, Li et al. (2023) show that the risk momentum exists at the intraday level. They decompose stock returns into two components: risk and residual. They find that the risk component exhibits a momentum pattern: stocks with a high (low) risk component have a high (low) risk component in the subsequent period. Furthermore, a long-short portfolio based on the risk momentum earns annualized 30-minute returns ranging from 3.82% to 14.68%, depending on various sets of risk anomalies. Another stream of literature analyzes the dynamics of residual and stock returns. For example, Blitz et al. (2011) examine the monthly momentum strategy based on past residuals, while Biltz et al. (2013) and Da et al. (2014) study the short-term reversal strategy based on the prior month's residuals. However, to our best knowledge, the intraday stock market predictability using residuals has not been explored. Analyzing residuals at the intraday level is crucial since they account for a huge portion of stock returns at the intraday level, suggesting that they might play a substantial role in explaining and predicting stock returns within higher frequency data.[1] Therefore, this paper studies the intraday residual return dynamics.

The noise inherent in stock return is defined as the deviation from the fundamental value. One possible explanation for its existence is that risk-averse liquidity providers are unwilling to provide sufficient liquidity to resolve illiquid status. The status of illiquidity prevents stocks from converging to their intrinsic value, resulting in temporary deviations from fair prices (i.e., price pressure) until sufficient liquidity is provided. In line with this idea, Brunnermeier and

[1] For example, Brogaard et al. (2022) show that the level of noise in daily returns is much smaller than the noise in intraday trade-to-trade returns. In particular, their estimates of the noise share in daily returns in 1989 is around 31%. However, by using the results from Hasbrouck (1991, 1993), they find that the estimates in intraday trade-to-trade returns are around 82% in 1989.

Pedersen (2009) use an absolute deviation from the fundamental value as a measure of illiquidity. Putting together, the noise temporally exists at least partially due to risk-averse liquidity providers' insufficient liquidity provision.

Then, how does the noise affect stock returns? Since the noise is transitory, it will eventually converge to zero if liquidity providers provide liquidity and resolve the temporary deviation from fair prices. In particular, the short-lived lifespan of noise is likely to create a reversal pattern in stock returns. That is, stocks with positive noise are likely to have negative returns, while stocks with negative noise are likely to have positive returns. Similarly, Nagel (2012) theoretically shows that market makers' limited risk-bearing capacity causes an insufficient supply of liquidity, which in turn induces a reversal pattern in the return process. Based on the idea above, the focus of our paper is to test whether the dynamics of the noise create a reversal pattern in stock returns and, if so, how large the pattern is.

The intraday market provides an appropriate setting for examining the reversal pattern. First, given the huge share of the noise in intraday returns (Hasbrouck, 1991; Hasbrouck, 1993; Brogaard et al., 2022), it is likely that the reversal pattern created from the noise, if exists, drives a large fraction of variation in intraday stock returns. For example, Hendershott and Menkveld (2014) show that even daily price changes are likely to be driven more by noise from price pressures than information about fundamentals. Their results provide evidence that the movement from the noise is likely to explain an even larger fraction of variation in intraday stock returns. Second, liquidity providers are likely to actively engage in resolving temporal illiquidity during trading hours. In other words, the noise inherent in intraday stock returns is likely to be resolved by liquidity providers during trading hours. Hence, studying intraday returns allows us to precisely capture the residual return dynamics, compared to returns at the lower frequencies.

To identify and examine noise return dynamics, we first decompose stock returns into two components: RISK and RESIDUAL. RISK is a part of the return explained by the risk a stock has, and RESIDUAL is a rest part of the return not explained by the risk. It means RESIDUAL measures how far the stock return deviates from its fair price, and therefore, we use RESIDUAL as a proxy for the noise in stock returns. Following Stambaugh et al. (2012), we use 11 risk-related anomalies and add four additional anomalies from Li et al. (2023) to capture the risk inherent in stocks. After regressing stock returns on these anomalies cross-sectionally, we predict fitted values. Then, we define the returns explained by the fitted values as RISK, and the remainder of the returns is RESIDUAL. Consistent with Li et al. (2023), we consider 13 intraday periods, where the first 12 periods are 30-minute windows starting from 10:00 A.M., and the last period is the overnight window from 16:00 P.M. to 10:00 A.M.

Our sample is S&P500 index constituents, covering the period from July 1996 to December 2022. We choose it because S&P500 stocks hold advantages for studying intraday trading. First, they have a deeper and larger order book than other index constituents such as Russell 2000. It prevents investors from suffering from price impact in trades. Second, the constituents also have a narrower bid-ask spread, minimizing transaction costs for investors. This combination of high liquidity and reduced trading costs makes S&P500 constituents more favorable and feasible for intraday trading.

Using the estimated residuals, we show that the residual reversal exists in the intraday market, and the residual reversal strategy built on the reversal pattern has consistently generated positive returns over the past three decades. Consistent with our expectation, stocks with positive residuals yield negative returns, and stocks with negative residuals yield positive returns in the next 30 minutes. The larger the residual, the greater the reversal. We formally show this by sorting individual stocks into deciles based on the level of residual. The lowest residual decile portfolio has the largest positive returns, and the highest residual decile portfolio has the largest negative returns in the next period. The annualized period return for the lowest decile portfolio is 5.39%, while the return for the highest decile portfolio showed a -2.31% return, resulting in a 7.70% return for the long-short portfolio on average. It means if an investor constructs a residual reversal-based portfolio, holds it for one period, and repeats the process over the next year, the investor expects to earn a return of 7.70%. With thirteen periods in a day, cumulating the individual period returns reveals that the strategy has yielded an annualized return of 162.3%. We further find that the results are not driven by the firm's size.

It might be possible that the residual reversal exists only in specific periods out of thirteen periods, such as the last 30 minutes before the market closes. To address this concern, we analyze the returns for each individual period. The outcomes find the presence of residual reversal across all periods, with the exception of the initial period from 10:00 a.m. to 10:30 a.m.

During financial crises, liquidity dries up quickly (Brunnermeier and Pedersen, 2009; Nagel, 2012). Since illiquidity can be thought of as the (absolute) deviation from the fundamental value, the overall level of residual, which is also a proxy for the deviation from the fundamental value, is likely to increase during financial downturns. This increased level of residual during financial downturns would lead to higher performance of the residual reversal strategy because a higher level of residual implies a higher level of noise, which needs to be corrected. To test this hypothesis, following Nagel (2012), we examine the relationship between the performance of the residual reversal strategy and financial downturns, which are proxied by the VIX index. We regress the returns of the residual reversal strategy on the lagged VIX index and find a significant and positive relationship between them. The result implies that illiquidity makes the reversal patterns more pronounced, supporting the argument that the returns of the residual reversal strategy capture the returns from liquidity provision. In particular, the reversal patterns became even more intensified during huge financial crises such as the dot-com bubble in 2002, the global financial crisis in 2008, and the COVID-19 pandemic in 2020.

So far, we primarily provide the returns of holding a decile portfolio for the next 30 minutes and rebalancing it every 30 minutes. However, we posit that the noise incorporated into stocks may not be resolved within a mere 30-minute interval, requiring more time for the noise to dissipate. To see how long the residuals last, we examine the persistency of residual reversal. The outcomes reveal a distinct pattern by decile portfolio. The portfolio stemming from the lowest residual decile consistently generates positive returns over the following 12 periods (6 hours). In contrast, the portfolio linked to the highest residual decile experiences no such persistence. It means while stocks with negative residuals need a few hours to reduce their residuals, stocks with positive residuals experience reversals only for the next 30 minutes. The persistence of the long-short portfolio dissipates after the 8 periods (4 hours).

Next we explore whether the residual reversal remains after incorporating risk. Since Li et al. (2023) predict intraday return using risk component, it might be possible that residual reversal might become insignificant when considered alongside risk. Nonetheless, we propose that residual reversal maintains its significance even after accounting for risk because the residuals are orthogonal to the risks. To assess this hypothesis, we employ a double-sorting approach. We create 5x5 (25) portfolios based on both RESIDUAL and RISK. Initially, stocks are sorted into quintile portfolios based on RISK. Subsequently, within each RISK quintile, stocks are sorted into quintile portfolios based on the RESIDUAL. By employing a double-sorting approach, we can identify whether the performance of the residual reversal strategy depends on the magnitude of RISK. The intriguing result emerges that across all RISK quintiles, residual-based reversal strategies consistently yield positive returns. It implies that residual reversal is not subsumed by risk. While the risk momentum strategy also yields positive returns regardless of RESIDUAL, it falls short in comparison to our residual reversal strategy. The result underscores that residual has a return predictive power regardless of risk, and its predictability power is stronger than that of risk.

Thus far, we have identified the presence of residual reversal, and Li et al. (2023) find risk momentum in the intraday stock market. However, the question of which of these components drives the returns is still unanswered. To ascertain the primary driver, we analyze the subsequent returns of 10 portfolios constructed based on total return. Given the contrasting directions of risk momentum and residual reversal, observing any patterns in the total return portfolios will help identify the primary driver in the intraday market. Our findings reveal that the intraday returns show reversal patterns. The portfolio with the lowest prior-period return yields the highest return in the subsequent period, and the subsequent returns consistently decline in a monotonic fashion as the deciles move up. We also find that the sign and the direction of total returns are closely aligned with those of residuals. This observation suggests that it is the residual reversal that influences the return patterns rather than risk momentum at the intraday level.

In the ongoing debate on momentum and reversal strategies, previous research has emphasized that these strategies lose their ability to generate positive profits when trading costs are incorporated into trades (Pastor and Stambaugh, 2003; Da et al., 2014). Given that intraday trading submits orders several times within a day, considering trading cost is particularly necessary and imperative. To address this concern, we integrate trading costs directly into our strategy rather than solely using midpoints when calculating returns. We present five scenarios with trading costs ranging from 3 to 7 basis points (bps). The results show that it requires more time for investors to hold the long-short portfolio based on the residual reversal strategy to generate positive returns. In other words, instead of rebalancing the portfolios every 30 minutes, investors are required to rebalance their portfolios every hour or more to yield positive returns. Nevertheless, the strategy consistently yields positive returns across different scenarios, except for when the trading cost is set at 7 bps.

As robustness tests, we explore the residual reversal over the various combinations of portfolio formation (K) and holding periods (M). Our primary examinations involve constructing residual reversal decile portfolios based on residuals from the preceding period (K=1) and holding them for the subsequent single period (M=1). We extend this analysis by spanning formation and holding periods from 1 to 13. We posit that the residual reversal pattern is valid across the periods because of the nature of noise that needs to dissipate. The results report that irrespective of the chosen formation and holding periods, the significance of residual reversal strategies remains consistent.

We next conduct subsample tests by year to address any potential concern that the strategy's effectiveness might be confined to specific years. We find that from 1996 to 2022, the residual reversal has existed, and the residual reversal strategy demonstrates validity and significance across all years except for 1997. It implies that the residual reversal pattern has persisted consistently and is not driven by particular years.

There might be a chance that the risk anomalies used in our study do not fully capture the risk portion in the returns, possibly making our noise proxy, RESIDUAL, biased. To address this concern, we conduct a parallel analysis using alternative sets of risk anomalies. We randomly select 15 risk anomalies from the pool of over 200 identified in the literature to explain stock risk. We additionally include these risk anomalies in the anomaly set we use and repeat this process 15 times. With these new sets, we recalculate RESIDUAL and assess whether the residual reversal pattern remains valid. Consistent with the original results, our findings show residual reversal in the intraday market. The results still demonstrate that stocks with positive residuals yield negative returns, and those with negative residuals yield positive returns in the subsequent period. These outcomes mitigate concerns that the pattern is confined to a specific set of anomalies.

Our research contributes to several strands of literature. First, our paper relates to work on return reversal. After Jegadeesh (1990) and Lehman (1990) report the profitability of return reversal strategies, several papers provide explanations for why return reversals exist. One plausible explanation is that return reversals act as a form of compensation for liquidity providers. (Campbell et al., 1993; Conrad et al., 1994; Jegadeesh and Titman, 1995b; Avramov et al., 2006; Hammed et al., 2010; Nagel, 2012). An alternative explanation for return reversals is that return reversals are the results of overreactions to firm-specific news from investors (Jegadeesh and Titman, 1995a; Cooper, 1999; Mase, 1999; Subrahmanyam, 2005). Our paper supports the first explanation by showing that the profitability of residual reversal strategies is high when the compensation for liquidity provision is high, especially during financial crises.

Second, our results add to the literature on the role of residuals in explaining stock returns. Grundy and Martin (2001) and Blitz et al. (2011) show that the residual-based momentum strategies perform better than the original momentum strategies. Similarly, Blitz et al. (2013) and Da et al. (2014) show that, at monthly frequency, the residual-based reversal strategies have better performance than the original reversal strategies. Our paper employs the residual-based reversal strategy at the intraday level and finds that return reversals are pervasive even in the intraday frequency and that the residual-based reversal strategy yields higher profits than the original reversal strategy.

Finally, this paper adds to the literature on patterns in intraday stock returns. How stock prices behave at intraday frequencies has received a great deal of academic attention. Several studies show the existence of both momentum and reversal patterns at the intraday level (Grant et al., 2005; Heston et al., 2010; Gao et al., 2018; Zhang et al., 2019; Lou et al., 2019; Baltussen et al., 2021). Most recently and related to our paper, Li et al. (2023) show that the risk component of return exhibits strong intraday momentum patterns. Our results support the existence of risk momentum patterns, but we also provide some evidence that the residual reversal effects dominate the risk momentum effects. In addition, our paper takes a closer look at return reversal effects at intraday frequency and finds that return reversals documented in the previous literature are mainly caused by residual reversals.

II. Data and Methodology

In this section, we present the main variables while explaining comprehensive information about the risk anomalies utilized in our research and providing data sources to formulate these variables. Subsequently, we provide a detailed methodology for constructing the residual reversal strategy.

A. Dependent Variable

We choose to utilize the 30-minute return as our primary dependent variable for intraday return. It is a frequently used time window in intraday studies (Heston et al., 2010; Li et al., 2023). This time interval offers a balanced trade-off between capturing meaningful market movements and avoiding excessive noise inherent in shorter intervals. To calculate the 30-minute intraday returns, we utilize the quote data from the Trade and Quote (TAQ) database from July 1996 to December 2022. Specifically, we select the last bid and ask quote prices every 30 minutes between the hours of 10:00 AM and 4:00 PM Eastern Time, resulting in a total of 13 quote price observations per day for each stock. We intentionally drop prices at the market open (9:30 AM) because of the greater volatility (e.g., Stoll and Whaley, 1990) and because some stocks may have no trading activity at that time. In cases where no quote occurred during a given period, we imputed the quote price of the previous period to ensure the continuity of the series. Then, we calculate the midpoint of the bid and ask quote prices to get a return measure to avoid a bid-ask bounce in the transaction price.

Stock splits or reverse stock splits can introduce a concern that the return between the periods before and after the splits might not be zero unless the prices are adjusted. The unadjusted prices could result in a significant, biased return jump or drop. To mitigate this potential problem, we employ the adjustment factor, CFACPR, from CRSP. The adjustment ensures that the returns remain accurate and unbiased despite the split events. However, we still find a few huge outliers, which can potentially be harmful to proper statistical inferences, in our 30-minute returns even after adjustment through CFACPR. To prevent those outliers from driving the entire empirical result, 30-minute returns are winsorized at the 0.5% level.

B. Risk Anomalies

It is necessary to specify and identify a degree of noise in a stock return to test whether residual reversal exists at the intraday level. In order to obtain the level of noise, we partition the 30-minute return into two distinct components: RISK and RESIDUAL. RISK corresponds to the part of a total return that can be attributed to firm-specific risk, while RESIDUAL is the rest portion of the total return, which cannot be explained by the firm-specific risk profile. After the partitioning, we use RESIDUAL as a proxy for noise in stock returns.

To divide a total return into two components, we first run the following cross-section regression with k anomalies.

$$RET_{s,d,i} = \alpha_{d,i} + \Sigma_{\mathrm{i=1}}^{\mathrm{k}} \beta_{d,i,j} Anomaly_{s,d-1,j} + \varepsilon_{s,d,i}, \quad (1)$$

where $RET_{s,d,i}$ is a return of stock $s,$ at date $d,$ and period i. j denotes anomaly.

We establish the term RISK to represent the portion of the total return that can be accounted for by the fitted values of risk anomalies, and RESIDUAL pertains to the remaining part. In our analysis, an intercept is incorporated within the RESIDUAL. Therefore, RISK and RESIDUAL are obtained through the equations below.

$$RISK_{s,d,i} = \Sigma_{\mathrm{i=1}}^{\mathrm{k}} \hat{\beta}_{d,i,j} Anomaly_{s,d-1,i} \quad (2)$$
$$RESIDUAL_{s,d,i} = RET_{s,d,i} - RISK_{s,d,i} \quad (3)$$

Risk anomalies serve as a proxy for risk that explains a firm's return. We choose 11 anomalies that explain firm-specific risk following Stambaugh et al. (2012) and four additional return-based risk anomalies (Li et al., 2023). A detailed description of 15 anomalies is reported in Table A1.

Because each anomaly has a different dispersion and scale, to make them aligned and comparable, we transform, standardize, and normalize each anomaly by following Kozak, Nagel, and Santosh (2020). We transform each anomaly, $A_{s,d-1,j}$, by using its cross-sectional rank within a given day.

$$CR_{s,d-1,j} = \frac{rank\left(A_{s,d-1,j}\right)}{n_{d-1} + 1} \quad (4)$$

where s, d and j denote stock, date, and anomaly, and n_{d-1} is the number of stocks on day d-1.

Then, we standardize these transformed values to have zero mean and then normalize by dividing them by the sum of absolute deviations from the mean.

$$Anomaly_{s,d-1,j} = \frac{CR_{s,d-1,j} - \overline{CR}_{s,d-1,j}}{\sum_{s=1}^{n_{d-1}} |CR_{s,d-1,j} - \overline{CR}_{s,d-1,j}|} \tag{5}$$

C. Sample

We employ stocks encompassing the S&P500 index to empirically examine and validate our conjecture concerning the presence of residual reversal in the intraday market. The rationale for employing S&P500 constituent stocks rests on their relatively high liquidity and small transaction costs.

High liquidity is pivotal in facilitating seamless and rapid order execution, a critical requisite for intraday trading that hinges upon the timely execution of orders within a few seconds. We underscore the consideration of stock liquidity regarding tradability within our sample. How easy it is to buy and sell stocks in our sample is important because it affects whether we can use our intraday trading strategies effectively. Should our sample stocks lack this characteristic, the viability of our proposed trading strategy would be fundamentally compromised.

The second reason why we stress the importance of selecting S&P500 stocks pertains to the issue of trading costs, particularly manifest in the form of bid-ask spreads. These costs bear the potential to substantially erode the profitability of intraday trading. Given the inherent nature of intraday trading, which entails multiple buy and sell actions within a single day, reducing trading expenses plays a crucial part in the main goal of achieving profitable results. S&P 500 stocks are more adequate than other index constituents because they typically have a narrower bid-ask spread (i.e. higher liquidity).

It should be noted that the composition of the S&P500 index undergoes several alterations throughout the course of a single year. To our best knowledge, for example, these constituents experienced approximately 20 changes during the calendar year of 2022. Given such frequency, it is possible to miss some changes that occurred over the sample period. To avoid the problem of missing changes and keep the consistency of our study, we employ the end of June as a cutoff date. For instance, consider the situation where we pick out S&P500 stocks at the end of June in the year 2015. These particular stocks become our designated sample, and we then proceed to examine them starting from July 2015 to June 2016. This systematic methodology ensures a certain stability within our study, mitigating a potential problem that could emanate from frequent changes in the constituents of the S&P500 index.

Table 1 shows descriptive statistics of variables that we use in the paper. Panel A provides information on our main dependent variable, the 30-minute return (RET), RISK, and RESIDUAL. Panel B shows descriptive information on risk anomalies that we employ in the paper. One thing to note is that the residual component comprises 95% of total returns, while the risk component 5% of total returns.

[Insert Table 1 here]

D. Constructing the Residual Reversal Strategy

After partitioning stock returns into two distinct constituents, RISK and RESIDUAL, we use RESIDUAL to construct the residual reversal strategy. We first split the S&P500 stocks into ten groups by RESIDUAL level. The first group, the RESIDUAL decile 1 portfolio, comprises stocks with the lowest RESIDUAL values. Given that RESIDUAL should be corrected for the fair stock price, our anticipation is that stocks in this group are likely to be undervalued and yield a positive return in the upcoming period. On the other hand, the RESIDUAL decile 10 portfolio contains stocks with the highest RESIDUAL values. Given that the RESIDUAL values for the stocks in this portfolio are positive, stocks in this group are likely to be overvalued and yield a negative return in the upcoming period. With this in mind, we take a long (short) position on stocks from the decile 1 (10) group using both a value-weighted and an equal-weighted method.

We hold the long-short portfolio for the next 30 minutes, one period. After holding one period, we rebalance the portfolios every 30 minutes. Thus, we rebalance the portfolios 13 times in a business day.

III. Does Intraday Residual Reversal Exist?

In this section, we first test whether the residual reversal exists at the intraday level and analyze the overall performance of the residual reversal strategy during our sample period. We further analyze whether certain period(s) during a day drives the performance of the strategy. Next, we test whether the performance of the residual reversal strategy is positively associated with the market liquidity and financial crises. Finally, we test how long the residual reversal effects persist over time.

A. The Existence of Residual Reversal

In this subsection, we document the presence of residual reversal. To examine our hypothesis that the residual reversal pattern exists at the intraday level, we divide our sample into ten groups by residual level. Subsequently, we track the performance of each group during the subsequent period to shed light on potential residual reversal.

[Insert Table 2 here]

The result is reported in Table 2, which illustrates the annualized period returns by each decile portfolio. We annualize the period returns for each decile by multiplying the period returns by 252. Panel A shows the result of value-weighted portfolios. Columns (1) and (10) report the average returns of the lowest and the highest residual portfolios, respectively. The results align with our expectations: the lowest residual portfolio tends to yield a positive return in the next period. The annualized period return is 5.39% and statistically significant at the 1% level. In contrast, the highest residual portfolio yields a negative annualized period return of 2.31%. It implies that residuals revert to zero-mean. Column (11) presents the return from a long-short portfolio that involves purchasing the lowest residual portfolio while simultaneously selling the highest residual portfolio. The long-short portfolio generates an average annualized return of 7.7% per period. It means if an investor constructs the portfolio, holds it for one period, and repeats the process over the next one year, the investor expects to earn a return of 7.70%. With thirteen periods in a day, cumulating the individual period returns reveals that the strategy has yielded an annualized return of 162.3%.[2]

Seeking further insights, we examine the potential influence of firm size on our results. In Panel B, we duplicate our analysis using equal-weighted portfolios, thus assessing the role of firm size in our outcomes. The results are consistent in that residuals show the reversal pattern. The long-short portfolio return is 8.06%, maintaining its statistical significance at the 1% level. The return in Panel B is slightly higher than the return in Panel A, but the difference is enough to

[2] Mathematically, $162.3\% = (1 + .077)^{13} - 1$.

reassure us that the residual reversal is not mainly driven by firm size, especially by small firms.

Figure 1 graphically illustrates Table 2. Irrespective of the chosen weighting approaches, there is a monotonic downward trend in the annualized period return as the residual decile increases. This pattern reinforces that our hypothesis holds true for deciles other than just the first and last.

[Insert Figure 1 here]

Figure 2 illustrates the cumulative return generated by the residual reversal strategy implemented between July 1996 and December 2022. It reports both the cumulative returns of value-weighted portfolios (blue line) and equal-weighted portfolios (red line). The strategy has produced consistent and large returns.

[Insert Figure 2 here]

B. Residual Reversal by Period

We examine if the findings in Table 2 are influenced by specific time periods. It is possible that the residual reversal strategy is valid only for certain periods. To address this concern and confirm that our results are consistent across different periods, we present the returns of each decile portfolio across all 13 periods.

[Insert Table 3 here]

In Panel A in Table 3, which represents portfolio returns constructed using a value-weighted approach, we show a parallel consistency with the patterns seen in Table 2. The returns in each period gradually decrease as we move from lower to higher deciles. This suggests that, in the subsequent period, higher residual returns tend to be penalized, while lower residual returns are rewarded, heading to fair pricing. Additionally, the long-short portfolios generally yield positive returns in most periods, except for the initial period (10:00 a.m. – 10:30 a.m.). An interesting point here is that, in most periods, the absolute returns in the lowest decile portfolio surpass those in the highest decile portfolio.

Turning to Panel B, where we consider equal-weighted portfolios, we observe a significant results across all periods, even including the first period. It implies the results are not driven by relatively small stocks. Furthermore, consistent with Panel A, the returns in subsequent periods are negatively related to the decile ranks, and the lowest portfolio consistently has higher absolute returns than the highest portfolio.

In summary, we conclude that the phenomenon of residual reversal is not confined to specific time periods but rather represents a universal trait within the intraday market. Our findings hold true regardless of the time frame considered, underlining the widespread nature of this phenomenon.

C. Residual Reversal Strategy and Financial Crisis

Nagel (2012) shows that liquidity evaporates during the financial crisis because liquidity providers require a higher expected return from liquidity provision. In addition, Brunnermeier and Pedersen (2009) use an absolute deviation from the fundamental value as a measure of illiquidity. In other words, residual, which is a proxy for the deviation from the fundamental value in our context, can also be interpreted as illiquidity. Hence, if liquidity dries up during the financial market turmoil, the overall level of residuals across stocks is also likely to increase, and this increased level of residuals can lead to higher returns of the residual reversal strategy. Therefore, in this subsection, we examine whether the residual reversal strategy can be predicted with the VIX index by using the VIX index as a financial crisis state variable (Nagel, 2012).

We divide the VIX index by the square root of 252 to scale it to a daily volatility level. Next, we compute the daily returns of the long-short portfolio from the residual reversal strategy by cumulating returns from period 1 to period 13. Then, we regress our long-short portfolio's returns on the lagged VIX index. Table 4 shows the results from the following regression:

$$R_t = \alpha + \beta VIX_{t-5} + \gamma Controls_{t-5} + \varepsilon_t \tag{6}$$

where R_t is the returns from the residual reversal strategy on a given day *t*. Following Nagel (2012), control variables are the stock market return and an indicator variable for pre-decimalization. Column (1) shows that the residual reversal strategy is positively associated with the lagged VIX index, suggesting that the residual reversal strategy performs better during financial crises. One percentage point increase in the VIX index is associated with a 44 basis points increase in the returns of the residual reversal strategy. Columns (2) and (3) add control variables, and the coefficients on the VIX index remain significant and are changed only marginally. Columns (4) to (6) show the results from the equal-weighted strategy, and the results are consistent with the strategy using the value-weighted approach.

[Insert Table 4 here]

We further study the performance of the residual reversal strategy each year to see whether the performance is better in years of higher VIX index, especially in financial crises. Figure 3 shows each year's cumulative returns of the residual reversal strategy and each year's average of the VIX index. First, over the entire sample period, the residual reversal strategy has never had a negative return. More importantly, consistent with our hypothesis, we observe notable increases in both returns and the VIX index during major financial crises. In 2002, the stock market was grappling with the aftermath of the dot-com bubble burst and the Enron scandal. Similarly, the global financial crisis occurred in 2008, followed by a stock market crash due to the COVID-19 pandemic in 2020. It turns out that our strategy has a higher performance during those crisis periods. It is also worth noting that, besides those years of crises, the VIX index and the performance of residual reversal strategy exhibit surprisingly similar trends across all years, except for 2022.

[Insert Figure 3 here]

In sum, the strong performance of the residual reversal strategy when the VIX index is high, especially during financial crises, suggests that the increased level of residual leads to higher returns for the residual reversal strategy. Moreover, the results imply that the returns of the residual reversal strategy capture the compensation to liquidity provision to the noise component of stock returns.

D. Persistency

Up until now, our observations have consistently indicated that the phenomenon of residual reversal holds true across all examined time periods. However, our previous analyses focus on returns in the immediate subsequent period (30 minutes), leaving us with an unanswered question regarding the duration of the residual reversal's persistency. To ascertain the extent of this persistency and its implications for price efficiency, we seek to determine the duration it takes for the residual reversal to dissipate.

[Insert Table 5 here]

For this purpose, we construct portfolios based on residual deciles at time *t* and then assess their performance over the following 13 individual periods. It should be noted that the returns presented are not cumulative but rather indicative of distinct period returns. After constructing portfolios, we track the performance of the portfolios for the next 13 periods. It shows the return from *t* to *t+1*, from *t+1* to *t+2*, and so forth. This approach avoids the cumulative effect that a sudden surge in one period could have on subsequent periods. We focus on distinct returns since our aim is to gauge the persistency of the phenomenon precisely.

Table 5 shows the residual reversal persistency by decile. The initial row suggests that the first decile portfolio consistently yields positive returns over the subsequent 12 periods, extending over a span of 6 hours after the portfolio construction. In contrast, the tenth row demonstrates that tenth decile portfolios lose their persistency right after the initial period, lasting only 30 minutes. The eleventh row reports the persistence of the long-short portfolio, which persists for the following 7 periods (equivalent to 3.5 hours). This portfolio achieves a return of 7.7% in the first period and 0.74% in the seventh period, and then the persistency disappears in the eighth period. Overall, it can be interpreted that stocks with negative residuals take more time than stocks with positive residuals to reach a fair price.

IV. Risk versus Residual

A recent paper from Li et al. (2023) finds that risk momentum exists at the intraday level and that a trading strategy based on the risk momentum can earn positive profits. Then, it is questionable 1) whether the residual-based reversal strategy can survive after controlling the risk and 2) whether the total return, which is the sum of RISK and RESIDUAL, exhibits momentum or reversal at the intraday frequency in general and which component drives such behavior. In this section, we carefully address these two questions.

A. Does Risk Matter?

We first examine the robustness of residual reversal to risk. We posit that the significance of the residual reversal will not be subsumed by risk. If the residual reversal is driven by risk, then we would observe that the residual reversal strategy becomes unprofitable after controlling the risk component. A double-sorting methodology is employed to test whether our residual-based strategy can survive even after we control the risk component. Stocks are sorted into quintile portfolios based on RISK. Subsequently, within each RISK quintile, stocks are sorted into quintile portfolios based on the RESIDUAL. In addition, we construct 5 risk-momentum strategies for each RESIDUAL quintile, and 5 residual-reversal strategies for each RISK quintile. Table 6 reports the average returns for each of the 25 (5×5) portfolios and 10 long-short portfolios based on risk momentum or residual reversal strategies.

[Insert Table 6 here]

In the 6th row of Table 6, regardless of the level of risk, all residual reversal strategies have positive and significant returns, implying that residual reversals are not dominated by risk. In addition, the performance of the residual reversal strategy increases as the level of risk decreases. It implies that residual reversal is the most pronounced when the compensable portion of the return is smaller. At the same time, in the 6th column of Table 6, all risk-momentum strategies also have positive and significant returns. It implies that risk momentum is also not subsumed by residual. In this case, the performance of the risk momentum strategy is higher when the residual is in the middle level. This result provides evidence that the risk momentum becomes stronger when the noise of the return gets closer to zero. Overall, the performance of the residual reversal strategy is slightly better than that of the risk momentum strategy (5.1% vs 3.7% on average) and the combined long-short strategy, which buys RISK5/RESIDUAL1 portfolio and sells RISK1/RESIDUAL5 portfolio, can earn an annualized return of 8.57% (4.95% + 3.62%) per period, which is higher than 7.70%, the performance of residual reversal strategy from Table 2.

B. Determinants of Intraday Patterns in Stock Return

Table 6 shows that the risk momentum and residual reversal coexist at the intraday level. In the next analysis, we examine whether the total return itself exhibits momentum, reversal, or no pattern at the intraday level. We also examine which component of the return drives the observed pattern of the total return. To test this idea, we first sort stocks into decile portfolios based on their prior period's total returns. Then, we construct ten portfolios and one long-short portfolio that takes a long position on the lowest decile portfolio and a short position on the highest decile portfolio.

Panel A of Table 7 reports the average return of the 11 portfolios. From decile 1 (LOW) to decile 10 (HIGH), the returns of portfolios are monotonically decreasing, implying the return reversal pattern at the intraday level. This result supports that the total returns are driven by residual reversal rather than risk momentum. Panel B of Table 7 reports the average return of each of the 11 portfolios over 13 periods. Column (11) shows that the return-based reversal strategy earns negative profits only in the first period, but in most periods, the strategy shows positive and significant returns. In addition, Column (1) to (10) show that the return becomes smaller from decile 1 (LOW) to decile 10 (HIGH) for the majority of periods. This result provides indirect evidence that the residual reversals drive the behavior of intraday stock returns.

[Insert Table 7 here]

Furthermore, to test the determinants of intraday patterns in stock returns, we decompose the total returns into RISK and RESIDUAL in each return-based decile. Then, we calculate value-weighted RISK and RESIDUAL in each return-based decile. Table 8 reports the results. Note that the sum of RISK and RESIDUAL is equal to the total return. Interestingly, risk momentum and residual reversal coexist even after we sort stocks based on the prior period's return. The RISK row demonstrates a positive correlation between the return of decile portfolios and the decile ranking, indicating a momentum pattern. Conversely, the RESIDUAL row illustrates a negative correlation, indicating a reversal pattern.

However, we find that stock returns are driven by residual rather than risk. Specifically, in decile 1 (LOW), the RESIDUAL part earns a positive return of 5.29%, and the RISK part earns a negative return of -1.02%. However, as a whole, decile 1 (LOW) earns a positive return of 4.28% (=5.29% -1.02%). It suggests that the residual reversal dominates the behavior of the total return. Other deciles, including the long-short portfolio, also provide evidence that residual reversal is dominant in determining the behavior of the total returns. Except for the middle deciles (5, 6, and 7), where RISK and RESIDUAL parts are likely to have the same sign, all the signs of total returns are determined by the sign of the RESIDUAL part. This directly supports that the reversal patterns in stock returns are mainly driven by residual reversals despite the existence of risk momentum.

[Insert Table 8 here]

V. Does Liquidity Matter?

Existing research has demonstrated that incorporating liquidity or trading costs into trading strategies, regardless of the frequency of data, tends to nullify the effectiveness of momentum or reversal strategies (Pastor and Stambaugh, 2003; Da et al., 2014). In the context of intraday trading, the significance of liquidity or trading costs is even more pronounced compared to lower-frequency trading due to the substantially higher number of trades conducted. Given that the residual reversal strategy adopted in this study utilizes midpoint values instead of more conservative quotes (employing ask price for buying stocks and bid price for selling stocks), we seek to examine the strategy's viability under more strict liquidity conditions.

Following Heston et al. (2010), which suggests an appropriate trading cost of 4 basis points (bps), we build upon and extend this premise. We proceed to assess our strategy's performance across varying trading cost scenarios. Through this meticulous investigation, our objective is to assess the robustness of our strategy by considering the influence of trading costs and the constraints posed by liquidity.

[Insert Table 9 here]

The n-th column in Table 9 presents the returns if we held a long-short portfolio for the next n periods after constructing the portfolio by purchasing the residual decile 1 portfolio and selling the decile 10 portfolio at t. For example, the 4th column reports the return attained from holding a long-short portfolio, constructed at time t, for the next four periods (2 hours).

From the first row to the fifth row in Table 9, the outcomes with varying trading cost scenarios, ranging from 3 to 7 bps, are provided. The first row reports that when trading cost is 3 bps, the residual reversal strategy yields a positive return if an investor holds the portfolio only for the next two periods (1 hour). The second row to the fifth row shows that the more expensive the trade cost is, the more time it naturally takes for the strategy to generate positive returns. Specifically, with trading costs set at 4 or 5 bps, it necessitates 3 or 5 periods, respectively, to have positive returns. However, in the case of trading costs at 7 bps, the residual reversal strategy's viability diminishes.

While the strategy employing 30-minute rebalancing intervals is unsustainable, even under a transaction cost of 3 bps, it should be noted that this approach should not be dismissed entirely. With 13 trades executed daily, it is not unexpected because the cumulative daily cost is approximately 40 bps. Nevertheless, the residual reversal strategy exhibits effectiveness in intraday trading if we hold the portfolio longer than 30 minutes. The effectiveness implies that the performance of the residual reversal strategy is sturdy.

VI. Robustness

In this section, we provide the robustness of our results. In particular, we first examine whether our residual reversal strategy is effective with different formation and holding periods. We then test how our strategy performs in different years through subsample analysis. Finally, we analyze whether our strategy is still valid even after we employ different sets of anomalies to estimate RESIDUAL.

A. Different Formation & Holding Periods for Residual Reversal Strategy

We assess the residual reversal with different formation and holding periods. In our prior tests, we formed portfolios based on residuals from the previous period and held them for the subsequent period. In simpler terms, both the formation and holding periods were set to 1. We extend the formation and holding periods from 1 to 13 periods. To examine residual reversal strategies based on different formation and holding periods, we describe a K/M strategy as follows. At each period i, we compute cumulative K-period residuals according to the following equation.

$$Cum\_RES_{s,d,i} = \prod_{k=0}^{K-1}\left(1 + RESIDUAL_{s,d,i-k}\right) - 1 \tag{7}$$

where s, d, and i denote stock, date, and period, respectively. K denotes the formation period and takes the value between 1 and 13.

We then sort stocks into decile portfolios based on the cumulative K-period residuals ($Cum\_RES_{s,d,i}$) and construct value-weighted portfolios. We hold these portfolios for the next M period(s) and then rebalance the portfolios. According to this specification, our baseline strategy in Table 2 is a 1/1 strategy. We test the robustness of our residual-based reversal strategy to different choices of K and M.

[Insert Table 10 here]

Table 10 reports the average return of the long-short portfolio (LOW – HIGH) with 169 (= 13x13) different combinations of K and M. Note that for $M > 1$, we report the average return of the long-short portfolio *per period* for easy comparison across different columns. For instance, the 1/3 strategy generates a return of 3.88% per period. Since the 1/3 strategy holds the portfolio for three periods, the total return over three periods is 12.1%.

Across all values of K and M, our residual reversal strategies earn positive and significant profits. Since the performance *per period* is always at its highest when M =1 for any given K, it is always better to choose M = 1 and rebalance the portfolio every period when assuming no transaction cost.

B. Subsample Analysis: By Year

Since our sample period spans more than 25 years, it might be possible that certain years drive the previous results or that each year has different results. To address this concern, our second robustness test is a subsample analysis by year. We replicate Table 2 for each year, and Panel A and B of Table 11 report the results for value-weighted and equal-weighted returns, respectively. Except for the year 1997 in Panel A, we find residual reversal exists, and residual reversal strategies earn positive and statistically significant profits in all years regardless of the weighting scheme. It is worth noting that in the first 12 years (1996 – 2007), the residual reversal strategy based on the equal weighting scheme yields higher returns than the value-weighting scheme, whereas, in recent years (2008 – 2022), the strategy with the value-weighting scheme earns higher returns than the strategy with the equal weighting scheme. This trend implies that the residual reversal effects at the intraday level were stronger for relatively small stocks in the S&P500 index in the first 12 years, and after that, the effects became stronger and stronger in the large stocks. As we have shown in Figure 3, it is interesting that the profitability of residual reversal strategies experiences a sharp increase in the case of market downturns: the early 2000s started by the dot-com bubble, the 2008 financial crisis, and 2020 due to COVID-19. Consistent with the conclusion of the result from Section 4.C, the result implies that the performance of the residual reversal strategy captures the elevated compensation of liquidity provision during financial downturns.

[Insert Table 11 here]

C. Different Sets of Anomalies

Although we follow Li et al. (2023) to estimate residuals, the choice of 15 anomalies can be arbitrary. It is possible that our results would become insignificant if other sets of anomalies were used in estimating RESIDUAL. In addition, if the current set of 15 anomalies does not appropriately capture the risk component, then RESIDUAL can be overestimated. To address this concern, we examine the performance of the residual reversal strategy based on different sets of anomalies. In particular, we use Open Source Asset Pricing from Chen and Zimmermann to construct more than 200 anomalies[3]. We select anomalies with 'Clear predictability' and 'Good replication' indicators from the full set of anomalies. Since some anomalies contain many missing values, we choose the top 100 anomalies based on the fraction of non-missing values and further exclude 3 of them due to no observations in certain years. Our final set contains 97 anomalies, and we randomly choose 15 anomalies from the final set. We add those selected 15 anomalies to our original set of anomalies and estimate residuals based on 30 (= 15 + 15) anomalies. Then, we estimate residuals based on the new set of anomalies and examine the performance of the residual reversal strategy. We repeat this operation 15 times, and Table 12 shows the results of five of them. A full list of five sets of randomly selected anomalies is reported in Table A2. The other fifteen cases are untabulated, but they have consistent results with the tabulated results. Panel A and B report the value-weighted and equal-weighted returns, respectively. In all cases, the results show the existence of the pattern of residual reversal. From Column (1) to Column (10), returns are monotonically decreasing, and the magnitude of returns is similar to or even stronger than the original result from Table 2. Column (11) shows that regardless of the set of anomalies and weighting scheme, all the residual reversal strategies earn significant returns. Hence, the results confirm that the residual reversal pattern and the significant performance of the residual reversal strategy is robust to different sets of anomalies used in estimating RESIDUAL.

[3] openassetpricing.com

[Insert Table 12 here]

VII. Conclusion

Since the stock market moves toward reducing noise, a residual component of stock returns, which captures the inherent noise, should exhibit reversals in subsequent periods. Consistent with this conjecture, we posit the existence of residual reversal effects at the intraday level and the effectiveness of the residual reversal strategy. We decompose the stock returns into risk and residual components by a cross-sectional regression of 30-minute returns on the set of well-known risk anomalies. We show the existence of the residual reversal pattern: Stocks with a low level of residual have positive returns, and stocks with a high level of residual have negative returns. We then show that the residual reversal strategy, which buys the stock with the lowest residuals and sells the stock with the highest residuals, earns an annualized return of 7.7% on average. We find that our strategy earns positive and significant returns in almost all periods rather than a few periods that drive overall profitability. These results suggest that the market moves in a way that decreases the absolute magnitude of the noise part of returns. To see this more clearly, we analyze how long the residual reversal effects persist over time and show the existence of persistency over a few hours.

Next, we study the behavior of intraday stock returns to compare the impact of risk and residual components on stock returns. We show that risk momentum and residual reversal effects coexist, and neither strategy drives the other. However, we find that stock returns exhibit reversals at intraday frequency. We then show that the reversal pattern of stock returns is mainly driven by the residual component by showing that the behavior of stock returns is closely aligned with that of residuals.

Finally, we test whether the residual reversal strategy can survive even after incorporating the transaction costs. Prior literature finds that most of the trading strategies cannot yield positive profits when the transaction costs are considered. We find that the residual reversal strategy is still profitable if we increase the holding period to longer than 1 hour. Although our strategy loses profitability if we increase the transaction costs to 7bp, the significant profitability of our strategy in other cases provides evidence of how sturdy the residual reversal pattern is.

Overall, our results shed light on the existence of residual reversal effects at the intraday frequency and the remarkable profitability of the residual reversal strategy. While prior literature primarily focuses on how large the noise is at different frequencies, the evidence in this paper emphasizes the role of noise in understanding the behavior of stock returns at a high frequency. The fundamental mean-reverting property of noise not only helps us to identify the profitability strategy but also drives the behavior of stock returns.

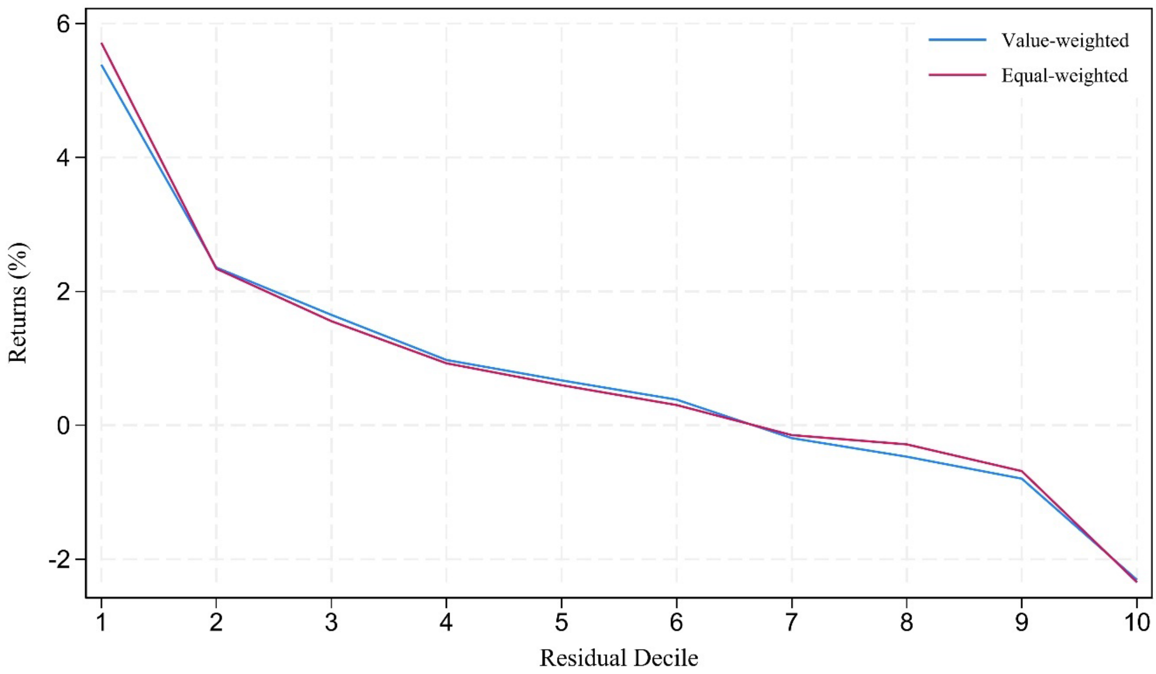

Figure 1. The Performance of Decile Portfolios by Residual.

This figure shows the annualized period returns for each decile portfolio based on the residual component of returns. We report both the returns of value-weighted portfolios (blue line) and equal-weighted portfolios (red line). The sample period is from July 1996 to December 2022.

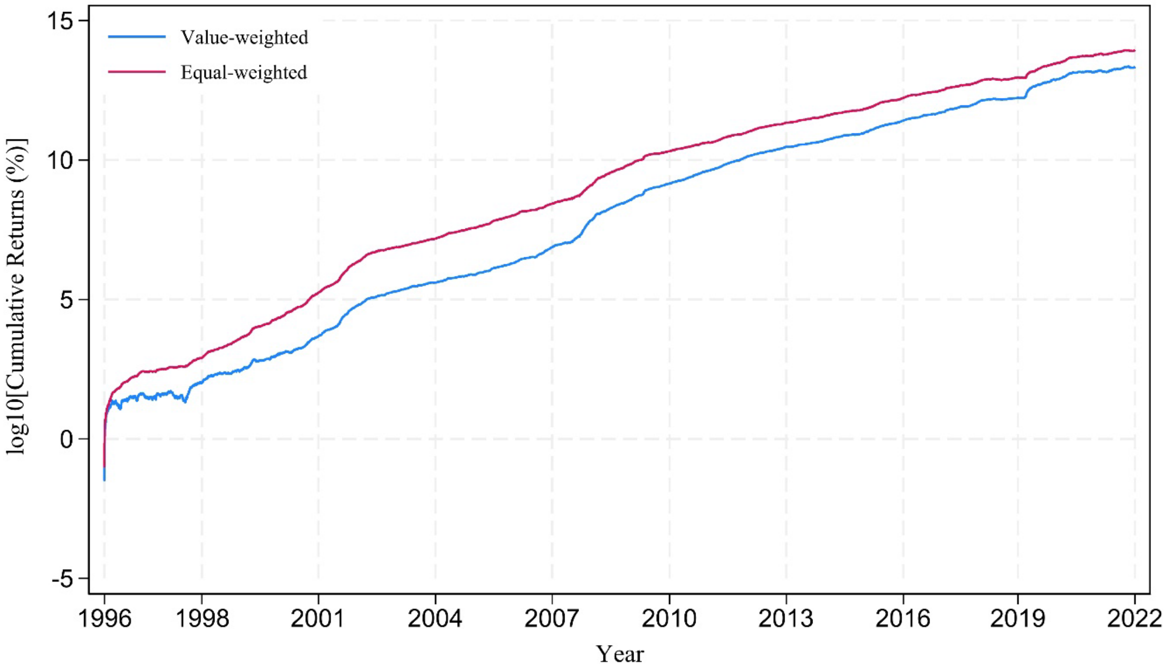

Figure 2. The Cumulative Performance of the Residual Reversal Strategy.

This figure plots the cumulative returns of the residual reversal strategy from July 1996 to December 2022. We report both the cumulative returns of value-weighted portfolios (blue line) and equal-weighted portfolios (red line). The unit of the cumulative returns (y-axis) is the log with the base of 10.

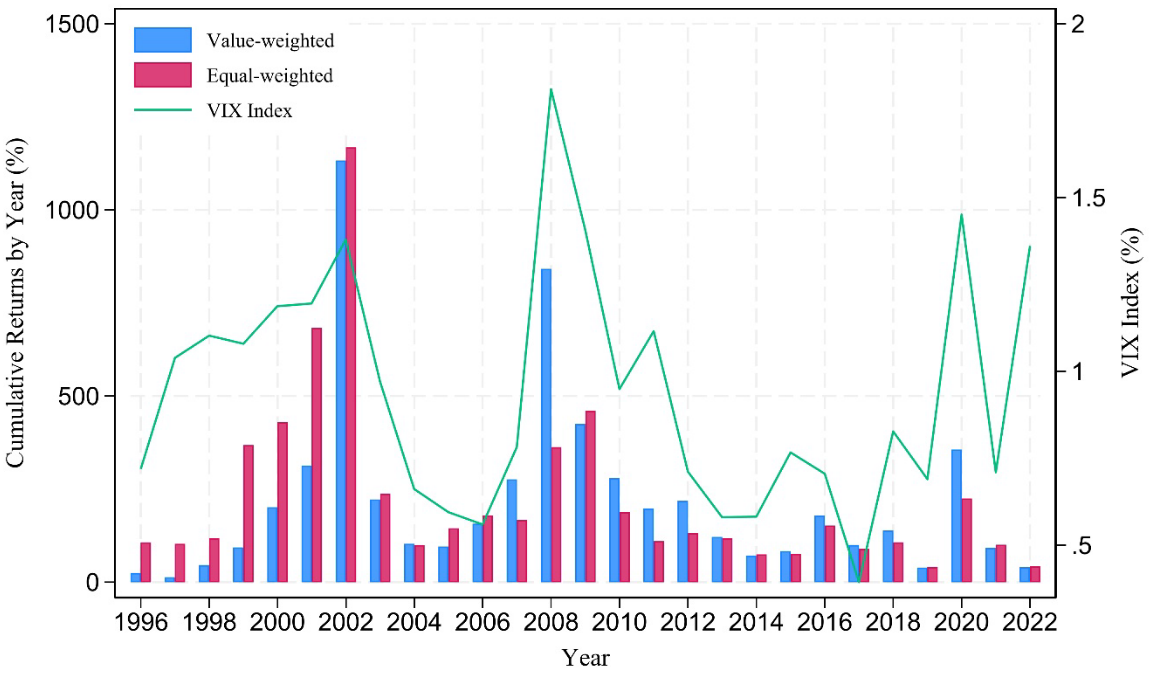

Figure 3. The Performance of the Residual Reversal Strategy and the VIX Index by Year.

This figure shows each year's cumulative returns of the residual reversal strategy and each year's average of the VIX index from July 1996 to December 2022. We report both the cumulative returns of value-weighted portfolios (blue bar) and equal-weighted portfolios (red bar). The green line represents the average of the VIX index. The unit of both the cumulative returns and volatilities is in percent.

Table 1. Descriptive Statistics

This table reports the descriptive statistics from July 1996 to December 2022. Panel A shows the distribution of stocks' one period (30 minutes) returns (RET) and their two components: RISK and RESIDUAL. RISK and RESIDUAL are computed according to Equations (1) and (5). Panel B shows the distribution of 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). Details of the anomaly variables are stated in Table A1. Returns are annualized.

Panel A: Summary Statistics of Return Variables

	N	Mean	SD	p10	Median	p90
RET	27,656,092	0.80	8.59	-126.35	0.00	127.23
RISK	27,656,092	0.04	2.96	-44.21	-0.00	44.43
RESIDUAL	27,656,092	0.76	8.20	-124.75	0.49	125.51

Panel B: Summary Statistics of Anomalies

	N	Mean	SD	p10	Median	p90
Accruals	27,656,022	-0.01	0.10	-0.10	-0.02	0.08
Asset Growth	27,656,092	0.11	0.34	-0.06	0.05	0.29
Beta	27,656,006	1.02	0.60	0.35	0.94	1.76
Book-to-market	27,656,053	0.49	0.74	0.10	0.34	0.98
Composite equity issues	27,656,092	0.04	0.25	-0.06	-0.00	0.10
Gross profitability	27,656,092	0.34	0.21	0.11	0.30	0.63
Investment-to-assets	27,656,078	0.05	0.14	-0.02	0.03	0.14
Momentum	27,655,983	0.12	0.36	-0.27	0.10	0.49
Net operating assets	27,656,079	0.62	0.31	0.33	0.62	0.85
Net stock issues	27,656,092	0.00	0.11	-0.05	-0.00	0.04
O-score	27,656,079	-5.58	1.52	-6.68	-5.54	-4.61
Return on assets	27,656,091	0.02	0.03	0.00	0.02	0.04
Reversal	27,656,086	0.01	0.10	-0.10	0.01	0.12
Size	27,656,092	16.34	1.33	14.80	16.30	18.02

Table 2. Residual Reversal

This table shows the period returns (Ret) of portfolios by residual deciles. We form decile portfolios every period (30 minutes) based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) residuals. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. Panel A and Panel B report the annualized period returns of value-weighted and equal-weighted portfolios. The period return refers to a portfolio return for holding one period (30 minutes). All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Panel A: Residual Reversal, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
Ret	5.39***	2.35***	1.65***	0.97***	0.67***	0.38	-0.19	-0.47*	-0.80***	-2.31***	7.70***
	(17.31)	(8.64)	(6.40)	(3.87)	(2.73)	(1.56)	(-0.77)	(-1.83)	(-2.98)	(-7.63)	(31.56)

Panel B: Residual Reversal, Equal-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
Ret	5.71***	2.34***	1.55***	0.93***	0.60**	0.30	-0.15	-0.29	-0.68***	-2.35***	8.06***
	(19.30)	(9.09)	(6.34)	(3.89)	(2.55)	(1.27)	(-0.62)	(-1.18)	(-2.68)	(-8.09)	(45.67)

Table 3. Residual Reversal by Period

This table shows the period returns of portfolios by residual deciles for each period. We form decile portfolios every period (30 minutes) based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). The first period is from 10:00 to 10:30, and the last (13th) period is from 16:00 to 10:00. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) residuals. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. Panel A and Panel B report the annualized period returns of value-weighted and equal-weighted portfolios. The period return refers to a portfolio return for holding one period (30 minutes). All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Panel A: Residual Reversal by period, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
10:00	-0.52	-0.18	0.43	0.21	0.63	0.11	-0.29	-0.71	-0.25	-0.64	0.12
- 10:30	(-0.41)	(-0.16)	(0.42)	(0.21)	(0.64)	(0.11)	(-0.29)	(-0.70)	(-0.23)	(-0.55)	(0.12)
10:30	2.27**	-0.41	-0.39	-0.54	-0.60	-0.38	-0.90	-0.16	0.42	-1.61	3.88***
- 11:00	(2.04)	(-0.43)	(-0.44)	(-0.64)	(-0.73)	(-0.45)	(-1.06)	(-0.18)	(0.45)	(-1.49)	(4.35)
11:00	2.26**	0.24	0.70	-0.37	-0.54	-0.09	0.36	0.47	-0.54	-1.47	3.73***
- 11:30	(2.40)	(0.30)	(0.94)	(-0.51)	(-0.76)	(-0.12)	(0.49)	(0.64)	(-0.68)	(-1.57)	(4.94)
11:30	3.24***	0.26	0.57	0.39	0.46	0.19	0.43	0.41	0.60	0.94	2.30***
- 12:00	(3.62)	(0.35)	(0.83)	(0.56)	(0.69)	(0.29)	(0.65)	(0.59)	(0.80)	(1.11)	(3.25)
12:00	2.07**	0.04	-0.32	-0.27	-0.64	-0.87	-1.34**	-1.02	-1.14*	-2.00**	4.07***
- 12:30	(2.46)	(0.05)	(-0.48)	(-0.42)	(-1.03)	(-1.39)	(-2.15)	(-1.58)	(-1.65)	(-2.49)	(6.20)
12:30	4.32***	2.15***	1.75***	1.35**	1.14*	1.24**	0.87	0.93	0.91	0.30	4.02***
- 13:00	(5.45)	(3.22)	(2.78)	(2.21)	(1.91)	(2.06)	(1.41)	(1.47)	(1.38)	(0.39)	(6.83)
13:00	2.97***	0.83	0.62	0.24	0.09	-0.61	-1.09*	-1.23**	-0.84	-2.03***	5.01***
- 13:30	(3.82)	(1.26)	(0.98)	(0.39)	(0.15)	(-1.04)	(-1.79)	(-1.99)	(-1.31)	(-2.65)	(8.64)
13:30	3.01***	0.46	0.45	-0.20	-0.22	-0.36	-1.07*	-1.28*	-1.36*	-2.82***	5.83***
- 14:00	(3.59)	(0.65)	(0.68)	(-0.31)	(-0.34)	(-0.58)	(-1.67)	(-1.92)	(-1.92)	(-3.43)	(9.45)
14:00	2.43***	0.70	0.03	-0.63	-0.60	-1.34*	-1.58**	-1.69**	-1.57**	-3.01***	5.44***
- 14:30	(2.69)	(0.90)	(0.04)	(-0.88)	(-0.86)	(-1.90)	(-2.17)	(-2.31)	(-2.00)	(-3.28)	(8.54)
14:30	5.13***	3.53***	2.71***	2.00***	1.67**	1.21	1.11	0.55	-0.05	0.51	4.62***
- 15:00	(5.41)	(4.35)	(3.47)	(2.67)	(2.23)	(1.64)	(1.50)	(0.72)	(-0.07)	(0.55)	(7.07)
15:00	4.29***	2.97***	2.01**	1.35	1.17	1.00	0.88	-0.04	0.09	-1.38	5.67***
- 15:30	(4.14)	(3.27)	(2.30)	(1.59)	(1.40)	(1.21)	(1.04)	(-0.05)	(0.10)	(-1.35)	(8.30)
15:30	7.43***	2.01*	0.96	0.38	-0.55	-1.78*	-2.76***	-2.54**	-4.61***	-6.89***	14.32***
- 16:00	(6.44)	(1.91)	(0.95)	(0.38)	(-0.56)	(-1.80)	(-2.78)	(-2.52)	(-4.33)	(-6.01)	(18.42)
16:00	31.28***	18.09***	11.98***	8.79***	6.75***	6.71***	2.89	0.22	-2.04	-10.00***	41.28***
- 10:00	(14.09)	(8.99)	(6.19)	(4.63)	(3.65)	(3.62)	(1.53)	(0.11)	(-1.03)	(-4.55)	(22.45)

Panel B: Residual Reversal by period, Equal-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
10:00	3.27***	1.55	1.74*	0.42	0.42	-0.45	-1.24	-1.92*	-2.80***	-4.45***	7.72***
- 10:30	(2.76)	(1.46)	(1.73)	(0.43)	(0.44)	(-0.47)	(-1.28)	(-1.95)	(-2.65)	(-3.83)	(9.67)
10:30	2.37**	-0.92	-1.26	-0.86	-0.93	-0.50	-0.75	-0.08	0.24	-1.44	3.81***
- 11:00	(2.20)	(-1.01)	(-1.52)	(-1.07)	(-1.18)	(-0.62)	(-0.93)	(-0.10)	(0.27)	(-1.38)	(5.72)
11:00	2.40***	0.03	0.08	-0.31	-0.18	-0.47	-0.19	0.36	-0.20	-1.60*	4.00***
- 11:30	(2.59)	(0.04)	(0.12)	(-0.45)	(-0.26)	(-0.69)	(-0.28)	(0.51)	(-0.27)	(-1.74)	(6.87)
11:30	2.89***	0.42	0.89	0.09	0.70	0.47	0.44	0.70	1.30*	1.12	1.78***
- 12:00	(3.36)	(0.60)	(1.34)	(0.14)	(1.11)	(0.76)	(0.69)	(1.08)	(1.87)	(1.38)	(3.31)
12:00	2.36***	0.16	-0.21	-0.42	-0.46	-0.48	-0.86	-0.52	-0.68	-1.15	3.51***
- 12:30	(2.96)	(0.24)	(-0.33)	(-0.69)	(-0.78)	(-0.80)	(-1.42)	(-0.84)	(-1.02)	(-1.47)	(7.16)
12:30	4.62***	2.27***	1.56***	1.45**	0.86	0.87	1.02*	1.08*	1.43**	0.66	3.95***
- 13:00	(6.24)	(3.61)	(2.64)	(2.53)	(1.53)	(1.55)	(1.78)	(1.84)	(2.31)	(0.93)	(8.86)
13:00	3.57***	0.96	0.71	0.22	0.23	-0.33	-0.61	-0.89	-0.64	-1.98***	5.55***
- 13:30	(4.80)	(1.52)	(1.19)	(0.39)	(0.42)	(-0.60)	(-1.10)	(-1.53)	(-1.04)	(-2.65)	(12.00)
13:30	2.62***	0.52	0.10	-0.34	-0.47	-0.66	-0.86	-1.04*	-1.43**	-2.49***	5.11***
- 14:00	(3.30)	(0.79)	(0.16)	(-0.55)	(-0.77)	(-1.11)	(-1.40)	(-1.66)	(-2.15)	(-3.16)	(11.01)
14:00	3.72***	1.25*	0.38	-0.05	-0.68	-0.73	-1.05	-1.35*	-1.77**	-3.39***	7.11***
- 14:30	(4.34)	(1.69)	(0.54)	(-0.07)	(-1.03)	(-1.10)	(-1.56)	(-1.93)	(-2.41)	(-3.93)	(14.91)
14:30	5.88***	3.46***	2.83***	2.29***	1.84***	1.34*	1.34*	0.77	0.44	-0.40	6.28***
- 15:00	(6.61)	(4.51)	(3.86)	(3.24)	(2.62)	(1.94)	(1.92)	(1.06)	(0.60)	(-0.46)	(13.40)
15:00	5.54***	3.32***	2.67***	2.05***	1.61**	0.92	0.70	0.27	-0.21	-1.61*	7.15***
- 15:30	(5.66)	(3.94)	(3.33)	(2.65)	(2.07)	(1.19)	(0.90)	(0.34)	(-0.24)	(-1.67)	(14.33)
15:30	9.46***	3.79***	2.02**	0.90	-0.02	-0.86	-1.76**	-2.50***	-3.60***	-6.00***	15.46***
- 16:00	(9.13)	(4.07)	(2.24)	(1.02)	(-0.02)	(-0.97)	(-1.98)	(-2.80)	(-3.86)	(-5.88)	(29.19)
16:00	25.69***	13.66***	8.73***	6.63***	4.89***	4.79***	1.91	1.39	-1.00	-7.83***	33.52***
- 10:00	(11.95)	(7.06)	(4.65)	(3.59)	(2.68)	(2.63)	(1.04)	(0.75)	(-0.52)	(-3.68)	(27.60)

Table 4. Residual Reversal and VIX

This table shows the relationship between the performance of the residual reversal strategy and market downturns proxied by the VIX index. We form decile portfolios every period (30 minutes) based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. The residual reversal strategy is constructed by taking the long position on the lowest decile portfolio and the short position on the highest decile portfolio. The VIX index is divided by $\sqrt{252}$ to match with the daily level returns. Pre Decimalization is an indicator variable equal to 1 before the decimalization. MKT is the value-weighted stock market return from the CRSP database. Columns (1) to (3) refer to the coefficients from the regression of the value-weighted long-short portfolio's returns on the VIX index. Columns (4) to (6) refer to the coefficients from the regression of the equal-weighted long-short portfolio's returns on the VIX index. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Residual Reversal and VIX

	Value-weighted			Equal-weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
VIX	0.44***	0.48***	0.48***	0.36***	0.36***	0.36***
	(8.25)	(9.41)	(9.41)	(9.60)	(9.18)	(9.10)
Pre Decimalization		-0.00***	-0.00***		0.00	0.00
		(-5.95)	(-5.95)		(0.42)	(0.42)
MKT			0.00			-0.00
			(0.28)			(-0.01)
Constant	-0.00***	-0.00***	-0.00***	-0.00	-0.00	-0.00
	(-2.80)	(-2.92)	(-2.94)	(-1.11)	(-1.17)	(-1.15)
Observations	6628	6623	6623	6628	6623	6623
Adj R^2	0.05	0.06	0.06	0.06	0.06	0.06

Table 5. Persistency of Residual Reversal

This table shows the persistency of portfolios by residual deciles. We form decile portfolios every period (30 minutes) based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. The column Next1 refers to the returns from the first period after the portfolio formation. The column Next2 refers to the returns from the second period after the portfolio formation, and the remaining columns refer to the returns from the third period to the 13th period after the portfolio formation, respectively. The row LOW (HIGH) refers to the annualized return of the portfolio of the stocks with the lowest (highest) residuals. The row L – H refers to the return difference between portfolio LOW and portfolio HIGH. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Persistency of Residual Reversal Strategy

	(1) Next1	(2) Next2	(3) Next3	(4) Next4	(5) Next5	(6) Next6	(7) Next7	(8) Next8	(9) Next9	(10) Next10	(11) Next11	(12) Next12	(13) Next13
LOW	5.39***	2.20***	1.96***	1.09***	1.71***	1.53***	1.18***	0.97***	1.08***	1.12***	0.89***	0.76**	-1.02***
	(17.31)	(6.41)	(5.67)	(3.23)	(5.07)	(4.58)	(3.52)	(2.86)	(3.23)	(3.32)	(2.64)	(2.24)	(-3.03)
2	2.35***	1.36***	1.01***	0.94***	0.75**	1.19***	1.06***	0.92***	0.94***	0.84***	0.97***	0.88***	0.12
	(8.64)	(4.64)	(3.42)	(3.21)	(2.55)	(3.97)	(3.68)	(3.15)	(3.23)	(2.87)	(3.26)	(2.91)	(0.39)
3	1.65***	1.10***	0.83***	0.70**	1.08***	1.03***	0.91***	0.76***	0.89***	1.18***	0.85***	0.58**	0.08
	(6.40)	(4.01)	(3.02)	(2.49)	(3.87)	(3.74)	(3.30)	(2.74)	(3.16)	(4.14)	(3.06)	(2.11)	(0.27)
4	0.97***	0.80***	0.59**	0.72***	0.81***	0.86***	0.68**	0.89***	0.85***	0.58**	0.88***	0.92***	0.42
	(3.87)	(3.01)	(2.15)	(2.61)	(3.01)	(3.18)	(2.50)	(3.27)	(3.10)	(2.13)	(3.26)	(3.40)	(1.55)
5	0.67***	0.43	0.60**	0.74***	0.81***	0.45*	0.80***	0.87***	0.59**	0.88***	0.72***	0.67**	0.53**
	(2.73)	(1.60)	(2.25)	(2.79)	(2.99)	(1.67)	(3.00)	(3.26)	(2.20)	(3.29)	(2.70)	(2.45)	(2.00)
6	0.38	0.54**	0.40	0.86***	0.48*	0.69***	0.60**	0.56**	0.61**	0.63**	0.61**	0.53**	0.76***
	(1.56)	(2.04)	(1.51)	(3.25)	(1.77)	(2.58)	(2.24)	(2.08)	(2.26)	(2.35)	(2.23)	(1.97)	(2.82)
7	-0.19	0.11	0.49*	0.47*	0.39	0.40	0.56**	0.50*	0.60**	0.57**	0.50*	0.87***	0.98***
	(-0.77)	(0.41)	(1.86)	(1.75)	(1.44)	(1.51)	(2.05)	(1.84)	(2.15)	(2.11)	(1.84)	(3.19)	(3.63)
8	-0.47*	0.43	0.53*	0.62**	0.68**	0.57**	0.47*	0.48*	0.63**	0.59**	0.69**	0.54*	1.15***
	(-1.83)	(1.57)	(1.96)	(2.28)	(2.49)	(2.05)	(1.70)	(1.76)	(2.28)	(2.15)	(2.53)	(1.96)	(4.19)
9	-0.80***	0.09	0.41	0.55*	0.26	0.48*	0.43	0.59**	0.39	0.45	0.65**	0.65**	1.70***
	(-2.98)	(0.32)	(1.43)	(1.90)	(0.89)	(1.66)	(1.43)	(2.03)	(1.34)	(1.57)	(2.24)	(2.26)	(5.84)
HIGH	-2.31***	0.09	0.41	0.36	0.52	0.14	0.44	0.70**	0.58*	0.60*	0.52	0.59*	2.23***
	(-7.63)	(0.26)	(1.24)	(1.09)	(1.57)	(0.41)	(1.35)	(2.10)	(1.78)	(1.82)	(1.61)	(1.81)	(6.96)
L - H	7.70***	2.12***	1.55***	0.74***	1.19***	1.40***	0.74***	0.27	0.50**	0.52**	0.37	0.16	-3.26***
	(31.57)	(8.04)	(6.00)	(2.90)	(4.58)	(5.53)	(2.96)	(1.04)	(1.98)	(2.08)	(1.49)	(0.66)	(-12.56)

Table 6. Residual Reversal and Risk Momentum

This table shows the returns of 25 portfolios double sorted by the risk and residual components computed from Equations (1) to (5). When estimating both components, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). We first sort stocks into five quintiles based on the RISK. Then, within each RISK quintile, we sort stocks into five portfolios sorted by RESIDUAL. Starting from 10 A.M., portfolios are formed every 30 minutes during trading hours (until 4 P.M.). The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. RESIDUAL1 (RISK1) is the portfolio of stocks with the lowest residuals (risks). RESIDUAL5 (RISK5) is the portfolio of stocks with the highest residuals (risks). The column 5-1 refers to the return difference between RISK5 and RISK1. The row 1-5 refers to the return difference between RESIDUAL1 and RESIDUAL5. All returns in the table are annualized period returns and are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Double-sorting RISK/RESIDUAL

	(1) RISK1	(2) RISK2	(3) RISK3	(4) RISK4	(5) RISK5	(6) 5 – 1
RESIDUAL1	3.15***	3.05***	3.36***	3.90***	4.95***	1.79***
	(8.65)	(9.82)	(11.22)	(13.31)	(16.18)	(5.35)
RESIDUAL2	-0.84***	0.41	1.00***	1.76***	3.20***	4.03***
	(-2.62)	(1.48)	(3.69)	(6.51)	(11.07)	(13.32)
RESIDUAL3	-1.79***	-0.44	0.18	1.63***	2.54***	4.33***
	(-5.99)	(-1.62)	(0.67)	(6.04)	(8.57)	(14.68)
RESIDUAL4	-2.33***	-0.96***	-0.35	0.87***	2.29***	4.61***
	(-7.97)	(-3.56)	(-1.28)	(3.13)	(7.21)	(15.05)
RESIDUAL5	-3.62***	-1.91***	-1.45***	-0.24	0.14	3.76***
	(-11.85)	(-6.56)	(-4.93)	(-0.78)	(0.40)	(11.31)
1 – 5	6.77***	4.96***	4.80***	4.14***	4.80***	
	(23.98)	(19.22)	(18.68)	(16.35)	(17.30)	

Table 7. Intraday Return-Based Patterns

This table shows the returns (Ret) of decile portfolios sorted by the prior period's returns. We form value-weighted decile portfolios every 30 minutes based on the prior period's returns. The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) returns in the prior period. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. Panel A reports the annualized period returns of value-weighted portfolios, and Panel B reports the annualized period returns of equal-weighted portfolios. The period return refers to a portfolio return for holding one period (30 minutes). All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Panel A: Return Reversal, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
Ret	4.28***	1.43***	0.75***	0.45*	0.51**	0.75***	0.55**	-0.01	-0.05	-1.12***	5.39***
	(13.12)	(5.15)	(2.89)	(1.79)	(2.05)	(3.00)	(2.18)	(-0.04)	(-0.18)	(-3.55)	(18.66)

Panel B: Return Reversal by Period, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
10:00	-3.05**	-1.38	-1.06	-0.16	-0.12	0.16	0.50	0.03	1.37	0.55	-3.73***
- 10:30	(-2.26)	(-1.27)	(-1.04)	(-0.16)	(-0.12)	(0.16)	(0.51)	(0.03)	(1.17)	(0.44)	(-2.97)
10:30	0.74	-2.12**	-2.03**	-2.26***	-0.29	0.55	0.98	1.15	1.55	0.38	0.36
- 11:00	(0.62)	(-2.18)	(-2.27)	(-2.63)	(-0.35)	(0.65)	(1.15)	(1.27)	(1.60)	(0.33)	(0.32)
11:00	0.95	-1.14	-0.54	-0.69	-0.37	0.16	0.37	1.37*	0.92	-0.08	1.03
- 11:30	(0.93)	(-1.36)	(-0.72)	(-0.96)	(-0.52)	(0.22)	(0.50)	(1.75)	(1.10)	(-0.08)	(1.07)
11:30	1.76*	-0.24	-0.83	-0.00	-0.01	0.72	0.91	1.19*	1.99**	2.24**	-0.48
- 12:00	(1.83)	(-0.31)	(-1.18)	(-0.00)	(-0.02)	(1.09)	(1.33)	(1.66)	(2.53)	(2.54)	(-0.57)
12:00	1.13	-0.89	-1.05	-1.15*	-0.96	-0.77	-0.41	-0.45	-0.63	-0.74	1.88**
- 12:30	(1.28)	(-1.23)	(-1.57)	(-1.80)	(-1.52)	(-1.25)	(-0.63)	(-0.68)	(-0.85)	(-0.89)	(2.45)
12:30	4.19***	1.42**	0.93	1.18**	1.06*	1.47**	1.45**	1.47**	0.85	1.46*	2.72***
- 13:00	(5.04)	(2.03)	(1.46)	(1.96)	(1.73)	(2.40)	(2.33)	(2.25)	(1.21)	(1.91)	(3.97)
13:00	2.24***	0.49	0.19	-0.57	-0.02	-0.08	-0.18	-0.79	-0.19	-1.11	3.36***
- 13:30	(2.78)	(0.71)	(0.30)	(-0.96)	(-0.03)	(-0.14)	(-0.30)	(-1.23)	(-0.27)	(-1.40)	(4.86)
13:30	1.76**	0.27	-0.61	-0.19	-0.15	-0.11	-0.11	-0.60	-1.57**	-1.64*	3.41***
- 14:00	(2.03)	(0.36)	(-0.93)	(-0.29)	(-0.23)	(-0.17)	(-0.16)	(-0.85)	(-2.02)	(-1.92)	(4.62)
14:00	1.61*	0.26	-0.55	-0.49	-1.09	-0.36	-0.86	-1.38*	-1.99**	-2.25**	3.85***
- 14:30	(1.70)	(0.33)	(-0.72)	(-0.69)	(-1.55)	(-0.50)	(-1.16)	(-1.79)	(-2.31)	(-2.37)	(5.03)
14:30	4.98***	2.54***	2.07***	1.94**	1.72**	1.93**	1.66**	0.87	0.68	0.89	4.09***
- 15:00	(5.05)	(3.04)	(2.62)	(2.52)	(2.31)	(2.53)	(2.17)	(1.09)	(0.78)	(0.93)	(5.21)
15:00	3.09***	1.25	1.27	0.89	0.98	1.81**	1.29	0.99	1.10	-0.08	3.17***
- 15:30	(2.87)	(1.34)	(1.48)	(1.04)	(1.17)	(2.16)	(1.51)	(1.11)	(1.14)	(-0.07)	(3.94)
15:30	6.07***	1.55	0.69	-0.85	-0.70	-0.91	-2.03**	-3.25***	-3.96***	-5.16***	11.23***

- 16:00	(5.14)	(1.46)	(0.69)	(-0.85)	(-0.71)	(-0.89)	(-2.03)	(-3.07)	(-3.56)	(-4.37)	(12.65)
16:00	30.24***	16.68***	11.31***	8.28***	6.63***	5.21***	3.62*	-0.78	-0.83	-9.08***	39.32***
- 10:00	(13.18)	(8.19)	(5.88)	(4.41)	(3.54)	(2.75)	(1.88)	(-0.39)	(-0.39)	(-3.95)	(18.50)

Table 8. Intraday Return Decomposition

This table shows the returns (RET) and their components (RISK and RESIDUAL) of decile portfolios sorted by the prior period's returns. We form value-weighted decile portfolios every 30 minutes based on the prior period's returns. The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. We decompose returns into risk and residual components from Equations (1) to (5). When estimating both components, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). At each period, we sort individual stocks into deciles based on returns in the prior period. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) returns in the prior period. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. The row RET refers to the annualized period returns of the decile portfolios. The rows RISK and RESIDUAL refer to the annualized period returns of risk and residual components, respectively. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Intraday Return Decomposition

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
RET	4.28***	1.43***	0.75***	0.45*	0.51**	0.75***	0.55**	-0.01	-0.05	-1.12***	5.39***
	(13.12)	(5.15)	(2.89)	(1.79)	(2.05)	(3.00)	(2.18)	(-0.04)	(-0.18)	(-3.55)	(18.66)
RISK	-1.02***	-0.71***	-0.45***	-0.19*	0.02	0.31***	0.43***	0.59***	0.90***	1.25***	-2.26***
	(-9.48)	(-7.20)	(-4.65)	(-1.93)	(0.20)	(3.12)	(4.37)	(5.82)	(8.52)	(11.65)	(-16.39)
RESIDUAL	5.29***	2.14***	1.19***	0.63**	0.49*	0.44*	0.12	-0.60**	-0.95***	-2.37***	7.65***
	(17.65)	(7.69)	(4.42)	(2.37)	(1.83)	(1.65)	(0.44)	(-2.14)	(-3.20)	(-8.05)	(34.57)

Table 9. Residual Reversal Strategy with Transaction Costs

This table shows the annualized returns when holding residual reversal long-short portfolios for the next *t* period with various transaction costs. We first form decile portfolios every 30 minutes based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). Then, we construct the long-short portfolio by taking a long position on the lowest residual portfolio and a short position on the highest residual portfolio. The first period is from 10:00 to 10:30, and the last (13th) period is from 16:00 to 10:00. The column *t* refers to the cumulatively annualized returns from holding the long-short portfolio for *t* periods (t = 1, 2, …, 13). Each row shows the return after incorporating the transaction costs ranging from 3bp to 7bp. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Residual Reversal Strategy with Transaction Costs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	t = 1	2	3	4	5	6	7	8	9	10	11	12	13
3bp	0.14	2.79***	4.32***	5.05***	6.25***	7.64***	8.35***	8.64***	9.13***	9.62***	9.98***	10.12***	6.79***
	(0.56)	(6.98)	(9.05)	(9.34)	(10.43)	(11.73)	(12.01)	(11.68)	(11.71)	(11.77)	(11.70)	(11.37)	(7.34)
4bp	-2.38***	0.27	1.80***	2.53***	3.73***	5.12***	5.83***	6.12***	6.61***	7.10***	7.46***	7.60***	4.27***
	(-9.78)	(0.68)	(3.77)	(4.67)	(6.23)	(7.86)	(8.39)	(8.27)	(8.48)	(8.69)	(8.74)	(8.54)	(4.62)
5bp	-4.90***	-2.25***	-0.72	0.01	1.21**	2.60***	3.31***	3.60***	4.09***	4.58***	4.94***	5.08***	1.75*
	(-20.11)	(-5.63)	(-1.51)	(0.01)	(2.02)	(3.99)	(4.76)	(4.87)	(5.25)	(5.60)	(5.79)	(5.71)	(1.89)
6bp	-7.42***	-4.77***	-3.24***	-2.51***	-1.31**	0.08	0.79	1.08	1.57**	2.06**	2.42***	2.56***	-0.77
	(-30.44)	(-11.93)	(-6.79)	(-4.65)	(-2.18)	(0.12)	(1.14)	(1.46)	(2.01)	(2.52)	(2.83)	(2.88)	(-0.83)
7bp	-9.94***	-7.29***	-5.76***	-5.03***	-3.83***	-2.44***	-1.73**	-1.44*	-0.95	-0.46	-0.10	0.04	-3.29***
	(-40.77)	(-18.23)	(-12.07)	(-9.31)	(-6.39)	(-3.75)	(-2.48)	(-1.95)	(-1.22)	(-0.57)	(-0.12)	(0.05)	(-3.56)

Table 10. Residual Reversal with K/M Strategy

This table shows the annualized period returns of residual reversal long-short portfolios with different formation (K) /holding (M) periods ranging from 1 to 13. We first form the portfolios every 30 minutes based on the K-period cumulative residuals computed from Equation (7). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). Then, we construct the long-short portfolio by taking a long position on the lowest cumulative K-period residual portfolio and a short position on the highest K-period cumulative residual portfolio. Then, we hold these portfolios for the next M periods. The first period is from 10:00 to 10:30, and the last (13th) period is from 16:00 to 10:00. The number in row K and column M refers to the annualized *per period* returns of the long-short portfolio from the K/M strategy. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Residual Reversal with K/M Strategy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	M=1	2	3	4	5	6	7	8	9	10	11	12	13
K=1	7.70***	5.11***	3.88***	3.06***	2.67***	2.44***	2.17***	1.92***	1.75***	1.62***	1.49***	1.37***	1.00***
	(31.55)	(25.62)	(24.44)	(22.72)	(22.30)	(22.51)	(21.95)	(20.87)	(20.28)	(19.81)	(19.28)	(18.50)	(14.07)
2	7.00***	4.99***	3.78***	3.11***	2.80***	2.57***	2.31***	2.08***	1.93***	1.81***	1.66***	1.37***	1.09***
	(28.52)	(24.30)	(23.21)	(22.50)	(22.85)	(23.13)	(22.63)	(21.97)	(21.69)	(21.50)	(20.74)	(17.86)	(14.82)
3	6.77***	4.75***	3.73***	3.24***	2.94***	2.70***	2.42***	2.21***	2.06***	1.90***	1.61***	1.36***	1.13***
	(27.50)	(23.30)	(22.99)	(23.39)	(23.88)	(24.23)	(23.58)	(22.97)	(22.87)	(22.27)	(19.93)	(17.56)	(15.25)
4	6.00***	4.41***	3.74***	3.30***	3.04***	2.77***	2.49***	2.27***	2.11***	1.79***	1.57***	1.38***	1.19***
	(24.37)	(21.26)	(22.50)	(23.30)	(24.27)	(24.39)	(23.95)	(23.49)	(23.25)	(20.77)	(19.22)	(17.52)	(15.83)
5	6.04***	4.58***	3.87***	3.41***	3.06***	2.78***	2.55***	2.33***	2.00***	1.76***	1.56***	1.41***	1.28***
	(24.42)	(22.29)	(23.42)	(24.17)	(24.55)	(24.60)	(24.52)	(24.10)	(21.90)	(20.41)	(18.97)	(17.98)	(17.00)
6	5.97***	4.67***	3.89***	3.38***	3.06***	2.80***	2.57***	2.17***	1.92***	1.72***	1.56***	1.45***	1.34***
	(23.89)	(22.18)	(23.08)	(23.65)	(24.14)	(24.35)	(24.27)	(22.04)	(20.80)	(19.70)	(18.77)	(18.25)	(17.55)
7	6.03***	4.76***	3.92***	3.38***	3.11***	2.84***	2.38***	2.07***	1.86***	1.69***	1.56***	1.47***	1.37***
	(24.26)	(22.69)	(23.36)	(23.67)	(24.63)	(24.79)	(22.50)	(20.99)	(20.19)	(19.30)	(18.81)	(18.49)	(17.98)
8	5.86***	4.57***	3.81***	3.32***	3.02***	2.48***	2.17***	1.92***	1.75***	1.63***	1.53***	1.46***	1.37***
	(23.60)	(22.04)	(22.72)	(23.31)	(23.81)	(21.62)	(20.50)	(19.49)	(18.98)	(18.60)	(18.38)	(18.38)	(18.04)
9	5.66***	4.26***	3.68***	3.24***	2.67***	2.31***	2.05***	1.83***	1.73***	1.62***	1.54***	1.49***	1.43***
	(22.73)	(20.54)	(22.01)	(22.71)	(21.05)	(20.01)	(19.28)	(18.49)	(18.59)	(18.48)	(18.47)	(18.75)	(18.72)
10	5.71***	4.34***	3.69***	2.91***	2.48***	2.19***	1.94***	1.79***	1.70***	1.64***	1.58***	1.52***	1.45***
	(22.98)	(20.74)	(21.96)	(20.18)	(19.40)	(18.89)	(18.22)	(18.08)	(18.28)	(18.64)	(18.87)	(19.01)	(18.99)
11	5.52***	4.09***	3.06***	2.52***	2.23***	2.00***	1.85***	1.74***	1.68***	1.62***	1.57***	1.51***	1.46***
	(22.34)	(19.44)	(17.91)	(17.33)	(17.33)	(17.13)	(17.26)	(17.41)	(18.03)	(18.35)	(18.69)	(18.89)	(18.97)
12	5.34***	3.20***	2.54***	2.18***	1.96***	1.82***	1.73***	1.65***	1.60***	1.57***	1.53***	1.48***	1.44***
	(21.64)	(15.36)	(15.09)	(15.16)	(15.33)	(15.74)	(16.29)	(16.71)	(17.25)	(17.82)	(18.24)	(18.57)	(18.80)
13	4.18***	2.72***	2.33***	2.05***	1.93***	1.84***	1.77***	1.69***	1.66***	1.63***	1.57***	1.53***	1.49***
	(16.92)	(12.88)	(13.77)	(14.18)	(15.04)	(15.84)	(16.50)	(16.98)	(17.74)	(18.39)	(18.73)	(19.07)	(19.38)

Table 11. Residual Reversal by Year

This table shows the period returns of portfolios by residual deciles for each year. We form decile portfolios every period (30 minutes) based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012) and 4 additional anomalies from Li et al. (2023). The first period is from 10:00 to 10:30, and the last (13^{th}) period is from 16:00 to 10:00. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) residuals. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. Panel A and Panel B report the annualized period returns of value-weighted and equal-weighted portfolios for each year, respectively. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Panel A: Residual Reversal, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
1996	6.15***	0.87	2.38*	1.44	0.38	0.22	0.38	-0.21	0.76	2.83*	3.33**
	(3.88)	(0.64)	(1.79)	(1.13)	(0.30)	(0.18)	(0.31)	(-0.17)	(0.56)	(1.83)	(2.38)
1997	5.24***	2.25*	0.75	1.57	0.31	1.23	0.09	2.93**	1.51	4.12***	1.12
	(3.61)	(1.70)	(0.60)	(1.29)	(0.26)	(1.03)	(0.07)	(2.32)	(1.21)	(2.93)	(0.97)
1998	5.84***	0.01	0.49	1.44	1.84	2.40*	1.16	3.65**	3.34**	2.87*	2.97**
	(3.39)	(0.01)	(0.34)	(1.01)	(1.32)	(1.71)	(0.82)	(2.53)	(2.29)	(1.77)	(2.06)
1999	6.76***	0.50	-0.08	0.69	0.40	-0.54	-0.12	2.70*	3.83**	1.61	5.16***
	(3.87)	(0.33)	(-0.06)	(0.50)	(0.28)	(-0.39)	(-0.09)	(1.92)	(2.56)	(0.95)	(2.99)
2000	6.77***	-0.48	-2.03	-4.04**	-1.58	-1.14	-0.10	-0.79	0.99	-2.46	9.24***
	(2.74)	(-0.24)	(-1.14)	(-2.33)	(-0.93)	(-0.69)	(-0.06)	(-0.43)	(0.52)	(-1.09)	(3.52)
2001	5.94***	-1.53	-0.41	-0.54	0.83	0.42	-2.68*	-2.10	0.67	-5.11**	11.05***
	(2.65)	(-0.87)	(-0.26)	(-0.36)	(0.58)	(0.28)	(-1.74)	(-1.30)	(0.38)	(-2.25)	(5.50)
2002	9.13***	2.28	1.61	0.32	-0.72	-0.93	-3.00*	-5.13***	-5.90***	-10.42***	19.55***
	(4.08)	(1.22)	(0.90)	(0.18)	(-0.43)	(-0.57)	(-1.80)	(-2.89)	(-3.15)	(-4.88)	(11.34)
2003	7.66***	4.23***	4.18***	2.07*	1.71	0.62	1.06	-0.18	-1.75	-1.53	9.18***
	(5.24)	(3.24)	(3.46)	(1.78)	(1.46)	(0.53)	(0.91)	(-0.15)	(-1.37)	(-1.07)	(8.20)
2004	5.22***	2.08**	0.85	0.60	-0.35	0.01	-0.32	-0.24	0.18	-0.29	5.51***
	(4.85)	(2.22)	(0.98)	(0.72)	(-0.43)	(0.01)	(-0.38)	(-0.28)	(0.20)	(-0.28)	(6.30)
2005	4.01***	1.76**	1.33	-0.28	-0.18	0.18	0.26	-0.51	-1.29	-1.17	5.18***
	(3.85)	(2.05)	(1.59)	(-0.35)	(-0.24)	(0.23)	(0.35)	(-0.65)	(-1.54)	(-1.25)	(5.76)
2006	5.60***	3.03***	0.84	1.26*	0.74	1.05	0.50	-0.63	0.11	-1.78*	7.38***
	(5.58)	(3.46)	(1.05)	(1.68)	(1.01)	(1.43)	(0.66)	(-0.80)	(0.13)	(-1.78)	(8.54)
2007	6.34***	3.11***	2.26**	1.35	1.51	-0.12	-0.20	-1.16	-1.74	-3.89***	10.23***
	(5.29)	(2.96)	(2.22)	(1.37)	(1.53)	(-0.12)	(-0.20)	(-1.19)	(-1.64)	(-3.36)	(11.34)
2008	5.67**	2.80	1.71	-0.25	-1.96	-2.67	-5.28**	-4.81**	-6.60***	-11.53***	17.20***
	(2.03)	(1.09)	(0.71)	(-0.11)	(-0.85)	(-1.17)	(-2.23)	(-2.01)	(-2.66)	(-4.17)	(9.85)
2009	9.43***	6.95***	4.26**	3.36**	1.65	1.35	-0.64	-1.01	-1.33	-3.67*	13.10***

	(4.71)	(3.87)	(2.56)	(2.04)	(1.02)	(0.82)	(-0.39)	(-0.59)	(-0.74)	(-1.80)	(10.29)
2010	6.91***	3.80***	2.95**	2.00*	1.05	0.14	-0.37	-1.86	-2.34*	-3.48**	10.38***
	(5.08)	(3.09)	(2.44)	(1.70)	(0.89)	(0.12)	(-0.32)	(-1.53)	(-1.89)	(-2.47)	(12.01)
2011	4.20**	2.55*	2.03	1.68	1.15	0.41	-0.40	-0.59	-2.54*	-4.12***	8.31***
	(2.56)	(1.71)	(1.39)	(1.19)	(0.84)	(0.30)	(-0.29)	(-0.41)	(-1.75)	(-2.63)	(9.75)
2012	5.56***	3.26***	2.10**	0.97	0.78	0.22	-0.57	-0.92	-0.97	-3.55***	9.11***
	(5.05)	(3.46)	(2.36)	(1.09)	(0.90)	(0.25)	(-0.65)	(-1.00)	(-0.99)	(-3.16)	(11.37)
2013	5.31***	3.95***	3.08***	2.03***	1.29*	1.34*	0.87	0.42	0.13	-0.82	6.14***
	(5.89)	(5.01)	(4.00)	(2.67)	(1.73)	(1.74)	(1.12)	(0.54)	(0.17)	(-0.94)	(8.69)
2014	3.81***	2.19***	1.33*	1.14	1.05	0.45	0.97	0.46	-0.75	-0.40	4.21***
	(3.90)	(2.69)	(1.72)	(1.46)	(1.37)	(0.57)	(1.25)	(0.59)	(-0.93)	(-0.45)	(5.90)
2015	2.39**	1.80*	1.26	0.31	-0.27	-0.10	-0.57	-0.93	-2.47**	-2.18*	4.58***
	(1.98)	(1.66)	(1.21)	(0.30)	(-0.26)	(-0.09)	(-0.56)	(-0.89)	(-2.34)	(-1.86)	(5.65)
2016	5.67***	2.15**	1.81*	2.01**	1.08	1.06	0.13	0.01	-1.32	-2.30**	7.98***
	(4.85)	(2.14)	(1.86)	(2.14)	(1.20)	(1.14)	(0.13)	(0.01)	(-1.34)	(-2.05)	(10.20)
2017	3.74***	2.75***	2.23***	1.48***	1.22**	1.67***	1.42***	0.39	0.29	-1.66**	5.41***
	(5.52)	(4.80)	(4.03)	(2.79)	(2.41)	(3.24)	(2.70)	(0.74)	(0.50)	(-2.49)	(8.75)
2018	3.54***	0.64	1.13	0.27	0.42	0.04	-0.28	-1.91	-1.10	-3.63***	7.16***
	(2.62)	(0.52)	(0.95)	(0.24)	(0.36)	(0.03)	(-0.24)	(-1.64)	(-0.93)	(-2.82)	(7.46)
2019	2.88***	2.81***	2.23**	2.09**	2.19**	1.59*	1.97**	1.91**	0.77	0.25	2.63***
	(2.80)	(2.94)	(2.46)	(2.30)	(2.50)	(1.75)	(2.21)	(2.07)	(0.85)	(0.25)	(3.49)
2020	7.54***	6.12***	2.67	2.36	2.92	0.83	-0.00	-0.58	-0.98	-4.15*	11.69***
	(3.36)	(2.94)	(1.31)	(1.19)	(1.51)	(0.42)	(-0.00)	(-0.29)	(-0.47)	(-1.89)	(7.61)
2021	4.51***	3.49***	3.01***	1.71*	0.93	1.76*	1.92**	0.42	0.65	-0.64	5.15***
	(3.74)	(3.18)	(2.86)	(1.72)	(0.95)	(1.87)	(2.03)	(0.42)	(0.62)	(-0.54)	(4.77)
2022	-0.09	-0.71	0.86	-0.58	-0.45	-1.21	-1.13	-1.95	-2.86	-2.83	2.74**
	(-0.04)	(-0.40)	(0.50)	(-0.34)	(-0.28)	(-0.74)	(-0.68)	(-1.16)	(-1.63)	(-1.43)	(2.02)

Table 11 (continued)

Panel B: Residual Reversal, Equal-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
1996	9.61***	2.15*	1.17	1.48	-0.20	-0.73	-0.52	-1.22	-1.04	-1.48	11.09***
	(7.70)	(1.91)	(1.13)	(1.44)	(-0.20)	(-0.74)	(-0.54)	(-1.20)	(-0.96)	(-1.16)	(11.46)
1997	7.22***	2.48**	1.54	1.08	0.40	0.46	0.53	0.47	0.39	1.58	5.64***
	(6.31)	(2.46)	(1.63)	(1.16)	(0.45)	(0.52)	(0.59)	(0.50)	(0.40)	(1.44)	(6.79)
1998	6.33***	0.16	-0.46	-1.02	-0.59	-0.15	0.34	1.26	1.57	0.45	5.88***
	(4.44)	(0.13)	(-0.40)	(-0.93)	(-0.55)	(-0.14)	(0.31)	(1.11)	(1.32)	(0.33)	(5.69)
1999	10.23***	0.08	-0.45	-0.74	-0.77	-0.76	-0.49	1.06	1.61	-1.72	11.95***
	(7.71)	(0.07)	(-0.44)	(-0.77)	(-0.81)	(-0.83)	(-0.51)	(1.09)	(1.49)	(-1.38)	(9.81)
2000	10.40***	1.04	-0.78	-1.22	-0.51	-1.04	-0.08	0.85	0.87	-2.75*	13.15***
	(6.46)	(0.85)	(-0.71)	(-1.21)	(-0.52)	(-1.05)	(-0.08)	(0.79)	(0.74)	(-1.85)	(8.34)
2001	10.82***	2.42*	1.06	0.13	0.12	0.46	-1.17	-1.40	-0.61	-5.30***	16.12***
	(5.81)	(1.74)	(0.84)	(0.11)	(0.10)	(0.39)	(-0.96)	(-1.11)	(-0.42)	(-2.79)	(11.07)
2002	9.79***	3.44**	1.47	-0.10	-0.96	-1.26	-2.17	-3.98**	-4.75***	-9.87***	19.66***
	(4.56)	(2.01)	(0.90)	(-0.06)	(-0.61)	(-0.81)	(-1.37)	(-2.43)	(-2.70)	(-4.59)	(14.34)
2003	9.53***	4.53***	4.16***	2.29**	1.83*	1.61	0.79	0.41	-0.56	0.10	9.43***
	(6.71)	(3.73)	(3.65)	(2.08)	(1.66)	(1.46)	(0.72)	(0.36)	(-0.45)	(0.07)	(10.67)
2004	4.97***	1.71*	1.48*	0.96	0.23	0.66	0.19	0.21	0.54	-0.45	5.42***
	(4.55)	(1.87)	(1.77)	(1.18)	(0.29)	(0.81)	(0.24)	(0.25)	(0.59)	(-0.43)	(7.91)
2005	5.23***	1.89**	1.11	0.44	0.31	-0.03	-0.21	-0.49	-1.08	-1.66*	6.89***
	(5.39)	(2.27)	(1.42)	(0.57)	(0.41)	(-0.04)	(-0.28)	(-0.64)	(-1.34)	(-1.86)	(10.08)
2006	5.91***	2.86***	1.72**	1.09	0.87	0.92	-0.06	-0.08	-0.43	-2.09**	8.00***
	(6.25)	(3.47)	(2.29)	(1.52)	(1.25)	(1.31)	(-0.08)	(-0.11)	(-0.54)	(-2.17)	(12.25)
2007	4.58***	1.85*	1.16	0.70	0.25	-0.21	-0.32	-0.60	-1.01	-2.95***	7.52***
	(4.04)	(1.81)	(1.18)	(0.73)	(0.26)	(-0.22)	(-0.34)	(-0.61)	(-0.98)	(-2.67)	(11.00)
2008	2.41	1.68	-0.37	-1.55	-1.66	-3.26	-4.31*	-4.36*	-6.03**	-9.32***	11.73***
	(0.84)	(0.64)	(-0.15)	(-0.63)	(-0.68)	(-1.36)	(-1.74)	(-1.77)	(-2.32)	(-3.26)	(8.53)
2009	10.86***	6.83***	5.24***	3.93**	2.97	1.85	-0.30	0.74	-0.36	-2.62	13.48***
	(4.70)	(3.39)	(2.76)	(2.11)	(1.61)	(1.00)	(-0.16)	(0.38)	(-0.18)	(-1.14)	(13.39)
2010	5.37***	3.31**	2.99**	2.27*	1.64	0.52	-0.07	-0.78	-1.17	-2.86**	8.23***
	(3.73)	(2.53)	(2.31)	(1.80)	(1.30)	(0.41)	(-0.05)	(-0.61)	(-0.89)	(-1.97)	(11.56)
2011	2.82*	1.50	1.32	0.67	0.20	0.30	-0.65	-0.32	-1.47	-2.90*	5.71***
	(1.69)	(0.96)	(0.87)	(0.46)	(0.13)	(0.20)	(-0.44)	(-0.22)	(-0.95)	(-1.76)	(9.07)
2012	4.38***	2.66***	1.73*	1.34	0.63	0.14	-0.18	-0.83	-0.73	-2.26**	6.63***
	(3.93)	(2.66)	(1.83)	(1.44)	(0.70)	(0.16)	(-0.20)	(-0.88)	(-0.72)	(-1.99)	(11.89)
2013	5.62***	3.71***	2.83***	2.33***	1.65**	1.70**	0.98	0.90	0.54	-0.32	5.94***
	(6.44)	(4.74)	(3.70)	(3.07)	(2.18)	(2.23)	(1.27)	(1.15)	(0.69)	(-0.38)	(11.78)
2014	3.41***	1.89**	1.40*	0.89	1.07	0.61	0.53	0.25	-0.13	-0.86	4.27***

	(3.71)	(2.39)	(1.82)	(1.16)	(1.43)	(0.80)	(0.70)	(0.33)	(-0.16)	(-1.00)	(8.21)
2015	2.11*	1.43	0.96	0.38	-0.16	-0.43	-0.81	-1.41	-2.32**	-2.31*	4.43***
	(1.76)	(1.38)	(0.95)	(0.38)	(-0.16)	(-0.43)	(-0.82)	(-1.40)	(-2.27)	(-1.95)	(6.42)
2016	5.51***	2.28**	2.18**	1.69*	1.56	1.00	0.28	0.11	-0.35	-1.58	7.10***
	(4.24)	(2.13)	(2.18)	(1.73)	(1.64)	(1.03)	(0.28)	(0.11)	(-0.34)	(-1.24)	(10.01)
2017	3.21***	2.49***	2.12***	1.64***	1.53***	1.30**	0.80	0.61	-0.14	-1.77***	4.98***
	(4.54)	(4.26)	(3.76)	(3.09)	(2.98)	(2.52)	(1.55)	(1.14)	(-0.24)	(-2.61)	(9.29)
2018	2.15*	1.06	0.83	0.03	-0.14	-0.03	-0.25	-1.36	-1.96*	-3.78***	5.92***
	(1.71)	(0.90)	(0.75)	(0.02)	(-0.13)	(-0.03)	(-0.23)	(-1.26)	(-1.77)	(-3.20)	(8.74)
2019	3.00***	2.42***	2.31**	2.46***	2.34***	2.15**	1.81**	2.02**	1.33	0.28	2.72***
	(2.93)	(2.58)	(2.56)	(2.78)	(2.71)	(2.47)	(2.09)	(2.29)	(1.46)	(0.28)	(4.90)
2020	5.63**	4.04*	2.23	2.01	1.97	0.79	0.64	0.37	-0.44	-3.43	9.06***
	(2.29)	(1.81)	(1.04)	(0.93)	(0.95)	(0.37)	(0.30)	(0.17)	(-0.20)	(-1.43)	(8.69)
2021	4.21***	3.42***	2.53**	2.11**	1.65*	2.07**	1.78*	0.90	0.68	-1.22	5.43***
	(3.61)	(3.32)	(2.56)	(2.22)	(1.77)	(2.23)	(1.92)	(0.96)	(0.70)	(-1.14)	(7.46)
2022	0.77	-0.35	0.23	-0.06	-0.51	-1.06	-1.24	-1.56	-1.61	-1.95	2.72***
	(0.40)	(-0.21)	(0.13)	(-0.04)	(-0.32)	(-0.66)	(-0.76)	(-0.96)	(-0.94)	(-1.05)	(3.20)

Table 12. Residual Reversal Strategy and Random Anomalies

This table shows the period returns (Ret) of portfolios by residual deciles with additional 15 anomalies. We form decile portfolios every 30 minutes based on the residuals computed from Equations (1) to (5). When estimating the level of residuals, we use 11 anomalies from Stambaugh et al. (2012), 4 additional anomalies from Li et al. (2023), and 15 randomly selected anomalies from Open Source Asset Pricing. The first period is from 10:00 to 10:30, and the last (13th) period is from 16:00 to 10:00. Portfolio LOW (HIGH) is the portfolio of stocks with the lowest (highest) residuals. The column L-H refers to the return difference between portfolio LOW and portfolio HIGH. Panel A and Panel B report the annualized period returns of value-weighted and equal-weighted portfolios. Each row reports the results from a different set of randomly selected anomalies. Each set of selected anomalies is reported in Table A2. All returns in the table are reported in percentage terms. Newey and West (1987) robust t-statistics are reported in parentheses. ***, and **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from July 1996 to December 2022.

Panel A: Residual Reversal, Value-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
Set 1	5.40***	2.52***	1.63***	1.14***	0.65**	0.20	-0.31	-0.49*	-0.94***	-2.52***	7.92***
	(17.51)	(9.19)	(6.15)	(4.44)	(2.56)	(0.79)	(-1.19)	(-1.85)	(-3.46)	(-8.24)	(33.67)
Set 2	5.41***	2.44***	1.79***	0.80***	0.72***	0.43*	-0.11	-0.47*	-0.85***	-2.46***	7.86***
	(17.41)	(8.80)	(6.69)	(3.06)	(2.75)	(1.65)	(-0.40)	(-1.74)	(-3.06)	(-7.97)	(31.74)
Set 3	5.32***	2.77***	1.64***	1.10***	0.69***	0.20	-0.27	-0.56**	-1.12***	-2.68***	8.01***
	(17.55)	(10.22)	(6.28)	(4.30)	(2.72)	(0.80)	(-1.06)	(-2.16)	(-4.17)	(-8.97)	(34.66)
Set 4	5.68***	2.52***	1.93***	1.11***	0.70***	0.35	-0.15	-0.74***	-1.24***	-2.59***	8.27***
	(18.26)	(9.09)	(7.22)	(4.24)	(2.69)	(1.34)	(-0.58)	(-2.77)	(-4.50)	(-8.41)	(34.46)
Set 5	5.41***	2.74***	1.76***	1.25***	0.92***	0.19	-0.27	-0.75***	-1.12***	-2.77***	8.18***
	(17.95)	(10.14)	(6.78)	(4.92)	(3.66)	(0.75)	(-1.05)	(-2.88)	(-4.16)	(-9.25)	(35.67)

Panel B: Residual Reversal, Equal-weighted

	(1) LOW	(2) 2	(3) 3	(4) 4	(5) 5	(6) 6	(7) 7	(8) 8	(9) 9	(10) HIGH	(11) L-H
Set 1	5.61***	2.45***	1.64***	1.13***	0.64***	0.24	-0.12	-0.43*	-0.88***	-2.38***	7.99***
	(18.88)	(9.32)	(6.49)	(4.58)	(2.61)	(0.99)	(-0.49)	(-1.72)	(-3.34)	(-8.07)	(47.84)
Set 2	5.63***	2.27***	1.71***	0.92***	0.72***	0.29	-0.01	-0.32	-0.78***	-2.35***	7.98***
	(18.77)	(8.50)	(6.60)	(3.63)	(2.87)	(1.16)	(-0.05)	(-1.24)	(-2.95)	(-7.84)	(45.22)
Set 3	5.53***	2.60***	1.57***	1.16***	0.74***	0.30	-0.08	-0.49*	-0.91***	-2.41***	7.94***
	(19.05)	(10.04)	(6.27)	(4.75)	(3.04)	(1.26)	(-0.31)	(-1.95)	(-3.52)	(-8.34)	(47.80)
Set 4	5.75***	2.56***	1.83***	1.06***	0.70***	0.19	-0.06	-0.63**	-0.90***	-2.53***	8.28***
	(19.36)	(9.70)	(7.19)	(4.29)	(2.84)	(0.76)	(-0.23)	(-2.49)	(-3.43)	(-8.55)	(48.93)
Set 5	5.78***	2.65***	1.68***	1.15***	0.67***	0.23	-0.16	-0.54**	-0.89***	-2.73***	8.50***
	(19.69)	(10.18)	(6.68)	(4.67)	(2.74)	(0.95)	(-0.66)	(-2.18)	(-3.44)	(-9.34)	(51.54)

Table A1. Definition of Anomaly Variables

Source	Anomaly	Definition
Stambaugh, Yu, and Yuan (2012)	Accruals	The annual change in noncash working capital minus depreciation and amortization expense, divided by average total assets for the previous two fiscal years
	Asset Growth	The growth rate of total assets in the previous fiscal year
	Composite equity issues	The 12-month growth in equity market capitalization minus the 12-month cumulative stock return
	Failure Probability	Strictly following Campbell, Hilscher, and Szilagyi (2008)
	Gross profitability	(Total revenue – the cost of goods sold) / total assets
	Investment-to-assets	The annual change in inventories, scaled by lagged book value of assets
	Momentum	Cumulative return over the past 22 to 252 days
	Net operating assets	Operating assets minus operating liabilities, divided by lagged
	Net stock issues	The annual log change in split-adjusted shares outstanding
	O-score	Strictly following Ohlson (1980)
	Return on assets	The ratio of quarterly earnings to last quarter's assets
Li, Yuan, and Zhou (2023)	Beta	The estimated coefficient by regressing monthly stock excess returns on monthly market excess returns using a 60-month rolling window
	Book-to-market	The ratio of the book value of common equity to the market value of equity
	Reversal	The cumulative return over the past 21 days
	Size	The natural logarithm of the market value of equity

Table A2. Sets of Randomly Selected Anomalies

This table reports the sets of randomly selected 15 anomalies for Table 12. The names of anomalies come from Open Source Asset Pricing.

Set 1	Set 2	Set 3	Set 4	Set 5
SmileSlope	AnnouncementReturn	DelEqu	zerotradeAlt12	Illiquidity
Tax	CompEqulss	BetaLiqudityPS	ChNNCOA	ChNNCOA
Mom12m	RDS	DelCOA	BetaLiquidityPS	zerotrade
hire	BPEBM	NetDebtFinance	Cash	IdioVol3F
XFIN	MomSeason	RIVolSpread	TotalAccruals	Cash
ChEQ	dVolCall	EntMult	MaxRet	LReversal
dNoa	BetaLiquidityPS	MomVol	REV6	RealizedVol
IdioVol3F	ChTax	dVolCall	CPVolSpread	EquityDuration
DelEqu	DelBreadth	Zerotrade	ReturnSkew3F	IntanBM
Illiquidity	OPLeverage	Mom12mOffSeason	AnnouncementReturn	IntMom
RIVolSpread	ChNNCOA	DelFINL	fg5yrLag	NetDebtFinance
roaq	DelEqu	PctAcc	IntMom	grcapx3y
MomOffSeason	MomVol	MomSeason11YrPlus	NetDebtFinance	EBM
CPVolSpread	AssetGrowth	BPEBM	PriceDelayRsq	IntanEP
grcapx3y	ReturnSkew	ChEQ	roaq	DelCOA

References

Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *Journal of Finance*, *61*(5), 2365-2394.

Ball, C. A., & Chordia, T. (2001). True spreads and equilibrium prices. *Journal of Finance*, *56*(5), 1801-1835.

Baltussen, G., Da, Z., Lammers, S., & Martens, M. (2021). Hedging demand and market intraday momentum. *Journal of Financial Economics*, *142*(1), 377-403.

Black, F. (1986). Noise. *Journal of Finance*, *41*(3), 528-543.

Blitz, D., Huij, J., & Martens, M. (2011). Residual momentum. *Journal of Empirical Finance*, *18*(3), 506-521.

Blitz, D., Huij, J., Lansdorp, S., & Verbeek, M. (2013). Short-term residual reversal. *Journal of Financial Markets*, *16*(3), 477-504.

Blume, M. E., & Stambaugh, R. F. (1983). Biases in computed returns: An application to the size effect. *Journal of Financial Economics*, *12*(3), 387-404.

Brogaard, J., Nguyen, T. H., Putnins, T. J., & Wu, E. (2022). What moves stock prices? The roles of news, noise, and information. *Review of Financial Studies*, *35*(9), 4341-4386.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*(6), 2201-2238.

Campbell, J. Y., & Kyle, A. S. (1993). Smart money, noise trading and stock price behaviour. *Review of Economic Studies*, *60*(1), 1-34.

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics*, *108*(4), 905-939.

Chen, A. Y., & Zimmermann, T. (2021). Open source cross-sectional asset pricing. *Critical Finance Review, Forthcoming*.

Chordia, T., Roll, R., & Subrahmanyam, A. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics*, *76*(2), 271-292.

Conrad, J. S., Hameed, A., & Niden, C. (1994). Volume and autocovariances in short-horizon individual security returns. *Journal of finance*, *49*(4), 1305-1329.

Cooper, M. (1999). Filter rules based on price and volume in individual security overreaction. *Review of Financial Studies*, *12*(4), 901-935.

Da, Z., Liu, Q., & Schaumburg, E. (2014). A closer look at the short-term return reversal. *Management Science*, *60*(3), 658-674.

Daniel, K., & Titman, S. (2006). Market reactions to tangible and intangible information. *Journal of Finance*, *61*(4), 1605-1643.

Edmans, A., Goldstein, I., & Jiang, W. (2012). The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance*, *67*(3), 933-971.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383-417.

Gao, L., Han, Y., Li, S. Z., & Zhou, G. (2018). Market intraday momentum. *Journal of Financial*

Economics, *129*(2), 394-414.

Grant, J. L., Wolf, A., & Yu, S. (2005). Intraday price reversals in the US stock index futures market: A 15-year study. *Journal of Banking & Finance*, *29*(5), 1311-1327.

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *Journal of Finance*, *43*(3), 617-633.

Grundy, B. D., & Martin, J. S. M. (2001). Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies*, *14*(1), 29-78.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance*, *65*(1), 257-293.

Hasbrouck, J. (1991). The summary informativeness of stock trades: An econometric analysis. *Review of Financial Studies*, *4*(3), 571-595.

Hasbrouck, J. (1993). Assessing the quality of a security market: A new approach to transaction-cost measurement. *Review of Financial Studies*, *6*(1), 191-212.

Heston, S. L., Korajczyk, R. A., & Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *Journal of Finance*, *65*(4), 1369-1407.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance*, *45*(3), 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*(1), 65-91.

Jegadeesh, N., & Titman, S. (1995a). Overreaction, delayed reaction, and contrarian profits. *Review of Financial Studies*, *8*(4), 973-993.

Jegadeesh, N., & Titman, S. (1995b). Short-horizon return reversals and the bid-ask spread. *Journal of Financial Intermediation*, *4*(2), 116-132.

Kozak, S., Nagel, S., & Santosh, S. (2020). Shrinking the cross-section. *Journal of Financial Economics*, *135*(2), 271-292.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics*, *105*(1), 1-28.

Li, S. Z., Yuan, P., & Zhou, G. (2023). Risk momentum: A new class of price patterns. *Available at SSRN 4062260*.

Lou, D., Polk, C., & Skouras, S. (2019). A tug of war: Overnight versus intraday expected returns. *Journal of Financial Economics*, *134*(1), 192-213.

Mase, B. (1999). The predictability of short-horizon stock returns. *Review of Finance*, *3*(2), 161-173.

Merton, R. C. (1975). Optimum consumption and portfolio rules in a continuous-time model. *Stochastic Optimization Models in Finance*, 621-661.

Nagel, S. (2012). Evaporating liquidity. *Review of Financial Studies*, *25*(7), 2005-2039.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685.

Scholes, M., & Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, *5*(3), 309-327.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, *104*(2), 288-302.

Stoll, H. R., & Whaley, R. E. (1990). Stock market structure and volatility. *Review of Financial Studies*, *3*(1), 37-71.

Subrahmanyam, A. (2005). Distinguishing between rationales for short-horizon predictability of stock returns. *Financial Review*, *40*(1), 11-35.

Zhang, Y., Ma, F., & Zhu, B. (2019). Intraday momentum and stock return predictability: Evidence from China. *Economic Modelling*, *76*, 319-329.