Risk-based Momentum*

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Abstract

Based on high-frequency data for a large cross section of individual stocks, we find that the risk component – the component of stock returns explained by common factors – exhibits strong intraday momentum, and this pattern holds during overnight and each 30-minute interval. Strikingly, the return on the long-short portfolio sorted by the risk component exhibits a similar return momentum, which is the first cross-sectional return momentum in the intraday literature. The risk-based momentum effect is strong, generating an annualized return around 40% before trading costs for strategies based on lagged one-intraday-period to one-day risk with a one-day holding period.

JEL classification: G11, G12, G40

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1. Introduction

The goal of various asset pricing models is to use either risk exposures to common risk factors to explain the cross-sectional return variation, or to use risk factors to explain the time-series average of returns.[1] While countless studies have examined how well the models work and various tests have been developed, there is barely any study on the times series property of the risk component (i.e., the component of stock returns explained by common factors) and its predictive power. Kelly, Moskowitz, and Pruitt (2021), which is an important exception, find that the total risk can predict future stock returns.

In this paper, we uncover the first momentum pattern in the risk component of stock returns, which are estimated from a cross-sectional regression of stock returns on standardized anomaly variables in each of the 13 intraday periods, including 12 half-hour periods between 10:00 and 16:00 and one overnight period between 16:00 and 10:00.[2] The simple approach decomposes intraday stock returns into two components, a risk component associated with factors (i.e., the sum of each estimated coefficient times the corresponding anomaly variable) and a residual component which includes alpha. Strikingly, the risk component exhibits a strong momentum pattern: a high risk component in the previous period leads to a high risk component in the subsequent period. This risk momentum holds during overnight between 16:00 and 10:00, and every half hour since then till 16:00 market close.

We also find that the risk momentum implies a similar *return momentum* resulted from sorting stocks by their past risk components, generating the first ever cross-sectional

[1]Popular models include the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, Fama and French (2015) five-factor model, Hou, Xue, and Zhang (2015) q-factor model, and Stambaugh and Yuan (2016) mispricing-factor model, etc. However, the explanatory ability of these models is challenged by Lopez-Lira and Roussanov (2022), among others.

[2]Note that our intraday periods extend over day trading hours, including half-hour trading periods and the overnight period.

stock return momentum intraday. At the monthly frequency, the stock return momentum, discovered by Jegadeesh and Titman (1993), is well known and is one of the most important anomalies in asset pricing.[3] However, it fails completely intraday as reversal dominates (Heston, Korajczyk, and Sadka, 2010). In contrast, it is quite interesting that our risk-based momentum is robust to various frequencies: the risk component of daily (weekly, monthly) stock returns continues to generate a risk-based return momentum at daily (weekly, monthly) frequency. Strikingly, our risk-based momentum also holds for corporate bonds at the monthly frequency.[4]

Our paper is related to Kelly, Moskowitz, and Pruitt (2021), who explain the traditional momentum as compensation for time-varying covariance risk with factors based on the IPCA model of Kelly, Pruitt, and Su (2019). In their study, they also find that stocks sorted by their risk component as measured by the IPCA have superior performance than the traditional momentum which is sorted by total returns. However, there are four major differences between their study and ours. First, they analyze momentum at the monthly frequency, and we study intraday price patterns on which no momentum has ever been documented before. Second, they focus on explaining the traditional momentum, but we aim at proposing a new momentum. Third, while they show that the IPCA risk has strong predictive power for future returns, they do not examine whether the risk itself has momentum or not. In contrast, we show that our risk component exhibits a momentum pattern. Fourth, they estimate the IPCA risk component from a time series perspective with five latent factors. Instead, we dynamically measure the time-varying total risk exposure of stocks, or the return component explained by common factors, based on a period-by-period cross-sectional regression on a large set of observable characteristics (from 15 to 60). As a result, they assume time-varying factor loadings and constant risk premia, whereas our factor loadings are constant intraday but the risk premia are allowed to vary over time. Our approach is not structural, but is what practitioners often use to attribute returns to various risks, and is what is used by most

[3] See. e.g., Schwert (2003), Hou, Xue, and Zhang (2015), and Chen and Zimmermann (2022).

[4] It is difficult to determine whether there is an intraday risk-based momentum for corporate bonds due to less frequent trading and data availability.

recent machine learning studies (see, e.g., Gu, Kelly, and Xiu, 2020) due to the large sample size in the cross section. In short, our paper is related to Kelly, Moskowitz, and Pruitt (2021), but is substantially different and contributes to the large momentum literature by discovering two new types of momentum, the risk momentum and the risk-based return momentum.

The persistence of the risk component is intriguing. Given that our risk component is aggregated from various anomaly components, persistent anomaly returns can be a driving source of the continuation of the entire risk component. Indeed, we find that the implied anomaly factor returns in our return decomposition exhibit positive and significant autocorrelation. Then why are anomaly returns persistent? First of all, anomaly returns are realized only when arbitrageurs start to trade on the perceived mispricing. Due to limits to arbitrage, arbitrageurs may trade on the mispricing gradually instead of eliminating mispricing all at once, and such gradual trading can result in persistent anomaly returns. Empirically, we examine how arbitrageur participation and limits to arbitrage affect the risk-based momentum. Based on the coordinated arbitrage model of Abreu and Brunnermeier (2002), rational arbitrageurs delay their arbitrage trading on known mispricing due to holding costs and synchronicity risk. We find that our risk-based momentum becomes notably stronger after more frequent news arrivals, which is consistent with the view that arbitrageurs are more willing to participate in trading as more peers become aware of the mispricing in light of the news (i.e., reduced synchronicity risk). We further document stronger risk-based momentum during high aggregate IVOL period, which corresponds to high limits-to-arbitrage time. When limits to arbitrage is high, arbitrageurs are more likely to trade gradually due to market frictions. Both empirical results are consistent with our hypotheses that increased arbitrageur participation in mispricing correction and gradual trading due to limits to arbitrage are associated with stronger risk-based momentum.

We also propose a simple measure to directly capture arbitrageur participation in any stock in real time. Our measure focuses on risk concentration, defined as the fraction of a stock's return variation explained by the risk component in a given intraday interval. The idea is that the more a stock's total return variation can be explained by the risk component aggregated from various anomaly factors, the more likely that arbitrageurs have already started trading this stock to correct the associated mispricing. Empirically, we find much stronger risk-based momentum among stocks with higher risk concentration.

The risk component, capturing the total systematic risk of stock returns, is a function of anomaly factors. We consider three sets of of anomalies. The first set consists of 15 representative anomalies, including the 11 major mispricing anomalies from Stambaugh, Yu, and Yuan (2012) and *Beta*, *Size*, *Book-to-market ratio*, and *Reversal*. The second set consists of 15 anomalies from Ehsani and Linnainmaa (2022). The third set includes 60 anomalies drawn from Green, Hand, and Zhang (2017), Freyberger, Neuhierl, and Weber (2020), Gu, Kelly, and Xiu (2020), and Kozak, Nagel, and Santosh (2020), covering numerous categories, such as value versus growth, profitability, investment, issuance activity, momentum, and trading frictions. We find that the risk-based momentum is quite robust to using different sets of anomalies to approximate the total systematic risk.[5] While the results for the first two sets are similar, with annualized return varying from 3.82% to 12.06% across overnight and intraday half-hour intervals, the third set performs the best, with a greater annualized return between 5.92% and 14.68%. For all three sets of anomalies, the best performance is obtained in the mornings rather than in the afternoons.

An interesting question is how the risk-based momentum performs when the holding horizon is more than one intraday period. Notably, we find that the momentum based on risk in the past intraday period is extremely persistent and lasts about 65 intraday periods or 5 days. Consistent with the previous intraday patterns, the risk-based momentum from the morning risk signal is more persistent than those from the afternoon signal, consistent with existing studies (see, e.g, Cushing and Madhavan, 2000; Foucault, Kadan, and Kandel, 2005; Bogousslavsky, 2021) that investors behave differently towards the end of the day.

Our paper adds to the growing literature on high-frequency studies as data become

[5]We also measure the risk component using the 205 anomalies from Chen and Zimmermann (2022) and the results remain robust.

increasingly available. Heston, Korajczyk, and Sadka (2010) document an intraday anomaly that there is a striking pattern of return continuation at half-hour intervals that are exact multiples of an earlier trading day. Gao, Han, Li, and Zhou (2018) uncover a time-series momentum pattern of the market: the first half-hour market return predicts the last half-hour return, on which Bogousslavsky (2016) explains theoretically that this market intraday momentum can be driven by investors' infrequent rebalancing to their portfolios. Lou, Polk, and Skouras (2020) find a tug of war in the returns of 14 trading strategies that profits are either earned entirely overnight or entirely intraday.[6] Baltussen, Da, Lammers, and Martens (2021) further analyze market intraday momentum in general via the lens of hedging. Bogousslavsky (2021) explores anomaly returns over the trading hours and overnight. To the best of our knowledge, our paper is the first to study the intraday patterns of the risk component of stock returns and discover the associated cross-sectional risk-based return momentum.

Our paper also adds new directions of research to the large momentum literature. Since the seminal work of Jegadeesh and Titman (1993), the momentum factor that buys winners and shorts losers plays an important role in factor models and in explaining mutual fund returns, among others. For example, Griffin, Ji, and Martin (2003) study global stock momentum and Asness, Moskowitz, and Pedersen (2013) examine momentum across asset classes. Since our risk-based momentum is unique and stronger than the traditional momentum, the great number of questions studied related to the traditional momentum can also be asked for the risk-based momentum, generating more studies and deeper understanding about momentum and risk in general.

The paper is organized as follows. Section 2 discusses the data and methodology of decomposing stock returns into risk and residual components. Section 3 presents the empirical results pertaining to the risk-based return momentum, the momentum of the risk component,

[6] Lou, Polk, and Skouras (2020) aggregate intraday and overnight return components within each month, and find that the intraday (overnight) component of lagged one-month return positively predicts the intraday (overnight) component of next-month return. In contrast, our paper is about using lagged one-intraday-period risk to predict the next, that is, our intraday momentum is about the positive relation between intraday signal and future intraday return.

the persistence of intraday factors, and the contribution of different anomalies to the risk-based momentum. Section 4 uncovers various conditions under which the risk-based momentum becomes stronger. Section 5 performs robustness tests. Section 6 concludes.

2. Data and Methodology

2.1. Data

Our stock sample consists of the Russell 1000 index constituents. This top 1000 stock sample comprises more than 90% of the total market cap of all stocks in the US equity market and also has the advantage of allowing for relatively reliable high-frequency return estimation. Our intraday price and quote data come from the NYSE trade and quote (TAQ) database, covering the period from data inception in January 1993 to December 2020. We obtain data on daily stock returns between January 1970 and December 2020 from the Center for Research in Security Prices (CRSP) database.[7]

We compute every 30-minute return between 10:00 and 16:00 and the overnight return between 16:00 on the previous trading day and 10:00 on the current trading day.[8] Our high-frequency returns are based on mid-quote prices to mitigate three undesirable properties caused by the use of transaction prices: the spurious correlation induced by the bid-ask bounce (Roll, 1984), the selection bias associated with the occurrence of a trade, and possible unachievability of transaction prices in the market place.[9] Similar to us, the main analysis in Bogousslavsky (2021) also uses returns computed from quote midpoints. Our results remain robust to using volume-weighted average prices for computing intraday returns. Since prices from TAQ are raw prices without adjusting for corporate actions such as dividend payout

[7]The Russell 1000 index, launched in January 1984, comprises the top 1,000 stocks by market capitalization and is rebalanced on the last Friday of June each year based on end-of-May stock capitalization. For the period before January 1984, we use the end-of-May stock capitalization to select the top 1,000 stocks.

[8]We use the price at 10:00 for the overnight return calculation to ensure that most securities have traded at least once after the market open.

[9]To see the last point, note that on average transaction prices have a 50% chance of being executed at the bid and another 50% at the ask price. Suppose for a given day, the last transaction price is at the ask price. The transaction price is the right price for the long position, but unachievable for the short position.

and stock splits, we apply the daily "cumulative factor to adjust price" and "dividend cash amount" variables in the CRSP database to adjust for split and dividend.

We consider three sets of anomalies. The first set consists of 15 representative anomalies, including 11 mispricing anomalies of Stambaugh, Yu, and Yuan (2012) and *Beta*, *Size*, *Book-to-market ratio*, and *Reversal*. The mispricing anomalies are updated monthly following Stambaugh, Yu, and Yuan (2012), with the exception of *Momentum*, which is updated daily and estimated by the cumulative return over the past 22 to 252 days. *Beta* is the estimated coefficient by regressing monthly stock excess returns on monthly market excess returns using a 60-month rolling window. *Size* is the natural logarithm of the market value of equity, estimated by the product of the closing price and the number of shares outstanding, and is updated daily. *Book-to-market ratio* is the ratio of the book value of common equity to the market value of equity. *Reversal* is defined as the cumulative return over the past 21 days. We refer to the first set of anomalies as "15 RP anomalies", where RP stands for "representative".

The second set consists of 15 anomalies investigated by Ehsani and Linnainmaa (2022), including *Accruals*, *Betting against beta*, *Book-to-market*, *Cash-flow to price*, *Earnings to price*, *Profitability*, *Residual variance*, *Liquidity*, *Investment*, *Long-term reversals*, *Momentum*, *Short-term reversals*, *Size*, *Quality minus junk*, and *Net share issues*. We refer to the second set of anomalies as "15 EL anomalies", where EL stands for "Ehsani and Linnainmaa".

The third is a comprehensive set of 60 anomalies drawn from Green, Hand, and Zhang (2017), Freyberger, Neuhierl, and Weber (2020), Gu, Kelly, and Xiu (2020), and Kozak, Nagel, and Santosh (2020), covering numerous categories, such as value versus growth, profitability, investment, issuance activity, momentum, and trading frictions. The list of these 60 well-known anomalies is provided in Table A.1 in the Online Appendix. We refer to the third set as "60 anomalies".[10]

Panel A of Table 1 reports the summary statistics of the 15 RP anomalies, and Panel B

[10] We include more anomaly variables than standard factor models such as the Fama-French-Carhart six characteristics to better measure the risk component of stock returns. In Section 5.2, we also examine a much larger set including 205 anomalies from Chen and Zimmermann (2022).

reports the same statistics for the 15 EL anomalies. Descriptive statistics on the last anomaly set are also calculated but untabulated to conserve space. For all three sets, the anomalies vary substantially on their means and standard deviations. Thus, we standardize all anomaly variables before using them for predictive analyses.

Following Kozak, Nagel, and Santosh (2020) and Ehsani and Linnainmaa (2022), we first transform each raw anomaly variable $V_{s,d-1,j}$ on each day into a cross-sectional rank, $rc_{s,d-1,j} = \frac{\text{rank}(V_{s,d-1,j})}{n_{d-1}+1}$, where s denotes the stock, j denotes the anomaly variable, and n_{d-1} denotes the number of stocks on day $d-1$. Next, we standardize these ranks by first centering them around zero and then normalizing them by the sum of absolute deviations from the mean:

$$C_{s,d-1,j} = \frac{rc_{s,d-1,j} - \overline{rc}_{s,d-1,j}}{\sum_{s=1}^{n_{d-1}} \left| rc_{s,d-1,j} - \overline{rc}_{s,d-1,j} \right|}. \tag{1}$$

Note that no future information is used in the transformation, so that any predictive regressions based on $C_{s,d-1,j}$ would be truly out-of-sample.

2.2. *Methodology*

In this paper, we consider stock returns and their risk decomposition in every intraday period. Such intervals are common in intraday studies such as Heston, Korajczyk, and Sadka (2010) and many others. Our first period ($i = 1$) is the overnight interval from the market close of the previous day to 10:00, where the ending time is chosen to ensure that almost all securities are traded at least once by then. The next period ($i = 2$) is from 10:00 to 10:30, and so on until the last period ($i = 13$) which is between 15:30 and 16:00. We obtain risk decomposition from running the following cross-sectional regression:

$$RET_{s,d,i} = \alpha_{d,i} + \sum_{j=1}^{p} C_{s,d-1,j}\theta_{d,i,j} + \epsilon_{s,d,i}, \tag{2}$$

where $RET_{s,d,i}$ is the return of stock s on day d in intraday period i, $\alpha_{d,i}$ is the intercept on day d in period i, $C_{s,d-1,j}$ is the standardized anomaly j of stock s observable at the market close of day d-1, and $\epsilon_{s,d,i}$ is the residual. The unknown slope estimates $\theta_{d,i,j}$ can be interpreted as factor returns (see, e.g., Fama and French, 2020), and so the second term captures the total systematic risk of the stocks at intraday frequency.

Using the estimated coefficients $\hat{\theta}_{d,i,j}$, we can then decompose the raw return of stock s on d in intraday period i into two parts:

$$RET_{s,d,i} = RISK_{s,d,i} + RES_{s,d,i}, \tag{3}$$

where

$$RISK_{s,d,i} = \sum_{j=1}^{p} C_{s,d-1,j}\hat{\theta}_{d,i,j}, \tag{4}$$

is the estimated systematic risk explained by common risk factors, which is simply referred as $RISK$.[11] The residual part $RES_{s,d,i} = RET_{s,d,i} - RISK_{s,d,i}$ is the return component unexplained by the factors, which includes the alpha component. While existing studies focus on the alpha component, there is rarely any analysis on $RISK$, the contribution of the systematic factors inspired by asset pricing theory.

Our objective is to study the properties of $RISK$ and its predictive power on future returns. We exploit its predictive power as follows. At the beginning of each intraday period i ($i = 1, ..., 13$) on each day d, we sort stocks into ten portfolios based on their realized $RISK$ values available at the time (i.e., the risk component of returns in the previous intraday period). We buy stocks in the top decile with high $RISK$ values and short those in the bottom decile with low $RISK$ values. We hold this long-short value-weighted portfolio during period i on day d, resulting in the risk-based portfolio return:

[11]The common factors used to extract the $RISK$ component include both risk-based and behavioral factors. As argued by Kozak, Nagel, and Santosh (2018), factor covariances should explain cross-sectional variation in expected returns even in a model of sentiment-driven asset prices, because time-varying investor sentiment can give rise to an ICAPM-like SDF.

$$RM_{d,i} = R_{10}^{d,i} - R_1^{d,i}, \qquad i = 1, 2, \ldots, 13, \tag{5}$$

where $R_1^{d,i}$ and $R_{10}^{d,i}$ are the returns of decile portfolios 1 and 10 during period i on day d, respectively. As a result, we have 13 long-short portfolios per day corresponding to the 13 intraday intervals. Each of these portfolios enters position at the beginning of the corresponding intraday period and exits position at the end of the corresponding intraday period (i.e., rebalancing once per day). Then for each intraday period i, we have a time series of such risk-based long-short portfolio over trading days. Besides the 13 long-short portfolios that are rebalanced once per day at a fixed time of the day and are held over one intraday period, we also consider a risk-based long-short portfolio investing in all 13 $RISK$ signals and obtain its time-series returns. These time series would allow us to examine whether the risk-based portfolio returns exhibit momentum patterns or not. If they do, then we have a risk-based momentum.

We use each of the three anomaly sets as $C_{s,d-1,j}$ and estimate the slope coefficients in Equation (2) to obtain the corresponding $RISK$. Panels A and B of Table A.2 in the Online Appendix respectively report the correlations among the 15 RP anomalies and the 15 EL anomalies. The correlations are generally low, suggesting that multicollinearity is unlikely an issue when we use 15 anomalies jointly to explain the cross-sectional returns of Russell 1000 stocks. Thus, for the first two anomaly sets, we run simple OLS regressions to obtain the risk decomposition. To improve the efficiency of the slope estimators, we purposely use inverse variances as regression weights.[12]

The third and larger set of 60 anomalies potentially contains more predictive information about future returns while raising challenges of efficiently estimating the increased number of unknown parameters. To alleviate concerns about overfitting, we apply two solutions. First, following Kozak, Nagel, and Santosh (2020) and Ehsani and Linnainmaa (2022), we use 15 principal components (PCs) to reduce the dimensionality. Specifically, we first fit the

[12]The variance for stock s on day d is estimated by the sum of squared returns over the $[d-21,\, d-1]$ day window.

PCA model with anomaly data from January 1970 to December 1992 and then construct 15 out-of-sample PCs between January 1993 and December 2020 matching the sample period in our main analysis. Second, we use a penalized regression with the LASSO method that encourages sparse estimates of regression coefficients by introducing the L_1 penalty. Following Dong, Li, Rapach, and Zhou (2022), we fit the LASSO model period by period using the Akaike Information Criterion (AIC). Such criteria are useful for selecting the value of the regularization parameter by making a trade-off between the goodness of fit and the complexity of the model.

3. Main Results

3.1. Risk-based Momentum

Table 2 reports the performance of 13 spread portfolios sorted by the $RISK$ signal available at time "Start" and held over the subsequent intraday period between "Start" and "End" each day. The last column reports the performance of the "All-together" portfolio that trades all 13 $RISK$ signals and is rebalanced every intraday period. The rows labeled "Return" report the annualized return of each spread portfolio in percentage (i.e., annualized by a multiplier of 252 in percentage points), with Newey-West robust t-statistics in parentheses. For example, the first column presents the return of the spread portfolio sorted by the $RISK$ signal available at 16:00 and held from 16:00 to 10:00 each day. The rows labeled "Alpha" report the annualized CAPM alphas, where the intraday market returns are approximated by using the returns on SPY.

Panel A reports the results based on $RISK$ estimated from 15 RP anomalies. In each of the intraday periods, the returns are decisively positive, suggesting a strong momentum. What is striking is that the pattern holds for every intraday period.[13] The spread portfolios are very stable with an average return ranging from 4.47% for the portfolio held from 13:00 to

[13]In sharp contrast, spread portfolios sorted by the total return in the previous intraday period all generate reversal, consistent with the short-term reversal documented in the existing literature.

13:30 to 12.06% for the portfolio held from 10:30 to 11:00. The results based on the CAPM alphas are numerically similar. Overall, the risk-based momentum is relatively stronger during the morning sessions. To have a sense of the gains from trading the momentum all day, we turn to the "All-together" portfolio in the last column that is rebalanced 13 times a day on investing in the spread portfolio every period. The average annualized return of 95.06% is astronomical. In the absence of trading costs, this level of profitability will clearly invite arbitrage and will go down quickly. On the other hand, the cost of trading individual stocks every intraday period is likely high, and the return may evaporate after trading costs. What we show here is simply the return patterns on the risk-based momentum, and we do not suggest in any way that the patterns can be profitable to investors who trade the strategy intraday. However, as shown in Table A.6 in the Online Appendix, our risk-based return momentum also extends to the monthly frequency with an annual alpha around 20%, and such high value would easily survive typical transaction costs.

Panel B reports the results for signals constructed based on 15 EL anomalies. The results indicate that the construction of the spread portfolios is quite robust to a different choice of the anomaly set. For instance, the overnight spread portfolio formed based on $RISK$ available at 16:00 has an average return of 8.88%. The average returns of the intraday spread portfolio range from 3.82% when holding the portfolio from 14:00 to 14:30, to 11.95% when holding the portfolio from 10:30 to 11:00. In addition, the "All-together" spread portfolio generates an average return of 93.67% with a t-statistic of 22.29.

Panel C reports the performance of the spread portfolios based on 15 PCs from the 60 well-known anomalies covering numerous categories. The results are almost uniformly stronger than before. For instance, the "All-together" portfolio has a return of 119.14%, compared with 95.06% and 93.67% from previous panels. With more factors, the resulting $RISK$ component likely better captures the total systematic risk, and in turn generates an extra momentum that adds to the already strong momentum based on a smaller anomaly set.

Panel D reports the performance of the spread portfolios based on $RISK$ estimated from 60 well-known anomalies with LASSO sparse estimators. There are several noteworthy findings. First, the results continue to show that the positive predictive power of $RISK$ on future stock returns is robust to different constructions of $RISK$. Second, the LASSO-based $RISK$ has an even stronger predictive power. As shown in the last column, the "All-together" spread portfolio has an average return of 125.21% with a t-statistic of 25.67. Both values are greater than those reported in the other panels. Furthermore, the increased predictability of $RISK$ can also be observed across 13 individual spread portfolios. For example, the average returns of intraday spread portfolios range from 6.16% when holding the portfolio from 14:00 to 14:30, to 14.68% when holding the portfolio overnight. Therefore, exploiting the 60 well-known anomalies by LASSO can better capture the $RISK$ component which has significantly positive predictability for future returns.[14]

The long-short spread portfolio in Table 2 only shows the return difference between the top and bottom decile portfolios. To examine whether the results are entirely driven by these two extreme deciles, Table 3 reports the performance across all deciles for strategies based on 15 RP anomalies or 15 EL anomalies. Interestingly, the monotonic pattern that high risk goes hand in hand with high return holds very well across all deciles for any given formation period. As a result, the long-short spread portfolio captures well the cross-sectional differences in $RISK$. While Table 3 presents the results for the first two sets of anomalies only, similar patterns also hold for the two cases of 60 anomalies via PCA and LASSO, as shown in Table A.4 in the Online Appendix.

3.2. Persistent Risk-Based Momentum

The holding period of our previous risk-based momentum strategies is either overnight or every 30-minute interval during the regular trading hours. Does the risk-based momentum only last one intraday period or much longer? To address this question, we increase the holding periods to up to five days and compute holding-period returns following an event

[14] Table A.3 in the Online Appendix reports the results based on Russell 3000 stocks, which are quantitatively similar to those based on Russell 1000 stocks in Table 2.

study approach. Specifically, at the end of each intraday interval i ($i = 1, 2, \ldots, 13$), we form a long-short portfolio based on the risk component of the return in interval i, and then hold the portfolio over the subsequent k intraday periods with k ranging from 1 to 65, corresponding to one intraday period to 5 days. For each portfolio formation time and each holding horizon k, we form decile portfolios and compute the cumulative returns for each decile portfolio. The spread between the cumulative returns in deciles 1 and 10 then forms a time series of cumulative returns on the spread portfolio constructed by the end of the interval i.

In Table 4, we measure the risk component using 15 RP anomalies, and report for each portfolio formation time (column labeled "Start") the cumulative returns in basis points (bps) and Newey-West robust t-statistics of the spread portfolios averaged across all trading days.[15] The columns labeled by numbers indicate the number of intraday periods the portfolios are held. For instance, the cell with the row and column labeled "10:30" and "12" corresponds to the portfolio formed at 10:30 and held for 12 periods until 10:00 the next day. To understand the overall pattern of the cumulative returns controlling for the time-of-day effect, we further average the returns and t-statistics across all 13 formation times and report the results at the bottom of the same table (row labeled "Mean").

There are several notable patterns in Table 4. First, the average cumulative return of the risk-based momentum portfolios generally increases as we extend the holding horizon to 13 intraday periods (one day); it declines afterward yet remains positive and significant for up to 65 intraday periods (5 days). For example, the row labeled "Mean" reports the average performance of the risk-based momentum portfolios constructed at different times of the day. The cumulative return monotonically increases from 2.9 bps for a one-intraday holding period to 12.48 bps for a one-day holding period. After the first day, the risk-based momentum drops to 9.39 bps by day 3 and stays relatively flat at 9.43 bps by day 5.

Second, the risk-based return continuation is stronger during the morning sessions than

[15] For holding horizons less than or equal to one day ($k = 13$), there is no overlap between the two consecutive observations of the spread series. For holding periods equal to 39 (65), there are 26 (42) intervals of overlap, so we use Newey-West robust t-statistics with lag 26 (42).

the afternoon sessions, and the contrast is more prominent for longer holding periods. For instance, for the risk-based momentum with a holding horizon of 13 intraday periods, the cumulative return decreases from 18.45 bps with a t-statistic of 9.93 for a portfolio formed at 10:00, to 4.88 bps with t-statistic of 3.03 for a portfolio formed at 16:00. Such pattern is consistent with the earlier results in Table 2 that the one-period returns are greater in the mornings than in the afternoons.

Table 4 only reports cumulative returns over the subsequent k days, where k takes every consecutive integer value between 1 and 13, and then 39 and 65, due to space constraints. To have a better sense of how cumulative return gradually evolves between day 1 and day 5, We plot in Figure 1 the average cumulative returns of the risk-based momentum strategies (using 15 RP anomalies) and their 95% confidence intervals against event time. In Panel A, we present cumulative returns averaged across spread portfolios formed at different times, the same as the values reported in row "Mean" of Table 4. We find that immediately after the portfolio formation, the cumulative return gradually increases to 12.48 bps after 13 periods, then slowly goes down to 9.39 bps after 39 periods, and stays relatively flat until 65 periods after.

Based on the early observation that risk-based momentum is stronger during the morning sessions, we separately plot the average returns of portfolios that are formed in the morning (from 10:00 to 12:30) and afternoon (from 13:00 to 16:00) in Panels B and C of Figure 1, respectively. Strikingly, the persistence of momentum highly depends on the portfolio formation time. From Panel B, the cumulative return of the momentum formed in the morning constantly increases to 16.2 bps after 13 periods and continues to rise to 17.8 bps until 20 periods. After that, the momentum slightly drops down to 15.8 bps by 36 periods and stays at the same level until the end of day 5. However, Panel B exhibits a relatively weaker and less persistent momentum formed in the afternoon. The cumulative return only increases to 9.6 bps after 11 periods; it quickly and surprisingly reverts to 5.8 bps after 18 periods and continues to go down to 2.9 bps after 46 periods. Eventually, the momentum stays at around

4 bps until the end of day 5. The sharply different momentum patterns are consistent with the finding that investors behave differently towards the end of the day (see, .e.g, Cushing and Madhavan, 2000; Foucault, Kadan, and Kandel, 2005; Bogousslavsky, 2021).[16] Later in Section 4.2, we present further evidence showing that the stronger risk-based momentum in the morning sessions can be explained by increased overall arbitrageur participation early in the day.

In summary, we find that the risk-based spread portfolios exhibit strong return momentum beyond one intraday period. The one-period positive return on the risk-based momentum portfolios can be explained by compensation for taking the factor risks summarized by the risk component. Consistent with the risk compensation story, the continual positive returns over a longer horizon are likely driven by the persistence in the risk component, which we will explore in the next subsection.

3.3. Decomposing Holding-Period Return of the Risk-based Momentum Strategy

We have shown that the risk component of lagged returns positively predicts future overall returns RET. To understand the source of such risk-based momentum, we now decompose the holding-period returns in Table 2 into risk ($RISK$) and residual (RES) components. If the risk-based momentum profit mainly arises from the holding-period $RISK$ component, this would reflect the momentum in risk, supporting the risk compensation explanation of the risk-based return momentum.

Panels A–D in Table 5 show the decomposition results of the risk-based momentum constructed from four different sets of anomalies. The results show that, regardless of the choice of anomalies, the majority of the risk-based momentum comes from the $RISK$ component. For example, the last column labeled "All" shows that under the four different

[16] Cushing and Madhavan (2000) and Foucault, Kadan, and Kandel (2005) point out that institutional traders place an enormous emphasis on closing prices, which are used to calculate portfolio returns, tally the net asset values of mutual funds, and mark-to-market various financial constraints; in the meanwhile, market makers prefer to unload inventory to avoid exposures to overnight risk. Bogousslavsky (2021) finds that mispricing is gradually corrected over the day but worsens at the end of the day when arbitrageurs are constrained to adjust their portfolios to reduce overnight risk.

$RISK$ specifications, the $RISK$ component contributes an annualized return of 79.10%, 77.12%, 108.92%, and 113.77%, respectively. In contrast, the RES component only contributes a return of 15.96%, 16.55%, 10.22%, and 11.44%, respectively. Thus, the risk continuation roughly explains 80% to 90% of the risk-based return momentum. The other columns corresponding to 13 different intraday holding periods show that the dominating role the risk continuation plays in the risk-based return momentum is robust across intraday intervals.

Comparing the decomposition results across the four panels in Table 5, we find that the higher total return based on the larger set of 60 anomalies over 15 RP or EL anomalies mainly comes from the stronger risk continuation generated by the 60 anomalies. For example, for the "All-together" portfolios in the last column, the holding-period $RISK$ based on 15 anomalies in the first two panels is around 80% per year, versus the $RISK$ based on 60 anomalies at around 110% per year in the last two panels, while the holding-period RES is similar in magnitude across panels. The comparison reaffirms that the additional information in the 60 anomalies can better capture the total systematic risk of stocks and thus generate stronger momentum effects.

To shed light on the source of the risk-based return momentum over longer horizons, we now decompose the longer-horizon returns in Table 4 into $RISK$ and RES components and present the decomposition results in Table 6. Consistent with the short-horizon decomposition analysis in Table 5, the longer-horizon decomposition analysis indicates that the continuation of $RISK$ over a longer period drives the long-horizon risk-based return momentum. For instance, the last row labeled "Mean" shows that the risk component has an average return of 2.41 bps, 12.33 bps, 13.02 bps, and 14.22 bps at one-intraday, 1-day, 3-day, and 5-day horizons, while the residual component only has an average return of 0.49 bps, 0.15 bps, -3.64 bps, and -4.78 bps for these horizons. Thus, the risk component accounts for 83%, 99%, 139%, and 151% of the risk-based momentum over these horizons. The ratios also point out that the decline in cumulative returns from day 1 to day 5 in Figure 1 is solely driven by the negative residual component of the holding period return, as the risk component continues to rise beyond day 1. Put it differently, the risk momentum is more persistent than the risk-based return momentum. This stronger risk momentum pattern is also robust to different portfolio formation times as shown in other rows.

To understand the source of the risk momentum, we follow Lo and MacKinlay (1990) by decomposing the holding-period $RISK$ into three components: the average autocovariance of individual stock $RISK$, the average cross-autocovariance across stocks, and the cross-sectional variance in expected stock $RISK$. The first component captures the serial correlation in individual stock $RISK$: a positive value would imply a positive average $RISK$ to a strategy that buys winners and sells losers conditional on past $RISK$. The second component reflects the lead-lag effects across stocks: a positive value would imply a negative average $RISK$ to our risk momentum strategy. The third component measures the dispersion in expected $RISK$ across stocks; if firms with positive $RISK$ on average have higher expected $RISK$, the risk momentum could be profitable due to the difference in expected individual stock $RISK$.

The requirement of the decomposition is that firms must exist over the entire sample period, which leaves us with 256 stocks in the Russell 1000 index that have complete return observations between January 1993 and December 2020. The decomposition results reported in Table 7 indicate that the majority of the risk momentum profit comes almost entirely from the positive autocovariance of individual stocks. For example, Panel A shows that, for the "All-together" strategy based on 15 RP anomalies, the total $RISK$ component is 107.98% and the autocovariance component is 103.28%, indicating that the autocovariance component explains 95.64% of the holding-period $RISK$. Similar conclusions hold for the remaining panels based on different anomaly sets. Thus, the risk momentum is driven primarily by the positive autocovariance in individual stock $RISK$.

3.4. *Factor Return Autocorrelations*

Section 3.3 shows the continuation of $RISK$ drives the risk-based return momentum. According to Equation (4), $RISK$ is the total systematic risk captured by the common factors, and is equal to the sum of the standardized anomaly ($C_{s,d-1,j}$) times the estimated intraday factor return ($\hat{\theta}_{d,i,j}$). Since the anomaly variable is relatively stable over time and, in fact, constant intraday, the intraday continuation of $RISK$ must partially come from the persistence of the intraday factor returns. To test if the factor returns are persistent, we turn to examining their autocorrelations.

Table 8 reports the autocorrelation of intraday factor returns as a function of lag k (in number of intraday periods), where k varies from 1 to 65. Panels A (B) reports the results for 15 RP (EL) anomaly factors, with *, **, and *** denoting significance at 10%, 5%, and 1% level, respectively. The column labeled "1" reports the first-order autocorrelation for each time series of the factor returns. Among all factors, *Beta*, *Distress*, *Gross profitability*, *Earnings to price*, and *Profitability* have a first-order autocorrelation of 0.1 or above. Strikingly, 26 out of the total 30 factors have a positive first-order autocorrelation at the 1% significance level, while none of them have significant negative first-order autocorrelations.[17]

At lag 2, although the autocorrelations decrease substantially in magnitude, most of them remain significantly positive. In particular, the autocorrelations at lag 2 for *Distress*, *Gross profitability*, *Earnings to price*, and *Profitability* remain at or above 0.05 and are highly significant. After lag 5, the magnitude of the autocorrelations decreases slowly to near zero. For instance, at lag 8, the autocorrelation for only one-third of the factors remains statistically significant. Interestingly, at lag 13, the positive autocorrelations of 13 out of 15 factors in Panel A and 14 out of 15 factors in Panel B become significant again. Moreover, the majority of the positive autocorrelations stay highly statistically significant at horizons that are exact multiples of 13 half hours as shown in the last two columns. The periodicity of the factors

[17] Because of the cross-sectional correlations among factors, the factor returns of some factors (e.g., *Size*) may be different depending on the control variables and thus have different autocorrelations under different regression specifications in Panels A and B.

is consistent with the intraday periodicity pattern documented by Heston, Korajczyk, and Sadka (2010).[18]

3.5. Anomaly Importance

How do different anomalies contribute to the risk-based momentum strategy? To answer this question, we decompose the $RISK$ component of the holding-period return for the risk-based spread portfolio into a sum of individual anomaly components according to Equation (4), and estimate the average value of each anomaly component $C_{s,d-1,j}\hat{\theta}_{d,i,j}$ during each intraday interval over all trading days, which captures the contribution of the associated anomaly to the spread portfolio return.

Panel A of Figure 2 shows the results for each of the 15 RP anomalies. The color gradients indicate the average spread portfolio returns of a given anomaly component over trading days, with dark blue and white indicating the highest and lowest values. For example, in the sixth column for the spread portfolio held between 12:00 and 12:30, *Beta*, *Distress*, *Momentum*, and *Reversal* are associated with the darkest colors (greatest values). This means that the $RISK$ calculated in the previous period between 11:30 to 12:00 significantly and positively predicts the *Beta*, *Distress*, *Momentum*, and *Reversal* components of the following period $RISK$. Noticeably, the order of the component importance remains stable as we move from the left to the right, indicating that the results are robust to the intraday holding periods.

Panel B reports the results for the 15 EL anomalies. The most important components across intraday periods include *Betting against beta*, *Residual variance*, *Momentum*, and *Short-term reversals*. Interestingly, both sets of anomalies point out the significant role of *Beta*, *Momentum*, and *Reversal* in explaining the high-frequency risk-based return momentum.

Overall, most anomalies contribute to the risk-based momentum strategies over time, which further corroborates the positive autocorrelation of the vast majority of factors as

[18]Based on Lo and MacKinlay (1990) decomposition with either the 15 RP or 15 EL factors, we find strong intraday autocovariance, consistent with the autocorrelation results, yet there is almost no lead-lag relation among factors.

shown in Table 8. In the next section, we provide insights on what drives the continuation of anomaly factor returns as a whole.

4. Explanation

From Equation (4), our risk component is aggregated from individual anomaly components. As further shown in Table 8, anomaly factor returns exhibit positive and significant autocorrelation, leading to continuation of risk and risk-based return momentum. Since anomaly returns are realized only when arbitrageurs trade on the perceived mispricing, to generate persistent anomaly returns, arbitrageurs need to participate in trading to correct the misprcing, and they also need to trade gradually instead of aggressively. Due to limits to arbitrage, arbitrageurs tend to trade gradually instead of eliminating all mispricing at once. In this section, we formally examine how the degree of arbitrageur participation affects the risk-based momentum, and propose a simple measure to directly capture arbitrageur participation level in real time.

4.1. News Effect

Abreu and Brunnermeier (2002) propose a coordinated arbitrage model in which rational arbitrageurs may be reluctant to trade on known mispricing because of holding costs and synchronicity risk - the risk that other arbitrageurs do not trade and so it will take time for anomaly returns to realize. More recently, Engelberg, McLean, and Pontiff (2018) find that anomaly returns are much higher on earnings announcement days, consistent with the notion that mispricing is driven by biased expectations which are at least partially corrected upon news arrival. Motivated by both studies, we conjecture that after news arrival, arbitrageurs as a group become more aware of the mispricing in light of the news, and thus the overall synchronicity risk is reduced. As a result, they are more willing to participate in trading to correct the perceived mispricing. Arbitrageurs still trade gradually due to limits to arbitrage, leading to persistent anomaly returns. Thus, we expect a stronger risk-based momentum upon news arrival.

To empirically test this idea, we investigate the performance of our risk-based momentum strategies conditional on firm news arrivals. We begin with collecting the high-frequency firm news data from the RavenPack news database between January 2000 (data inception) and December 2020. The RavenPack news data provide a comprehensive sample of firm-specific news stories from the Dow Jones News Wire.[19] Following the standard practice of the literature, we only keep fundamental news that is most fresh and relevant to a particular company. To consider only news about company fundamentals, we select 12 news groups of acquisitions-mergers, analyst ratings, assets, bankruptcy, loans, credit ratings, dividends, earnings, corporate actions, labor issues, product services, and revenue from a total of 29 news groups. To keep only fresh news about a company, we exclude repeated news by requiring news in our sample to have an "event novelty score" of 100. To ensure that the news is company-specific, we select news with a "relevance score" of 100, meaning that the entity is mentioned predominantly in a news article.[20] After processing the firm news, we construct a time series of news arrival measures using the total number of news counts for Russell 1000 stocks in each intraday interval over the period from January 2000 to December 2020. For simplicity, we construct risk signals based on the 15 RP anomalies throughout this section.

We examine the effect of firm news on our risk-based momentum by conducting a similar event study as described in Section 3.2. Specifically, we compute the time-series median of the news arrivals for each of the 13 intraday periods, and the time-series median of the arrivals using all intraday periods and all days. In other words, we have 13 different median values for 13 strategies formed by signals in a specific intraday period, and a median value for the "All-together" strategy that trades on signals from all intraday periods. Then we compute the average returns of the risk-based momentum strategies conditional on whether the news arrival in the signal formation period is above or below the median. Figure 3

[19] Recent studies using this data set include Kelley and Tetlock (2017), Jiang, Li, and Wang (2021), and Jiang, Li, and Yuan (2022).

[20] Applying these filters will not result in look-ahead bias, as all news articles are processed by RavenPack within milliseconds of receipt, and the resulting data are sent to subscribers immediately.

presents the firm news results during the period of January 2000 and December 2020 when the RavenPack news data are available. Strikingly, we find a distinct difference between the risk-based momentum performance conditional on high and low news arrival. For example, the risk-based momentum conditional on high news arrival rapidly increases to 12.8 bps after 13 periods, then gradually decreases to 8.7 bps after 43 periods, and rises to around 11 bps until day 5. On the contrary, the momentum conditional on low news arrival only slowly increases to a much lower level at 7.5 bps after 13 periods, continues to decline to 3.8 bps after 33 periods, and stays at the same level until day 5. Thus, we identify a strong and instantaneous effect of firm news arrivals on the risk-based momentum, consistent with the idea of improved arbitrageur participation after news arrivals. Their gradual trading due to limits to arbitrage leads to higher autocorrelations in anomaly returns and stronger risk-based return momentum.

4.2. Aggregate Idiosyncratic Volatility

The recent literature has emphasized the important role of idiosyncratic volatility (IVOL) in affecting asset prices.[21] Garcia, Mantilla-García, and Martellini (2014) argue that aggregate IVOL is related to consumption volatility, a measure of economic uncertainty in the inter-temporal asset pricing model of Bansal and Yaron (2004). Motivated by these studies, we conjecture that our risk-based momentum is also stronger during high aggregate IVOL periods due to limits to arbitrage. Specifically, high IVOL leads to a shortage of funds available for arbitrageurs, resulting in slow responsiveness of arbitrage capital to mispricing. The greater limits to arbitrage they face will render more gradual mispricing correlation and thus enhance the performance of the risk-based momentum strategy.

To verify our conjecture, we follow Garcia, Mantilla-García, and Martellini (2014) and use return dispersion (RD), defined as the cross-sectional standard deviation of stock returns, to measure aggregate IVOL. There are two advantages of the RD measure: being model-free

[21] See, e.g., Campbell, Lettau, Malkiel, and Xu (2001), Bali, Cakici, Yan, and Zhang (2005), Ang, Hodrick, Xing, and Zhang (2006), and Arena, Haggard, and Yan (2008), among others.

and measurable at any return frequency. We first calculate RD for each intraday period on all trading days from January 1993 to December 2020 to obtain a time series of RD measures. Then we compute the time-series median of RD for each of the 13 intraday periods, and the time-series median of RD using all intraday periods on all days. That is, we have 13 different median values corresponding to 13 strategies that trade during a specific intraday period, and a median value for the "All-together" strategy that trades every intraday period. Finally, we calculate the average annualized returns during high (i.e., above median) and low (i.e., below median) RD periods for each strategy.

Table 9 reports the results for the momentum strategies during high and low RD periods formed by different $RISK$ signals. Interestingly, although the risk-based momentum exists in both high and low RD periods, the effect is much stronger during the high RD period. Across Panels A to D, the "All-together" spread portfolio during high RD periods delivers an annualized return of 157.57%, 156.81%, 203.46%, and 210.28%, about five times as much as the annualized return of 32.16%, 30.34%, 38.50%, and 42.79% during low RD periods. The returns on the spread portfolios during high RD periods are highly statistically significant with t-statistics all above 21. The higher momentum during high RD periods is also robust to all intraday holding periods. In sum, the results lend strong support to our conjecture that a stronger risk-based momentum exists during periods with elevated aggregate IVOL.

In earlier sections, we have documented a stronger risk-based momentum in the morning. It is of interest to explore whether the result can be explained by higher return dispersion early in the day. In Figure 4, we plot the time-series average of intraday RD in percentage along with the 95% confidence intervals over the course of the day. Notably, we observe a decreasing smirk pattern: the average RD starts from the highest value of 1.3% at 10:00, monotonically decreases to 0.38% at 13:30, stays around 0.4%, and eventually slightly rises to 0.48% at the market close. Overall, the average RD is much higher in the morning than in the afternoon. Moreover, more than half of the firm news are released overnight, which could spur arbitrageurs to correct mispricing right after market open. Therefore, both the time-of-day variation of RD and the great amount of news released overnight can potentially explain the stronger risk-based momentum in the morning in addition to the clientele effect.

4.3. Risk Concentration

From previous sections, both news arrivals and high aggregate IVOL correspond to more arbitrageur participation in trading and stronger risk-based momentum. In this section, we directly measure the degree of arbitrageur participation in any stock in real time using a simple risk concentration measure, i.e., the fraction of a stock's return variation explained by risk in a given intraday interval. The idea is that the more a stock's total return variation can be explained by the risk component aggregated from various anomaly factors, the more likely arbitrageurs have already started trading this stock to correct the associated mispricings. As a result, greater arbitrageur participation would lead to stronger risk-based momentum among stocks with higher risk concentration.

To test the above hypothesis, we measure a stock's risk concentration as follows,

$$RiskCon_{s,d,i} = RISK^2_{s,d,i}/RET^2_{s,d,i}, \tag{6}$$

where $RISK_{s,d,i}$ and $RET_{s,d,i}$ are the risk component and the total return of the stock s in interval i on day d, respectively.[22] A higher value of $RiskCon_{s,d,i}$ indicates stock s has more risk concentration by the end of intraday period i on day d. To put the risk concentration into perspective, its average value upon high news arrivals is 29.26%, versus the average value of 28.68% upon low news arrivals, generating a difference of 0.58% with a t-statistic of 5.46. The contrast indicates that our risk concentration measure appears to capture the degree of arbitrageur participation.

We next test the impact of risk concentration on the risk-based return momentum as follows. By the end of each intraday period, we sort stocks into quintile portfolios on the basis

[22] We assume the population mean of intraday returns is zero as the cross-sectional intraday mean is almost negligible in comparison with the cross-sectional variance.

of their previous risk concentration; we classify stocks in quintile 1 as low-risk-concentration stocks and those in quintile 5 as high-risk-concentration stocks. Within each group of stocks, we form a spread portfolio that longs stocks in the top $RISK$ decile and shorts stocks in the bottom $RISK$ decile, and we hold the spread portfolio over the subsequent intraday period.

Table 10 reports the risk-based portfolio returns formed by low or high risk-concentration stocks based on different anomaly sets in Panels A to D. Strikingly, the high risk-concentration stocks produce an even stronger risk-based momentum universally, whereas the low risk-concentration stocks generate a risk-based reversal instead of momentum. For example, across the four panels, the "All-together" spread portfolio constructed based on high risk-concentration stocks (rows labeled by "High") yields an annualized return between 151.64% and 185.85%, about 50% to 60% higher than the return between 95.06% and 125.21% based on the full sample in Table 2. In contrast, the spread portfolio constructed using low risk-concentration stocks (rows labeled by "Low") produces a negative return between -41.83% and -30.28% with t-statistics all below -5. The stronger risk-based momentum among high risk-concentration stocks and the reversal among low risk-concentration stocks largely hold for each of the 13 intraday holding periods shown in the other columns. Consistent with Table 2, the risk-based momentum effect conditional on high risk-concentration stocks is the strongest based on 60 anomalies via the LASSO method. Overall, the results of Table 10 confirm our conjecture that a stronger risk-based momentum exists among high-risk concentration stocks, supporting our initial hypothesis.[23]

Given the superior performance of the risk-based momentum among high risk-concentration stocks, it is of interest to see how its cumulative return evolves over time. From a practical perspective, the "All-together" portfolio that is rebalanced every 30 minutes can also result

[23]To mitigate the concern that stocks in the high (low) risk-concentration quintile simply have more (less) extreme $RISK$ in absolute magnitude ($|RISK|$) and thus tend to generate greater (smaller) $RISK$-based return spread, we sort stocks into five portfolios by $|RISK|$, and then, within each quintile, we sort them further into quintiles based on their risk concentration (e.g., 5×5 grouping). Next, we average across the five $|RISK|$ portfolios to produce five one-period R^2 portfolios with large cross-portfolio variation in risk concentration but little variation in $|RISK|$, and construct risk-based long-short portfolios within the highest and lowest risk-concentration portfolios, respectively. The results are reported in Table A.5, confirming the robustness of the early finding that the risk-based momentum is stronger among high risk-concentration stocks.

in high trading costs. Thus, for a given $RISK$ signal, we form a daily-rebalanced portfolio sorted by the corresponding close-to-close $RISK$ signal from the previous day. Specifically, at the market close of each day t, we aggregate the 13 intraday $RISK$ signals between market close on day $t-1$ and market close on day t into one cumulative $RISK$ signal, then form a long-short portfolio based on the close-to-close $RISK$, and hold the portfolio over the subsequent close-to-close period. Finally, we compute the cumulative profits for the resulting value-weighted daily-rebalanced strategy based on an initial investment of $W_1 = \$1$. That is, we compound the returns of the spread portfolio on day d as follows,

$$W_d = W_{d-1} \times (1 + R_{high,d} - R_{low,d}), \quad d = 1, 2, \ldots, \tag{7}$$

where $R_{high,d}$ and $R_{low,d}$ are the returns of decile 10 and decile 1 on day d, respectively.

Figure 5 plots the trajectory of W_d starting from a given $W_1 = \$1$ initial investment at the start of January 1993. We further take the logarithm of the portfolio value with base ten, so the trajectory in the plot starts from 0. The portfolio value based on all four $RISK$ strategies continues to rise throughout the entire sample without experiencing major drawdowns. Furthermore, consistent with Table 10, the LASSO-based momentum strategy exhibits the best performance throughout the sample period.

Table 11 further reports the performance of all decile portfolios formed on the basis of various daily $RISK$ signals using either all stocks in our sample in Panel A or stocks in the top risk-concentration quintile in Panel B. Across different signals and stock samples, we observe a strong monotonically increasing relation between past-day $RISK$ and next-day return. For the full sample in Panel A, the annualized returns of the $RISK$-sorted spread portfolios are between 44.37% and 48.01% with t-statistics all above 9. For the high-risk-concentration stocks in Panel B, the annualized returns uniformly increase to between 57.24% and 64.87% with higher t-statistics all above 11. The return spreads based on Fama and French (2015) five-factor alphas are numerically similar.[24]

[24]Figure 6 and Table A.6 in the Online Appendix show that the risk-based return momentum continues

In this section, we have explored three possible drives for the risk-based momentum. Understanding further the economic forces of the heterogeneity in the factor return continuation across anomalies is important but difficult. This will be an interesting topic for future research.

5. Robustness

5.1. Different Portfolio Formation and Holding Periods

The risk-based momentum strategy forms portfolios based on the one-period $RISK$ component computed from returns over the previous overnight or 30-minute interval. We would like to ensure that the results are not sensitive to this particular choice of portfolio formation period. In this section, we investigate the performance of different portfolio formation periods. Specifically, we first estimate one-period $RISK$ using 15 RP anomalies and compute M-period $RISK$ by aggregating the one-period $RISK$ in the prior M periods. We consider M to be 1, 3, 5, 8, 13, 26, 39, and 65 periods, corresponding to a formation period of 30-, 90-, 150-, 240-minutes, 1-, 2-, 3-, and 5-days. We also consider different portfolio holding periods by following the portfolio rebalancing schedule of Jegadeesh and Titman (1993). That is, to construct a portfolio with a holding period of N, we revise the weights on $1/N$ of the stocks in our strategy in any intraday interval and carry over the rest from the previous interval.

Panels A and B in Figure 6 show the average annualized returns and their annualized Sharpe ratios of the long-short risk-based momentum portfolios based on the different combinations of portfolio formation period M (rows) and holding period N (columns). For example, the entry with row labeled "3" ($M = 3$) and the column labeled "3" ($N = 3$) reports the performance of the long-short portfolio that is formed based on sorting the past 3-period $RISK$ and is held for 3 intraday periods. The dark (light) color in the figure indicates a high (low) value of the entry. As can be seen, almost all long-short portfolios have positive

to hold at daily, weekly, and monthly frequencies over the expanded sample period from January 1970 to December 2020. Figure A.2 in the Online Appendix further shows that the risk-based return momentum phenomenon exists in the corporate bond market at the monthly frequency.

returns, except for the 65/39 and 65/65 strategies. Many of the individual strategies have both high returns and high Sharpe ratios. Out of the total 64 strategies, 56 strategies have an annualized return of 10% or above, and 54 strategies have an annualized Sharpe ratio greater than 1. The most successful strategies seem to be selecting stocks based on their $RISK$ signal over the past one-intraday period to one-day period and then holding the long-short portfolios for one-intraday period to one day. Such strategies, as shown by the upper-left regions of Panels A and B in Figure 6, can generate an annualized return between 37.51% and 100.88% with an annualized Sharpe ratio between 2.38 and 4.51. In particular, at the one-day holding horizon, the signal from the past one-intraday period generates the highest Sharpe ratio of 4.51.

Another noticeable pattern is that there is a significant performance drop in terms of both return and Sharpe ratio when the signal formation period or the holding horizon is longer than one day. For example, the strategies based on the $RISK$ signal over the past 2-day period (row labeled "26") yield a return of 8.48% to 67.21 % with a Sharpe ratio between 0.55 and 2.81, both of which are much lower than those based on the $RISK$ signal over the past one-intraday period to one-day period. These results suggest that our use of high-frequency intraday data is crucial in effectively uncovering the strong risk-based return momentum.

5.2. A 205 Anomaly Set

In this section, we extend our anomaly set to the comprehensive one studied by Chen and Zimmermann (2022), which includes 205 anomalies in total. The results are reported in Table 12.

Panel A reports the results for signals constructed based on 15 PCs from the 205 anomalies. The results are very similar to our main findings in Table 2. For instance, the overnight spread portfolio formed on the basis of the last half-hour $RISK$ from the prior day has an average annualized return of 10.00% and a t-statistic of 3.69. The average returns of the intraday spread portfolios range from 4.31% with a t-statistic of 5.94, when holding the portfolio from

13:30 to 14:00, to 10.07% with a t-statistic of 9.54, when holding the portfolio from 10:30 to 11:00. In addition, the "All-together" spread portfolio generates an average return of 88.33% with a t-statistic of 22.10. Panel B reports the performance of the spread portfolios based on the 205 anomalies with the LASSO dimension reduction technique. The results clearly show that the resulting $RISK$ continues to have strong positive predictability for future stock returns, and the corresponding spread portfolio returns are almost uniformly higher than those in Panel A. For instance, the "All-together" spread portfolio has an average return of 105.26% with a t-statistic of 21.75, and both values are greater than those reported in Panel A. The increased predictability of $RISK$ can be observed in other 13 individual spread portfolios as well. Overall, the results are largely similar to those in Table 2. Taking together, this additional analysis with the 205 anomaly set reaffirms our earlier results, suggesting that the risk-based return momentum is quite robust to the choice of the anomaly set.

5.3. *Financial Crisis and Momentum Crash*

Does the documented risk-based momentum exist during the 2008 financial crisis? Does the strategy continue to work when the traditional momentum crashes? To answer these intriguing questions, we zoom into the subsample periods from December 2007 to March 2013. This subsample can be further divided into two periods: the 2008 financial crisis period which is between December 2007 and February 2009, and the momentum crash period which, according to Daniel and Moskowitz (2016), is from March 2009 to March 2013 when the aggregate market rebounded and the traditional momentum strategy experienced a huge drawdown. For each subsample period, we form conditional risk-based momentum strategies using stocks in the top risk-concentration quintile.

Table 13 reports the results for the financial crisis period. We can see that the conditional risk-based momentum continues to exist and becomes notably stronger. Specifically, the "All-together" portfolio has an average return of 239.96%, 241.26%, 216.99%, and 269.72%, roughly 50% higher than the full-sample values in Table 10. The stronger momentum during the financial crisis is in line with the stellar performance of the risk-based momentum during the high return dispersion period documented in Section 4.3. Table 14 further reports the results of the conditional strategies over the momentum crash period. The risk-based momentum becomes weaker but remains positive and statistically significant, with the "All-together" portfolio delivering average returns between 99.07% and 113.43% and t-statistics above 10 across the four panels. In short, our results show that the risk-based momentum is sharply distinct from the traditional momentum. It performs well during the financial crisis period, and it continues to perform well when the traditional momentum experiences crash.

5.4. Day-of-Week Effect

In this subsection, we test if the risk-based momentum is affected by a weekend effect or any other day-of-week effects.

Table 15 summarizes the performance of the long-short portfolios on different days of the week formed by stocks in the top risk-concentration quintile. The "All" column indicates that, on average, the risk-based momentum is statistically significant and economically large across all days of the week: the average annualized returns of the spread portfolios are all above 130% and with t-statistics all above 13. The other columns report the results of the portfolios held during overnight or one of the 30-minute intervals. As can be seen, positive and statistically significant portfolio returns are present in almost all scenarios, indicating the risk-based momentum is robust across not only days of the week but also times of the day. While the momentum is strong on each day of the week, the annualized return monotonically decreases from Monday (162.8%) to Friday (131.49%). One possibility is that arbitragers are reluctant to carry positions over the weekend, resulting in less persistent mispricing correction and weaker anomaly return continuation as the weekend approaches. Indeed, the annualized returns of the intraday risk-based momentum portfolios held on Friday afternoons are much smaller than the afternoon returns on other weekdays. Furthermore, the strategy formed based on the last half-hour $RISK$ signal on Friday and held over the weekend produces an annualized return of 11.56%, only one-third to one-half of the overnight returns on other days as shown in the first column. In contrast, the "All-together" strategy on Monday still yields the highest return spread, likely because arbitrager participation greatly increases after the weekend is over. For example, the strategy that is held between 10:00 and 10:30 on Monday generates an annualized return spread of 24.62%, about two to three times those during the same time interval on other weekdays.

6. Conclusion

One of the fundamental insights of asset pricing theory is that greater systematic risk implies greater expected return. In this paper, we uncover the first ever cross-sectional return momentum in the intraday literature based on the risk component, or the return component explained by common factors. We show that there is not only a risk momentum (i.e., the continuation of the risk component itself), but also a strong return momentum when stocks are sorted by their past risk components. Both risk momentum and risk-based return momentum hold across different times of the day. Moreover, the effect is strong, generating an annualized return of around 40% before transaction cost for a strategy based on the last one-intraday period to one-day risk with a one-day holding horizon.

While the positive return of our risk-based momentum is a manifestation of asset pricing theory on compensation for bearing risk even intraday, the continuation of the risk component is intriguing. Since our risk component is aggregated from various anomaly components, the continuation of the entire risk component can be driven by persistent anomaly returns, which can be further explained by arbitrageurs' participation in mispricing correction and gradual trading due to limits to arbitrage. Particularly, anomaly returns are realized only when arbitrageurs trade on the perceived mispricing; they participate in trading to correct mispricing, and they trade gradually instead of eliminating mispricing at once due to market frictions. Indeed, we document stronger risk-based momentum in the morning sessions, during periods with more frequent firm news arrivals, when aggregate idiosyncratic volatility is high, and among stocks with higher risk concentration, all consistent with increased arbitrageur participation or greater limits to arbitrage under those scenarios.

Moreover, we find that the risk component of daily (weekly, monthly) stock returns continues to generate a risk-based return momentum at daily (weekly, monthly) frequency, and the same phenomenon well exists in the corporate bond market at the monthly frequency. Exploring such risk-based momentum in other asset markets would be of great interest. For example, it would be intriguing, in the foreign exchange market, to apply factors suggested by Lustig, Roussanov, and Verdelhan (2011) and perhaps along with more country characteristics to estimate currency risk exposure, and then examine whether there is, and to what extent, a risk-based currency momentum. All of these are important avenues for future research.

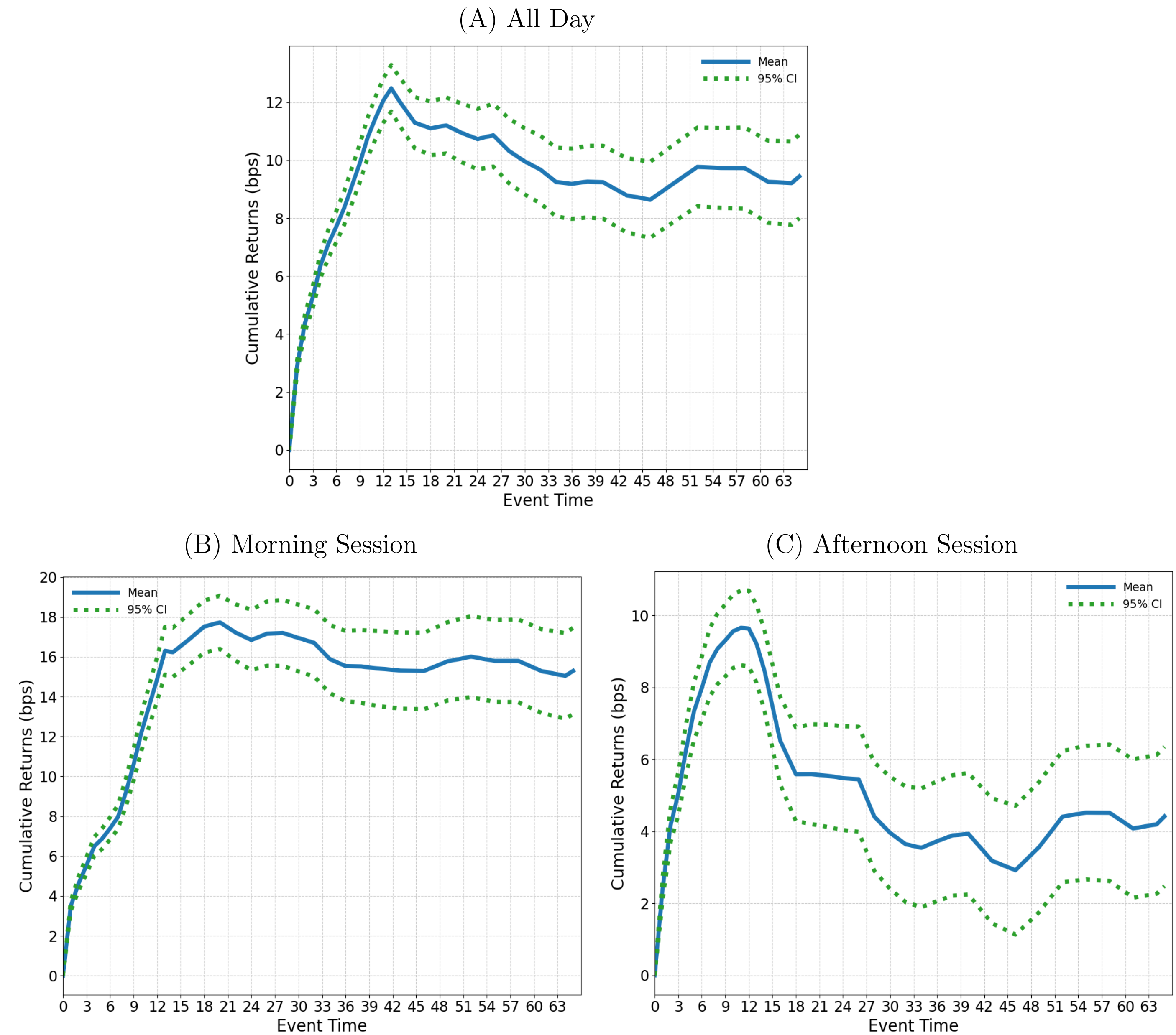

Fig. 1 Risk-based Momentum Strategy Over Event Time

This figure plots the cumulative returns of the momentum strategy based on the risk component constructed from the 15 RP anomalies and their 95% confidence intervals for each event time. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 on day $d-1$ to 10:00 on day d and 12 half-hour periods. The portfolios are formed at the beginning of each 13 intraday period and held up to 65 periods. Panel A shows the cumulative return averaged across all 13 formation periods. Panels B and C display the cumulative return averaged from portfolios that are formed in the morning (from 10:00 to 12:30) and afternoon (from 13:00 to 16:00) sessions, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

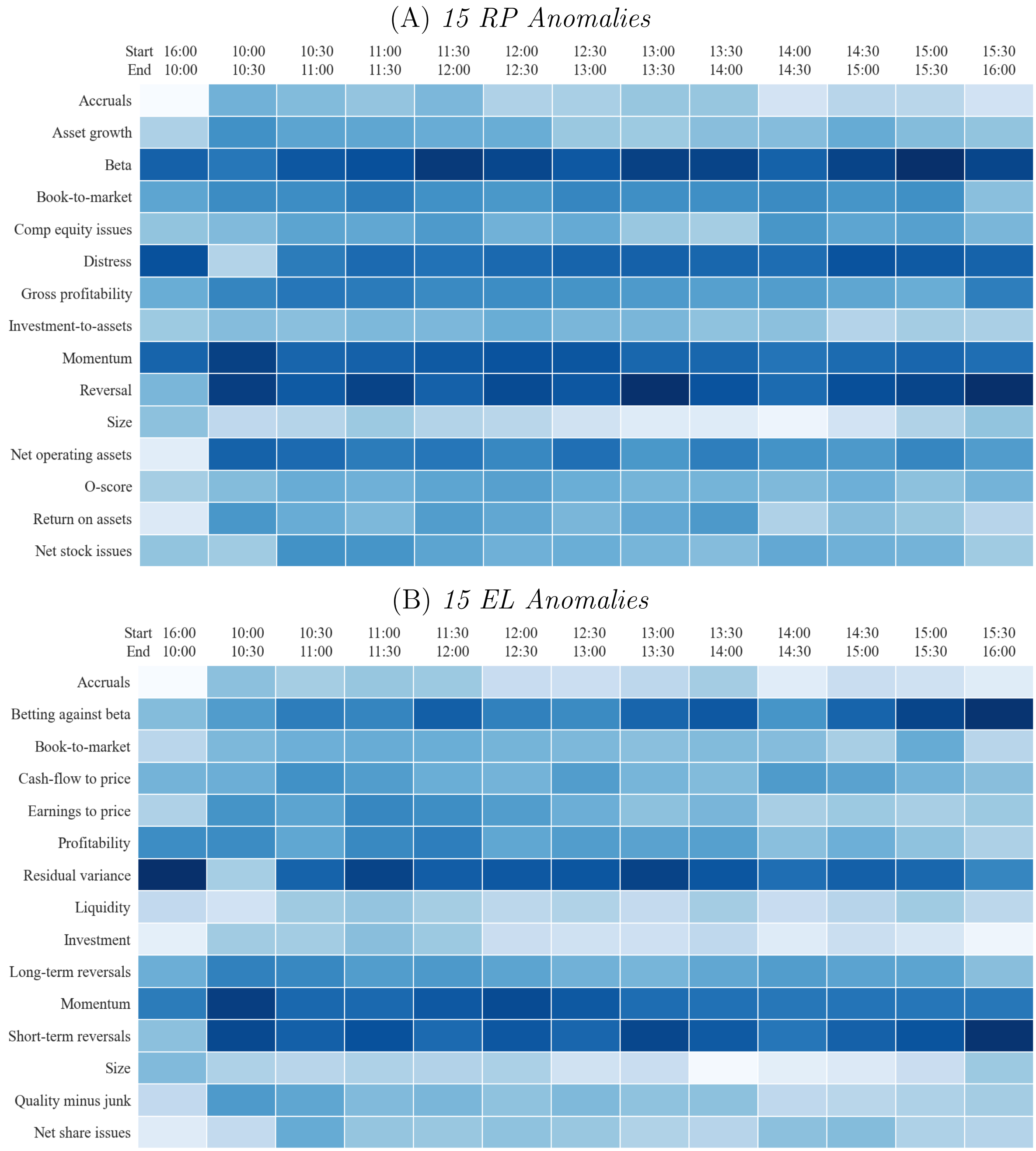

Fig. 2 Anomaly Importance

We decompose the $RISK$ component of the holding-period return for the risk-based spread portfolio into a sum of individual anomaly components according to Equation (4). The x-axis on top of each figure denotes the start and end of the portfolio holding period, and the y-axis denotes the anomaly component. The color gradients within each square indicate the average value of the anomaly component across all trading days, with dark blue and white indicating the highest and lowest values. Panels A and B display the results based on 15 RP anomalies and 15 EL anomalies, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

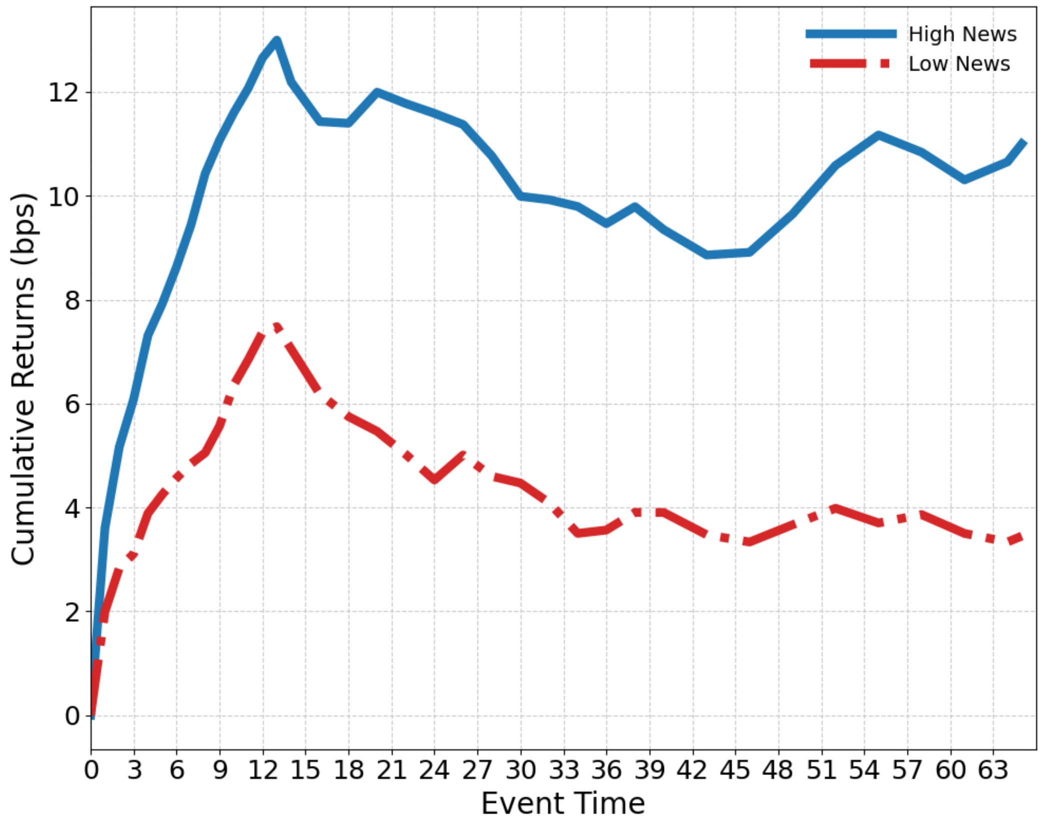

Fig. 3 Risk-based Momentum Strategy Over Event Time: News Arrivals

This figure plots the cumulative returns of the momentum strategy based $RISK$ constructed from the 15 RP anomalies for each event time conditional on news arrivals. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 on day $d-1$ to 10:00 on day d and 12 half-hour periods. The portfolios are formed at the beginning of each 13 intraday period and held up to 65 periods. The solid (dash-dotted) line corresponds to the period with above (below) median number of news arrivals. The sample includes all stocks in the Russell 1000 index over the period from January 2000 to December 2020 when the RavenPack news data are available.

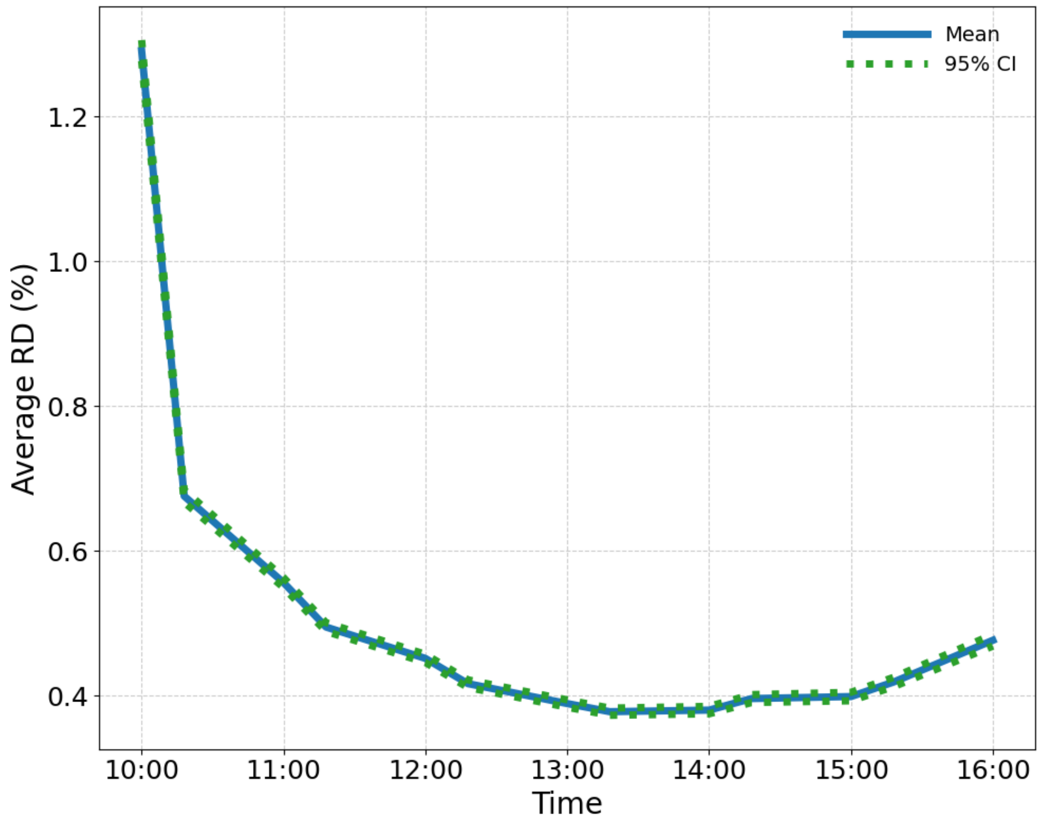

Fig. 4 Intraday Return Dispersion Pattern

This figure plots the time-series average of return dispersion (RD) over the course of the day. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 to 10:00 and 12 half-hour periods. We first measure RD in each intraday period on each day as the cross-sectional standard deviation of stock returns and then calculate the average RD for each intraday period over all trading days. The x-axis labels the end of each intraday period. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

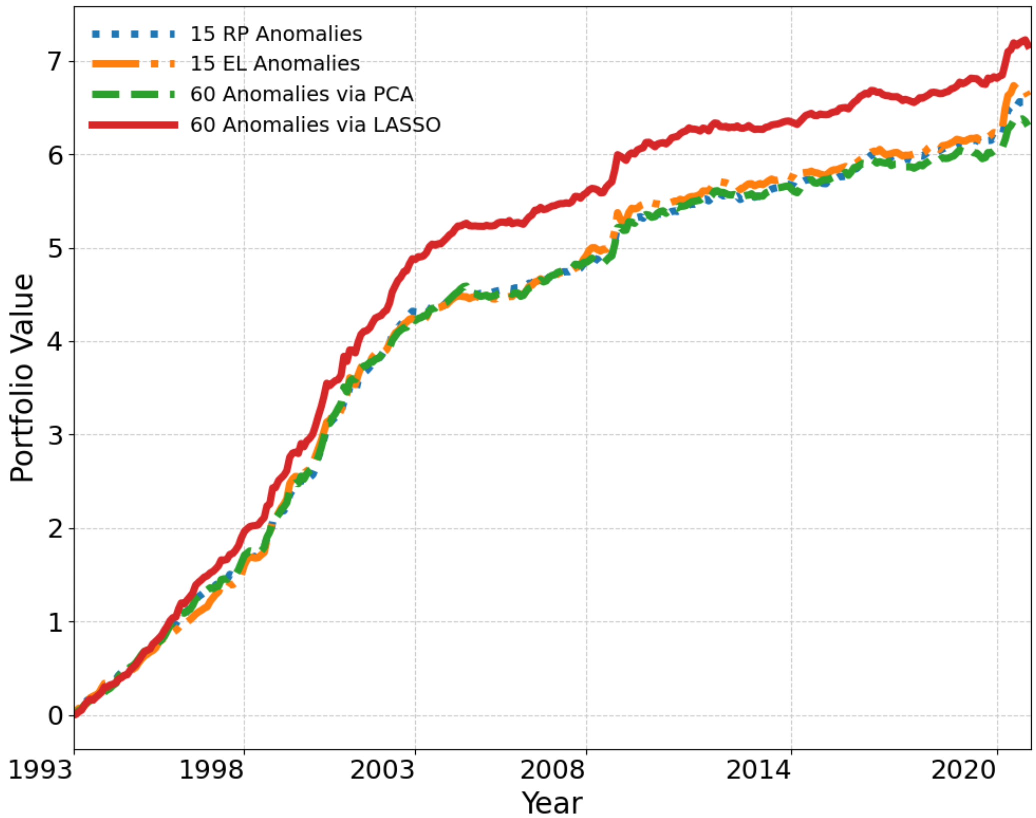

Fig. 5 Performance of Daily Conditional Risk-based Momentum

This figure plots the cumulative portfolio value from investing in different daily conditional risk-based momentum strategies. Conditional risk-based momentum is based on Russell 1000 stocks in the top risk-concentration quintile, where risk concentration is defined in Equation (6). Daily strategies are formed on the basis of the past-day close-to-close RISK estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively, and are held over the subsequent day. The initial investment is \$1. We further take the logarithm of the portfolio value with base ten so the trajectory starts from 0. The sample period is from January 1993 to December 2020.

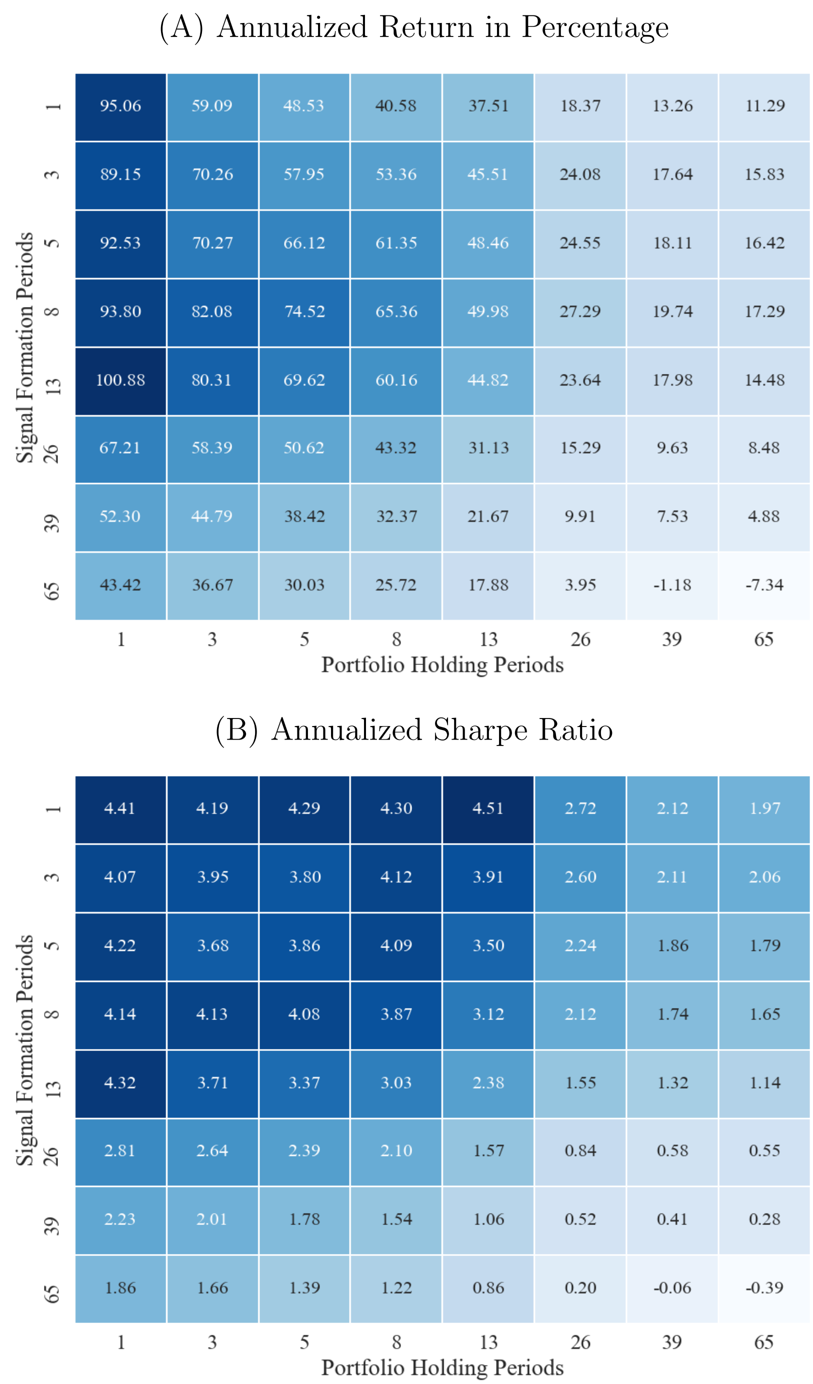

Fig. 6 Risk-based Momentum: Different Signal Formation and Return Holding Periods

This figure shows the performance of the long-short portfolio based on the risk component constructed from the 15 RP anomalies for various combinations of signal formation and portfolio holding periods. The x-axis denotes the number of intraday periods (N) in holding the long-short portfolios. The y-axis denotes the number of intraday periods (M) in calculating the signal. Following Jegadeesh and Titman (1993), our trading strategy includes portfolios with overlapping holding periods. That is, for return holding period N, we revise the weights on $1/N$ of the securities in our strategy on any given interval and carry over the rest from the previous interval. Panel A shows the annualized return in percentage and Panel B shows the annualized Sharpe ratio. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

Table 1 Summary Statistics of Anomalies

Panel A reports the time-series average of the cross-sectional mean, standard deviation, and quantiles of 15 RP anomalies. Panel B reports the same for 15 EL anomalies. RP anomalies are 15 representative anomalies including 11 mispricing anomalies of Stambaugh, Yu, and Yuan (2012) and *Beta*, *Size*, *Book-to-market ratio*, and *Reversal.* EL anomalies are the 15 anomalies investigated by Ehsani and Linnainmaa (2022). The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

Panel A: 15 RP Anomalies

Acronym	Anomaly	Mean	Std	P1	P25	Median	P75	P99
acc	Accruals	0.00	0.05	-0.15	-0.02	0.00	0.02	0.16
agr	Asset growth	0.17	0.36	-0.26	0.01	0.08	0.20	2.04
beta	Beta	0.99	0.52	0.13	0.62	0.90	1.27	2.57
bm	Book-to-market	0.64	1.58	-0.12	0.23	0.40	0.66	5.81
cei	Composite equity issues	-0.08	0.26	-0.99	-0.11	-0.05	-0.02	0.76
dis	Distress	-6.05	1.58	-8.04	-6.99	-6.38	-5.53	-0.52
gpf	Gross profitability	0.29	0.23	-0.03	0.11	0.25	0.42	1.00
inta	Investment-to-assets	0.10	0.29	-0.23	0.01	0.04	0.10	1.90
mom	Momentum	0.20	0.38	-0.44	-0.02	0.13	0.33	1.59
rev	Reversal	0.02	0.09	-0.19	-0.03	0.01	0.06	0.28
size	Size	15.71	0.86	14.59	14.97	15.51	16.32	17.44
noa	Net operating assets	0.58	0.36	-0.18	0.38	0.58	0.74	1.88
oscore	O-score	-3.64	1.70	-7.59	-4.65	-3.71	-2.79	1.19
roa	Return on assets	0.01	0.03	-0.07	0.00	0.01	0.02	0.09
nsi	Net stock issues	0.30	0.77	-0.13	-0.01	0.01	0.15	3.38

Panel A: 15 EL Anomalies

Acronym	Anomaly	Mean	Std	P1	P25	Median	P75	P99
acc	Accruals	0.00	0.05	-0.15	-0.02	0.00	0.02	0.16
bab	Betting against beta	1.03	0.44	0.27	0.72	0.97	1.27	2.24
bm	Book-to-market	0.64	1.58	-0.12	0.23	0.40	0.66	5.81
cfp	Cash-flow to price	0.10	0.11	-0.16	0.05	0.08	0.13	0.49
ep	Earnings to price	0.04	0.10	-0.29	0.03	0.05	0.07	0.18
prof	Profitability	0.33	0.22	-0.03	0.16	0.29	0.45	1.02
rvar	Residual variance	0.04	0.02	0.02	0.03	0.04	0.05	0.10
liq	Liquidity	0.00	0.00	0.00	0.00	0.00	0.00	0.00
invest	Investment	1.01	0.36	0.22	0.81	0.98	1.15	2.29
lrev	Long-term reversals	0.48	0.75	-0.51	0.06	0.32	0.67	3.68
mom	Momentum	0.20	0.38	-0.44	-0.02	0.13	0.33	1.59
srev	Short-term reversals	0.02	0.09	-0.19	-0.03	0.01	0.06	0.28
size	Size	15.71	0.86	14.59	14.97	15.51	16.32	17.44
qmj	Quality minus junk	0.65	0.85	-1.48	0.10	0.87	1.36	1.70
nsi	Net share issues	0.30	0.77	-0.13	-0.01	0.01	0.15	3.38

Table 2 Risk-based Momentum

This table reports the performance of 13 long-short portfolios over a given intraday period based on the *RISK* signal in the previous intraday period. Each of these portfolios enters position at time "Start" and exits position at time "End" once per day. The last column "All" reports the performance of the long-short portfolio that is held during all 13 intraday periods but is rebalanced every intraday period based on the *RISK* signal in the previous intraday period (i.e., investing in all 13 signals). The rows labeled "Return" report the annualized return of the long-short portfolio in percentage with Newey and West (1987) robust t-statistics in parentheses. The rows labeled "Alpha" report the annualized CAPM alpha. Panels A, B, C, and D report the results based on *RISK* estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
Return	9.45	9.83	12.06	10.59	9.46	6.06	4.90	4.47	4.77	4.49	5.81	7.15	6.12	95.06
	(3.50)	(6.94)	(10.33)	(10.53)	(11.26)	(7.82)	(7.36)	(6.23)	(6.28)	(5.32)	(6.86)	(7.95)	(6.21)	(22.74)
Alpha	9.33	9.66	11.87	10.48	9.45	6.01	5.04	4.46	4.74	4.51	5.85	7.22	6.04	95.10
	(3.46)	(6.77)	(10.15)	(10.53)	(11.44)	(7.75)	(7.53)	(6.28)	(6.09)	(5.26)	(6.89)	(8.09)	(6.20)	(22.50)
Panel B: 15 EL Anomalies														
Return	8.88	8.94	11.95	10.58	9.76	5.82	5.08	4.79	4.77	3.82	5.85	7.16	6.33	93.67
	(3.25)	(6.22)	(10.21)	(10.69)	(11.79)	(7.15)	(7.80)	(6.68)	(6.17)	(4.58)	(7.04)	(8.15)	(6.43)	(22.29)
Alpha	8.73	8.77	11.78	10.46	9.75	5.78	5.24	4.78	4.74	3.83	5.87	7.23	6.26	93.70
	(3.19)	(6.11)	(10.03)	(10.69)	(11.93)	(7.09)	(8.04)	(6.75)	(5.99)	(4.53)	(7.03)	(8.27)	(6.41)	(22.20)
Panel C: 60 Anomalies via PCA														
Return	12.75	10.31	13.61	12.24	11.00	7.93	7.00	6.37	6.11	5.92	8.05	9.09	8.70	119.14
	(4.08)	(6.92)	(10.28)	(10.66)	(11.32)	(8.59)	(8.86)	(7.35)	(6.74)	(5.89)	(7.86)	(8.73)	(7.46)	(24.69)
Alpha	12.66	10.04	13.40	12.11	10.96	7.87	7.14	6.37	6.06	5.93	8.10	9.19	8.60	119.17
	(4.05)	(6.78)	(10.15)	(10.65)	(11.53)	(8.54)	(9.04)	(7.45)	(6.52)	(5.81)	(7.88)	(8.89)	(7.41)	(24.36)
Panel D: 60 Anomalies via LASSO														
Return	14.68	11.68	14.19	12.76	10.83	8.18	7.20	6.20	6.90	6.16	8.47	9.27	8.48	125.21
	(4.62)	(7.55)	(10.77)	(11.23)	(11.46)	(8.84)	(8.99)	(7.28)	(7.78)	(6.14)	(8.36)	(8.94)	(7.08)	(25.67)
Alpha	14.58	11.48	13.98	12.62	10.80	8.12	7.34	6.20	6.85	6.16	8.53	9.40	8.41	125.23
	(4.59)	(7.42)	(10.62)	(11.21)	(11.62)	(8.77)	(9.12)	(7.30)	(7.52)	(6.04)	(8.41)	(9.13)	(7.11)	(25.62)

Table 3 Decile Portfolio Performance: RP and EL Anomalies

This table reports the annualized return in percentage of decile portfolios over a given intraday period based on the *RISK* signal in the previous intraday period. Each of these portfolios enters position at time "Start" and exits position at time "End" once per day. The last column "All" reports the performance of the decile portfolios that are held during all 13 intraday periods but are rebalanced every intraday period based on the *RISK* signal in the previous intraday period (i.e., investing in all 13 signals). The row labeled "High-Low" reports the annualized return of the long-short portfolios in percentage with Newey and West (1987) robust t-statistics in parentheses. Panels A and B report the results based on *RISK* estimated from 15 RP anomalies and 15 EL anomalies, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
1	2.77	-7.80	-7.51	-5.91	-4.25	-3.58	-0.70	-1.46	-2.94	-2.70	-1.37	-2.77	-1.00	-39.14
2	1.51	-4.99	-4.85	-4.09	-2.71	-2.37	-0.53	-0.98	-1.89	-2.22	-0.38	-1.27	-0.29	-25.05
3	2.37	-3.25	-3.99	-2.70	-2.00	-1.30	-0.24	-0.40	-1.27	-1.35	0.61	-0.21	0.18	-13.57
4	4.21	-2.46	-3.02	-1.82	-1.26	-1.12	0.77	0.03	-0.77	-0.94	1.10	0.30	0.49	-4.49
5	4.62	-1.58	-1.70	-0.57	0.13	-0.39	1.09	0.34	-0.20	-0.51	1.51	0.85	1.21	4.79
6	4.68	-0.96	-0.39	0.07	0.55	0.18	1.69	0.80	-0.24	0.00	1.99	1.53	1.90	11.80
7	6.54	-0.10	0.77	0.81	1.59	0.49	1.79	1.40	0.02	0.47	2.70	2.30	2.35	21.11
8	7.31	0.71	2.20	1.60	2.40	0.94	2.46	1.68	0.58	0.63	3.13	3.24	2.82	29.72
9	8.77	1.59	3.43	2.50	3.35	1.67	3.40	2.44	0.87	0.91	3.84	3.67	3.65	40.09
10	12.22	2.03	4.55	4.68	5.21	2.48	4.19	3.01	1.83	1.79	4.43	4.38	5.12	55.92
High-Low	9.45	9.83	12.06	10.59	9.46	6.06	4.90	4.47	4.77	4.49	5.81	7.15	6.12	95.06
	(3.50)	(6.94)	(10.33)	(10.53)	(11.26)	(7.82)	(7.36)	(6.23)	(6.28)	(5.32)	(6.86)	(7.95)	(6.21)	(22.74)
Panel B: 15 EL Anomalies														
1	3.21	-7.41	-7.16	-5.78	-4.31	-3.45	-0.86	-1.65	-2.74	-2.36	-1.20	-2.57	-1.02	-37.24
2	2.02	-4.65	-5.33	-4.14	-2.72	-2.31	-0.17	-0.86	-1.84	-1.75	-0.32	-1.47	-0.34	-23.87
3	2.54	-3.30	-3.69	-2.75	-1.77	-1.63	0.31	-0.35	-1.37	-1.20	0.61	-0.36	-0.17	-13.12
4	3.29	-2.29	-2.16	-1.88	-1.09	-0.90	0.65	0.15	-0.73	-1.04	1.26	0.33	0.76	-3.63
5	4.31	-1.57	-1.64	-1.01	-0.13	-0.56	0.97	0.18	-0.35	-0.30	1.70	1.23	1.39	4.21
6	4.76	-1.23	-0.51	-0.13	0.50	-0.04	1.34	0.87	-0.22	0.03	2.02	1.43	1.83	10.63
7	5.13	-0.11	0.50	0.90	1.28	0.51	2.00	1.44	0.08	0.07	2.14	2.16	2.45	18.57
8	7.22	0.63	1.80	1.80	2.44	1.23	2.52	1.99	0.43	0.47	2.93	3.06	2.77	29.29
9	9.89	1.30	2.86	2.69	3.39	1.69	3.03	1.96	0.84	0.59	3.66	3.74	3.77	39.40
10	12.10	1.52	4.79	4.80	5.45	2.38	4.22	3.14	2.03	1.46	4.65	4.59	5.31	56.43
High-Low	8.88	8.94	11.95	10.58	9.76	5.82	5.08	4.79	4.77	3.82	5.85	7.16	6.33	93.67
	(3.25)	(6.22)	(10.21)	(10.69)	(11.79)	(7.15)	(7.80)	(6.68)	(6.17)	(4.58)	(7.04)	(8.15)	(6.43)	(22.29)

Table 4 Event-Time Return: RP Anomalies

This table reports the event-time cumulative returns to the long-short portfolios based on the intraday *RISK* signal available at time "Start" and held up to 65 intraday periods. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 on day $d-1$ to 10:00 on day d and 12 half-hour periods. The event-time returns are reported in basis points (bps) with Newey and West (1987) robust t-statistics in parentheses. The row labeled "Mean" reports the average return and t-statistic across different signal times. The results are based on *RISK* estimated from 15 RP anomalies. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Return-Holding Horizon (in Number of Intraday Periods)								
Start	1	2	3	5	8	12	13	39	65
10:00	3.90	5.08	7.28	10.43	12.13	13.68	18.45	21.63	19.46
	(6.94)	(6.68)	(8.47)	(10.51)	(11.08)	(9.87)	(9.93)	(7.70)	(5.79)
10:30	4.78	5.81	6.47	9.01	10.80	17.44	18.39	17.33	16.54
	(10.33)	(9.25)	(8.54)	(10.52)	(10.69)	(9.78)	(9.73)	(6.05)	(5.05)
11:00	4.20	5.83	7.06	7.87	8.97	16.34	17.17	17.36	15.01
	(10.53)	(10.32)	(10.85)	(10.23)	(9.82)	(9.65)	(9.81)	(6.12)	(4.32)
11:30	3.75	5.03	5.71	6.12	8.03	15.98	16.90	18.28	21.34
	(11.26)	(11.20)	(10.34)	(8.97)	(9.09)	(9.65)	(9.80)	(6.53)	(6.54)
12:00	2.41	3.15	3.38	3.35	4.09	12.22	12.49	9.31	11.32
	(7.82)	(7.42)	(6.67)	(4.58)	(4.30)	(7.04)	(7.15)	(3.53)	(3.65)
12:30	1.94	2.90	3.33	4.46	11.05	13.65	14.39	9.56	8.08
	(7.36)	(7.75)	(7.13)	(6.86)	(8.22)	(8.38)	(8.63)	(3.68)	(2.63)
13:00	1.77	2.42	2.95	3.50	6.87	9.27	9.67	6.91	5.72
	(6.23)	(5.88)	(5.70)	(5.09)	(4.51)	(5.47)	(5.64)	(2.65)	(1.80)
13:30	1.89	2.72	3.04	3.86	7.74	9.95	10.23	7.82	6.73
	(6.28)	(6.38)	(5.91)	(5.34)	(5.06)	(5.98)	(6.05)	(3.00)	(2.18)
14:00	1.78	2.44	2.77	7.40	8.75	9.52	9.36	7.04	8.72
	(5.32)	(5.29)	(4.41)	(5.42)	(5.34)	(5.49)	(5.41)	(2.55)	(2.82)
14:30	2.30	4.23	4.88	11.30	12.45	12.94	12.45	3.03	3.18
	(6.86)	(8.32)	(7.10)	(7.39)	(7.45)	(7.38)	(7.01)	(1.11)	(1.02)
15:00	2.84	4.33	6.19	8.02	9.50	9.36	8.40	0.19	3.00
	(7.95)	(7.09)	(4.49)	(5.01)	(5.39)	(5.10)	(4.56)	(0.07)	(0.95)
15:30	2.43	7.32	9.03	10.67	11.44	10.05	9.42	5.13	5.43
	(6.21)	(5.83)	(6.50)	(6.85)	(6.79)	(5.70)	(5.35)	(1.93)	(1.75)
16:00	3.75	5.60	6.48	6.60	6.78	6.38	4.88	-1.57	-1.87
	(3.50)	(4.59)	(4.95)	(4.72)	(4.48)	(4.06)	(3.03)	(-0.63)	(-0.64)
Mean	2.90	4.37	5.27	7.12	9.12	12.06	12.48	9.39	9.43
	(7.43)	(7.38)	(7.00)	(7.04)	(7.09)	(7.20)	(7.09)	(3.41)	(2.91)

Table 5 Holding-Period Return Decomposition

This table decomposes the holding-period return in Table 2 into risk (*RISK*) and residual (*RES*) components according to Equation (3), and reports the annualized return of the two components in percentage with Newey and West (1987) robust t-statistics in parentheses. Panels A, B, C, and D report the results based on *RISK* estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

		Return-Holding Period													
Start End	Ret Component	16:00 10:00	10:00 10:30	10:30 11:00	11:00 11:30	11:30 12:00	12:00 12:30	12:30 13:00	13:00 13:30	13:30 14:00	14:00 14:30	14:30 15:00	15:00 15:30	15:30 16:00	All
Panel A: 15 RP Anomalies															
	RISK	4.52	10.22	11.50	9.54	8.56	5.28	4.37	3.80	3.79	3.18	4.57	5.70	3.95	79.10
		(2.57)	(8.53)	(12.17)	(12.17)	(12.79)	(8.45)	(8.40)	(6.96)	(6.57)	(4.97)	(7.25)	(8.74)	(5.40)	(24.60)
	RES	4.93	-0.39	0.55	1.05	0.89	0.79	0.53	0.67	0.98	1.31	1.23	1.45	2.17	15.96
		(4.74)	(-0.72)	(1.19)	(2.50)	(2.62)	(2.47)	(1.72)	(2.05)	(2.96)	(3.74)	(3.33)	(3.62)	(4.98)	(9.51)
Panel B: 15 EL Anomalies															
	RISK	5.53	9.68	11.22	9.73	8.54	4.75	4.07	3.71	3.76	2.52	4.30	5.58	3.73	77.12
		(2.79)	(8.01)	(11.92)	(12.50)	(12.85)	(7.62)	(8.08)	(6.93)	(6.53)	(4.01)	(7.01)	(8.76)	(5.21)	(23.95)
	RES	3.36	-0.74	0.74	0.85	1.22	1.07	1.01	1.08	1.02	1.30	1.55	1.58	2.60	16.55
		(3.15)	(-1.38)	(1.54)	(2.10)	(3.61)	(3.13)	(3.38)	(3.22)	(2.97)	(3.74)	(4.09)	(4.00)	(5.92)	(9.78)
Panel C: 60 Anomalies via PCA															
	RISK	12.14	8.76	12.07	11.12	10.02	6.89	6.61	6.07	5.90	5.89	7.68	8.31	7.17	108.92
		(4.62)	(6.59)	(10.44)	(11.29)	(11.95)	(8.91)	(10.02)	(8.26)	(7.75)	(6.85)	(8.87)	(9.47)	(7.39)	(26.47)
	RES	0.61	1.55	1.54	1.12	0.98	1.04	0.40	0.30	0.21	0.03	0.36	0.78	1.53	10.22
		(0.78)	(4.26)	(4.55)	(3.49)	(3.62)	(3.85)	(1.54)	(1.22)	(0.79)	(0.12)	(1.27)	(2.70)	(4.49)	(8.20)
Panel D: 60 Anomalies via LASSO															
	RISK	13.60	10.16	12.95	11.55	9.95	7.21	6.50	6.08	6.19	5.92	7.80	8.27	7.15	113.77
		(5.03)	(7.46)	(11.13)	(11.51)	(11.92)	(9.33)	(9.81)	(8.26)	(8.17)	(6.93)	(9.01)	(9.31)	(7.05)	(27.11)
	RES	1.08	1.52	1.24	1.20	0.88	0.97	0.70	0.12	0.71	0.24	0.68	1.00	1.33	11.44
		(1.31)	(3.93)	(3.69)	(4.07)	(3.29)	(3.63)	(2.76)	(0.51)	(2.90)	(0.90)	(2.46)	(3.49)	(4.14)	(9.28)

Table 6 Event-Time Return Decomposition: RP Anomalies

This table decomposes the event-time cumulative returns in Table 4 into risk ($RISK$) and residual (RES) components according to Equation (3), and reports the cumulative return of the two components in basis points (bps) with Newey and West (1987) robust t-statistics in parentheses. The row labeled "Mean" reports the average return and t-statistic across different signal times. The results are based on $RISK$ estimated from 15 RP anomalies. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

		Return-Holding Horizon (in Number of Intraday Periods)								
Start	Ret Component	1	2	3	5	8	12	13	39	65
10:00	RISK	4.05	5.43	7.31	9.93	11.84	13.74	18.12	25.13	24.87
		(8.53)	(8.46)	(10.09)	(11.91)	(12.59)	(11.79)	(11.22)	(9.42)	(7.35)
	RES	-0.15	-0.34	-0.03	0.50	0.28	-0.06	0.33	-3.51	-5.41
		(-0.72)	(-0.95)	(-0.07)	(1.09)	(0.54)	(0.09)	(0.39)	(-2.64)	(-3.33)
10:30	RISK	4.56	5.79	6.57	8.96	10.70	16.13	17.44	20.57	21.09
		(12.17)	(11.34)	(10.72)	(12.43)	(12.57)	(10.75)	(10.80)	(7.53)	(6.39)
	RES	0.22	0.02	-0.10	0.06	0.10	1.31	0.95	-3.24	-4.56
		(1.19)	(0.08)	(-0.26)	(0.14)	(0.21)	(1.64)	(1.14)	(-2.51)	(-2.85)
11:00	RISK	3.78	5.64	6.79	7.98	9.35	16.26	17.52	21.70	21.48
		(12.17)	(12.58)	(12.86)	(12.49)	(12.55)	(11.39)	(11.72)	(8.00)	(6.10)
	RES	0.42	0.19	0.27	-0.11	-0.37	0.08	-0.35	-4.34	-6.47
		(2.50)	(0.67)	(0.85)	(-0.29)	(-0.78)	(0.10)	(-0.43)	(-3.18)	(-3.95)
11:30	RISK	3.40	4.94	5.73	6.56	8.49	14.91	15.88	20.69	25.57
		(12.79)	(13.68)	(12.99)	(12.03)	(11.80)	(10.81)	(10.98)	(7.85)	(7.78)
	RES	0.36	0.09	-0.02	-0.45	-0.46	1.07	1.02	-2.41	-4.23
		(2.62)	(0.40)	(-0.08)	(-1.27)	(-1.05)	(1.42)	(1.31)	(-1.87)	(-2.71)
12:00	RISK	2.10	3.00	3.48	3.70	4.75	12.06	12.55	12.98	15.23
		(8.46)	(8.85)	(8.68)	(6.49)	(6.48)	(8.24)	(8.44)	(5.33)	(5.00)
	RES	0.31	0.14	-0.09	-0.35	-0.66	0.15	-0.06	-3.67	-3.92
		(2.47)	(0.63)	(-0.33)	(-0.91)	(-1.26)	(0.19)	(-0.08)	(-2.75)	(-2.47)
12:30	RISK	1.73	2.72	3.22	4.49	9.54	12.43	13.41	13.83	13.45
		(8.40)	(9.42)	(8.90)	(8.87)	(8.83)	(9.08)	(9.53)	(5.69)	(4.34)
	RES	0.21	0.18	0.10	-0.03	1.51	1.21	0.98	-4.26	-5.37
		(1.72)	(0.81)	(0.40)	(-0.08)	(2.33)	(1.58)	(1.24)	(-3.27)	(-3.35)
13:00	RISK	1.51	2.12	2.81	3.53	6.41	8.71	9.25	10.00	10.17
		(6.97)	(6.70)	(6.97)	(6.61)	(5.14)	(6.13)	(6.37)	(4.21)	(3.19)
	RES	0.26	0.30	0.13	-0.03	0.46	0.55	0.41	-3.08	-4.45
		(2.05)	(1.31)	(0.47)	(-0.09)	(0.65)	(0.68)	(0.51)	(-2.37)	(-2.75)
13:30	RISK	1.50	2.37	3.02	4.09	8.15	10.50	10.80	10.47	10.86
		(6.57)	(7.11)	(7.81)	(7.38)	(6.61)	(7.50)	(7.59)	(4.38)	(3.63)
	RES	0.39	0.36	0.02	-0.23	-0.41	-0.55	-0.57	-2.65	-4.13
		(2.96)	(1.54)	(-0.06)	(-0.59)	(-0.56)	(-0.71)	(-0.73)	(-2.05)	(-2.58)
14:00	RISK	1.26	2.00	2.42	6.18	7.61	8.36	8.52	9.69	12.02
		(4.97)	(5.82)	(5.24)	(5.86)	(5.85)	(5.98)	(6.03)	(3.88)	(4.05)
	RES	0.52	0.44	0.34	1.22	1.14	1.16	0.84	-2.64	-3.30
		(3.74)	(1.78)	(1.06)	(1.81)	(1.44)	(1.36)	(0.99)	(-1.96)	(-2.05)
14:30	RISK	1.82	3.27	3.78	9.25	11.04	11.91	11.75	7.79	9.10
		(7.25)	(8.67)	(7.26)	(7.74)	(8.05)	(8.05)	(7.84)	(3.12)	(3.01)
	RES	0.49	0.96	1.11	2.05	1.42	1.03	0.70	-4.77	-5.92
		(3.33)	(3.57)	(3.12)	(2.67)	(1.73)	(1.20)	(0.81)	(-3.44)	(-3.51)
15:00	RISK	2.26	3.49	4.64	6.87	8.45	8.99	8.60	4.61	7.06
		(8.74)	(8.06)	(4.38)	(5.37)	(5.80)	(5.82)	(5.50)	(1.87)	(2.28)
	RES	0.58	0.84	1.55	1.15	1.04	0.37	-0.20	-4.42	-4.05
		(3.62)	(2.50)	(2.31)	(1.51)	(1.29)	(0.42)	(-0.22)	(-3.01)	(-2.40)
15:30	RISK	1.57	5.50	7.53	9.34	10.72	10.53	10.35	9.48	11.89
		(5.40)	(5.77)	(6.87)	(7.36)	(7.70)	(7.05)	(6.91)	(3.81)	(3.87)
	RES	0.86	1.82	1.50	1.33	0.72	-0.48	-0.93	-4.35	-6.46
		(4.98)	(2.89)	(2.21)	(1.80)	(0.90)	(-0.55)	(-1.04)	(-3.22)	(-4.00)
16:00	RISK	1.79	3.73	4.56	5.40	5.86	6.29	6.08	2.37	2.03
		(2.57)	(3.86)	(4.40)	(4.70)	(4.63)	(4.72)	(4.47)	(1.03)	(0.71)
	RES	1.96	1.87	1.92	1.20	0.92	0.09	-1.20	-3.93	-3.90
		(4.74)	(3.04)	(2.91)	(1.75)	(1.24)	(0.11)	(-1.43)	(-2.90)	(-2.42)
Mean	RISK	2.41	3.85	4.76	6.64	8.69	11.60	12.33	13.02	14.22
		(8.08)	(8.49)	(8.24)	(8.40)	(8.35)	(8.26)	(8.26)	(5.09)	(4.44)
	RES	0.49	0.53	0.52	0.49	0.44	0.46	0.15	-3.64	-4.78
		(2.71)	(1.40)	(0.96)	(0.58)	(0.51)	(0.58)	(0.19)	(-2.71)	(-2.95)

Table 7 Holding-Period $RISK$ Component Decomposition

This table reports the three components of the Lo and MacKinlay (1990) decomposition of the holding-period $RISK$ from the risk-based momentum strategy. The row labeled "Total" denotes the total holding-period $RISK$; "Auto" is the first component attributable to the autocovariance of $RISK$; "Cross" is the second component attributable to the cross-autocovariance; and "Dispersion" is the third component representing the dispersion in expected $RISK$ captured by past average $RISK$. Newey and West (1987) robust t-statistics are reported in parentheses. Panels A, B, C, and D report the results based on $RISK$ estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample period is from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
Total	12.49	13.03	13.46	12.94	9.28	7.79	5.83	4.26	3.61	4.17	6.39	8.11	6.36	107.98
	(4.33)	(9.93)	(12.63)	(13.44)	(11.86)	(10.87)	(8.65)	(6.31)	(5.09)	(4.99)	(7.42)	(8.81)	(6.51)	(24.83)
Auto	13.83	11.81	12.63	11.80	8.17	7.07	5.45	3.40	3.91	2.79	6.00	8.61	6.96	103.28
	(4.11)	(7.22)	(10.22)	(11.85)	(8.47)	(8.42)	(6.82)	(4.67)	(4.48)	(2.83)	(5.36)	(7.32)	(5.65)	(20.29)
Cross	-1.88	1.84	0.78	1.05	1.06	0.68	0.36	0.85	-0.29	1.38	0.37	-0.55	-0.58	4.70
	(-0.86)	(1.59)	(0.93)	(1.50)	(1.39)	(1.30)	(0.74)	(1.47)	(-0.50)	(2.12)	(0.46)	(-0.56)	(-0.65)	(1.37)
Dispersion	0.54	-0.62	0.05	0.09	0.05	0.04	0.01	0.01	0.00	0.01	0.02	0.04	-0.02	0.00
Panel B: 15 EL Anomalies														
Total	11.59	12.69	12.76	12.88	9.27	7.39	5.83	4.17	3.33	3.63	5.89	8.09	6.10	103.70
	(4.02)	(9.38)	(11.75)	(13.03)	(11.60)	(10.18)	(8.57)	(6.20)	(4.63)	(4.36)	(7.03)	(8.88)	(6.21)	(23.75)
Auto	12.31	11.70	11.86	11.57	8.14	6.79	5.39	3.06	3.82	2.18	5.56	8.37	6.32	97.30
	(3.64)	(6.77)	(9.42)	(11.31)	(8.28)	(8.27)	(6.87)	(4.21)	(4.26)	(2.18)	(5.03)	(6.91)	(4.99)	(18.87)
Cross	-1.07	1.81	0.84	1.23	1.08	0.57	0.43	1.10	-0.49	1.43	0.30	-0.35	-0.22	6.41
	(-0.47)	(1.49)	(0.99)	(1.65)	(1.39)	(1.10)	(0.90)	(1.87)	(-0.82)	(2.16)	(0.39)	(-0.35)	(-0.25)	(1.82)
Dispersion	0.35	-0.82	0.05	0.08	0.05	0.03	0.01	0.01	0.00	0.02	0.03	0.06	0.00	-0.02
Panel C: 60 Anomalies via PCA														
Total	15.32	13.53	14.82	14.39	10.45	9.75	7.75	6.08	4.91	5.95	8.74	10.51	8.88	132.64
	(4.62)	(9.88)	(12.33)	(13.27)	(11.37)	(11.31)	(9.66)	(7.11)	(5.77)	(5.79)	(8.78)	(9.42)	(7.77)	(26.41)
Auto	14.21	12.84	13.66	12.89	9.15	8.53	7.06	4.61	5.30	4.09	7.06	8.69	6.98	117.13
	(4.04)	(7.45)	(11.23)	(12.50)	(9.48)	(9.68)	(8.65)	(5.98)	(5.94)	(3.86)	(6.44)	(7.68)	(5.62)	(22.32)
Cross	0.76	1.56	1.09	1.44	1.26	1.22	0.69	1.46	-0.38	1.81	1.67	1.75	1.87	15.47
	(0.33)	(1.18)	(1.26)	(1.88)	(1.50)	(2.13)	(1.33)	(2.11)	(-0.58)	(2.43)	(2.07)	(1.76)	(2.02)	(4.20)
Dispersion	0.35	-0.87	0.07	0.06	0.04	0.01	0.01	0.02	0.00	0.06	0.01	0.07	0.04	0.04
Panel D: 60 Anomalies via LASSO														
Total	15.95	14.67	15.58	15.56	10.57	9.73	7.65	6.01	5.36	6.21	9.13	11.11	8.66	137.84
	(4.67)	(10.87)	(13.07)	(13.68)	(11.94)	(11.04)	(9.68)	(7.03)	(6.26)	(6.00)	(8.75)	(10.09)	(7.45)	(26.94)
Auto	18.17	14.00	14.53	14.37	9.24	8.79	7.23	4.47	5.79	4.40	8.10	10.94	8.18	130.75
	(4.82)	(8.41)	(11.39)	(13.14)	(8.84)	(8.95)	(8.32)	(5.22)	(5.86)	(3.97)	(6.29)	(8.65)	(5.99)	(23.14)
Cross	-2.59	1.34	0.97	1.13	1.27	0.90	0.42	1.53	-0.43	1.75	1.00	0.10	0.49	7.02
	(-1.05)	(1.05)	(1.07)	(1.43)	(1.48)	(1.46)	(0.76)	(2.21)	(-0.61)	(2.29)	(1.08)	(0.10)	(0.49)	(1.81)
Dispersion	0.37	-0.68	0.08	0.06	0.06	0.03	0.00	0.01	0.00	0.06	0.03	0.07	0.00	0.07

Table 8 Intraday Factor Return Autocorrelation

This table reports the autocorrelation of intraday factor returns. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 on the day $d-1$ to 10:00 on the day d and 12 half-hour periods. For each intraday period, factor returns are estimated by the slope coefficients in Equation (2). The order of the autocorrelations ranges from 1 to 65 intraday periods. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. Panel A reports the results for 15 RP anomalies and Panel B reports the same for 15 EL anomalies. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Order of Autocorrelation (in Number of Intraday Periods)							
Factor	1	2	3	5	8	13	39	65
Panel A: 15 RP Anomalies								
Accruals	0.01*	-0.01	0.00	0.00	0.00	0.02***	0.01*	0.00
Asset growth	0.02***	0.01*	0.00	0.01***	0.00	0.02***	0.01*	0.00
Beta	0.10***	0.03***	0.02***	0.03***	0.01***	0.00	0.01*	0.00
Book-to-market	0.04***	0.01**	0.01***	0.01***	0.01	0.02***	0.02***	0.02***
Composite equity issues	0.02***	0.01	0.01***	0.01***	0.00	0.02***	0.02***	0.02***
Distress	0.11***	0.05***	0.03***	0.03***	0.02***	0.05***	0.02***	0.02***
Gross profitability	0.12***	0.05***	0.04***	0.03***	0.02***	0.07***	0.06***	0.04***
Investment-to-assets	0.06***	0.01***	0.02***	0.01***	0.00	0.01***	0.01**	0.01***
Momentum	0.05***	0.01***	0.00	0.00	0.00	0.01***	0.00	0.00
Reversal	0.03***	-0.01	0.00	0.00	0.00	0.03***	0.01**	0.01**
Size	-0.01	-0.01	-0.01	0.00	0.00	0.01**	0.00	0.01 ***
Net operating assets	0.06***	0.02***	0.01***	0.01***	0.01*	0.02***	0.01***	0.01***
O-score	0.02***	0.01	0.00	0.01**	0.00	0.00	0.02***	0.01***
Return on assets	0.03***	0.00	0.00	0.00	0.00	0.01***	0.00	0.00
Net stock issues	0.02***	0.00	0.00	0.01***	0.00	0.03***	0.02***	0.02***
Panel B: 15 EL Anomalies								
Accruals	0.00	0.00	0.00	0.00	0.00	0.02***	0.01**	-0.01
Betting against beta	0.09***	0.02***	0.02***	0.02***	0.01***	-0.01	0.00	-0.01
Book-to-market	0.02***	0.00	0.00	0.00	0.00	0.01**	0.01***	0.00
Cash-flow to price	0.03***	0.01**	0.01***	0.00	0.00	0.02***	0.01***	0.01***
Earnings to price	0.12***	0.06***	0.03***	0.03***	0.02***	0.05***	0.02***	0.01***
Profitability	0.12***	0.05***	0.04***	0.03***	0.02***	0.08***	0.06***	0.04***
Residual variance	0.04***	0.01***	0.01*	0.01**	0.01**	0.03***	0.01***	0.00
Liquidity	0.06***	0.01**	0.01***	0.01***	0.01*	0.01***	0.01***	0.01***
Investment	0.07***	0.02***	0.01***	0.01***	0.01***	0.03***	0.01***	0.03***
Long-term reversals	0.04***	0.00	0.01***	0.01***	0.00	0.01***	0.01***	0.01***
Momentum	0.01***	0.00	0.00	0.00	0.01*	0.01***	0.01*	0.00
Short-term reversals	0.06***	0.02***	0.01***	0.01***	0.00	0.01***	0.02***	0.02***
Size	0.05***	0.01**	0.01**	0.01***	0.00	0.01***	0.02***	0.01***
Quality minus junk	0.04***	0.01***	0.01**	0.00	0.00	0.01**	0.00	0.00
Net share issues	0.00	-0.01	0.00	0.00	0.00	0.04***	0.02***	0.02***

Table 9 Risk-based Momentum over High and Low Return Dispersion Periods

This table reports the performance of the risk-based momentum over high and low return dispersion periods. Each trading day is divided into 13 intraday periods, including one overnight period from 16:00 on day $d-1$ to 10:00 on day d and 12 half-hour periods. For each intraday period on each day, we compute return dispersion (RD) as the cross-sectional standard deviation of stock returns. We compute the time-series median of RD for each of the 13 intraday periods, and the time-series median of RD using all intraday periods. The row labeled "High" ("Low") corresponds to the sample period with above (below) median RD level. Newey and West (1987) robust t-statistics are reported in parentheses. Panels A, B, C, and D report the results based on $RISK$ estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

		Return-Holding Period													
	Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
RD	End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies															
High		16.06	16.35	19.40	17.18	15.60	9.47	7.97	6.87	7.23	7.74	9.95	13.07	11.71	157.57
		(3.38)	(6.25)	(9.23)	(9.61)	(10.51)	(6.69)	(6.66)	(5.16)	(5.13)	(4.94)	(6.33)	(7.83)	(6.22)	(21.18)
Low		2.79	3.32	4.71	3.99	3.31	2.66	1.82	2.06	2.31	1.23	1.64	1.20	0.50	32.16
		(1.13)	(3.20)	(4.89)	(5.17)	(4.72)	(4.20)	(3.33)	(4.02)	(4.33)	(2.02)	(2.97)	(2.22)	(0.97)	(8.74)
Panel B: 15 EL Anomalies															
High		16.56	14.64	18.98	17.27	16.40	8.78	8.14	7.23	7.49	7.01	9.79	12.69	11.86	156.81
		(3.48)	(5.53)	(8.98)	(9.87)	(11.33)	(5.89)	(6.96)	(5.45)	(5.20)	(4.57)	(6.34)	(7.75)	(6.30)	(21.11)
Low		1.14	3.24	4.92	3.89	3.12	2.87	2.02	2.34	2.06	0.60	1.89	1.61	0.77	30.34
		(0.45)	(3.06)	(5.06)	(5.05)	(4.41)	(4.47)	(3.80)	(4.44)	(3.77)	(1.02)	(3.46)	(3.07)	(1.49)	(8.02)
Panel C: 60 Anomalies via PCA															
High		22.25	15.72	21.10	20.35	17.64	12.55	11.63	10.04	9.45	10.12	13.26	16.14	16.33	203.46
		(3.93)	(5.78)	(8.79)	(9.90)	(10.18)	(7.37)	(8.11)	(6.18)	(5.54)	(5.40)	(6.91)	(8.20)	(7.34)	(23.04)
Low		3.45	4.83	6.14	4.16	4.40	3.39	2.46	2.80	2.82	1.75	2.84	2.16	1.16	38.50
		(1.28)	(4.16)	(5.82)	(4.89)	(5.50)	(4.90)	(3.99)	(4.63)	(4.58)	(2.51)	(4.65)	(3.65)	(1.95)	(9.62)
Panel D: 60 Anomalies via LASSO															
High		22.92	18.92	21.87	20.74	17.20	13.33	12.08	9.95	10.66	10.37	14.00	16.30	15.47	210.28
		(4.03)	(6.70)	(9.31)	(10.29)	(10.25)	(7.85)	(8.34)	(6.21)	(6.38)	(5.51)	(7.36)	(8.38)	(6.74)	(23.64)
Low		6.57	4.38	6.49	4.77	4.49	3.05	2.38	2.56	3.20	1.97	2.98	2.31	1.55	42.79
		(2.32)	(3.71)	(5.89)	(5.50)	(5.69)	(4.28)	(3.76)	(4.36)	(5.38)	(2.96)	(4.84)	(3.83)	(2.65)	(10.54)

Table 10 Risk-based Momentum Conditional on Risk Concentration

This table reports the performance of risk-based momentum for Russell 1000 stocks in the top and bottom *RiskCon* quintiles. *RiskCon*, defined in Equation (6), captures a stock's risk concentration. The rows labeled "High" ("Low") denotes stocks in the top (bottom) risk-concentration quintile. Newey and West (1987) robust t-statistics are reported in parentheses. Panels A, B, C, and D report the results based on *RISK* estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample period is from January 1993 to December 2020.

		Return-Holding Period													
	Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
RiskCon	End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies															
High		23.21	14.52	16.41	15.17	11.86	9.50	7.97	7.13	7.80	7.58	9.42	11.23	9.98	151.64
		(7.70)	(9.37)	(13.78)	(14.91)	(13.38)	(11.85)	(10.52)	(9.51)	(10.31)	(9.27)	(10.96)	(12.34)	(10.19)	(33.97)
Low		-16.52	-0.72	-2.03	-2.75	1.85	-2.65	-2.89	-1.10	-3.32	-2.11	0.21	-1.65	-1.47	-35.29
		(-6.09)	(-0.53)	(-1.59)	(-2.64)	(1.88)	(-2.68)	(-3.31)	(-1.25)	(-3.59)	(-2.26)	(0.21)	(-1.57)	(-1.25)	(-7.82)
Panel B: 15 EL Anomalies															
High		24.26	15.01	16.27	15.61	12.54	8.93	8.83	7.86	7.92	6.94	9.67	11.17	9.74	154.64
		(8.21)	(9.65)	(13.80)	(15.11)	(14.52)	(10.53)	(11.95)	(10.37)	(10.55)	(8.62)	(11.74)	(12.64)	(10.57)	(34.99)
Low		-17.57	-0.45	-3.16	-2.46	-1.35	-2.85	-2.91	-2.32	-1.54	-2.56	-2.18	-0.93	-1.40	-41.83
		(-6.54)	(-0.31)	(-2.63)	(-2.20)	(-1.39)	(-2.85)	(-3.46)	(-2.59)	(-1.70)	(-2.46)	(-2.08)	(-0.91)	(-1.13)	(-9.18)
Panel C: 60 Anomalies via PCA															
High		28.98	15.50	17.17	16.65	14.13	11.01	9.89	8.37	8.83	9.35	11.97	12.41	11.53	176.00
		(8.49)	(10.16)	(12.82)	(14.62)	(14.20)	(12.38)	(11.69)	(9.76)	(10.63)	(10.32)	(12.65)	(12.38)	(10.23)	(35.34)
Low		-17.89	-1.13	-2.71	-0.65	-0.81	-1.75	-2.18	-0.11	-1.19	-1.05	0.65	0.42	-2.09	-30.28
		(-5.41)	(-0.70)	(-1.77)	(-0.52)	(-0.72)	(-1.52)	(-2.11)	(-0.11)	(-1.02)	(-0.95)	(0.53)	(0.31)	(-1.46)	(-5.56)
Panel D: 60 Anomalies via LASSO															
High		31.85	16.21	18.41	17.65	13.66	11.41	10.32	8.94	10.27	9.34	12.45	13.07	11.70	185.65
		(9.02)	(10.13)	(14.00)	(15.39)	(14.09)	(12.06)	(11.67)	(10.28)	(11.70)	(10.04)	(12.56)	(12.53)	(10.63)	(36.09)
Low		-18.81	1.95	-2.23	-1.16	1.57	-2.94	-2.45	0.31	-1.51	-1.47	-0.41	-1.53	-3.07	-31.50
		(-6.88)	(1.33)	(-1.69)	(-1.03)	(1.50)	(-2.85)	(-2.84)	(0.33)	(-1.50)	(-1.41)	(-0.38)	(-1.40)	(-2.48)	(-6.67)

Table 11 Daily Risk-based Momentum

This table reports the performance of decile portfolios formed on the basis of daily close-to-close $RISK$ signal and held over the subsequent day. Panel A reports the annualized portfolio returns in percentage for the unconditional risk-based momentum strategies formed on all stocks in the Russell 1000 index. Panel B reports the results for the conditional risk-based momentum strategies formed on Russell 1000 stocks in the top risk-concentration quintile, where risk concentration is defined in Equation (6). The $RISK$ signal is constructed using 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, or 60 anomalies via LASSO. The rows labeled "High-Low" and "FF5 Alpha" respectively report the annualized return and the Fama and French (2015) five-factor alpha of the long-short portfolio in percentage, with Newey and West (1987) robust t-statistics in parentheses. The sample period is from January 1993 to December 2020.

	15 RP Anomalies	*15 EL Anomalies*	*60 Anomalies via PCA*	*60 Anomalies via LASSO*
Panel A: Unconditional Risk-based Momentum				
1 (Low)	-17.58	-16.82	-16.93	-19.42
2	-9.89	-8.60	-10.13	-11.45
3	-5.45	-3.48	-4.12	-4.99
4	-0.08	-0.57	-0.07	-0.20
5	4.45	4.15	4.94	3.59
6	7.62	8.27	7.72	9.16
7	12.85	11.80	11.34	12.00
8	15.07	15.15	15.38	16.01
9	20.01	18.88	19.28	21.59
10 (High)	27.24	27.56	28.22	28.59
High-Low	44.82	44.37	45.15	48.01
	(9.02)	(9.05)	(9.16)	(9.11)
FF5 Alpha	43.72	44.62	45.34	47.83
	(8.70)	(9.12)	(9.22)	(9.17)
Panel B: Conditional Risk-based Momentum				
1 (Low)	-22.77	-23.05	-22.15	-27.52
2	-14.56	-14.07	-17.00	-17.96
3	-5.29	-8.35	-7.46	-8.04
4	1.24	-1.48	-1.68	-0.18
5	4.30	3.77	4.30	4.65
6	9.95	9.45	10.11	10.58
7	14.69	13.69	15.47	14.42
8	21.22	23.01	19.97	21.91
9	26.66	27.81	29.44	27.80
10 (High)	34.47	36.87	36.69	37.35
High-Low	57.24	59.93	58.85	64.87
	(11.46)	(11.63)	(11.96)	(12.24)
FF5 Alpha	57.21	60.15	59.15	64.80
	(11.64)	(11.73)	(12.04)	(12.35)

Table 12 Risk-based Momentum: 205 Anomalies in Chen and Zimmermann (2022)

This table reports the performance of risk-based momentum, where the *RISK* signal is estimated from 205 anomalies in Chen and Zimmermann (2022). Panels A and B report the results based on *RISK* estimated via PCA and LASSO, respectively. Newey and West (1987) robust t-statistics are reported in parentheses. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 205 Anomalies via PCA														
	10.00	8.32	10.07	9.42	8.31	5.62	4.92	4.89	4.31	4.47	6.42	6.51	5.03	88.33
	(3.69)	(6.87)	(9.54)	(10.08)	(10.63)	(7.46)	(7.55)	(6.54)	(5.94)	(5.38)	(7.75)	(7.63)	(5.20)	(22.10)
Panel B: 205 Anomalies via LASSO														
	4.22	11.96	13.36	11.94	10.96	7.36	6.38	5.64	5.44	4.79	7.17	8.29	7.35	105.26
	(1.39)	(7.46)	(9.74)	(10.07)	(11.01)	(7.63)	(8.11)	(6.31)	(5.99)	(4.70)	(7.01)	(7.86)	(6.24)	(21.75)

Table 13 Conditional Risk-based Momentum during 2008 Financial Crisis

This table reports the performance of conditional risk-based momentum during the 2008 financial crisis period from December 2007 to February 2009. Conditional risk-based momentum is formed on Russell 1000 stocks in the top risk-concentration quintile, where risk concentration is defined in Equation (6). Panels A, B, C, and D report the results based on $RISK$ estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. Newey and West (1987) robust t-statistics are reported in parentheses.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
	28.79	10.16	21.51	17.02	31.64	9.69	10.69	0.50	26.69	13.61	24.97	21.64	23.39	239.96
	(1.45)	(0.93)	(2.29)	(2.43)	(4.63)	(1.38)	(1.85)	(0.10)	(4.13)	(2.02)	(3.73)	(3.20)	(3.05)	(7.40)
Panel B: 15 EL Anomalies														
	39.95	9.09	25.43	16.05	32.65	-1.17	5.66	0.86	31.33	11.94	23.55	22.42	24.27	241.26
	(2.07)	(0.82)	(2.93)	(2.02)	(5.03)	(-0.14)	(1.06)	(0.15)	(5.02)	(1.73)	(3.48)	(3.12)	(2.97)	(7.30)
Panel C: 60 Anomalies via PCA														
	8.93	14.96	17.35	16.49	23.16	7.64	10.24	0.75	24.67	24.23	25.07	27.30	15.86	216.99
	(0.43)	(1.44)	(1.98)	(2.07)	(3.62)	(1.10)	(1.75)	(0.14)	(3.91)	(3.96)	(3.52)	(4.16)	(2.00)	(6.66)
Panel D: 60 Anomalies via LASSO														
	45.50	17.43	22.11	24.07	25.78	11.39	12.05	-0.18	30.03	17.15	25.11	17.85	21.96	269.72
	(1.98)	(1.64)	(2.44)	(3.10)	(3.38)	(1.59)	(2.00)	(-0.03)	(4.31)	(2.49)	(3.48)	(2.64)	(2.82)	(7.69)

Table 14 Conditional Risk-based Momentum during Momentum Crash Period

This table reports the performance of conditional risk-based momentum during the momentum crash period from March 2009 to March 2013. Conditional risk-based momentum is formed on Rusell 1000 stocks in the top risk-concentration quintile, where risk concentration is defined in Equation (6). Panels A, B, C, and D report the results based on $RISK$ estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. Newey and West (1987) robust t-statistics are reported in parentheses.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
	14.32	6.84	9.75	12.59	11.32	7.48	4.21	5.92	6.57	3.61	5.86	7.28	3.20	99.07
	(2.08)	(2.24)	(3.80)	(5.59)	(5.25)	(4.38)	(2.64)	(3.45)	(3.94)	(2.48)	(3.18)	(4.03)	(1.64)	(10.07)
Panel B: 15 EL Anomalies														
	18.20	7.85	12.26	13.93	11.92	8.42	4.58	7.04	6.44	1.49	4.22	7.72	4.39	108.37
	(2.59)	(2.53)	(4.71)	(5.51)	(5.55)	(5.07)	(2.82)	(3.89)	(4.04)	(0.98)	(2.36)	(4.09)	(2.30)	(10.76)
Panel C: 60 Anomalies via PCA														
	13.22	6.99	10.94	14.21	12.00	9.99	5.88	7.62	7.96	3.28	7.78	8.95	3.80	112.34
	(1.76)	(2.28)	(4.20)	(5.78)	(5.52)	(5.50)	(3.17)	(4.02)	(4.59)	(1.91)	(3.76)	(4.72)	(1.83)	(10.78)
Panel D: 60 Anomalies via LASSO														
	10.48	8.19	11.46	13.80	13.93	9.66	5.07	7.75	8.55	2.74	9.17	9.23	3.08	113.43
	(1.41)	(2.71)	(4.18)	(5.65)	(6.15)	(5.78)	(2.85)	(4.25)	(5.31)	(1.81)	(4.61)	(4.62)	(1.61)	(10.95)

Table 15 Conditional Risk-based Momentum: Day-of-week Effect

This table reports the performance of conditional risk-based momentum on each day of the week. Conditional risk-based momentum is formed on Russell 1000 stocks in the top risk-concentration quintile,where risk concentration is defined in Equation (6). Panels A, B, C, and D report the results based on *RISK* estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. Newey and West (1987) robust t-statistics are reported in parentheses. The sample period is from January 1993 to December 2020.

		Return-Holding Period													
	Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
Weekday	End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Mon		11.56	24.62	20.40	16.70	11.06	11.48	8.03	8.57	7.62	7.43	12.41	12.87	9.57	162.80
		(1.81)	(6.15)	(8.18)	(8.28)	(5.44)	(6.57)	(5.44)	(5.19)	(5.11)	(4.02)	(7.89)	(5.87)	(4.41)	(16.55)
Tue		21.66	12.09	17.18	14.68	11.36	8.91	6.40	7.00	7.86	6.93	11.19	15.62	17.06	158.13
		(3.51)	(3.63)	(5.97)	(6.57)	(5.87)	(5.44)	(4.03)	(4.27)	(4.37)	(4.24)	(5.53)	(7.70)	(6.20)	(16.10)
Wed		23.06	14.85	16.10	17.79	14.12	9.51	10.75	7.19	8.81	7.97	8.54	11.95	9.90	160.59
		(3.45)	(5.28)	(4.84)	(7.70)	(6.52)	(5.27)	(5.90)	(3.70)	(5.19)	(4.20)	(4.59)	(6.38)	(4.81)	(15.92)
Thu		26.54	13.61	14.82	12.92	9.87	6.59	9.24	7.88	8.33	10.19	8.22	10.87	7.91	146.46
		(3.58)	(4.30)	(5.69)	(5.54)	(4.74)	(3.43)	(5.72)	(4.66)	(4.77)	(5.63)	(4.45)	(5.51)	(4.00)	(14.26)
Fri		32.74	8.07	13.80	13.79	12.80	11.17	5.39	5.08	6.31	5.36	6.85	4.71	5.22	131.49
		(4.43)	(2.61)	(5.33)	(6.06)	(5.92)	(7.42)	(3.79)	(3.26)	(4.23)	(3.66)	(4.26)	(2.51)	(2.77)	(13.25)

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Online Appendix

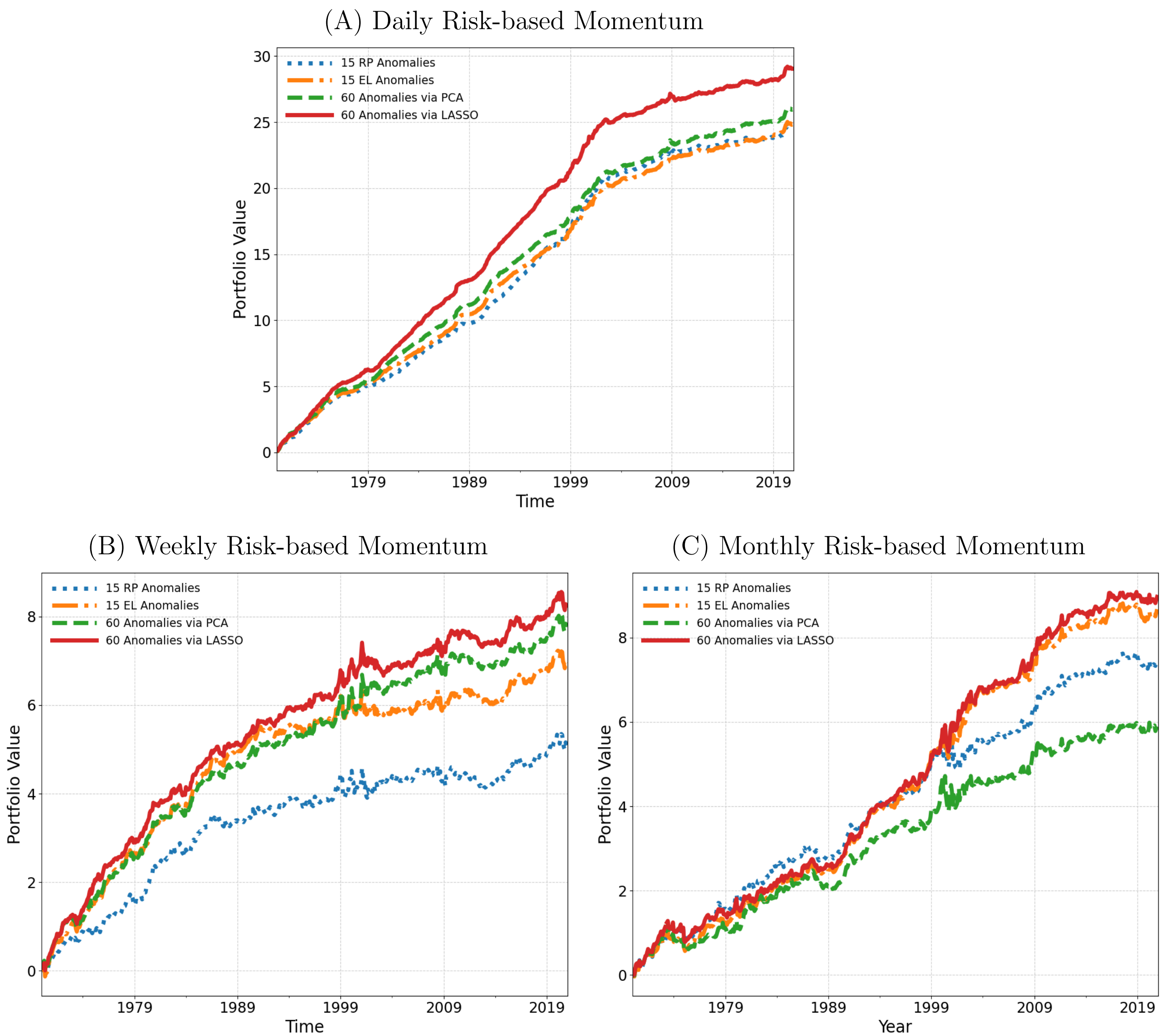

Fig. A.1 Performance of Low-Frequency Risk-based Momentum for Stocks

The figures plot the cumulative portfolio value from investing in different risk-based momentum strategies at lower frequencies, with portfolios formed by the past-day (-week, -month) RISK estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The portfolios are held over the subsequent day (week, month) with an initial investment of $1. We further take the logarithm of the portfolio value with base ten so the trajectory starts from 0. The sample period is from January 1970 to December 2020.

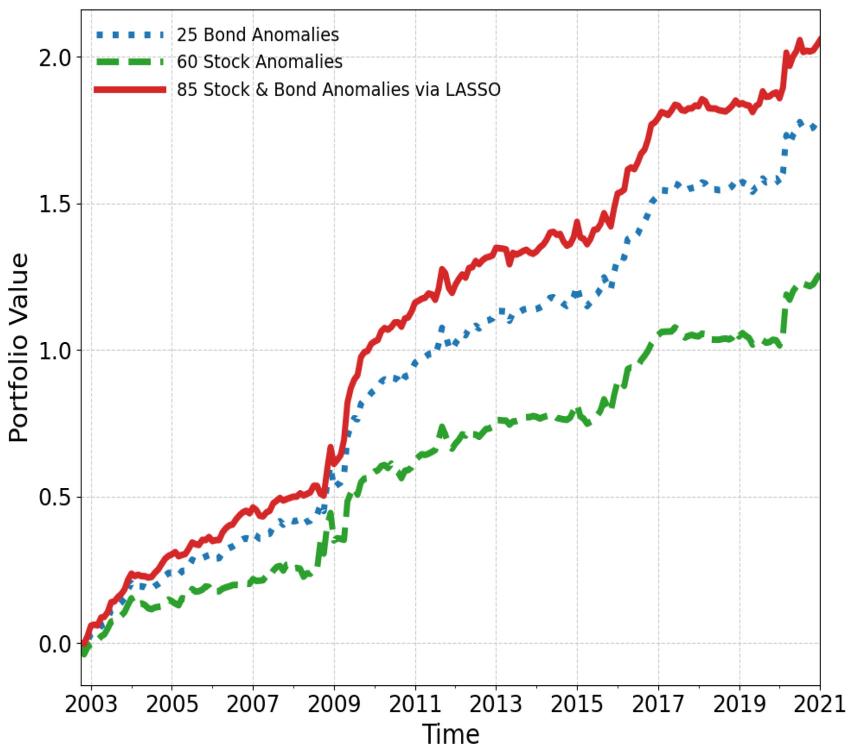

Fig. A.2 Performance of Monthly Risk-based Momentum for Corporate Bonds

This figure plots the cumulative portfolio value from investing in different momentum strategies for corporate bonds, with portfolios formed by the last-month bond RISK estimated from 25 bond anomalies, 60 stock anomalies, and 85 stock + bond anomalies, respectively. The portfolios are held over the subsequent month with an initial investment of \$1. We further take the logarithm of the portfolio value with base ten so the trajectory starts from 0. The corporate data are from the TRACE Enhanced database over the period from July 2002 to December 2020. The 25 corporate bond characteristics are drawn from Kelly, Palhares, and Pruitt (2022) and Bali, Goyal, Huang, Jiang, and Wen (2022), including "Bond age", "Amihud illiquidity", "Bond market beta", "Credit risk beta", "Coupon", "Default beta", "Downside risk beta", "Duration", "Illiquidity beta", "Illiquidity", "Kurtosis", "Long-term reversal", "Momentum", "Six-month momentum", "Credit rating", "Reversal", "Issuance size", "Skewness", "Bid-ask spread", "Downside risk", "Term beta", "Time-to-maturity", "Macroeconomic uncertainty beta", "Volatility beta", and "Volatility". The 60 stock characteristics are the same as in the paper.

Table A.1 List of 60 Anomalies

This table lists the 60 anomalies drawn from Green, Hand, and Zhang (2017), Freyberger, Neuhierl, and Weber (2020), Gu, Kelly, and Xiu (2020), and Kozak, Nagel, and Santosh (2020), covering numerous categories, such as value versus growth, profitability, investment, issuance activity, momentum, and trading frictions.

No.	Anomaly	Acronym	No.	Anomaly	Acronym
1	Abnormal earnings announcement return	abr	31	Employee growth rate	hire
2	Accruals	acc	32	Industry momentum	indmom
3	Accrual volatility	acvol	33	Investment-to-assets	inta
4	Abnormal earnings announcement volume	aeavol	34	Investment	invest
5	# years since first Compustat coverage	age	35	Leverage	lev
6	Asset growth	agr	36	Growth in long-term debt	lgr
7	Bid-ask spread	baspread	37	Liquidity	liq
8	Beta	beta	38	Maximum daily return	maxret
9	Betting against beta	bab	39	Long-term reversals	lrv
10	Book-to-market	bm	40	Momentum	mom
11	Cash holdings	cash	41	Short-term reversals	rev
12	Cash flow to debt	cashdebt	42	Residual variance	rvr
13	Cash productivity	cashpr	43	Size	size
14	Cash-flow to price	cfp	44	Net operating assets	noa
15	Change in shares outstanding	chcsho	45	Net stock issues	nis
16	Change in inventory	chinv	46	Profitability	prof
17	Change in 6-month momentum	chmom	47	O-score	oscore
18	Industry-adjusted change in profit margin	chpmia	48	Price delay	pricedelay
19	Corporate investment	cinvest	49	Quality minus junk	qmj
20	Composite equity issues	cei	50	Return on assets	roa
21	Current ratio	currat	51	Return on equity	roe
22	Dividend initiation	divi	52	Return on invested capital	roic
23	Dollar trading volume	dolvol	53	Revenue surprise	rsup
24	Dividend to price	dy	54	Sales growth	sgr
25	Expected growth	eg	55	Sales to price	sp
26	Growth in common shareholder equity	egr	56	Volatility of liquidity	voliq
27	Earnings to price	ep	57	Debt capacity/rm tangibility	tang
28	Distress	dis	58	Tax income to book income	tb
29	Gross profitability	gpf	59	Share turnover	turn
30	Industry sales concentration	herf	60	Zero trading days	zerotrade

Table A.2 Correlations of Standardized Anomalies

Panel A reports the time-series average of the cross-sectional correlations of 15 standardized RP anomalies. Panel B reports the same for 15 standardized EL anomalies. RP anomalies are 15 representative anomalies including 11 mispricing anomalies of Stambaugh, Yu, and Yuan (2012) and *Beta*, *Size*, *Book-to-market ratio*, and *Reversal*. EL anomalies are the 15 anomalies investigated by Ehsani and Linnainmaa (2022), including *Accruals*, *Betting against beta*, *Book-to-market*, *Cash-flow to price*, *Earnings to price*, *Profitability*, *Residual variance*, *Liquidity*, *Investment*, *Long-term reversals*, *Momentum*, *Short-term reversals*, *Size*, *Quality minus junk*, and *Net share issues*. Each anomaly is standardized according to Equation (1). The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

Panel A: 15 RP Anomalies

	acc	agr	beta	bm	cei	dis	gpf	inta	mom	rev	size	noa	oscore	roa	nsi
acc	1.00	0.10	0.03	-0.01	0.03	0.02	0.06	0.13	-0.03	0.00	-0.03	0.17	-0.02	0.08	0.04
agr	0.10	1.00	0.14	-0.05	0.11	0.14	-0.03	0.43	0.04	0.00	-0.04	0.50	0.03	0.00	0.21
beta	0.03	0.14	1.00	-0.02	-0.11	0.37	-0.03	0.08	0.07	0.04	-0.15	0.00	0.10	-0.09	0.10
bm	-0.01	-0.05	-0.02	1.00	0.05	-0.02	-0.45	-0.01	-0.05	-0.01	-0.08	-0.02	0.00	-0.10	-0.09
cei	0.03	0.11	-0.11	0.05	1.00	-0.12	-0.07	0.09	-0.30	-0.03	0.01	0.10	-0.01	-0.04	0.09
dis	0.02	0.14	0.37	-0.02	-0.12	1.00	-0.05	0.10	0.00	0.02	-0.22	0.04	0.21	-0.15	0.10
gpf	0.06	-0.03	-0.03	-0.45	-0.07	-0.05	1.00	-0.03	0.05	0.01	0.00	0.06	-0.27	0.44	0.03
inta	0.13	0.43	0.08	-0.01	0.09	0.10	-0.03	1.00	0.01	0.00	-0.05	0.40	0.04	-0.01	0.15
mom	-0.03	0.04	0.07	-0.05	-0.30	0.00	0.05	0.01	1.00	0.03	-0.01	-0.03	0.08	0.04	0.06
rev	0.00	0.00	0.04	-0.01	-0.03	0.02	0.01	0.00	0.03	1.00	-0.01	-0.01	0.04	-0.01	0.00
size	-0.03	-0.04	-0.15	-0.08	0.01	-0.22	0.00	-0.05	-0.01	-0.01	1.00	-0.12	-0.28	0.07	0.02
noa	0.17	0.50	0.00	-0.02	0.10	0.04	0.06	0.40	-0.03	-0.01	-0.12	1.00	0.19	0.02	0.10
oscore	-0.02	0.03	0.10	0.00	-0.01	0.21	-0.27	0.04	0.08	0.04	-0.28	0.19	1.00	-0.44	-0.04
roa	0.08	0.00	-0.09	-0.10	-0.04	-0.15	0.44	-0.01	0.04	-0.01	0.07	0.02	-0.44	1.00	0.06
nsi	0.04	0.21	0.10	-0.09	0.09	0.10	0.03	0.15	0.06	0.00	0.02	0.10	-0.04	0.06	1.00

Panel B: 15 EL Anomalies

	acc	agr	beta	bm	cei	dis	gpf	invest	mom	rev	size	noa	oscore	roa	nsi
acc	1.00	0.03	-0.03	-0.20	0.06	0.07	0.01	0.02	0.05	0.07	-0.03	0.00	-0.04	0.19	0.04
bab	0.03	1.00	-0.13	-0.15	-0.17	0.09	0.53	-0.10	-0.01	0.06	-0.03	0.01	0.00	0.22	0.15
bm	-0.03	-0.13	1.00	0.45	0.30	-0.45	-0.19	0.16	-0.01	-0.27	-0.09	-0.01	-0.10	-0.25	-0.06
cfp	-0.20	-0.15	0.45	1.00	0.44	-0.20	-0.18	0.04	0.00	-0.21	-0.02	0.00	0.01	-0.05	-0.17
ep	0.06	-0.17	0.30	0.44	1.00	0.03	-0.32	-0.01	0.04	-0.01	-0.04	-0.01	0.06	0.15	-0.24
prof	0.07	0.09	-0.45	-0.20	0.03	1.00	0.06	-0.08	-0.01	0.11	0.05	0.02	0.03	0.34	-0.13
rvar	0.01	0.53	-0.19	-0.18	-0.32	0.06	1.00	0.05	-0.03	0.06	0.08	0.04	-0.20	0.01	0.24
liq	0.02	-0.10	0.16	0.04	-0.01	-0.08	0.05	1.00	0.00	-0.03	-0.04	0.02	-0.78	-0.18	0.06
invest	0.05	-0.01	-0.01	0.00	0.04	-0.01	-0.03	0.00	1.00	0.08	-0.04	0.00	0.01	0.03	0.01
lrev	0.07	0.06	-0.27	-0.21	-0.01	0.11	0.06	-0.03	0.08	1.00	0.00	0.01	0.02	0.14	0.22
mom	-0.03	-0.03	-0.09	-0.02	-0.04	0.05	0.08	-0.04	-0.04	0.00	1.00	0.01	0.02	0.00	0.05
srev	0.00	0.01	-0.01	0.00	-0.01	0.02	0.04	0.02	0.00	0.01	0.01	1.00	0.00	-0.01	0.00
size	-0.04	0.00	-0.10	0.01	0.06	0.03	-0.20	-0.78	0.01	0.02	0.02	0.00	1.00	0.13	-0.08
qmj	0.19	0.22	-0.25	-0.05	0.15	0.34	0.01	-0.18	0.03	0.14	0.00	-0.01	0.13	1.00	-0.07
nsi	0.04	0.15	-0.06	-0.17	-0.24	-0.13	0.24	0.06	0.01	0.22	0.05	0.00	-0.08	-0.07	1.00

Table A.3 Risk-based Momentum: Russell 3000 Stock Universe

This table reports the performance of 13 long-short portfolios over a given intraday period based on the *RISK* signal in the previous intraday period. Each of these portfolios enters position at time "Start" and exits position at time "End" once per day. The last column "All" reports the performance of the long-short portfolio that is held during all 13 intraday periods but is rebalanced every intraday period based on the *RISK* signal in the previous intraday period (i.e., investing in all 13 signals). We report the annualized return of the long-short portfolio in percentage with Newey and West (1987) robust t-statistics in parentheses. Panels A, B, C, and D report the results based on *RISK* estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample includes all stocks in the Russell 3000 index over the period from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies														
	9.42	8.63	11.30	9.97	8.79	5.85	4.84	4.36	4.91	4.04	5.41	6.82	6.29	90.48
	(3.88)	(6.61)	(10.80)	(11.02)	(11.38)	(8.06)	(8.23)	(6.63)	(7.28)	(5.34)	(7.12)	(8.22)	(6.87)	(23.89)
Panel B: 15 EL Anomalies														
	10.54	8.23	11.82	10.14	9.81	5.89	5.12	4.76	4.96	4.21	5.97	6.95	6.87	94.95
	(4.34)	(6.24)	(11.16)	(11.19)	(12.36)	(8.00)	(8.55)	(6.96)	(7.27)	(5.60)	(7.74)	(8.45)	(7.38)	(24.89)
Panel C: 60 Anomalies via PCA														
	14.88	9.62	13.47	12.50	10.83	7.90	6.93	6.41	6.51	6.20	7.91	9.21	8.80	121.35
	(5.18)	(6.84)	(10.83)	(11.55)	(11.93)	(9.01)	(9.39)	(7.78)	(7.74)	(6.59)	(8.21)	(9.39)	(8.01)	(26.89)
Panel D: 60 Anomalies via LASSO														
	13.42	11.63	15.02	14.10	12.15	8.61	7.92	7.11	7.00	6.51	8.74	9.83	9.49	131.52
	(4.65)	(7.79)	(11.68)	(12.55)	(12.68)	(9.50)	(10.38)	(8.29)	(8.16)	(6.83)	(8.80)	(9.62)	(8.46)	(28.51)

Table A.4 Decile Portfolio Performance: 60 Anomalies

This table reports the annualized return in percentage of decile portfolios over a given intraday period based on the *RISK* signal in the previous intraday period. Each of these portfolios enters position at time "Start" and exits position at time "End" once per day. The last column "All" reports the performance of the decile portfolios that are held during all 13 intraday periods but are rebalanced every intraday period based on the *RISK* signal in the previous intraday period (i.e., investing in all 13 signals). The row labeled "High-Low" reports the annualized return of the long-short portfolios in percentage with Newey and West (1987) robust t-statistics in parentheses. Panels A and B report the results based on *RISK* estimated from 60 anomalies via PCA and 60 anomalies via LASSO, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

	Return-Holding Period													
Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 60 Anomalies via PCA														
1	-0.47	-7.35	-8.33	-6.97	-5.24	-4.85	-2.02	-2.11	-3.66	-3.89	-2.64	-3.82	-2.33	-53.75
2	0.54	-4.77	-5.43	-4.98	-3.36	-2.98	-1.38	-1.62	-2.60	-2.60	-1.21	-2.20	-1.09	-33.69
3	2.13	-3.40	-3.76	-3.45	-2.20	-1.76	-0.27	-0.70	-1.68	-1.72	0.16	-0.76	-0.12	-17.53
4	2.87	-2.62	-3.08	-1.86	-1.03	-1.02	0.12	-0.42	-1.26	-1.10	0.86	0.15	0.39	-8.01
5	3.90	-1.60	-1.48	-0.67	-0.42	-0.63	1.00	0.12	-0.63	-0.99	1.71	0.87	1.32	2.51
6	5.10	-0.82	-0.43	0.02	0.38	0.15	1.33	1.00	-0.29	-0.29	2.34	2.11	1.71	12.31
7	5.98	0.04	0.58	1.17	1.36	0.83	1.65	1.37	0.14	0.14	2.94	2.19	2.37	20.76
8	7.10	0.55	1.96	1.95	2.38	1.39	2.88	2.02	0.80	1.20	3.76	3.45	3.07	32.52
9	10.08	1.50	3.47	3.38	3.74	1.97	3.75	3.07	1.18	1.54	4.28	4.19	4.05	46.18
10	12.28	2.97	5.28	5.27	5.76	3.08	4.99	4.26	2.45	2.03	5.41	5.27	6.36	65.40
High-Low	12.75	10.31	13.61	12.24	11.00	7.93	7.00	6.37	6.11	5.92	8.05	9.09	8.70	119.14
	(4.08)	(6.92)	(10.28)	(10.66)	(11.32)	(8.59)	(8.86)	(7.35)	(6.74)	(5.89)	(7.86)	(8.73)	(7.46)	(24.69)
Panel B: 60 Anomalies via LASSO														
1	-1.00	-8.71	-8.76	-7.40	-5.03	-4.67	-2.04	-2.27	-4.25	-3.91	-2.74	-3.68	-2.12	-56.79
2	0.38	-5.62	-5.60	-5.13	-3.45	-2.94	-1.08	-1.83	-2.49	-2.62	-1.06	-1.42	-1.01	-33.89
3	1.33	-3.62	-4.00	-3.25	-1.96	-1.89	-0.26	-1.08	-1.81	-2.06	0.32	-0.33	0.26	-18.36
4	3.02	-2.58	-2.93	-2.04	-1.24	-0.86	0.63	-0.42	-1.24	-1.09	1.01	0.29	0.42	-7.02
5	3.16	-1.60	-1.76	-1.04	-0.31	-0.54	1.25	0.30	-0.89	-0.65	1.41	1.35	0.98	1.67
6	4.81	-0.79	-0.58	0.34	0.54	0.03	1.49	0.77	-0.46	-0.22	2.53	1.96	1.46	11.89
7	6.14	-0.25	0.60	1.10	1.26	0.67	2.24	1.18	-0.02	0.34	2.78	2.76	2.31	21.11
8	7.51	1.02	2.30	1.77	2.54	1.10	2.71	2.03	0.46	0.62	3.40	3.24	3.07	31.78
9	9.41	2.36	3.80	3.39	3.82	2.30	3.65	2.83	1.15	1.39	4.44	4.55	4.35	47.43
10	13.68	2.97	5.43	5.35	5.80	3.51	5.17	3.93	2.65	2.25	5.73	5.59	6.35	68.42
High-Low	14.68	11.68	14.19	12.76	10.83	8.18	7.20	6.20	6.90	6.16	8.47	9.27	8.48	125.21
	(4.62)	(7.55)	(10.77)	(11.23)	(11.46)	(8.84)	(8.99)	(7.28)	(7.78)	(6.14)	(8.36)	(8.94)	(7.08)	(25.67)

Table A.5 Risk-based Momentum Conditional on Risk Concentration: Controlling for $|RISK|$ Level

This table reports the performance of risk-based momentum for Russell 1000 stocks in the top and bottom *RiskCon* quintiles controlling for $|RISK|$ level. *RiskCon*, defined in Equation (6), captures a stock's risk concentration. We first sort stocks into five portfolios by $|RISK|$, and then within each $|RISK|$ quintile we sort the stocks into quintiles based on their risk concentration (5×5 grouping). Next, we average across the five $|RISK|$ portfolios to produce five *RiskCon* portfolios with large cross-portfolio variation in risk concentration but little variation in $|RISK|$. Finally, we construct risk-based long-short portfolios within the highest and lowest *RiskCon* portfolios, respectively. The rows labeled "High" ("Low") denotes stocks in the top (bottom) *RiskCon* quintile. Panels A, B, C, and D report the results based on $RISK$ estimated from 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, and 60 anomalies via LASSO, respectively. The sample period is from January 1993 to December 2020.

		Return-Holding Period													
	Start	16:00	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	All
RiskCon	End	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	
Panel A: 15 RP Anomalies															
High		21.30	14.42	13.32	12.88	11.09	8.63	6.35	6.70	7.19	6.80	7.99	9.85	8.62	134.94
		(7.93)	(10.64)	(12.77)	(14.13)	(14.36)	(12.21)	(9.92)	(10.09)	(11.14)	(9.81)	(11.08)	(12.86)	(10.03)	(34.49)
Low		-7.47	6.05	4.32	3.98	5.46	-0.17	-0.07	-0.69	0.91	-0.08	1.73	2.17	0.61	16.97
		(-2.14)	(3.45)	(2.93)	(2.86)	(4.57)	(-0.14)	(-0.07)	(-0.67)	(0.81)	(-0.07)	(1.47)	(1.71)	(0.42)	(3.05)
Panel B: 15 EL Anomalies															
High		21.57	14.33	12.97	12.34	10.78	7.55	6.77	7.24	6.61	6.30	8.06	9.47	7.99	131.89
		(8.08)	(9.96)	(12.50)	(13.50)	(14.17)	(10.54)	(10.94)	(10.59)	(10.48)	(8.98)	(11.40)	(12.84)	(9.72)	(33.61)
Low		-13.14	5.20	3.33	4.93	5.50	0.24	-0.29	0.22	0.55	-2.06	2.35	1.34	2.91	11.29
		(-3.74)	(2.93)	(2.19)	(3.61)	(4.61)	(0.20)	(-0.28)	(0.21)	(0.49)	(-1.76)	(1.90)	(1.08)	(2.11)	(2.02)
Panel C: 60 Anomalies via PCA															
High		22.45	14.17	14.90	14.62	11.53	9.30	9.11	7.44	7.59	7.71	10.06	10.66	9.77	149.61
		(7.42)	(9.94)	(12.45)	(14.32)	(13.48)	(11.74)	(12.25)	(9.90)	(10.51)	(9.68)	(11.81)	(12.15)	(10.18)	(33.95)
Low		-8.85	6.55	4.15	4.82	7.29	3.74	1.40	2.54	1.37	2.30	4.72	4.45	5.24	40.36
		(-2.37)	(3.41)	(2.42)	(3.08)	(5.33)	(2.76)	(1.17)	(2.14)	(1.05)	(1.63)	(3.35)	(3.21)	(3.33)	(6.44)
Panel D: 60 Anomalies via LASSO															
High		25.61	17.05	15.86	15.06	12.06	10.49	8.12	8.01	8.93	8.11	10.32	11.11	9.64	160.67
		(8.21)	(11.71)	(14.11)	(14.91)	(14.21)	(12.91)	(11.38)	(10.51)	(11.96)	(10.40)	(12.02)	(12.67)	(9.87)	(35.85)
Low		-7.31	7.44	6.46	5.26	7.59	2.61	1.89	1.16	3.23	1.43	4.76	3.74	5.49	43.93
		(-1.90)	(3.88)	(3.77)	(3.42)	(5.59)	(2.01)	(1.57)	(0.95)	(2.50)	(1.05)	(3.51)	(2.69)	(3.43)	(6.95)

Table A.6 Monthly Risk-based Momentum

This table reports the performance of decile portfolios formed on the basis of the monthly *RISK* signal and held over the subsequent month. Panel A reports the annualized portfolio returns in percentage for the unconditional risk-based momentum strategies formed on all stocks in the Russell 1000 index. Panel B reports the results for the conditional risk-based momentum strategies formed on Russell 1000 stocks in the top risk-concentration quintile. Risk concentration is defined in Equation (6). The *RISK* signal is constructed using 15 RP anomalies, 15 EL anomalies, 60 anomalies via PCA, or 60 anomalies via LASSO. The rows labeled "High-Low", "FF5 Alpha" and "q-factor Alpha" respectively report the annualized return, the Fama and French (2015) five-factor alpha, and the Hou, Xue, and Zhang (2015) q-factor alpha of the long-short spread portfolio in percentage, with Newey-West robust t-statistics in parentheses. The sample period is from January 1970 to December 2020.

	15 RP Anomalies	*15 EL Anomalies*	*60 Anomalies via PCA*	*60 Anomalies via LASSO*
Panel A: Unconditional Risk-based Momentum				
1 (Low)	2.99	1.96	3.46	1.14
2	7.92	6.63	7.98	6.20
3	9.22	8.98	8.68	8.93
4	10.55	11.12	11.38	10.43
5	12.73	12.50	13.03	12.03
6	14.14	13.03	14.35	14.24
7	15.40	16.11	14.86	16.06
8	15.88	16.79	15.67	16.76
9	16.16	17.42	17.33	17.89
10 (High)	19.26	20.56	17.15	20.58
High-Low	16.27	18.60	13.69	19.44
	(5.88)	(6.30)	(4.31)	(6.44)
FF5 Alpha	17.48	19.16	14.08	19.68
	(5.77)	(5.87)	(3.56)	(5.78)
q-factor Alpha	18.83	20.73	14.79	20.59
	(5.56)	(5.69)	(3.39)	(5.47)
Panel B: Conditional Risk-based Momentum				
1 (Low)	0.61	-1.50	1.29	-1.47
2	1.95	3.34	6.24	2.54
3	6.70	6.43	7.06	6.64
4	9.35	11.41	9.69	11.75
5	11.91	12.79	12.76	11.97
6	15.39	15.08	14.15	15.67
7	17.44	17.60	17.39	16.23
8	19.01	17.41	18.48	20.38
9	20.86	22.46	21.79	21.14
10 (High)	25.64	24.69	22.48	25.37
High-Low	25.03	26.19	21.19	26.84
	(7.01)	(7.22)	(5.66)	(7.44)
FF5 Alpha	25.02	27.00	20.54	26.73
	(6.62)	(6.86)	(4.51)	(6.46)
q-factor Alpha	26.34	27.72	21.08	27.61
	(6.47)	(6.57)	(4.42)	(6.17)