Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Systematic Momentum: A New Class of Price Patterns

Sophia Zhengzi Li, Peixuan Yuan, Guofu Zhou

To cite this article:
Sophia Zhengzi Li, Peixuan Yuan, Guofu Zhou (2025) Systematic Momentum: A New Class of Price Patterns. Management Science

Published online in Articles in Advance 25 Nov 2025

. https://doi.org/10.1287/mnsc.2024.08236

informs
https://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Articles in Advance, pp. 1–25
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Systematic Momentum: A New Class of Price Patterns

Sophia Zhengzi Li,[a] Peixuan Yuan,[b,*] Guofu Zhou[c]

[a] Rutgers Business School, Rutgers University, Newark, New Jersey 07102; [b] School of Business, Hong Kong Baptist University, Hong Kong, China; [c] Olin Business School, Washington University, Saint Louis, Missouri 63130

*Corresponding author

Contact: zhengzi.li@business.rutgers.edu, https://orcid.org/0000-0002-0448-8125 (SZL); peixuan@hkbu.edu.hk, https://orcid.org/0000-0002-7378-514X (PY); zhou@wustl.edu, https://orcid.org/0000-0002-4104-403X (GZ)

Received: October 23, 2024
Revised: March 17, 2025; June 13, 2025
Accepted: July 18, 2025
Published Online in Articles in Advance: November 25, 2025

https://doi.org/10.1287/mnsc.2024.08236

Abstract. We uncover a new price pattern: The stock systematic component exhibits momentum. This systematic momentum further yields a return momentum: Stocks sorted by systematic component have persistent positive returns. In comparison with the extremely popular and extensively studied momentum sorted by return, which is valid only monthly, our systematic return momentum holds intraday, daily, weekly, and monthly. Furthermore, our systematic momentum, the strongest ever discovered, is different from the factor momentum sorted by factor performance.

History: Accepted by Kay Giesecke, finance.
Funding: S. Z. Li thanks the Rutgers Business School Dean's Research Seed Fund for financial support. P. Yuan acknowledges support from the National Natural Science Foundation of China [Grants 72233003 and 72303233].
Supplemental Material: The online appendix and data files are available at https://doi.org/10.1287/mnsc.2024.08236.

Keywords: momentum • systematic component • intraday • mispricing • limits to arbitrage

1. Introduction

Different asset pricing models propose different factors to price the cross section of stocks. The capital pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, the Hou et al. (2015) *q*-factor model, and the Stambaugh and Yuan (2016) mispricing-factor model are the most widely used and studied models, and each of them proposes a total of no more than five factors. Although countless studies have examined how well these models work in terms of the alphas, there is barely any study on the times series property of the *systematic component*, the component of stock returns explained by all the factors that include those above and beyond them. Given that different factors might contain useful information that arbitrageurs could use simultaneously to identify mispriced stocks (Stambaugh and Yuan 2016, Engelberg et al. 2018), it is of great economic interest to study the systematic component, the contribution of all the factors instead of examining it from each factor or from only a few of them.

In this paper, we uncover a new pattern: the stock systematic component exhibits momentum—Stocks with higher systematic component in the current period tend to maintain greater systematic component in the next period. We construct cross-sectional factors by using observable characteristics as factor loadings and estimating regression coefficients through cross-sectional regressions of stock returns on these characteristics.[1] We then define systematic component as the sum of the products of these coefficients and characteristics. This systematic momentum yields an economically significant return momentum: Stocks sorted by past systematic component have persistent and sizable positive returns. Although our results holds daily, weekly, and monthly, we focus on the less studied intraday data and estimate the systematic component 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 1000 and 1600 hours and one overnight period between 1600 and 1000 hours.[2] Specifically, we decompose intraday stock returns into two components, a systematic component associated with factors (i.e., the sum of each estimated coefficient times the corresponding anomaly variable) and a residual component that includes the intercept, which can be interpreted as alpha relative to cross-sectional factors. To capture various systematic exposures, we use three different sets of representative anomaly factors, respectively. Our novel finding is that the systematic component, regardless of the choice of anomaly set, exhibits a strong intraday momentum pattern: a high systematic component in the previous period leads to a high systematic component in the subsequent period. The systematic momentum holds every half hour from 1000 hours until the 1600-hour market close and then overnight until 1000 hours the next day.

The systematic momentum, although not tradable itself, generates a tradable *return momentum*. Sorting stocks by their past systematic component, the resulting long-short portfolio has an intraday return momentum pattern. At the monthly frequency, it produces a monthly return momentum, similar to the monthly momentum discovered by Jegadeesh and Titman (1993) (JT), which is extremely widely applied and is one of the most important anomalies in asset pricing.[3] However, the JT momentum fails intraday because the reversal effect dominates (Heston et al. 2010). In contrast, our systematic return momentum, robust to various time frequencies, has a monthly momentum stronger than that of the JT, yielding a much higher return and Sharpe ratio. Moreover, our momentum does not suffer from crash risk, whereas the JT does, an important fact discovered first by Daniel and Moskowitz (2016).[4]

The persistence of the systematic component (*SYS*) is intriguing. To understand the origins of systematic momentum, we first adopt the approach of Lo and MacKinlay (1990) to decompose the holding-period *SYS* into three elements: the average autocovariance of individual stock *SYS*, the average cross-autocovariance among stocks, and the cross-sectional variance in expected stock *SYS*. Our findings reveal that the main driving force behind systematic momentum is the positive autocovariance observed in individual stock *SYS*. Given that the *SYS* component is aggregated from multiple anomaly components, we further break down the autocorrelation in stock *SYS* into two parts: an *Auto* part capturing the autocorrelation of *SYS* explained by the same factor and a *Cross* part capturing the autocorrelation of *SYS* arising from cross-serial lead-lag among different factors. Notably, both the *Auto* and *Cross* components contribute positively and substantially to the persistence of individual stock *SYS* across various frequencies. In other words, the positive lead-lag relationships among different factors can generate systematic momentum, in addition to the positive autocorrelation of individual factors. This highlights the significance of cross-factor interactions in driving the observed momentum in total *SYS*. On the other hand, the positive lead-lag relationships among different factors do not contribute to time series factor momentum and even contribute negatively to cross-sectional factor momentum. As a result, our systematic momentum effect is distinct from and surpasses factor momentum.

Where do the positive autocorrelations of individual anomaly factors and the cross-serial lead-lag among different factors come from? We consider limits to arbitrage as the explanation. From Stambaugh and Yuan (2016), anomalies in part reflect mispricing, which has common components across stocks. In addition, Engelberg et al. (2018) find evidence supporting the notion that anomaly returns are driven by biased expectations, which are at least partly corrected upon news arrival. Therefore, arbitrageurs, aiming to correct their biased expectations, may engage in trading multiple anomalies, thereby realizing returns on various anomalies. However, because of limits to arbitrage, arbitrageurs may trade on the perceived mispricing gradually instead of eliminating mispricing all at once, and such gradual trading can result in persistent returns on the same anomaly or lead-lag relationship among different anomaly factors.

Empirically, we examine how arbitrageur participation and limits to arbitrage affect the systematic return momentum. According to 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 systematic return 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). Jiang et al. (2022) also find that arbitrageurs use high attention as a coordination device to trade and profit from mispricing. We further document stronger systematic return momentum during the high aggregate idiosyncratic volatility (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 systematic return momentum.

Kozak et al. (2018) demonstrate that, when mispricing does not align with covariances, arbitrageurs can trade the mispricing aggressively without assuming any systematic risk. Therefore, arbitrageurs who want to avoid systematic risk may not trade aggressively to neutralize the systematic momentum effect. To capture a stock's exposure to systematic risk, we construct a measure called systematic risk concentration, defined as the fraction of a stock's return variation explained by the systematic component within a given intraday interval. The higher risk embedded in higher-risk-concentration stocks can reduce arbitrageurs' incentive to trade on mispricing aggressively. Empirically, we find significantly stronger systematic return momentum among stocks with higher risk concentration. These results align with the explanation of limits to arbitrage.

The systematic component is a function of anomaly factors. Systematic component is traditionally measured with respect to benchmark models such as the Capital Asset Pricing Model (CAPM) or the Fama-French three-factor model. Given the recent identification of additional anomalies influencing the cross-section of stock returns, we utilize three sets of anomalies to extract the systematic component. The first set consists of 15 representative anomalies, including the 11 major mispricing anomalies from Stambaugh et al. (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 et al. (2017), Freyberger et al. (2020), and Gu et al. (2020), covering numerous categories, such as value versus growth, profitability, investment, issuance activity, momentum, and trading frictions. With machine learning tools in dimension reduction and modeling, we find that the systematic return momentum is quite robust to using different sets of anomalies to approximate the total systematic component.[5] Although 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 systematic return momentum performs when the holding horizon is more than one intraday period. Notably, we find that the momentum based on the systematic component in the past intraday period is extremely persistent and lasts about 65 intraday periods or five days. Consistent with the previous intraday patterns, the systematic return momentum from the morning systematic component signal is more persistent than those from the afternoon signal, consistent with existing studies (Cushing and Madhavan 2000, Foucault et al. 2005, Bogousslavsky 2021) that investors behave differently toward the end of the day.

Our paper is related to Kelly et al. (2021). They focus on explaining the traditional momentum as compensation for time-varying covariance risk with factors based on the Instrumented Principal Components Analysis (IPCA) model of Kelly et al. (2019), and discover a risk-based momentum using the IPCA risk. In contrast, we are the first to study the momentum pattern of the systematic component. Although their study of risk-based momentum provides an improved momentum over the JT momentum, they do not generate to alternative time frequency. In general, 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 cross-sectional momentum has ever been documented before. Second, they focus on explaining the traditional momentum, whereas we aim at uncovering systematic momentum and its wide implications to different time frequencies. Third, they estimate the IPCA risk component from a time series perspective with five latent factors. Instead, we measure the time-varying total systematic component of stocks based on a period-by-period cross-sectional regression on a large set of observable firm characteristics (from 15 to 60). As a result, they assume time-varying factor loadings and constant risk premia, whereas our factor loadings are constant but the risk premia are allowed to vary over time. Our approach is what practitioners often use to attribute returns to various risks and is what is used by most recent machine learning studies (Gu et al. 2020) due to the large sample size in the cross section. In short, our paper is related to Kelly et al. (2021) but is fundamentally different and contributes to the large momentum literature by discovering a novel systematic momentum that has wide implications.

Our paper is also related to Ehsani and Linnainmaa (2022), but differs manifestly. First, we rely on the *total* systematic component of stocks that can be an arbitrary function of factors, and we have uncovered both momentum for the total systematic component itself and for the stocks sorted by the total systematic component. In contrast, their factor momentum solely measures the *relative* performance among a set of tradable factors and is about the spread between long and short portfolios of these factors: a pure factor momentum without direct implications on stock momentum per se. To further illustrate the difference, consider adding useless factors to our systematic measure. Theoretically and empirically, this does not impact our momentum but could affect the performance of the factor momentum greatly.[6] Second, our systematic momentum is the spread between long and short portfolios of stocks sorted by total systematic component, allowing for a large number of stocks to be included. In contrast, the total number of factors is small, resulting in limited sorting. From an investment perspective, more ways of sorting can only enhance the attractiveness of the investment strategy. Third, we uncover momentum cross frequencies, including intraday, whereas they focus on using factor momentum to explain the traditional JT momentum at monthly frequency.[7] Lastly, in spanning tests from Section 5.2, we provide direct evidence showing that systematic momentum cannot be explained by factor momentum, whereas factor momentum no longer survives after controlling for systematic momentum. As mentioned earlier, our systematic momentum benefits from both positive autocorrelation in factors and positive cross-serial correlation among different factors, which contribute positively to its performance. In contrast, the positive cross-serial correlation among factors does not contribute to time series factor momentum and even adversely affects cross-sectional factor momentum, which is extensively discussed in Section 3.3.

Our paper adds to the growing literature on high-frequency studies as data become increasingly available. Heston et al. (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 et al. (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. Aït-Sahalia and Xiu (2019) study high-frequency covariance structure of the constituents of the S&P 100 Index. Based on high-frequency data, Pelger (2020) estimates the time-varying systematic risk factors that explain individual stock returns. These risk factors carry an intraday risk premium that reverses overnight. Baltussen et al. (2021) analyze market intraday momentum in general via the lens of hedging. Bogousslavsky (2021) explores anomaly returns over the trading hours and overnight. Da and Xiu (2021) propose a method for estimating volatility from noisy high-frequency data by maximizing the likelihood of a mis-specified moving-average model. To the best of our knowledge, our paper is the first to study the intraday patterns of the *systematic component* of stock returns and discover the associated cross-sectional systematic 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 et al. (2003) study global stock momentum, and Asness et al. (2013) examine momentum across asset classes. Because our systematic return momentum is stronger and more general than the traditional momentum that vanishes at daily/weekly frequencies and in other asset classes, the great number of questions studied related to the traditional momentum can also be asked for the systematic return momentum, generating more studies and deeper understanding about momentum in general.

The paper is organized as follows. Section 2 discusses the data and methodology of decomposing stock returns into systematic and residual components. Section 3 presents the empirical results pertaining to the systematic momentum and systematic return momentum. Section 4 uncovers various conditions under which the systematic return momentum becomes stronger. Section 5 performs robustness tests and extensions. Section 6 concludes. The Online Appendix provides additional summary statistics and results.

2. Data and Methodology

2.1. Data

Our stock sample consists of the Russell 1000 index constituents or the largest 1,000 stocks.[8] This top 1,000 stock sample comprises more than 90% of the total market cap of all stocks in the U.S. 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.[9]

We compute every 30-minute return between 1000 and 1600 hours and the overnight return between 1600 hours on the previous trading day and 1000 hours on the current trading day.[10] Our high-frequency returns are based on midquote 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.[11] 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. Because prices from TAQ are raw prices without adjusting for corporate actions such as dividend payout 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 et al. (2012) and *Beta*, *Size*, *Book-to-market ratio*, and *Reversal*. The mispricing anomalies are updated monthly following Stambaugh et al. (2012), with the exception of *Momentum*, which is updated daily and estimated by the cumulative return over the past 22–252 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 et al. (2017), Freyberger et al. (2020), Gu et al. (2020), and Kozak et al. (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."

Table A.2 in the Online Appendix reports the summary statistics of the all anomalies included in RP or EL anomaly sets. 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 et al. (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:

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

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 decomposition in every intraday period. Such intervals are common in intraday studies such as Heston et al. (2010) and many others. Our first period ($i = 1$) is the overnight interval from the market close of the previous day to 1000 hours, 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 1000 to 1030 hours and so on until the last period ($i = 13$), which is between 1530 and 1600 hours. We obtain systematic 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 (Fama and French 2020), and so the second term captures the total systematic component of the stocks at intraday frequency.[12]

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:

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

where

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

is the estimated *systematic component* explained by common systematic factors, which is simply referred to as *SYS*.[13]

It is important to point out that for simplicity we refer to the total systematic component, the right-hand side of Equation (4), as *SYS*. This is consistent with Fama and French (1993) and Stambaugh et al. (2012), although they focus on the time series version of the factors. Our definition of *SYS* is quite general and can include any cross-sectional tradable or nontradable factors that contribute systematically to expected returns. In particular, *SYS* can include both risk-based and behavioral factors. As argued by Kozak et al. (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 Intertemporal Capital Asset Pricing Model-like Stochastic discount factor. As a result, the *SYS* component can reflect both compensation for risk and exposure to (systematic) mispricing correction.

The residual part $RES_{s,d,i} = RET_{s,d,i} - SYS_{s,d,i}$ captures the return component unexplained by the factors, including the intercept, which can be viewed as alpha relative to cross-sectional factors. Although there is an extensive literature on various properties of alpha from time series regressions, there is little analysis on *SYS*, a measure that reflects the total contribution of various systematic factors.

Our objective is to study the properties of *SYS* and its predictive power on future returns. We exploit its predictive power as follows. At the beginning of each intraday period i ($i = 1, \ldots, 13$) on each day d, we sort stocks into 10 portfolios based on their realized *SYS* values available at the time (i.e., the systematic component of returns in the previous intraday period). We buy stocks in the top decile with high *SYS* values and short those in the bottom decile with low *SYS* values. We hold this long-short value-weighted portfolio during period i on day d, resulting in the systematic portfolio return:

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

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 systematic 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 systematic long-short portfolio investing in all 13 *SYS* signals and obtain its time series returns. For each long-short portfolio, we further decompose the holding-period return into systematic and residual components. These time series would allow us to examine whether the systematic component itself exhibits momentum and if such systematic momentum can imply a systematic return 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 *SYS*. Panels A and B of Table A.3 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 Ordinary Least Squares regressions to obtain the systematic decomposition. To improve the efficiency of the slope estimators, we purposely use inverse variances as regression weights.[14]

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 based on machine learning dimension reductions. First, following Kozak et al. (2020) and Ehsani and Linnainmaa (2022), we use 15 principal components (PCs) to reduce the dimensionality. Specifically, we first fit the 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 et al. (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 tradeoff between the goodness of fit and the complexity of the model.[15]

3. Main Results

3.1. Systematic Momentum

We first investigate the predictability of *SYS* for future *SYS* and *RES* components, which are constructed according to Equations (4) and (5). As outlined in Section 2.2, we form 13 long-short portfolios based on the *SYS* signal in the previous intraday period. In addition, we also form an "All-together" portfolio that trades all 13 *SYS* signals and is rebalanced every intraday period. Then we calculate the value-weighted *SYS* and *RES* components for each portfolio. If systematic momentum exists, we expect the long-short portfolios to yield significantly positive *SYS* in the future.

Table 1 reports the results of 13 spread portfolios sorted by the *SYS* 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 *SYS* signals and is rebalanced every intraday period. The rows labeled SYS (RES) report the annualized *SYS* (*RES*) component 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 *SYS* and *RES* of the spread portfolio sorted by the previous *SYS* signal available at 1600 hours and held from 1600 to 1000 hours each day.

Panel A reports the results based on *SYS* estimated from 15 RP anomalies. In each of the intraday periods, the *SYS* are decisively positive, suggesting a strong systematic momentum. What is striking is that the pattern holds for every intraday period. The spread portfolios are very stable with an average *SYS* ranging from 3.18% for the portfolio held from 1400 to 1430 hours to 11.50% for the portfolio held from 1030 to 1100 hours. Overall, the systematic momentum is relatively stronger during the morning sessions. To have a sense of the systematic momentum through 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 *SYS* of 79.10% is astronomical. In stark contrast, the average annualized *RES* is only 15.96%. Therefore, *SYS* has a much weaker predictability for future stock *RES* component. 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 All-together spread portfolio generates an average *SYS* of 77.12% with a *t*-statistic of 23.95 and *RES* of 16.55% with a *t*-statistic of 9.78.

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 *SYS* of 108.92% compared with 79.10% and 77.12% from previous panels. With more factors, the resulting *SYS* component likely better captures the total systematic component and in turn generates an extra momentum that adds to the already strong momentum based on a smaller anomaly set. On the contrary, PCA-based *SYS* shows a relatively weaker predictive power for the future *RES*, yielding a smaller *RES* spread of 10.22% for the All-together portfolio. Panel D reports the performance of the spread portfolios based on *SYS* estimated from 60 well-known anomalies with LASSO sparse estimators. The results continue to show that the positive predictive power of *SYS* on future stock *SYS* component is robust to different constructions of *SYS*. The LASSO-based *SYS* has an even stronger predictive power. As shown in the last column, the All-together spread portfolio has an average *SYS* of 113.77% with a *t*-statistic of 27.11. Both values are greater than those reported in the other panels.

Table 1. Systematic Momentum

		Return-holding period (hours)													
Start		1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
End	Ret component	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
Panel A: 15 RP anomalies															
	SYS	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															
	SYS	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															
	SYS	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															
	SYS	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)

Notes. This table shows the predictability of *SYS* for future *SYS* and *RES* components of returns. The systematic (*SYS*) and residual (*RES*) components are constructed according to Equations (3) and (4). We form 13 long-short portfolios over a given intraday period based on the *SYS* 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 *SYS* signal in the previous intraday period (i.e., investing in all 13 signals). The row labeled "*SYS*" ("*RES*") report the value-weighted *SYS* (*RES*) component for each long-short portfolio. We report 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 *SYS* 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.

Interestingly, in Panels A and B, lagged systematic return positively and significantly predicts future residual return overnight (e.g., 4.93% and 3.36% annual returns during overnight, respectively, with t-statistics above three) or toward the end of the day. On one hand, this finding is consistent with Bogousslavsky (2021) that institutional constraints and overnight risk incentivize arbitrageurs who trade on mispricing to reduce their positions before the end of the day. As a result, returns of 15 anomalies generated by arbitrager trading during these time intervals are less persistent compared with the returns at the beginning of the day. On the other hand, 15 anomalies may not fully capture the total systematic component of stock returns. Turning to Panels C and D that rely on 60 anomalies to estimated the systematic component, the residual return spreads during overnight and late afternoon sorted by lagged systematic component become much smaller and often statistically insignificant.

3.2. Persistent Systematic Momentum

The holding period of our previous systematic momentum strategies is either overnight or every 30-minute interval during the regular trading hours. Does the systematic 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 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 systematic 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 five days. For each portfolio formation time and each holding horizon k, we form decile portfolios and compute the cumulative *SYS* (*RES*) for each decile portfolio. The spread between the cumulative *SYS* (*RES*) in deciles 1 and 10 then forms a time series of cumulative *SYS* (*RES*) on the spread portfolio constructed by the end of the interval i.

In Table 2, we measure the systematic component using 15 RP anomalies and report for each portfolio formation time (column labeled "Start") the cumulative *SYS* and *RES* in basis points (bps) and Newey-West robust t-statistics of the spread portfolios averaged across all trading days.[16] The columns labeled by numbers

Table 2. Systematic Momentum over Longer Horizon

		Return-holding horizon (in number of intraday periods)								
Start (hours)	Return component	1	2	3	5	8	12	13	39	65
1000	RISK	10.22	13.68	18.41	25.01	29.85	34.62	45.66	63.34	62.66
		(8.53)	(8.46)	(10.09)	(11.91)	(12.59)	(11.79)	(11.22)	(9.42)	(7.35)
	RES	−0.38	−0.86	−0.12	1.26	0.72	0.02	1.91	−4.82	−7.35
		(−0.71)	(−1.18)	(−0.15)	(1.36)	(0.68)	(0.02)	(1.14)	(−1.80)	(−2.25)
1030	RISK	11.50	14.58	16.54	22.57	26.96	40.65	43.95	51.85	53.15
		(12.17)	(11.34)	(10.72)	(12.43)	(12.57)	(10.75)	(10.80)	(7.53)	(6.39)
	RES	0.55	0.04	−0.23	0.30	0.64	4.57	3.78	−4.39	−5.87
		(1.19)	(0.06)	(−0.30)	(0.36)	(0.63)	(2.82)	(2.26)	(−1.69)	(−1.82)
1100	RISK	9.54	14.21	17.11	20.12	23.56	40.98	44.16	54.69	54.12
		(12.17)	(12.58)	(12.86)	(12.49)	(12.55)	(11.39)	(11.72)	(8.00)	(6.10)
	RES	1.04	0.47	0.68	−0.10	−0.91	0.43	−0.34	−6.87	−10.20
		(2.48)	(0.82)	(1.06)	(−0.13)	(−0.94)	(0.27)	(−0.21)	(−2.49)	(−3.09)
1130	RISK	8.56	12.44	14.44	16.54	21.40	37.57	40.03	52.13	64.44
		(12.79)	(13.68)	(12.99)	(12.03)	(11.80)	(10.81)	(10.98)	(7.85)	(7.78)
	RES	0.90	0.26	−0.04	−1.07	−1.19	2.98	2.90	−1.94	−1.68
		(2.63)	(0.54)	(−0.07)	(−1.52)	(−1.33)	(1.96)	(1.85)	(−0.75)	(−0.53)
1200	RISK	5.28	7.57	8.76	9.33	11.97	30.40	31.64	32.70	38.39
		(8.46)	(8.85)	(8.68)	(6.49)	(6.48)	(8.24)	(8.44)	(5.33)	(5.00)
	RES	0.78	0.37	−0.28	−1.05	−2.15	0.16	−0.58	−8.13	−8.00
		(2.43)	(0.81)	(−0.49)	(−1.35)	(−2.05)	(0.10)	(−0.35)	(−3.03)	(−2.51)
1230	RISK	4.37	6.86	8.13	11.31	24.04	31.33	33.79	34.84	33.90
		(8.40)	(9.42)	(8.90)	(8.87)	(8.83)	(9.08)	(9.53)	(5.69)	(4.34)
	RES	0.52	0.43	0.21	−0.17	3.77	2.46	2.26	−6.86	−9.99
		(1.68)	(0.99)	(0.39)	(−0.23)	(2.88)	(1.60)	(1.42)	(−2.61)	(−3.09)
1300	RISK	3.80	5.35	7.09	8.91	16.15	21.96	23.31	25.19	25.62
		(6.97)	(6.70)	(6.97)	(6.61)	(5.14)	(6.13)	(6.37)	(4.21)	(3.19)
	RES	0.66	0.75	0.35	−0.09	1.29	2.16	1.73	−5.22	−10.80
		(2.04)	(1.63)	(0.62)	(−0.12)	(0.90)	(1.32)	(1.05)	(−1.99)	(−3.31)
1330	RISK	3.79	5.97	7.61	10.30	20.54	26.46	27.23	26.39	27.36
		(6.57)	(7.11)	(7.81)	(7.38)	(6.61)	(7.50)	(7.59)	(4.38)	(3.63)
	RES	0.98	0.78	−0.01	−0.58	−0.20	−0.43	−0.60	−4.95	−9.00
		(2.94)	(1.68)	(−0.01)	(−0.74)	(−0.14)	(−0.28)	(−0.38)	(−1.90)	(−2.79)
1400	RISK	3.18	5.04	6.11	15.58	19.17	21.07	21.46	24.41	30.29
		(4.97)	(5.82)	(5.24)	(5.86)	(5.85)	(5.98)	(6.03)	(3.88)	(4.05)
	RES	1.31	1.11	0.87	3.34	3.13	3.08	2.54	−4.02	−5.71
		(3.70)	(2.20)	(1.33)	(2.45)	(1.96)	(1.79)	(1.49)	(−1.48)	(−1.76)
1430	RISK	4.57	8.23	9.52	23.30	27.81	30.01	29.60	19.64	22.92
		(7.25)	(8.67)	(7.26)	(7.74)	(8.05)	(8.05)	(7.84)	(3.12)	(3.01)
	RES	1.23	2.43	2.82	5.10	3.97	2.81	1.84	−11.60	−14.64
		(3.33)	(4.48)	(3.95)	(3.30)	(2.41)	(1.64)	(1.05)	(−4.15)	(−4.30)
1500	RISK	5.70	8.79	11.70	17.31	21.30	22.66	21.68	11.63	17.78
		(8.74)	(8.06)	(4.38)	(5.37)	(5.80)	(5.82)	(5.50)	(1.87)	(2.28)
	RES	1.45	2.11	3.92	3.11	3.02	1.19	−0.13	−11.53	−7.53
		(3.61)	(3.13)	(2.91)	(2.04)	(1.85)	(0.66)	(−0.07)	(−3.89)	(−2.21)
1530	RISK	3.95	13.86	18.98	23.55	27.01	26.53	26.09	23.90	29.95
		(5.40)	(5.77)	(6.87)	(7.36)	(7.70)	(7.05)	(6.91)	(3.81)	(3.87)
	RES	2.17	4.46	3.84	3.47	2.33	−0.40	−2.02	−7.90	−11.98
		(4.98)	(3.51)	(2.80)	(2.34)	(1.43)	(−0.23)	(−1.12)	(−2.90)	(−3.68)
1600	RISK	4.52	9.40	11.48	13.60	14.78	15.84	15.33	5.97	5.11
		(2.57)	(3.86)	(4.40)	(4.70)	(4.63)	(4.72)	(4.47)	(1.03)	(0.71)
	RES	4.16	4.89	4.91	3.33	3.02	1.08	−2.24	−9.70	−8.94
		(3.87)	(3.95)	(3.69)	(2.40)	(2.02)	(0.67)	(−1.32)	(−3.55)	(−2.76)
Mean	RISK	6.07	9.69	11.99	16.73	21.89	29.24	31.07	32.82	35.82
		(8.08)	(8.49)	(8.24)	(8.40)	(8.35)	(8.26)	(8.26)	(5.09)	(4.44)
	RES	1.18	1.33	1.30	1.30	1.34	1.55	0.85	−6.76	−8.59
		(2.63)	(1.74)	(1.21)	(0.78)	(0.79)	(0.95)	(0.52)	(−2.48)	(−2.62)

Notes. This table decomposes the event-time return (with different portfolio formation time and holding period) into systematic (*SYS*) and residual (*RES*) components according to Equations (4) and (5), and reports the cumulative return of the two components as annualized percentages with Newey and West (1987) robust *t*-statistics in parentheses. The column labeled "Start" indicates when the portfolios are formed. The portfolios are held with a different number of intraday periods ranging from 1 to 65, as shown in the columns. The row labeled "Mean" reports the average return and *t*-statistic across different signal times. The results are based on *SYS* estimated from 15 RP anomalies. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

indicate the number of intraday periods the portfolios are held. For instance, the cell with the row and column labeled 1030 and 12 corresponds to the portfolio formed at 1030 and held for 12 periods until 1000 hours 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. First, the average cumulative *SYS* of the systematic momentum portfolios generally increases as we extend the holding horizon to 65 intraday periods (five days). For example, the row labeled "Mean" reports the average *SYS* of the systematic momentum portfolios constructed at different times of the day. The cumulative *SYS* monotonically increases from 6.07% for a one-intraday holding period to 35.82% for a five-day holding period.

Second, the systematic component continuation is stronger during the morning sessions than the afternoon sessions, and the contrast is more prominent for longer holding periods. For instance, for the systematic momentum with a holding horizon of 13 intraday periods, the cumulative *SYS* decreases from 45.66% with a *t*-statistic of 11.22 for a portfolio formed at 1000 hours to 15.33% bps with *t*-statistic of 4.47 for a portfolio formed at 1600 hours. Such pattern is consistent with the earlier results in Table 1 that the one-period *SYS*s are greater in the mornings than in the afternoons. Third, *SYS* has no predictive power for future *RES* component of the systematic momentum portfolios even for longer periods. As shown in the last two rows, the cumulative *RES* decreases from 1.18% for a portfolio held for one intraday period to 0.85% for a portfolio held for one day, and it even becomes negative when the portfolio is held for three or five days.

To have a better sense of how cumulative *SYS* gradually evolves between day 1 and day 5, we plot in Figure 1 the average cumulative *SYS* of the systematic momentum strategies (using 15 RP anomalies) and their 95% confidence intervals against event time. In Figure 1(a), we present cumulative *SYS* averaged across spread portfolios formed at different times, the same as the values reported in row Mean of Table 2. We find that immediately after the portfolio formation, the cumulative *SYS* gradually increases to 12.33 bps after 13 periods, then slowly goes up to 14.22 bps after five days.

To further investigate the intraday pattern of systematic momentum, we separately plot the average *SYS* of portfolios that are formed in the morning (from 1000 to 1230 hours) and afternoon (from 1300 to 1600 hours) in (b) and (c) of Figure 1, respectively. Strikingly, the persistence of *SYS* momentum highly depends on the portfolio formation time. From Figure 1(b), the cumulative *SYS* of the momentum formed in the morning constantly increases to 16 bps after 13 periods and continues to rise to 20.2 bps until 65 periods. However, Figure 1(b) exhibits a relatively weaker and less persistent *SYS* momentum formed in the afternoon. The cumulative *SYS* only increases to 9.5 bps after 13 periods; it quickly reverts to 7.8 bps after 18 periods and stays around 8 bps until five days. The sharply different momentum patterns are consistent with the finding that investors behave differently toward the end of the day (Cushing and Madhavan 2000, Foucault et al. 2005, Bogousslavsky 2021). Later in Section 4.2, we present further evidence showing that the stronger systematic momentum in the morning sessions can be explained by increased overall arbitrageur participation early in the day.

3.3. Source of Systematic Momentum

To understand the source of the systematic momentum, we follow Lo and MacKinlay (1990) by decomposing profits of systematic momentum into three components: the average autocovariance of individual stock *SYS*, the average cross-serial covariance across stocks, and the cross-sectional variance (mean effect) in the expected stock *SYS*. Specifically, this method constructs trading strategies in which the weights are proportional to stocks' *SYS* on d in intraday period i. The investment in stock s is proportional to its *SYS* relative to the other stocks in the cross section:

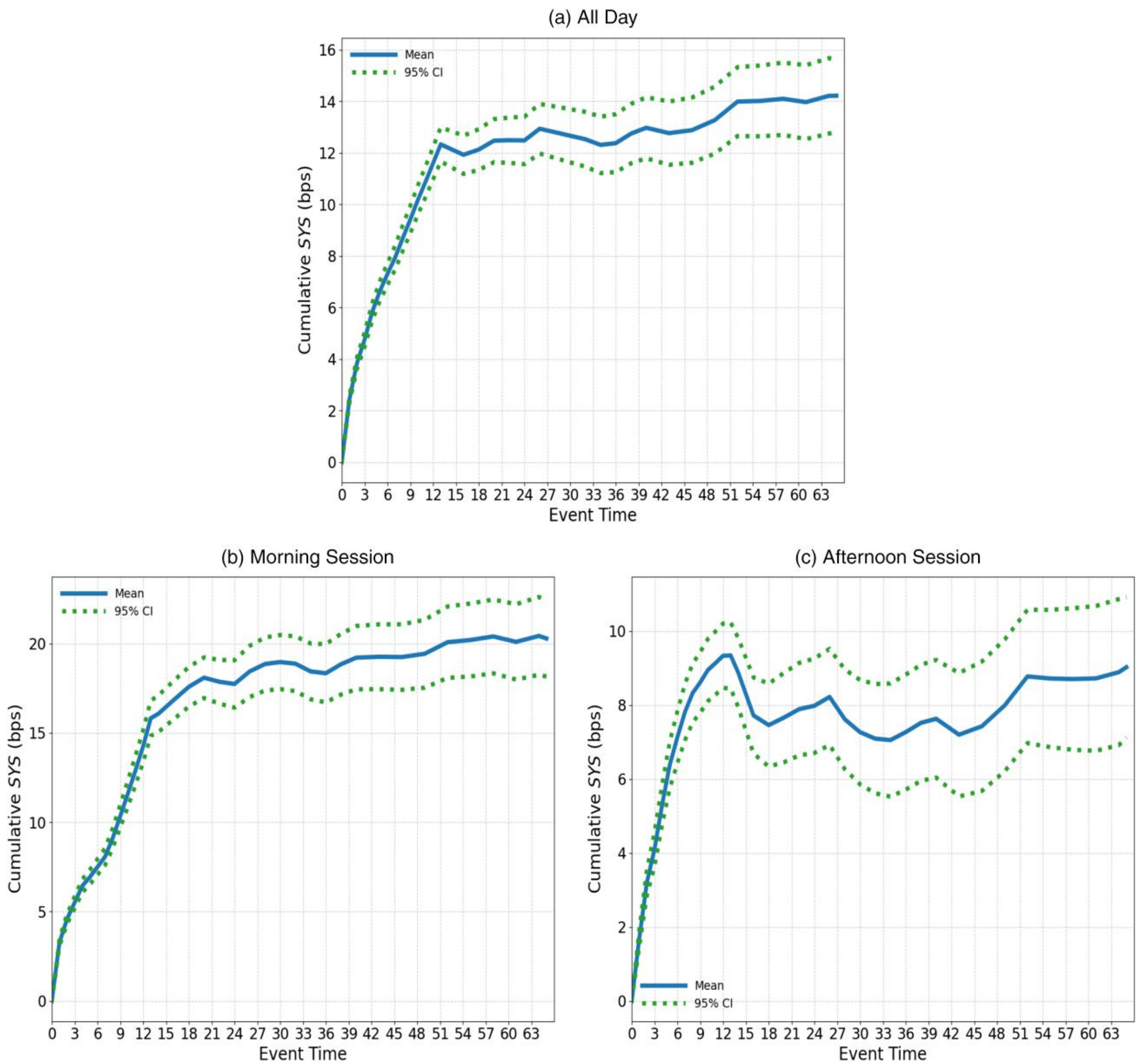
$$w_{s,d,i} = \frac{1}{N}(SYS_{s,d,i} - \overline{SYS}_{d,i}), \tag{6}$$

where $\overline{SYS}_{d,i}$ is the cross-sectional average of the N stocks in the cross section. Let $\pi_{d,i+1} = \sum_N w_{s,d,i} \cdot SYS_{s,d,i+1}$ denote the profit on systematic momentum portfolio on day d in period $I+1$. Then, following Lo and MacKinlay (1990), the expected profit is naturally decomposed into three separate terms:

$$\mathrm{E}(\pi_{d,i+1}) = \frac{N-1}{N^2}\mathrm{tr}(\Gamma) - \frac{1}{N^2}(1'\Gamma 1 - \mathrm{tr}(\Gamma)) + \sigma_\mu^2, \tag{7}$$

where $\Gamma = \mathrm{E}[(SYS_{s,d,i} - \mu)(SYS_{s,d,i+1} - \mu)']$ is the autocovariance matrix of stock *SYS* on day d in period $I+1$, $\mathrm{tr}(\cdot)$ is the trace of a matrix, and σ_μ^2 is the cross-sectional variance of mean stock *SYS* on day d in period $I+1$. The first term, $(N-1)\mathrm{tr}(\Gamma)/N^2$, captures the serial correlation in an individual stock *SYS*: A positive value would imply a positive average of *SYS* in a strategy that buys winners and sells losers conditional on the past *SYS*. The second term, $-(1'\Gamma 1 - \mathrm{tr}(\Gamma))/N^2$, reflects the lead-lag effects across stocks: a positive value would imply a negative average of *SYS* to systematic momentum. The third term, σ_μ^2, measures the dispersion in expected *SYS* across stocks; if firms with positive *SYS* on average have higher expected *SYS*, systematic momentum could be profitable due to the difference in expected individual stock *SYS*.

Figure 1. (Color online) Systematic Momentum



Notes. This figure plots the cumulative systematic component (*SYS*) of the momentum strategy based on the systematic signal constructed from the 15 RP anomalies and their 95% confidence intervals for each event time. The cumulative *SYS* is calculated by compounding all hold-period systematic components derived according to Equation (4). Each trading day is divided into 13 intraday periods, including one overnight period from 1600 hours on day $d-1$ to 1000 hours 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. (a) Cumulative return averaged across all 13 formation periods. (b) and (c) Cumulative return averaged from portfolios that are formed in the morning (from 1000 to 1230 hours) and afternoon (from 1300 to 1600 hours) sessions, respectively. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

The decomposition results reported in Table 3 indicate that the majority of the systematic momentum profit comes almost entirely from the positive autocovariance of individual stocks.[17] We estimate standard errors for all decompositions by bootstrapping the data by month. For example, Panel A shows that, for the All-together strategy based on 15 RP anomalies, the total *SYS* component is 109.05% and the autocovariance component is 105.06%, indicating that the autocovariance component explains 96.34% of the holding-period *SYS*. Similar conclusions hold for the remaining panels based on different anomaly sets. Thus, the systematic momentum is driven primarily by the positive autocovariance in individual stock *SYS*.

According to Equation (4), *SYS* is the total systematic component 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 ($\hat{\theta}_{d,i,j}$), with the product denoted by $\hat{\Theta}_{d,i,j}$. Therefore, we can further decompose the autocovariance in individual stock *SYS* into two parts:

$$\begin{aligned} \mathrm{Cov}(SYS_{s,d,i}, SYS_{s,d,i+1}) &= \mathrm{Cov}\left(\sum_{j=1}^{p}\hat{\Theta}_{d,i,j}, \sum_{m=1}^{p}\hat{\Theta}_{d,i+1,m}\right) \\ &= \sum_{j=1}^{p}\sum_{m=1}^{p}\mathrm{Cov}(\hat{\Theta}_{d,i,j}, \hat{\Theta}_{d,i+1,m}) \\ &= \sum_{j=1}^{p}\mathrm{Cov}(\hat{\Theta}_{d,i,j}, \hat{\Theta}_{d,i+1,j}) \\ &\quad + \sum_{j\neq m}\sum \mathrm{Cov}(\hat{\Theta}_{d,i,j}, \hat{\Theta}_{d,i+1,m}) \\ &= \mathrm{AutoCov} + \mathrm{CrossCov}, \end{aligned} \tag{8}$$

where *AutoCov* captures the autocovariance of *SYS* explained by the same factor, and *CrossCov* captures the autocovariance of *SYS* driven by cross-serial covariance among different factors. As such, the positive values of both parts could increase the autocovariance of stock *SYS*. Similarly, we can also decompose the autocorrelation of stock *SYS* into two parts:

$$\begin{aligned} \mathrm{Corr}(SYS_{s,d,i}, SYS_{s,d,i+1}) &= \frac{\mathrm{Cov}(SYS_{s,d,i}, SYS_{s,d,i+1})}{\mathrm{Std}(SYS_{s,d,i})\mathrm{Std}(SYS_{s,d,i+1})} \\ &= \frac{\mathrm{AutoCov} + \mathrm{CrossCov}}{\mathrm{Std}(SYS_{s,d,i})\mathrm{Std}(SYS_{s,d,i+1})} \\ &= \mathrm{Auto} + \mathrm{Cross}. \end{aligned} \tag{9}$$

We calculate the *Auto* and *Cross* for each individual stock and average the two measures across all stocks. Figure 2, (a) and (b), displays the results based on 15 RP and 15 EL anomalies, respectively. The x axis labels the starting time of the leading variable. For example, 1000 hours shows the correlation between overnight (1600 to 1000 hours) and the first-half hour (1000 to 1030 hours) components. The two figures exhibit similar patterns. The average *Auto* and *Cross* are 3.709% and 3.714%, respectively, when constructing *SYS* based on 15 RP anomalies. The corresponding numbers are 4.632% and 2.320%, respectively, for 15 EL anomalies. Therefore, both *Auto* and *Cross* contribute substantially to the continuation of individual stock *SYS*.[18] As a result, systematic momentum is expected to be stronger and more robust than factor momentum. This is because factor momentum solely bets on the factor autocorrelation, whereas the positive lead-lag relationship among factors actually contributes *negatively* to factor momentum.

Our *SYS* not only effectively captures both positive relationship effects but also measures them as a whole. In particular, when the explanatory power of factors fluctuates over time, it becomes challenging to disentangle these two effects. However, by constructing *SYS* using a large set of anomalies via LASSO, we can easily tackle this problem and capitalize on the overall momentum effect. Furthermore, the *Auto* component spikes at the market open and gradually decreases, eventually reaching a negative value by market close. In contrast, the *Cross* component begins with the lowest value at market opening and then remains stable around 4%, exhibiting a dominant role near the market close.

To investigate the contribution of each individual factor, we further decompose the total autocovariance of individual stock *SYS* into its components in Figure 3. Specifically, for each individual factor j, we calculate its $AutoCov_j = Cov(\hat{\Theta}_{d,i,j}, \hat{\Theta}_{d,i+1,j})$ and $CrossCov_j = \sum_{m\neq j} Cov(\hat{\Theta}_{d,i,j}, \hat{\Theta}_{d,i+1,j})$. Finally, we normalize all covariance by dividing them by $\mathrm{Std}(SYS_{s,d,i})\mathrm{Std}(SYS_{s,d,i+1})$. Figure 3(a) presents the results based on 15 RP anomalies. Evidently, "Beta" is the most important factor to systematic momentum, resulting in highest Auto and Cross values. Therefore, Beta factor exhibits the greatest autocorrelation and largely leads other factors. Additionally, Gross profitability and Distress factors also show substantial autocorrelation and lead other factors. Investment-to-assets contributes the second most to Cross. In contrast, the Size factor negatively contributes to systematic momentum.[19]

Figure 3(b) displays the results based on 15 EL anomalies, revealing findings similar to those in Figure 3(a). We consistently find Beta as the leading factor, contributing the most to both Auto and Cross. Profitability, Earnings to price, and Investment also make significant contributions to systematic momentum, because they are largely autocorrelated and tend to lead other factors. However, Long-term reversals and Size negatively contribute to systematic momentum. Interestingly, both panels indicate that Momentum and Reversal contribute little to the systematic momentum.

In sum, our systematic momentum captures the overall lead-lag relationship of the *total* systematic component of individual stocks and thus is distinct from the factor momentum of Ehsani and Linnainmaa (2022), which solely bet on the factor autocorrelation. Furthermore, a positive cross-serial relationship among factors negatively impacts the cross-sectional factor momentum (Ehsani and Linnainmaa 2022, Arnott et al. 2023), whereas the systematic momentum takes advantage of the positive cross-sectional lead-lag effect.[20]

3.4. Systematic Return Momentum

Thus far, we have shown a strong systematic momentum intraday, which is driven by both the autocorrelation in individual factors and the cross-serial lead-lag among different factors. However, we cannot trade on the *SYS* component. To investigate the economic gain of systematic momentum, we construct a similar but tradable systematic return momentum resulted from sorting stocks by their past systematic components, as described in Section 2.2.

Table 3. *SYS* Component Decomposition

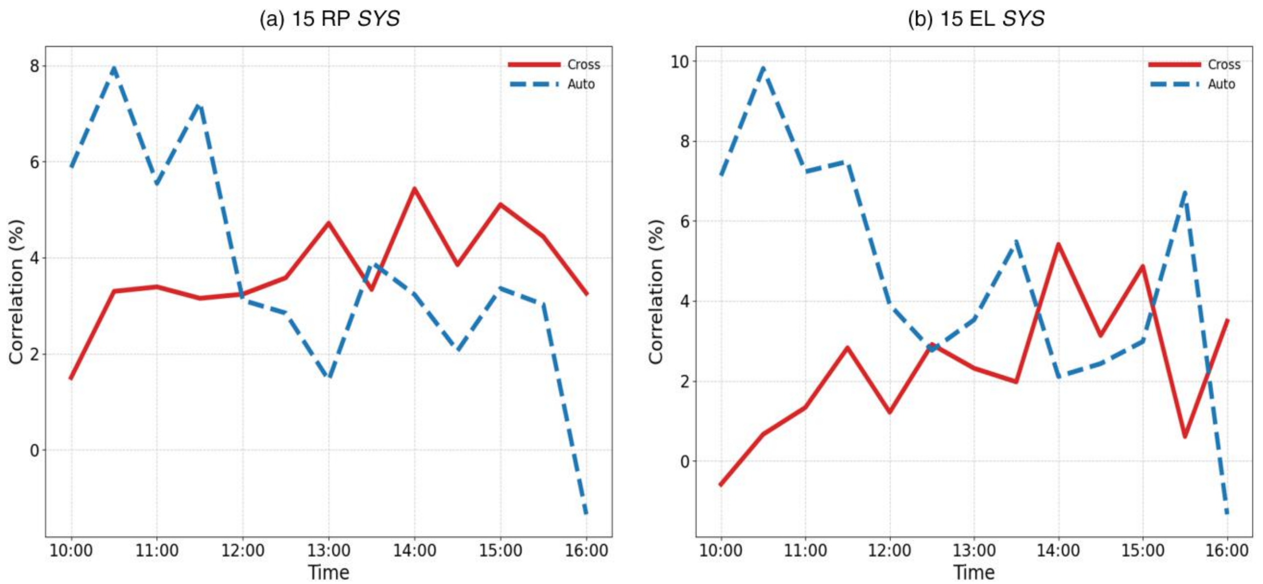
	Return-holding period													
Start	1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
End	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
Panel A: 15 RP anomalies														
Total	13.30	12.66	13.52	12.96	9.10	7.64	5.63	4.17	3.41	4.24	6.28	8.05	6.06	109.05
	[3.53]	[2.10]	[1.56]	[1.34]	[1.02]	[1.01]	[0.68]	[0.86]	[0.85]	[0.88]	[1.05]	[1.09]	[1.29]	[12.50]
Auto	14.73	11.47	12.90	11.93	7.99	6.93	5.28	3.43	3.70	2.88	5.85	8.53	6.66	105.06
	[4.43]	[2.54]	[1.74]	[1.42]	[1.21]	[1.12]	[0.82]	[0.92]	[1.01]	[1.12]	[1.33]	[1.47]	[1.53]	[14.24]
Cross	−2.02	1.84	0.54	0.94	1.06	0.68	0.33	0.72	−0.30	1.35	0.41	−0.52	−0.59	3.98
	[2.63]	[1.34]	[0.98]	[0.97]	[1.03]	[0.57]	[0.54]	[0.55]	[0.60]	[0.86]	[0.75]	[1.19]	[1.11]	[6.63]
Dispersion	0.59	−0.64	0.07	0.09	0.05	0.04	0.02	0.02	0.00	0.02	0.02	0.05	−0.01	0.00
	[0.22]	[0.17]	[0.10]	[0.05]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]	[0.03]	[0.04]	[0.04]	[0.05]	[0.09]
Panel B: 15 EL anomalies														
Total	12.35	12.34	12.83	12.88	9.12	7.24	5.72	4.08	3.23	3.71	5.72	7.97	5.75	105.08
	[3.47]	[2.17]	[1.52]	[1.38]	[1.02]	[1.00]	[0.68]	[0.90]	[0.79]	[0.89]	[1.00]	[1.04]	[1.28]	[12.17]
Auto	13.23	11.42	12.18	11.73	8.04	6.64	5.28	3.10	3.71	2.29	5.38	8.18	5.94	99.35
	[4.37]	[2.69]	[1.79]	[1.39]	[1.21]	[1.09]	[0.78]	[1.00]	[0.97]	[1.21]	[1.33]	[1.49]	[1.52]	[14.04]
Cross	−1.26	1.77	0.58	1.06	1.03	0.56	0.42	0.96	−0.48	1.40	0.31	−0.27	−0.20	5.76
	[2.76]	[1.41]	[1.07]	[1.03]	[1.01]	[0.55]	[0.51]	[0.62]	[0.60]	[0.87]	[0.75]	[1.17]	[1.01]	[6.75]
Dispersion	0.39	−0.85	0.07	0.08	0.05	0.03	0.02	0.01	0.00	0.03	0.03	0.07	0.00	−0.02
	[0.23]	[0.19]	[0.11]	[0.05]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]	[0.03]	[0.04]	[0.04]	[0.05]	[0.09]
Panel C: 60 anomalies via PCA														
Total	16.38	13.17	14.94	14.38	10.37	9.61	7.57	6.01	4.77	6.01	8.59	10.51	8.53	133.60
	[3.79]	[2.10]	[1.69]	[1.55]	[1.23]	[1.15]	[0.91]	[1.04]	[0.93]	[1.14]	[1.12]	[1.26]	[1.32]	[14.00]
Auto	15.43	12.58	13.95	13.02	9.13	8.44	6.94	4.61	5.20	4.18	6.87	8.61	6.65	118.56
	[4.64]	[2.67]	[1.73]	[1.57]	[1.30]	[1.23]	[1.04]	[1.04]	[0.92]	[1.28]	[1.35]	[1.53]	[1.61]	[16.32]
Cross	0.59	1.48	0.90	1.29	1.20	1.15	0.61	1.38	−0.42	1.77	1.69	1.83	1.83	15.00
	[2.83]	[1.60]	[1.06]	[1.04]	[1.13]	[0.65]	[0.60]	[0.70]	[0.64]	[0.87]	[0.82]	[1.31]	[1.13]	[7.58]
Dispersion	0.36	−0.89	0.09	0.07	0.04	0.02	0.01	0.03	0.00	0.06	0.02	0.07	0.05	0.04
	[0.19]	[0.20]	[0.13]	[0.05]	[0.03]	[0.03]	[0.03]	[0.03]	[0.02]	[0.05]	[0.06]	[0.05]	[0.05]	[0.10]
Panel D: 60 anomalies via LASSO														
Total	17.03	14.26	15.68	15.45	10.40	9.57	7.51	5.89	5.18	6.26	8.98	11.05	8.31	138.40
	[4.09]	[2.05]	[1.75]	[1.59]	[1.12]	[1.14]	[0.85]	[1.00]	[1.00]	[1.13]	[1.23]	[1.27]	[1.40]	[14.04]
Auto	19.38	13.66	14.84	14.37	9.09	8.69	7.15	4.50	5.64	4.45	7.89	10.88	7.89	132.00
	[4.96]	[2.48]	[1.80]	[1.61]	[1.34]	[1.24]	[0.96]	[1.05]	[1.13]	[1.38]	[1.52]	[1.65]	[1.62]	[15.88]
Cross	−2.76	1.31	0.74	1.02	1.25	0.84	0.35	1.38	−0.47	1.75	1.04	0.10	0.41	6.35
	[3.06]	[1.51]	[1.14]	[1.04]	[1.16]	[0.67]	[0.58]	[0.66]	[0.64]	[0.95]	[0.95]	[1.35]	[1.25]	[7.37]
Dispersion	0.40	−0.71	0.10	0.06	0.06	0.04	0.01	0.01	0.00	0.07	0.04	0.07	0.00	0.06
	[0.19]	[0.18]	[0.11]	[0.06]	[0.03]	[0.04]	[0.03]	[0.02]	[0.02]	[0.05]	[0.07]	[0.05]	[0.05]	[0.11]

Notes. This table reports the three components of the Lo and MacKinlay (1990) decomposition of the holding-period *SYS* from the systematic momentum strategy. The row labeled "Total" denotes the total holding-period *SYS*; "Auto" is the first component attributable to the autocovariance of *SYS*; "Cross" is the second component attributable to the cross-autocovariance; and "Dispersion" is the third component representing the dispersion in expected *SYS* captured by past average *SYS*. Standard errors are reported in parentheses. We compute standard errors by bootstrapping the data by month. Panels A, B, C, and D report the results based on *SYS* 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.

Table 4 reports the performance of 13 spread portfolios sorted by the *SYS* 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 *SYS* signals and is rebalanced every intraday period. Panels A–D show the results of the systematic return momentum constructed from four different sets of anomalies. The results indicate that, regardless of the choice of anomaly sets, the lagged *SYS* can positively predict future stock return. For example, the last column labeled All shows that under the four different *SYS* specifications, the lagged *SYS* component generates a stellar annualized future return of 95.06%, 93.67%, 119.14%, and 125.21%, respectively. Additionally, the results are robust after accounting for market risk, as shown in the Alpha rows.[21]

Thus, we discover a strong systematic return momentum intraday. Yet 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,

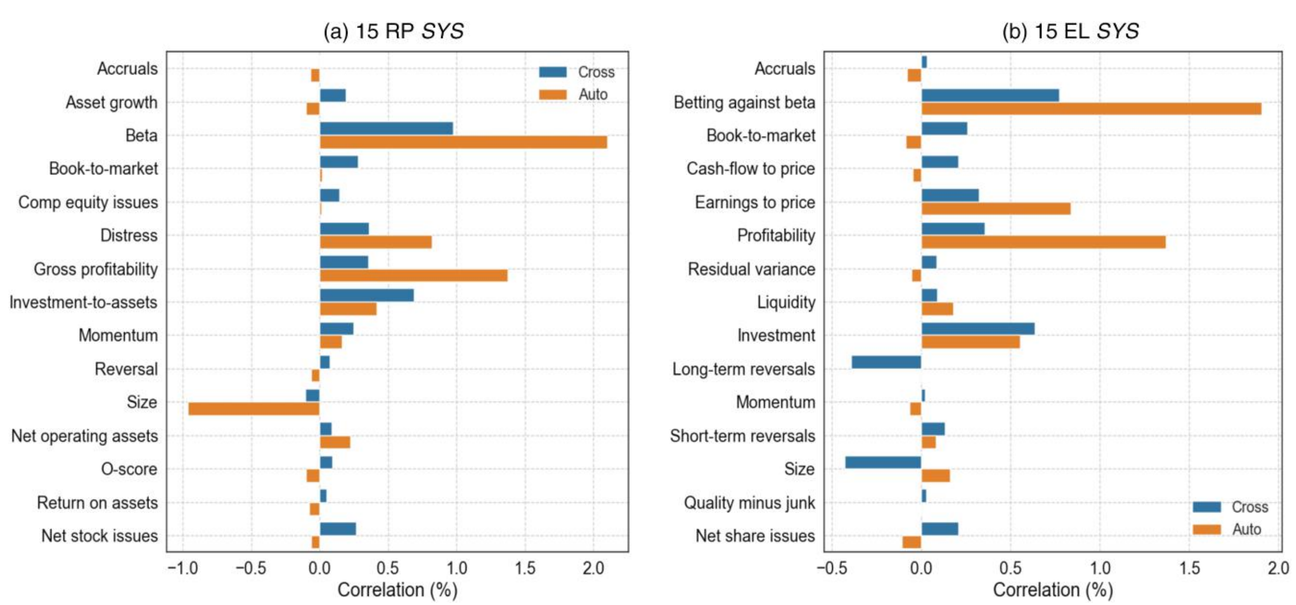
Figure 2. (Color online) Decomposing Autocorrelation of Individual Stock *SYS*



Notes. This figure displays the intraday variation in the two components of the autocorrelation of stock *SYS* based on Equation (9). The *Auto* component captures the autocorrelation of *SYS* explained by the same factor, and the *Cross* component captures the autocorrelation of *SYS* explained by the cross-serial correlation among different factors. (a) and (b) Results based on 15 RP anomalies and 15 EL anomalies, respectively. The x axis denotes the starting time of the leading variable. For example, time 1000 hours shows the correlation between overnight (1600 to 1000 hours) and the first-half hour (1000 to 1030 hours) components. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

and the return may evaporate after trading costs.[22] What we show here is simply the return patterns on the systematic return 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 9 in Section 5.3, our systematic return momentum also extends to the monthly frequency with an annual alpha around 20%, and such high value would easily

Figure 3. (Color online) Decomposing Autocorrelation of Individual Stock *SYS* into Individual Factors



Notes. This figure illustrates the contribution of individual factors to the autocorrelation of stock *SYS* based on Equation (9). The *Auto* component captures the contribution of the autocorrelation of each individual factor to the overall autocorrelation of stock *SYS*, whereas the *Cross* component reflects the contribution of the lead-lag relationships between each individual factor and other factors to the overall autocorrelation of stock *SYS*. (a) and (b) Results based on 15 RP anomalies and 15 EL anomalies, respectively. The sample includes all stocks in the Russell 1000 index from January 1993 to December 2020.

Table 4. Systematic Return Momentum

	Return-holding period													
Start	1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
End	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
	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)

Notes. This table reports the performance of 13 long-short portfolios over a given intraday period based on the *SYS* 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 *SYS* 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 *SYS* 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.

survive typical transaction costs, with a net-cost Sharpe ratio of 0.62. The other columns corresponding to 13 different intraday holding periods further confirm the pervasive systematic return momentum effect.[23]

To shed light on the systematic return momentum over longer horizons, we increase the holding periods to up to five days and compute holding-period returns following an event study approach. In Table A.8 in the Online Appendix, we measure the systematic 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. Table A.8 reveals that the average cumulative return of the systematic return momentum portfolios generally increases as we extend the holding horizon to 13 intraday periods (one day), and it declines afterward yet remains positive and significant for up to 65 intraday periods (five days). Therefore, the systematic return momentum is persistent and robust to different portfolio formation times as shown in other rows.

In summary, we find that the systematic spread portfolios exhibit strong return momentum beyond one intraday period, and such systematic return momentum is driven by the continuation of the systematic component itself. In the next section, we offer further explanations on the systematic momentum.

4. Explanation

From Section 3.3, both the autocorrelation of anomaly factors and the cross-serial lead-lag among different factors contribute to the momentum in *SYS*. We consider limits to arbitrage as the explanation for both drivers. According to Stambaugh and Yuan (2016), anomalies in part reflect mispricing, which has common components across stocks. Further, Engelberg et al. (2018) document evidence supporting the idea that anomaly returns arise from biased expectations. As a result, arbitrageurs who aim to correct their biased expectations may engage in trading multiple anomalies, thereby realizing returns on various anomalies. However, because of limits to arbitrage, arbitrageurs may trade on the perceived mispricing gradually instead of eliminating mispricing all at once, and such gradual trading can result in persistent returns on the same anomaly or lead-lag relationship among different anomalies. In this section, we formally examine how the degree of arbitrageur participation and limits to arbitrage affects the systematic momentum.

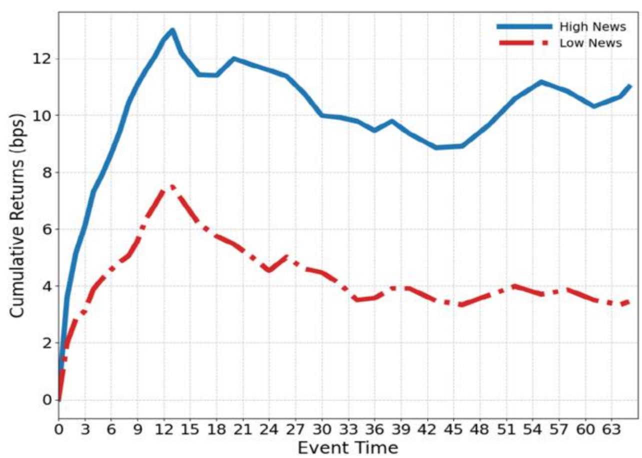
4.1. News Effect

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 et al. (2018) find that anomaly returns are much higher on earnings announcement days, consistent with the notion that mispricing is driven by biased expectations that 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 systematic return momentum upon news arrival.

To empirically test this idea, we investigate the performance of our systematic return 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.[24] Following the standard practice of the literature, we only keep fundamental news that is most fresh and relevant to a particular company.[25] 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 systematic signals based on the 15 RP anomalies throughout this section.

We examine the effect of firm news on our systematic return 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 systematic return momentum strategies conditional on whether the news arrival in the signal formation period is above or below the median. Figure 4 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

Figure 4. (Color online) Systematic Return Momentum: News Arrivals



Notes. This figure plots the cumulative returns of the momentum strategy based on *SYS* 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 1600 hours on day $d-1$ to 1000 hours 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.

distinct difference between the systematic return momentum performance conditional on high and low news arrival. For example, the systematic return 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 systematic return 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 total systematic component and stronger systematic return momentum.

4.2. Aggregate IVOL

The recent literature has emphasized the important role of IVOL in affecting asset prices. Garcia et al. (2014) argue that aggregate IVOL is related to consumption volatility, a measure of economic uncertainty in the intertemporal asset pricing model of Bansal and Yaron (2004). Motivated by these studies, we conjecture that our systematic return momentum is also stronger during high aggregate IVOL periods due to limits to arbitrage. Specifically, high IVOL increases the implementation

Table 5. Systematic Return Momentum over Different Return Dispersion Periods

		Return-holding period													
	Start	1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
RD	End	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
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)

Notes. This table reports the performance of the systematic return momentum over high and low return dispersion periods. Each trading day is divided into 13 intraday periods, including one overnight period from 1600 hours on day $d-1$ to 1000 hours 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 *SYS* 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.

costs of short arbitrage, leading to a slower responsiveness of arbitrage capital to mispricing.[26] The greater limits to arbitrage they face will render more gradual mispricing correction and thus enhance the performance of the systematic return momentum strategy.

To verify our conjecture, we follow Garcia et al. (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 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 5 reports the results for the momentum strategies during high and low RD periods formed by different *SYS* signals. Interestingly, although the systematic return momentum exists in both high and low RD periods, the effect is much stronger during the high RD period. Across Panels A–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, respectively. 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 systematic return momentum exists during periods with elevated aggregate IVOL.

In earlier sections, we documented a stronger systematic return 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 A.3 in the Online Appendix, 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 1000 hours, monotonically decreases to 0.38% at 1330 hours, 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 systematic return momentum in the morning in addition to the clientele effect.[27]

4.3. Market-Wide Sentiment

Stambaugh et al. (2012) find that overpricing is more pronounced than underpricing due to short-sale impediments and market anomalies are stronger following high levels of sentiment. If systematic return momentum is related to gradual correction of mispricing due to limits-to-arbitrage, then we should also observe stronger momentum effect following high-sentiment period.[28]

We measure investor sentiment using the monthly market-based sentiment series constructed by Baker and Wurgler (2006). we first compute the time series median of investor sentiment. Then, we calculate the performance of systematic momentum following high (i.e., above median) and low (i.e., below median) market-wide sentiment periods.

Table 6 reports the results for the momentum strategies during high and low sentiment periods formed by different *SYS* signals. Evidently, the systematic return momentum exists in both high and low sentiment periods, but the effect is much pronounced during the high sentiment period. Across Panels A–D, the All-together spread portfolio during high sentiment periods delivers an annualized return of 126.78%, 125.77%, 170.78%, and 164.55%, more than double the annualized return of 66.91%, 64.62%, 86.10%, and 82.08%, respectively, during low sentiment periods. The returns on the spread portfolios during high sentiment periods are highly statistically significant with *t*-statistics all above 21. The higher momentum during high sentiment periods is also robust to all intraday holding periods. In sum, the results lend strong support to our conjecture that a stronger systematic return momentum exists during periods with high market-wide sentiment.

4.4. Systematic Risk Concentration and Limits to Arbitrage

Thus far, we have shown that systematic momentum potentially arises from the gradual correction

Table 6. Systematic Return Momentum over Different Market-Wide Sentiment Periods

		Return-holding period													
	Start	1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
Sent	End	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
Panel A: 15 RP anomalies															
High		15.93	13.58	16.47	14.11	11.23	8.47	5.84	5.64	4.81	6.16	7.79	8.72	8.15	126.78
		(4.26)	(7.10)	(10.40)	(10.12)	(9.48)	(8.19)	(6.20)	(5.33)	(4.45)	(4.82)	(6.32)	(6.29)	(5.43)	(21.52)
Low		5.39	5.98	7.40	7.31	7.88	3.87	3.71	2.64	4.93	2.39	4.51	6.37	4.33	66.91
		(1.39)	(2.97)	(4.20)	(4.71)	(6.20)	(3.28)	(3.81)	(2.75)	(4.43)	(2.21)	(3.60)	(5.24)	(3.13)	(11.06)
Panel B: 15 EL anomalies															
High		15.38	13.22	15.82	13.58	11.35	8.94	6.28	6.36	4.95	5.37	7.87	8.35	8.33	125.77
		(4.25)	(6.89)	(10.05)	(10.01)	(10.00)	(8.53)	(6.94)	(6.05)	(4.50)	(4.36)	(6.65)	(6.30)	(5.61)	(21.81)
Low		4.87	4.21	7.95	7.91	8.20	3.08	3.63	2.93	4.58	1.83	4.29	6.85	4.38	64.62
		(1.22)	(2.02)	(4.43)	(5.10)	(6.30)	(2.39)	(3.70)	(2.91)	(4.04)	(1.63)	(3.36)	(5.54)	(3.13)	(10.40)
Panel C: 60 anomalies via PCA															
High		24.16	15.83	19.31	17.35	13.11	11.39	8.92	8.55	7.87	8.80	12.05	11.91	10.77	170.78
		(5.35)	(7.44)	(10.60)	(10.79)	(9.74)	(8.63)	(7.63)	(6.53)	(5.90)	(5.63)	(7.88)	(7.19)	(5.74)	(24.06)
Low		7.56	7.55	9.53	8.72	8.84	5.82	5.36	3.49	6.08	3.12	5.65	7.68	6.50	86.10
		(1.72)	(3.43)	(4.79)	(5.11)	(6.21)	(4.42)	(4.74)	(3.15)	(5.02)	(2.50)	(3.97)	(5.82)	(3.99)	(12.66)
Panel D: 60 anomalies via LASSO															
High		21.79	15.46	18.96	16.24	13.39	11.19	8.67	9.45	6.51	8.56	11.13	11.09	11.61	164.55
		(4.89)	(7.39)	(10.08)	(9.99)	(9.27)	(8.58)	(7.62)	(6.90)	(4.75)	(5.50)	(7.13)	(6.68)	(6.58)	(23.32)
Low		6.81	5.49	8.47	8.94	8.72	5.43	5.50	3.17	6.14	3.09	5.73	8.19	6.20	82.08
		(1.53)	(2.56)	(4.45)	(5.17)	(6.25)	(4.00)	(4.67)	(2.90)	(4.88)	(2.39)	(3.94)	(6.14)	(3.70)	(12.04)

Notes. This table reports the performance of the systematic return momentum over high and low market sentiment periods. Each trading day is divided into 13 intraday periods, including one overnight period from 1600 hours on day $d-1$ to 1000 hours on day d and 12 half-hour periods. We measure investor sentiment using the monthly market-based sentiment series constructed by Baker and Wurgler (2006). The row labeled "High" ("Low") corresponds to the sample period with above (below) median level of the market-wide sentiment. Newey and West (1987) robust *t*-statistics are reported in parentheses. Panels A, B, C, and D report the results based on *SYS* 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.

of mispricing due to limits to arbitrage. As such, we expect that stocks facing greater constraints on systematic trading exhibit stronger systematic momentum. Importantly, Kozak et al. (2018) demonstrate that when mispricing does not align with covariances, arbitrageurs can trade the mispricing aggressively without assuming any systematic risk; only those mispricings that align with covariances persist. Therefore, arbitrageurs who want to avoid systematic risk may not trade aggressively to neutralize the momentum effect. In other words, although risk-averse arbitrageurs may recognize that systematic components are predictable, the high systematic risk associated with such stocks reduces their incentive to trade aggressively on the mispricing, as doing so would expose them to systematic risk. Thus, we would expect the systematic return momentum to be stronger among stocks with high systematic risk concentration.

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

$$RiskCon_{s,d,i} = SYS^2_{s,d,i}/RET^2_{s,d,i}, \qquad (10)$$

where $SYS_{s,d,i}$ and $RET_{s,d,i}$ are the systematic component and the total return of stock s in interval i on day d, respectively.[29] A higher value of $RiskCon_{s,d,i}$ indicates stock s has more systematic risk concentration by the end of intraday period i on day d.

We next test the impact of systematic risk concentration on the systematic return momentum as follows. By the end of each intraday period, we sort stocks into quintile portfolios on the basis 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 *SYS* decile and shorts stocks in the bottom *SYS* decile, and we hold the spread portfolio over the subsequent intraday period.

Table 7 reports the portfolio returns formed by low or high systematic risk-concentration stocks based on different anomaly sets in Panels A–D. Strikingly, the high systematic risk-concentration stocks produce an even stronger systematic return momentum universally, whereas the low risk-concentration stocks generate a 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 185.65%, about 50%–60% higher than the return between 95.06% and 125.21% based on the full sample in Table 4. In contrast, the spread portfolio

Table 7. Systematic Return Momentum Conditional on Risk Concentration

		Return-holding period													
	Start	1600	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	
RiskCon	End	1000	1030	1100	1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	All
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)

Notes. This table reports the performance of systematic return momentum for Russell 1000 stocks in the top and bottom *RiskCon* quintiles. *RiskCon*, defined in Equation (10), 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 *SYS* 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.

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 systematic return 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 4, the systematic return momentum effect conditional on high risk-concentration stocks is the strongest based on 60 anomalies via the LASSO method.[30] Overall, the results of Table 7 confirm our conjecture that a stronger systematic return momentum exists among high-risk concentration stocks, supporting our initial hypothesis.[31]

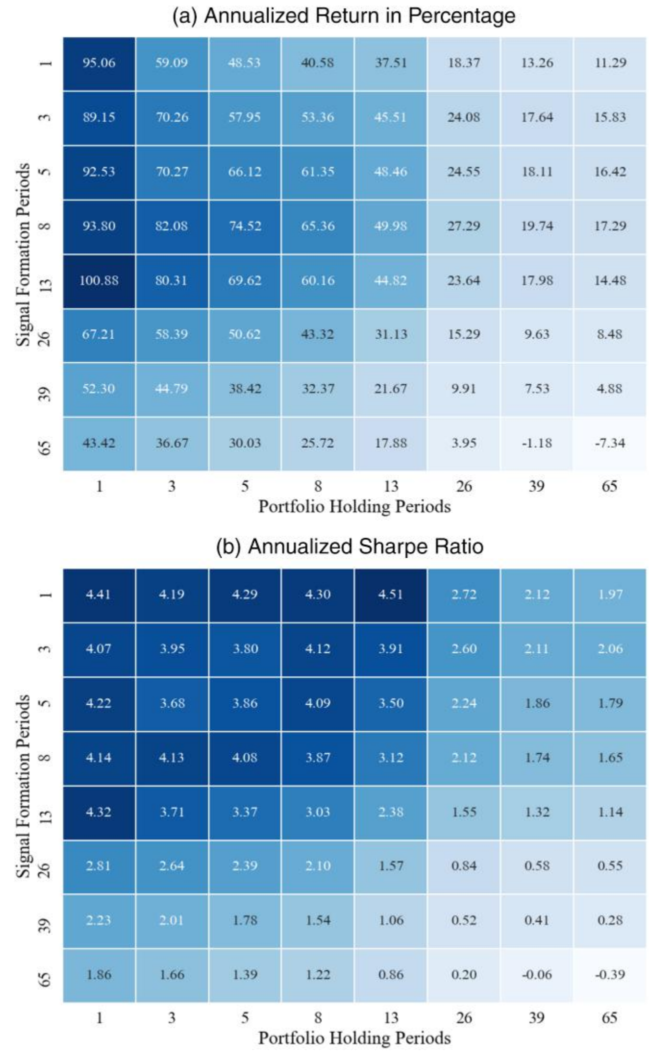
5. Robustness and Extensions

5.1. Different Portfolio Formation and Holding Periods

The systematic return momentum strategy forms portfolios based on the one-period *SYS* 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 *SYS* using 15 RP anomalies and compute *M*-period *SYS* by aggregating the one-period *SYS* 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 minutes, 90 minutes, 150 minutes, 240 minutes, 1 day, 2 days, 3 days, and 5 days, respectively. 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.

Figure 5, (a) and (b), shows the average annualized returns and their annualized Sharpe ratios of the long-short systematic return momentum portfolios based on different combinations of portfolio formation period *M* (rows) and holding period *N* (columns). 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 returns, except for the 65/39 and 65/65 strategies. 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 one. The most successful strategies seem to be selecting stocks based on their *SYS* 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. 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

Figure 5. (Color online) Different Signal Formation and Return Holding Periods



Notes. This figure shows the performance of the long-short portfolio based on the systematic 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. (a) Annualized return in percentage. (b) Annualized Sharpe ratio. The sample includes all stocks in the Russell 1000 index over the period from January 1993 to December 2020.

horizon is longer than one day. These results suggest that our use of high-frequency intraday data are crucial in effectively uncovering the strong systematic return momentum.[32]

5.2. Spanning Test

Thus far, we demonstrated the pervasive effect of the systematic momentum. Importantly, in Section 3.3, we show that systematic momentum captures the overall lead-lag relation of *total* systematic component of individual stocks, but factor momentum of Ehsani and Linnainmaa (2022) only bets on the factor autocorrelation. Therefore, our systematic momentum explores the dynamic feature of the *total* systematic component of stocks instead of each individual factor, which can also potentially ease the concern of the factor selection bias. Furthermore, we construct stock-level measures which largely facilitate the portfolio formation. To compare our systematic momentum and factor momentum strategies, in this section, we conduct the spanning test.

We construct intraday and monthly factor momentum strategies with different factor sets following Ehsani and Linnainmaa (2022). Specifically, the factor momentum (FMOM) is formed by longing factors with positive returns during the past period and shorting those with negative returns.[33] The intraday and monthly systematic momentum (SMOM) strategies are constructed by following the same procedure described in Section 3. In addition, we form the conditional systematic momentum (C-SMOM) by selecting stocks in the top risk-concentration quintile.

Panel A of Table 8 reports the intercepts (alphas) along with their *t*-statistics from spanning regressions of intraday momentum strategies. In the first two rows, we regress the FMOM returns on the SMOM returns. All three specifications show that FMOM earns insignificant alphas after controlling for SMOM. In contrast, as shown in the next two rows, FMOM only partially explains SMOM, resulting in significant annualized alphas earned by SMOM ranging from 45.36% to 57.99%. Impressively, the last two rows demonstrate that C-SMOM is largely distinct from FMOM. Specifically, the C-SMOM yields highly significant alphas ranging from 109% to 127.43%, with *t*-statistics above 20. As such, the systematic momentum can explain the factor momentum, but not vice versa.

Table 8. Spanning Test

	15 RP	15 EL	60 anomalies
Panel A: Intraday alpha			
FMOM versus SMOM	1.88	1.36	−12.51
	(0.63)	(0.46)	(−5.42)
SMOM versus FMOM	45.36	45.54	57.99
	(9.38)	(11.48)	(13.69)
C-SMOM versus FMOM	109.00	113.58	127.43
	(22.42)	(26.69)	(27.57)
Panel B: Monthly alpha			
FMOM versus SMOM	2.60	0.57	−1.24
	(1.62)	(0.33)	(−0.81)
SMOM versus FMOM	5.23	8.49	8.25
	(2.35)	(3.44)	(3.93)
C-SMOM versus FMOM	14.73	17.00	16.30
	(4.94)	(5.45)	(5.93)

Notes. This table reports annualized alphas from spanning regressions by regressing returns of the first strategy on those of the second strategy. Panels A and B perform spanning regressions based on intraday and monthly momentum strategies, respectively. In each panel, the factor momentum (FMOM) is formed by longing factors with positive returns during the past period and shorting those with negative returns. The intraday and monthly systematic momentum (SMOM) strategies are constructed by following the procedure described in Section 3. The conditional systematic momentum (C-SMOM) is formed by selecting stocks in the top risk-concentration quintile. All alphas are annualized in percentage, with Newey-West robust *t*-statistics in parentheses.

Consistent with Ehsani and Linnainmaa (2022), we also find positive cross-serial lead-lag relationship among factors in low frequency, which can contribute to the *total* systematic momentum as shown in Section 3.3 but does not affect time series factor momentum (it even adversely affects cross-sectional factor momentum). Therefore, we expect a stronger effect of the monthly systematic momentum than factor momentum. In Panel B, we perform spanning tests based on the monthly momentum strategies. Consistent with the results in Panel A, we continue to find that factor momentum can be largely explained by systematic momentum and, thus, earn insignificant alphas for all model specifications after controlling for SMOM. By contrast, SMOM remains highly profitable net of the factor momentum strategy. Finally, the returns to the C-SMOM strategy remains highly significant despite controlling for FMOM. The annualized alphas of the conditional systematic momentum strategy ranges from 14.73% to 16.30%, with *t*-statistics between 4.9 and 5.9.

In sum, we provide compelling evidence supporting the notion that systematic momentum delivers substantial returns that cannot be explained by factor momentum. However, factor momentum is hard to survive after controlling for systematic momentum. Furthermore, the performance of systematic momentum becomes much stronger if we form the strategy by selecting stocks in the top risk-concentration quintile, which highlights the importance of constructing stock-level risk measurement to enhance the effectiveness of the trading strategy. As such, we provide a relatively more efficient way for exploring the nature of the return component that can be attributed to firm characteristics.

5.3. Monthly Momentum

Thus far, we focused on the intraday or daily analysis of the systematic momentum effect. This section shows that this effect exists even at the lower monthly frequency and is stronger than traditional momentum documented in Jegadeesh and Titman (1993). We first exploit the predictive power of *SYS* on future returns as follows. At the end of each month t, we sort stocks into decile portfolios based on the *SYS* component of returns in month t. We buy stocks in the top decile with high *SYS* values and short those in the bottom decile with low *SYS* values. We hold this long-short value-weighted portfolio over month $t+1$ and rebalance it every month, resulting monthly systematic return momentum (SMOM). The *SYS* components are constructed by using 60 stock anomalies via LASSO. We also construct conditional systematic return momentum strategy (C-SMOM) by selecting stocks in the top risk-concentration quintile. Following Jegadeesh and Titman (1993), we also form return momentum strategy, namely JT. JT is the traditional momentum strategy that long (short) stocks with the highest (lowest) cumulative returns over the past two to six months. Lastly, we also consider industry momentum (Ind-MOM) from Moskowitz and Grinblatt (1999). Ind-MOM involves buying industry portfolios if their returns in the previous month exceed the median, and selling industries if their returns fall below the median. For this strategy, we utilize the 49 Fama-French industry classification.

Panel A of Table 9 reports the performance for each momentum strategies. The returns are annualized in percentage, and Newey and West (1987) *t*-statistics are reported in parentheses. The results indicate that C-SMOM exhibits the highest performance, with an average annual return of 19.52% (*t*-statistic = 6.64) and an annualized Sharpe ratio of 0.94. Following closely is SMOM, which generates an average return of 16.58% (*t*-statistic = 6.44) and an annualized Sharpe ratio of 0.82. JT momentum delivers an average return of 13.41% (*t*-statistic = 4.15) and a Sharpe ratio of 0.55. Ind-MOM also performs well, with an average return of 5.79% (*t*-statistic = 4.40) and a Sharpe ratio of 0.59.

Consideration of trading costs is important for understanding the real world practicality of a research-based strategy. Therefore, we further report strategy performance accounting for trading costs in Panel A. We use trading cost estimates from Frazzini et al. (2018) and Jiang et al. (2021) who recommend a round-trip cost of 20 bps and 18 bps, respectively. To be conservative, we apply a round-trip cost of 20 bps (or one-way cost of 10 bps) to all trades. We follow Kelly et al. (2023) to calculate portfolio net returns as

$$r_{p,t+1} = \sum_s w_{s,t} r_{s,t+1} - 10\text{bps} \times \sum_s |w_{s,t} - w_{s,t-1}|, \tag{11}$$

where $w_{s,t}$ is the weight in stock s at time t. Along with this net return calculation, we also compute a turnover statistic that describes the fraction of the portfolio that turns over each month on average:

$$\text{Turnover} = \frac{1}{T}\sum_t \frac{\sum_s |w_{s,t} - w_{s,t-1}|}{\sum_s w_{s,t-1}}. \tag{12}$$

Panel A indicates that, although C-SMOM demonstrates the best performance before trading costs, it also incurs the highest turnover at 133%, resulting in the highest trading costs. SMOM is associated with the second highest turnover of 126%. Ind-MOM also has a high turnover of 101%, whereas JT shows a turnover of 103%. The higher turnover of systematic momentum strategies is expected, as they are based on short-term signals. Therefore, it is important to compare momentum strategies based on their performance after trading costs. Notably, in terms of net Sharpe ratio, both C-SMOM and SMOM continue to outperform traditional momentum strategies. Specifically, the net Sharpe ratios are 0.78 and 0.67 for C-SMOM and SMOM, respectively, whereas JT and Ind-MOM have net Sharpe ratios of only 0.45 and 0.34, respectively.

In Panel B, we examine the relative performance among various momentum strategies by conducting spanning tests. Specifically, we take the returns on one momentum strategy as the dependent variable, whereas a different strategy is an independent variable. The dependent variables are listed in a row, and the independent variables are in a column. We report the intercepts and their corresponding *t*-statistics in a 4 × 4 matrix. For example, in the first row, the dependent variable is C-SMOM, allowing us to investigate whether C-SMOM can be subsumed by other momentum strategies. Evidently, C-SMOM is robust after controlling for other strategies. As expected, it is mostly related to SMOM but exhibits better performance. Interestingly, as shown in the third row, Ind-MOM is entirely subsumed by

Table 9. Monthly Momentum Strategies

	C-SMOM	SMOM	Ind-MOM	JT
Panel A: Performance				
Return	19.52	16.58	5.79	13.41
	(6.64)	(6.44)	(4.40)	(4.15)
Turnover	133	126	101	103
Gross Sharpe ratio	0.94	0.82	0.59	0.55
Net Sharpe ratio	0.78	0.67	0.34	0.45
Panel B: Spanning test, $row_i = \alpha_{i,j} + \beta_{i,j} \cdot column_j$				
C-SMOM		4.34	12.12	17.64
		(2.65)	(4.86)	(5.96)
SMOM	−0.29		8.32	13.77
	(−0.20)		(3.45)	(5.23)
Ind-MOM	0.19	0.16		4.72
	(0.15)	(0.13)		(3.71)
JT	9.71	8.42	10.62	
	(3.34)	(2.87)	(3.37)	

Notes. This table compares different monthly momentum strategies, which include the conditional (C-SMOM) and unconditional (SMOM) systematic return momentum strategy, the traditional return momentum strategies from Jegadeesh and Titman (1993), and industry momentum (Ind-MOM) from Moskowitz and Grinblatt (1999). Panel A reports the performance for momentum strategies. Panel B compares different strategies by conducting spanning tests. Specifically, we take the returns on one momentum strategy as the dependent variable, whereas a different strategy is an independent variable. The dependent variables are listed in a row, and the independent variables are in a column. We report the intercepts and their corresponding *t*-statistics in a 4 × 4 matrix. All returns and alphas are annualized in percentage, with Newey-West robust *t*-statistics in parentheses. The sample period for the analysis spans from January 1970 to December 2020.

C-SMOM or SMOM. Moreover, the results indicate that C-SMOM is largely independent of JT momentum because they are based on different formation periods. systematic momentum capitalizes on short-term trends, whereas JT momentum is related to mid- to long-term stock performance.

6. Conclusion

In this paper, we uncover the first cross-sectional systematic momentum in the intraday literature. We find that there is not only a systematic momentum (i.e., the continuation of the systematic component, the return component explained by common factors), but also a strong return momentum when stocks are sorted by their past systematic components. Both systematic momentum and the systematic return momentum hold across different times of the day. In addition, we find that the systematic component of daily (weekly, monthly) stock returns also exhibits momentum and generates a systematic return momentum at the corresponding frequency. Lastly, the monthly systematic return momentum is crash-free and much stronger than the widely cited Jegadeesh and Titman (1993) momentum.

The continuation of the systematic component itself is intriguing. We show that the persistence in systematic component is driven by the positive autocorrelation in individual factors and the positive cross-serial lead-lag among anomaly factors, both of which can be further explained by gradual trading due to limits to arbitrage. Particularly, we argue that anomaly returns are realized only when arbitrageurs trade on the perceived mispricing, who participate in trading to correct mispricing, and trade only gradually instead of eliminating mispricing at once due to market frictions. Indeed, we document stronger systematic return momentum in the morning sessions, during periods with more frequent firm news arrivals, when aggregate idiosyncratic volatility is high and among stocks with greater systematic risk concentration. All the evidence appears consistent with the explanation from limits to arbitrage.

What is particularly intriguing is that we discover the momentum in systematic component is not solely driven by positively autocorrelation of factors but also by positive lead-lag relationships among different factors. Consequently, our systematic momentum is distinct from the time series factor momentum of Ehsani and Linnainmaa (2022), where positive lead-lag among factors does not contribute to its performance (the lead-lag among factors even adversely affects cross-sectional factor momentum). As a result, our systematic momentum exhibits greater strength compared with factor momentum across various frequencies. In particular, systematic momentum cannot be explained by factor momentum, whereas factor momentum no longer survives after controlling for systematic momentum.

Numerous explanations have been proposed over the past decades after the discovery of the Jegadeesh and Titman (1993) momentum, and we anticipate more explanations to be developed on the economic channels for our systematic momentum pattern. Regardless of whether one agrees on our current explanations or not, the bottom line is that our paper provides what seems to be the strongest momentum pattern in asset pricing, which holds intraday, daily, weekly, and monthly, versus the JT momentum, which holds only at the monthly frequency. Additionally, our systematic momentum outperforms JT momentum in terms of a higher Sharpe ratio and being crash-free. Exploring our systematic momentum in global markets and other assets is an important avenue for future research. In follow-up work, we have discovered that the systematic return momentum holds for corporate bonds, currencies, commodities, and options, respectively (Beckmeyer et al. 2023, Gao et al. 2023). Given that momentum is one of the major anomalies in finance and is extensively studied and applied, our discovery of a new class of momentum patterns may provide a fresh stimulus for research in the area and garner widespread interest.

Acknowledgments

The authors thank the editor, Kay Giesecke, associate editor, and two referees for insightful comments that significantly improved the paper and Vincent Bogousslavsky, Youngmin Choi (discussant), Zhi Da (discussant), Kent Daniel, Jianqing Fan, Ed Fang, Daniel Giamouridis, Amit Goyal (discussant), Bing Han, Steve Heston, Jiantao Huang (discussant), Bryan Kelly, Jiahan Li, Kunpeng Li, Victor Liu, Alejandro Lopez-Lira, Siyuan Ma, David McLean, Alessandro Melone (discussant), Lasse Pedersen, Jeffrey Pontiff, Larry Schmidt, Karlye Dilts Stedman, Sheridan Titman, Xiye Yang (discussant), Xintong Zhan (discussant), Yingquang Zhang, Geng Zhe, seminar participants at Boston College, Capital University of Economics and Business, Fudan University, Georgia State University, Human Normal University, Hunan University, Jiangxi University of Finance and Economics, Merrill Lynch International, Nanjing University, Peking University, Renmin University of China, Rutgers Business School, Tongji University, Tsinghua University, University of Nottingham, Washington University in St. Louis, Xian Jiaotong University, and conference participants at China Fintech Research Conference, the 3rd International Fintech Research Forum, FMA Annual Meeting, New Zealand Finance Meeting, Australasian Finance and Banking Conference, MFA Annual Meeting, 2023 SFS Cavalcade North America, Hong Kong Conference for Fintech, AI and Big Data in Business, and 2023 CFEA Annual Meeting for helpful comments.

Endnotes

[1] Fama and French (2020) adopt a similar approach to construct cross-sectional factors and find that time series models incorporating these factors can better explain the average returns of stocks.

[2] Note that our intraday periods extend over day trading hours, including the period from market close to market open.

[3] The Google Scholar Citation of Jegadeesh and Titman (1993) is over 16,861, and the authors have won many awards for their discovery of momentum, including the recent Wharton-Jacobs Levy Prize for Quantitative Financial Innovation.

[4] An extensive but incomplete list of rational and behavioral explanations for momentum includes Chan et al. (1996), Barberis et al. (1998), Conrad and Kaul (1998), Daniel et al. (1998), Berk et al. (1999), Hong and Stein (1999), Chordia and Shivakumar (2002), Johnson (2002), Lewellen (2002), Gomes et al. (2003), Sagi and Seasholes (2007), Liu and Zhang (2008), Li et al. (2009), Vayanos and Woolley (2013), Da et al. (2014), Liu and Zhang (2014), Andrei and Cujean (2017), Li (2018), Mortal and Schill (2018), and Kelly et al. (2021).

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

[6] For example, although our systematic momentum remains similar using the 205 anomalies from Chen and Zimmermann (2022), it becomes challenging to detect factor momentum among the 205 anomalies.

[7] Gao et al. (2024) show interestingly that the factor momentum is also different from and cannot subsume the traditional return momentum.

[8] Our results are robust to the Russell 3000 index constituents as shown in Table A.4 in the Online Appendix.

[9] 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.

[10] We use the price at 1000 hours for the overnight return calculation to ensure that most securities have traded at least once after the market open.

[11] 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.

[12] We also consider a nonlinear version of the standard model. Following Han et al. (2024), we incorporate products of the anomaly variables into Equation (2) and find that our results remain robust (See Table A.14 of the Online Appendix).

[13] The traditional approach is to use the sum of betas multiplied by their respective factors. Here, we adopt the cross-sectional approach for two reasons. First, Fama and French (2020) show that this approach provides a better description of average returns. Chib et al. (2022) also find that this is true in a more general setting. Second, betas estimated using high-frequency data tend to be very noisy, making the systematic component less accurate.

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

[15] The average total R^2 explained by 60 anomalies via LASSO is around 17%, typically higher during the morning and overnight (19%) but lower in the middle of the day (15%).

[16] 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).

[17] 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.

[18] *Auto* and *Cross* contribute substantially to the autocorrelation in *SYS* at lower frequencies as well. For example, the average *Auto* and *Cross* of monthly *SYS* autocorrelation are 3.76% and 2.11%, respectively.

[19] We interpret systematic momentum as the gradual correction of anomaly-driven mispricing under limits to arbitrage, relying not on specific anomalies but on persistent systematic trading caused by market frictions. van Binsbergen et al. (2023) distinguish between resolution and build-up anomalies (those that resolve versus exacerbate firm-level mispricing) and show that price-level deviations (asset price wedges) and return patterns can differ. Although we do not study firm-level mispricing per se, our findings suggest that systematic momentum is more closely tied to resolution anomalies (e.g., beta, value, investment), with little contribution from build-up anomalies (e.g., momentum, variance), except for profitability.

[20] Arnott et al. (2023) find that there is a strong positive cross-serial correlation among monthly returns to factors, industries, and individual stocks, which detracts from cross-sectional momentum strategies.

[21] To examine whether the results are entirely driven by these two extreme deciles, Tables A.5 and A.6 in the Online Appendix report the performance across all deciles. The tables document a monotonic pattern that high *SYS* goes hand in hand with high return holds very well across all deciles for any given formation period.

[22] Based on the definition of turnover in Equation (12) in Section 5.3, the average turnover across the 13 intraday strategies is 174%.

[23] In sharp contrast, spread portfolios sorted by the total return in the previous intraday period all generate reversal, as shown in Table A.7 in the Online Appendix, consistent with the short-term reversal documented in the existing literature. Furthermore, the short-term reversal mainly come from the residual return. Heston et al. (2010) discover a striking pattern of return continuation at half-hour intervals that are multiples of a day. Figure A.1 in the Online Appendix confirms their results that there is a large return reversal at lag 1, and there are positive return responses peaking at horizons that are exact multiples of 13 half-hours. In contrast, *SYS* exhibits strong positive predictability for the next-period return. Strikingly, the predictability can last for several periods until one day. As such, different from the return reversal or periodic continuation, the intraday systematic return momentum is a persistent phenomenon and lasts for a trading day.

[24] Recent studies using this data set include Kelley and Tetlock (2017), Jiang et al. (2021), and Jiang et al. (2025).

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

[26] Shleifer and Vishny (1997) point out that idiosyncratic volatility is more important than systematic volatility to arbitrageurs, because it cannot be hedged and arbitrageurs typically lack diversification. Wurgler and Zhuravskaya (2002) also defend the use of idiosyncratic risk as an arbitrage cost, noting that arbitrageurs are often not fully diversified. Pontiff (2006) argue that idiosyncratic risk, as a significant holding cost, forces arbitrageurs to take limited positions in mispriced securities, allowing mispricings to persist.

[27] The clientele effect refers to the phenomenon where different groups of traders or investors prefer to trade at specific times of the day. For instance, Berkman et al. (2012) argue that retail investors tend to buy stocks that catch their attention at market open. This buying pressure leads to high overnight returns, followed by intraday reversals. Additionally, Bogousslavsky (2021) documents that, consistent with clientele effects, arbitrageurs are averse to holding positions in stocks with high overnight risk and/or high capital costs.

[28] We thank the referee for suggesting this insightful analysis.

[29] 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.

[30] In the Online Appendix, Figure A.4 shows superior performance of the daily systematic return momentum among high systematic risk-concentration stocks. The portfolio value based on all four *SYS* strategies continues to rise throughout the entire sample without experiencing major drawdowns. Table A.9 in the Online Appendix further reports the performance of all decile portfolios formed on the basis of various daily *SYS* signals. Figure A.5 and Table A.10 in the Online Appendix show that the systematic return momentum continues to hold at daily, weekly, and monthly frequencies over the expanded sample period from January 1970 to December 2020.

[31] To mitigate the concern that stocks in the high (low) risk-concentration quintile simply have more (less) extreme *SYS* in absolute magnitude ($|SYS|$) and thus tend to generate greater (smaller) *SYS*-based return spread, we sort stocks into five portfolios by $|SYS|$, 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 $|SYS|$ portfolios to produce five risk-concentration portfolios with large cross-portfolio variation in risk concentration but little variation in $|SYS|$ and construct long-short portfolios within the highest and lowest risk-concentration portfolios, respectively. The results are reported in Table A.11 in the Online Appendix, confirming the robustness of the finding that the systematic return momentum is stronger among high risk-concentration stocks.

[32] The Online Appendix provides additional robustness checks. In Section A.1, we examine a larger set that includes 205 anomalies from Chen and Zimmermann (2022), obtaining results similar to our main findings. In Section A.2, we further demonstrate that the systematic return momentum is not affected by a weekend effect or any other day-of-week effect.

[33] Ehsani and Linnainmaa (2022) show that time series factor momentum is stronger than cross-sectional factor momentum due to the negative effect of cross-serial lead-lag among factors on the latter. Thus, we compare the systematic momentum with time series factor momentum.

References

Abreu D, Brunnermeier MK (2002) Synchronization risk and delayed arbitrage. *J. Financial Econom.* 66:341–360.

Aït-Sahalia Y, Xiu D (2019) Principal component analysis of high-frequency data. *J. Amer. Statist. Assoc.* 114:287–303.

Andrei D, Cujean J (2017) Information percolation, momentum and reversal. *J. Financial Econom.* 123:617–645.

Arnott RD, Kalesnik V, Linnainmaa JT (2023) Factor momentum. *Rev. Financial Stud.* 31:3034–3070.

Asness CS, Moskowitz TJ, Pedersen LH (2013) Value and momentum everywhere. *J. Finance* 68:929–985.

Baker M, Wurgler J (2006) Investor sentiment and the cross-section of stock returns. *J. Finance* 61:1645–1680.

Baltussen G, Da Z, Lammers S, Martens M (2021) Hedging demand and market intraday momentum. *J. Financial Econom.* 142:377–403.

Bansal R, Yaron A (2004) Risks for the long run: A potential resolution of asset pricing puzzles. *J. Finance* 59:1481–1509.

Barberis N, Shleifer A, Vishny R (1998) A model of investor sentiment. *J. Financial Econom.* 49:307–343.

Beckmeyer H, Filippou I, Zhou G (2023) A new option momentum: The role of the systematic component. Preprint, submitted September 28, http://dx.doi.org/10.2139/ssrn.4404190.

Berk JB, Green RC, Naik V (1999) Optimal investment, growth options, and security returns. *J. Finance* 54:1553–1607.

Berkman H, Koch PD, Tuttle L, Zhang YJ (2012) Paying attention: Overnight returns and the hidden cost of buying at the open. *J. Financial Quant. Anal.* 47:715–741.

Bogousslavsky V (2016) Infrequent rebalancing, return autocorrelation, and seasonality. *J. Finance* 71:2967–3006.

Bogousslavsky V (2021) The cross-section of intraday and overnight returns. *J. Financial Econom.* 141:172–194.

Chan LKC, Jegadeesh N, Lakonishok J (1996) Momentum strategies. *J. Finance* 51:1681–1713.

Chen AY, Zimmermann T (2022) Open source cross sectional asset pricing. *Critical Finance Rev.* 27:207–264.

Chib S, Lin YC, Pukthuanthong K, Zeng X (2022) Asset pricing with slope factors: Model and evidence of outperformance. Preprint, submitted July 22, http://dx.doi.org/10.2139/ssrn.4137888.

Chordia T, Shivakumar L (2002) Momentum, business cycle, and time-varying expected returns. *J. Finance* 57:985–1019.

Conrad J, Kaul G (1998) An anatomy of trading strategies. *Rev. Financial Stud.* 11:489–519.

Cushing D, Madhavan A (2000) Stock returns and trading at the close. *J. Financial Markets* 3:45–67.

Da R, Xiu D (2021) When moving-average models meet high-frequency data: Uniform inference on volatility. *Econometrica* 89:2787–2825.

Da Z, Gurun UG, Warachka M (2014) Frog in the pan: Continuous information and momentum. *Rev. Financial Stud.* 27:2171–2218.

Daniel KD, Moskowitz TJ (2016) Momentum crashes. *J. Financial Econom.* 122:221–247.

Daniel K, Hirshleifer D, Subrahmanyam A (1998) Investor psychology and security market under-and overreactions. *J. Finance* 53:1839–1885.

Dong X, Li Y, Rapach DE, Zhou G (2022) Anomalies and the expected market return. *J. Finance* 77:639–681.

Ehsani S, Linnainmaa JT (2022) Factor momentum and the momentum factor. *J. Finance* 77:1877–1919.

Engelberg J, McLean RD, Pontiff J (2018) Anomalies and news. *J. Finance* 73:1971–2001.

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33:3–56.

Fama EF, French KR (2015) A five-factor asset pricing model. *J. Financial Econom.* 116:1–22.

Fama EF, French KR (2020) Comparing cross-section and time series factor models. *Rev. Financial Stud.* 33:1891–1926.

Foucault T, Kadan O, Kandel E (2005) Limit order book as a market for liquidity. *Rev. Financial Stud.* 18:1171–1217.

Frazzini A, Israel R, Moskowitz JT (2018) Trading costs. Preprint, submitted August 22, http://dx.doi.org/10.2139/ssrn.3229719.

Freyberger J, Neuhierl A, Weber M (2020) Dissecting characteristics nonparametrically. *Rev. Financial Stud.* 33:2326–2377.

Gao L, Han Y, Li SZ, Zhou G (2018) Market intraday momentum. *J. Financial Econom.* 129:394–414.

Gao C, Li SZ, Yuan P, Zhou G (2024) Momentum and factor momentum: A re-examination. Preprint, submitted December 17, http://dx.doi.org/10.2139/ssrn.5057525.

Gao C, Li SZ, Yuan P, Zhou G (2023) Systematic momentum in corporate bond returns. Preprint, submitted March 2, http://dx.doi.org/10.2139/ssrn.4374766.

Garcia R, Mantilla-García D, Martellini L (2014) A model-free measure of aggregate idiosyncratic volatility and the prediction of market returns. *J. Financial Quant. Anal.* 49:1133–1165.

Gomes J, Kogan L, Zhang L (2003) Equilibrium cross section of returns. *J. Political Econom.* 3:693–732.

Green J, Hand JR, Zhang XF (2017) The characteristics that provide independent information about average US monthly stock returns. *Rev. Financial Stud.* 30:4389–4436.

Griffin JM, Ji X, Martin S (2003) Momentum investing and business cycle risk: Evidence from pole to pole. *J. Finance* 58:1515–1547.

Gu S, Kelly B, Xiu D (2020) Empirical asset pricing via machine learning. *Rev. Financial Stud.* 33:2223–2273.

Han Y, He A, Rapach DE, Zhou G (2024) Cross-sectional expected returns: New Fama–Macbeth regressions in the era of machine learning. *Rev. Finance* 28:1807–1831.

Heston SL, Korajczyk RA, Sadka R (2010) Intraday patterns in the cross-section of stock returns. *J. Finance* 65:1369–1407.

Hong H, Stein JC (1999) A unified theory of underreaction, momentum trading, and overreaction in asset markets. *J. Finance* 54:2143–2184.

Hou K, Xue C, Zhang L (2015) Digesting anomalies: An investment approach. *Rev. Financial Stud.* 28:650–705.

Jegadeesh N, Titman S (1993) Returns to buying winners and selling losers: Implications for stock market efficiency. *J. Finance* 48: 65–91.

Jiang H, Li SZ, Wang H (2021) Pervasive underreaction: Evidence from high-frequency data. *J. Financial Econom.* 141:573–599.

Jiang H, Li SZ, Yuan P (2025) Granular information and sectoral movements. *J. Econom. Dynamic Control* 171:1050–1018.

Jiang L, Liu J, Peng L, Wang B (2022) Investor attention and asset pricing anomalies. *Rev. Finance* 26:563–593.

Johnson TC (2002) Rational momentum effects. *J. Finance* 57:585–608.

Kelley EK, Tetlock PC (2017) Retail short selling and stock prices. *Rev. Financial Stud.* 30:801–834.

Kelly BT, Moskowitz TJ, Pruitt S (2021) Understanding momentum and reversal. *J. Financial Econom.* 140:726–743.

Kelly B, Palhares D, Pruitt S (2023) Modeling corporate bond returns. *J. Finance* 78:1967–2008.

Kelly BT, Pruitt S, Su Y (2019) Characteristics are covariances: A unified model of risk and return. *J. Financial Econom.* 134:501–524.

Kozak S, Nagel S, Santosh S (2018) Interpreting factor models. *J. Finance* 73:1183–1223.

Kozak S, Nagel S, Santosh S (2020) Shrinking the cross-section. *J. Financial Econom.* 135:271–292.

Lewellen J (2002) Momentum and autocorrelation in stock returns. *Rev. Financial Stud.* 15:533–564.

Li J (2018) Explaining momentum and value simultaneously. *Management Sci.* 64:4239–4260.

Li EXN, Livdan D, Zhang L (2009) Anomalies. *Rev. Financial Stud.* 22:4301–4334.

Lintner J (1965) The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets. *Rev. Econom. Statist.* 47:13–37.

Liu LX, Zhang L (2008) Momentum profits, factor pricing, and macroeconomic risk. *Rev. Financial Stud.* 21:2417–2448.

Liu LX, Zhang L (2014) A neoclassical interpretation of momentum. *J. Monetary Econom.* 67:109–128.

Lo AW, MacKinlay AC (1990) When are contrarian profits due to stock market overreaction? *Rev. Financial Stud.* 3:175–205.

Mortal SC, Schill MJ (2018) The role of firm investment in momentum and reversal. *J. Empirical Finance* 48:255–278.

Moskowitz TJ, Grinblatt M (1999) Do industries explain momentum? *J. Finance* 54:1249–1290.

Newey W, West K (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55:703–708.

Pelger M (2020) Understanding systematic risk: A high-frequency approach. *J. Finance* 75:2179–2220.

Pontiff J (2006) Costly arbitrage and the myth of idiosyncratic risk. *J. Accounting Econom.* 42:35–52.

Roll R (1984) A simple implicit measure of the effective bid-ask spread in an efficient market. *J. Finance* 39:1127–1139.

Sagi JS, Seasholes MS (2007) Firm-specific attributes and the cross-section of momentum. *J. Financial Econom.* 84:389–434.

Sharpe WF (1964) Capital asset prices: A theory of market equilibrium under conditions of risk. *J. Finance* 19:425–442.

Shleifer A, Vishny RW (1997) The limits of arbitrage. *J. Finance* 52:35–55.

Stambaugh RF, Yuan Y (2016) Mispricing factors. *Rev. Financial Stud.* 30:1270–1315.

Stambaugh RF, Yu J, Yuan Y (2012) The short of it: Investor sentiment and anomalies. *J. Financial Econom.* 104:288–302.

van Binsbergen JH, Boons M, Opp CC, Tamoni A (2023) Dynamic asset (mis) pricing: Build-up versus resolution anomalies. *J. Financial Econom.* 147:406–431.

Vayanos D, Woolley P (2013) An institutional theory of momentum and reversal. *Rev. Financial Stud.* 26:1087–1145.

Wurgler J, Zhuravskaya E (2002) Does arbitrage flatten demand curves for stocks? *J. Bus.* 75:583–608.