(Every) 15 seconds to alpha: Long/short optimization with EVT

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Abstract

In this paper we model conditional distributions of intraday maximum and minimum REIT prices with extreme value theory ('EVT') techniques. We condition the parameters of these distributions on continuously evolving risk decomposition values derived from the CMBX market. These risk decompositions are interpreted as dynamic state variables, and serve as signals for changing likelihoods of daily REIT extrema. By assessing the model at fifteen-second intervals, intraday, our model generates high-confidence signals of single optimal stopping times for long/short trades for REITs in our study and extraordinary profits with positive and significant alphas in some 90% of our tests. By considering all fifteen-second intervals for 833 trading days, out of sample, our paper appears to optimize trading decisions, dynamically, as informed by our adaptation of Gumbel (1958, 2004), in near real time.

Key Words: CMBS/X, Extreme value theory, HFT, Liquidity, REITs, Risk decomposition

JEL Codes: C58, G17, R30

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Introduction

This paper is focused on developing intraday trading optimization strategies for publicly traded real estate investment trusts ('REITs') based on intraday risk decompositions from commercial mortgage backed securities ('CMBS') indexed credit default swaps ('CMBX'). These risk decompositions are generated in fifteen-second intervals during the trading day and build off the immediate prior work of Christopoulos and Barratt (2025a). In that study, the daily cross-sectional aggregations of intraday CMBX risk decompositions form 'risk terrains' which exhibit time and credit varying characteristics for the risks of default, rates, and liquidity as embedded within market observed spreads. The pricing phenomena of risk partitions disclosed in the cross-section observed in the first thirty minutes of the trading day is consistent with the findings of much of the 'overnight effect' literature. To validate the relationship between REITs and CMBX risk partitions, this phenomenon is exploited in trading strategies which were constructed from risk terrain values coupled with REIT prices in the first fifteen-seconds of the trading day over the sample period. Sensitivity to apparent mispricing allowed for generation of excess returns over sector benchmarks and demonstrated positive and significant alphas using the intertemporal capital asset pricing model ('ICAPM') of Merton and Samuelson (1992) in 90% of the tests in that study. While the results of Christopoulos and Barratt (2025a) established a CMBX x REIT relationship at the very beginning- and very end- of trading days, that earlier work is inconclusive as to the presence of a persistent meaningfulness of that relationship *throughout* the trading day. In this paper, we focus specifically on this extant issue through an adaptation of Gumbel (1958, 2004) (the 'Gumbel adaptation') in an application of extreme value theory ('EVT') to specifically face-down the problem of intraday portfolio formation through disclosed optimal stopping times.

In the Gumbel adaptation, we predict extreme values of maxima and minima prices for each of the REITs in our sample, updated in fifteen-second intervals intraday, as a function of the CMBX risk decomposition values updated with the same frequency. The training period for the Gumbel adaptation begins during the first year of the Covid pandemic. The out of sample period of 833 days begins on April 29, 2021 and ends on October 20, 2025. Upon isolating the extrema, we interpret them as signals for portfolio formation, whereby for signals of minimum we buy (aka 'long') and for signals of maximum we sell (aka 'short'). All positions are equally weighted for returns computations and there are at most one buy and one sell signal, per REIT, per day. This strategy yields significant and profitable results of approximately 96% annualized returns in the out of sample period. Since at most two signals are received for each REIT on any given day in this construct, there is not excessive trading ('churning') in our experiment; it is a day trading strategy with daily rebalancing strategy where no overnight holdings or financings are permitted.

To validate the signals' contributions to portfolio construction, we compare our equal weighted portfolios constructed intraday from Gumbel signals to standard Markowitz (Markowitz (1952), Markowitz (1990)) mean variance portfolio techniques (which necessarily do *not* use the CMBX risk decomposition signals which are not found in nature). In our tests we find our Gumbel portfolios dwarf those formed from the corresponding mean-variance Markowitz techniques with positive and statistically significant alphas in about 90% of the tests for our Gumbel portfolios. Together, these results are consistent with the earlier work in this immediate area of the literature. Our work validates a key relationship between CMBX risk decomposition signals as meaningful, intraday, to REIT market pricing and related risk assessments. It also highlights the benefit of re-framing the portfolio allocation decision-making process along the lines introduced in our paper, with potential applications to regulatory policy, lending, and risk monitoring, with near real time signals.

The remainder of this paper is organized as follows: Section 1 provides a brief literature review. Section 2 discusses the data used in this study. Section 3 reviews the core intraday risk decompositions and cross-sectional risk terrains introduced by Christopoulos and Barratt (2025a). Section 4 introduces our adaptation of Gumbel (1958, 2004) for prediction of extreme values of maxima and minima of REITs using the intraday risk decompositions. Section 5 discusses the trading strategy algorithm and reports related results. Section 6 summarizes with suggestions for future work. The Appendix summarizes the principal component analysis ('PCA') techniques of Christopoulos and Barratt (2024, 2025a).

1 Literature Review

This section discusses some of the literature related to our study in the areas of real estate asset pricing, liquidity pricing, overnight effect, artificial intelligence ('AI') and machine learning ('ML'), and extreme value theory.

The work in the area of real estate asset pricing[1] related to our study begins with the risk neutral valuation for real estate securities and underlying commercial real estate ('CRE') mortgage collateral asset pricing using the reduced form approach for comprehensive derivatives securities pricing. The reduced form techniques are state of the art and standard practice in derivatives pricing as discussed in Christopoulos, Jarrow and Yildirim (2008); Christopoulous and Jarrow, et al (2014, 2020) and most recently as found in reduced form state transition risk model work for stress testing as adopted by the Federal Reserve Board (see Federal Reserve Board (2025)). For this class of models, the loans are considered the atomic objects, the values of which are determined based on simulation of loan state transitions utilizing a Cox (1955) process, as motivated by Lando (1998) reflecting statistical relationships between property and mortgage characteristics and the modelled economy. This approach differs from those taken by Sagi (2021) who evaluates the property returns identifying an imperative for the use of structural models to adjust for transactions costs to account for an illiquidity premia for CRE using the National Council of Real Estate Investment Fiduciairies ('NCREIF') data set. Our work focuses on securities backed by CRE equity or debt instruments and does not directly address CRE property valuation. Our work also differs from the calibrated Merton (1974) structural approach applied to CRELs underlying CMBS and related CMBS valuation as discussed in Driessen and Van Hemert (2012).

The reduced form risk neutral approach lends itself nicely to the liquidity pricing exercise. It allows in the implementation for event risks of default and rates sensitivity to be isolated as shown in Christopoulos (2017) and Christopoulos and Jarrow (2018). These studies estimate and price risk events under risk neutral conditions. By isolating the implied risk neutral prices for default and interest rate risks, liquidity availability residual risk premia are revealed. These works are similar in motivation to those of Gilchrist, Wei, Yue and Zakrajšek (2021) who consider the risk decompositions with the EBP approach for Corporate bonds in a study focusing on the Covid pandemic and the policy response of the Federal Reserve, on a daily basis, using the last transaction prices and volumes and of the broader area of inquiry into liquidity embedded in risk premia through a variety of approaches as found in Constantinides (1986); Amihud (2002); Cetin, Jarrow and Protter (2004); Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2008); Nashikkar, Subrah-

[1]Good treatments of this extensive literature are found in Christopoulos, Jarrow and Yildirim (2008), among others.

manyam, and Mahanti (2011); Bao, Pan and Wang (2011); Gilchrist and Zakrajšek (2012); Han and Zhou (2016); Bao, O'Hara and Zhou (2018); Logan (2021), among others. Recently, Christopoulos and Barratt (2024) introduced the daily estimation risk decomposition approach for CMBX using a combination of PCA and ordinary least squares ('OLS'), to create a projection model of the risk partitions from Christopoulos and Jarrow (2018) which allows for the increase in risk partitioning frequency for CMBX from monthly to daily.

Christopoulos and Barratt (2025a) extend their work to intraday frequency revealing considerable variation in the cross-section for each of the risk partitions intraday, generating substantial positive excess returns and showing positive and significant alphas under the ICAPM of Merton and Samuelson (1992). As part of that study, key findings of aberrations between model and market pricing are found in the cross-section. These findings are consistent with work in the area of the overnight effect area of the literature, which has provided insights into phenomena of overnight variance and information absorption and re-pricing into assets upon the opening of New York markets. Key work in this area, originally motivated by weekend effect insights from Fama (1965), include O'Hara and Oldfield (1986); Lou, Polk and Skouras (2019); Akbas, Boehmer, Jiang and Koch (2022); Boyarchenko, Larsen and Whelan (2023); Papagelis and Dotsis (2025), among others. As much of the overnight literature is focused on equities, important expansions to the corporate bond market to address credit sensitive sensitivities to these phenomena where this effect is also observed have also benefited the literature.

Interesting recent work from Iannucci (2023); Vojtko and Dujava (2024); Feng, He, Wang and Wu (2025); Hjalmarsson, Palmstierna, Zernov and Droeyvold (2025); Li, Lu, Qi and Zhou (2025) explore the area of overnight effect phenomena and corporate bond return predictability with a variety of statistical and machine learning ('ML') approaches. Our contribution in this study, due to our techniques, also makes a contribution to this growing part of the literature which is expanding into the domain of the real estate literature focused on artificial intelligence ('AI') and ML techniques as found in Jenet, Nagl, Nagl, Price and Schaefers (2025); Leow and Lindenthal (2025); Letdin, Seagraves and Sirmans (2025), among others. Extensions of our approach apart from real estate securities, are applicable to consideration of bubble formation as discussed for example in Fama (1965), Shiller (2008) and Jarrow and Liu (2024), among others. In our work the signal and the target are both real estate objects, but in future work, a different signal and different target apart from real estate can be considered as part of a broader project. Our investigations adapting the seminal work of Gumbel (1958, 2004) in EVT will help in this framing and are part of a thread of recent work from De Haan and Ferreira (2006) and Mangin (2025) among others considering this framing in search and trading studies such as ours.

2 Data and systems

In this section we discuss the data used throughout this study.

The data series under consideration is composed of two parts, with small modifications in extent applied where technically required. The first, the training set, is composed of all intraday observations of the twenty-five REITs we select, the Chicago Board Options Exchange's CBOE Volatility Index (the 'VIX'), and four constant maturity ('CMT') US Treasury yields. These asset prices are captured in fifteen-second intervals throughout all the trading days in our sample. The prices are obtained from Yahoo! Finance through our RapidAPI subscription. For our study, the first period (the training set) is in the beginning of the Covid pandemic; that period starts on April 8, 2020 and ends on April 7, 2021. The second period of our study is the out of sample period (the prediction set), that period starts on April 29, 2021 and ends on October 20, 2025. We compute simulated returns for the out of sample period periods and perform for ICAPM analysis, censoring data where required based on data availability or rolling window restrictions. These assets are used in countless research studies.

In the estimation of the 'Intraday Model' described in the Appendix and Section 3, we poll the data above in fifteen-second time-stamped intervals and it is always 'most-recent', where pricing updates are driven by trading dynamics and changing investor sentiment in the marketplace in near real time. The data polling for each day starts at approximately 9:30:15am EST and ends at approximately 4:15:00pm EST. All Federal holidays are excluded with trading in our study only taking place on days when both bond and stock markets were open. Reporting terminates early with early market closings and market circuit breaker triggers.

Following Christopoulos and Barratt (2025a), Table 1 lists the names of the twenty-five REITs used in this study along with their property type, ticker, and market capitalization as of June 27, 2021. We select these REITs due to their strong representation of the entire REIT market and similarity to property risk reflected in properties collateralizing CMBS. Indeed several of the REITs in our study are also borrowers in the CMBS market for acquisitions and/or refinancing (for example, Simon Property Group ('SPG') and SL Green ('SLG')). Additionally most of these REITs are also found in the iShares ICF REIT index which we will use at a later point in this study. Finally, the market capitalization of these twenty-five selected REITs total $478.45 billion. According to the National Association of Real Estate Investment Trusts ('NAREIT'), the total market capitalization (market cap) of US REITs was $1249.19 billion as of December 31, 2020[2], and so our sample captures about 38% of the US REIT sector by market cap. NAREIT also states that the total number of US REITs to be 223, and so our sample represents about 11% of the US REIT sector by count. Additionally, these REITs are well distributed across multiple property types as shown in a further summary of the REIT sample broken down by property type and represent about 30% of iShares by market cap as of November 27, 2025.[3] Finally, these twenty-five REITs are used as part of our estimated economy through PCA. They are included in the training data and in the PCA model to estimate CMBX risk partitions and for continuity with the prior study of Christopoulos and Jarrow (2018) we also retain them in this study.

[Insert Table 1 about here]

The CMBX underlying the simulations in Christopoulos and Jarrow (2018), and the PCA estimates in Christopoulos and Barratt (2024, 2025a), represent approximately $400 billion of CMBS underlying first lien mortgage collateral secured by CRE properties. We use, as training data, the monthly simulations of risk decompositions from Christopoulos and Jarrow (2018) for our PCA model. Additionally, we have CMBX pricing data for March 18, 2020 which is held constant. This restriction permits us to consider the intraday results as cross-sectional intraday stress tests of the response of risk decompositions holding market spreads held constant on that date. Note that the market magnitudes of the sizes of our REIT sample and our CMBX sample are similar and our sample is broadly representative of the US REIT sector overall.

For ICAPM testing we obtain daily values from two sources. For the factors we obtain the market portfolio ('Mkt-Rf', which consists of all NYSE, AMEX, and NASDAQ firms), small minus big ('SMB'), high minus low ('HML'), and momentum

[2]See Christopoulos and Barratt (2025a).
[3]See Table 2 in Christopoulos and Barratt (2025a).

('MOM') indices from Ken French's website.[4] To control for the REIT sector, in our ICAPM analysis, we also capture the daily returns for the iShares REIT index ('ICF') from the iShares website.[5]

All computations are done with various R-packages through R-Studio on our Google Cloud account. All non-public technology and non-public data is either owned by the authors or licensed by them.

3 The core signals of risk decompositions

This section reviews the Intraday Model used in this study and in Christopoulos and Barratt (2025a).

3.1 Historical setup and the Intraday Model

The PCA model we extend in this paper uses monthly risk partitions at the tranche level for the CMBX universe with an aggregate composite of about $400 billion (notional). We calculate projections based on the training set of simulated risk partition primitives introduced in Christopoulos and Jarrow (2018) re-introduced at daily frequency in Christopoulos and Barratt (2024).[6] Recall from Christopoulos and Jarrow (2018), and following the earlier work in the literature, interest rate risk is modelled using a multi-factor Heath, Jarrow and Morton (1992)('HJM') model. Credit risk is captured using a reduced-form model first introduced by Jarrow and Turnbull (1992, 1995). A reduced-form model is selected because CMBS is valued, not from the borrower's perspective, but rather from the perspective of the market *under risk neutral conditions*.[7]

In Christopoulos and Jarrow (2018), we are given a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\in[0,\mathcal{T})}, \mathbb{P})$ satisfying the usual conditions[8] with $\mathbb{P}$ the statistical probability measure. The trading interval is $[0, \mathcal{T}]$. Traded are default free bonds of all maturities $T \in [0, \mathcal{T}]$ with time t prices denoted $p(t, T)$, and various property indices, REITs, commercial real estate loans ('CRELs', aka CRE mortgages), CMBS bonds, and CMBX indexed credit default swaps. The default-free spot rate of interest at time t is denoted r_t, with $(X_t)_{t\in[0,T])}$ a vector of state variables, adapted to the filtration,

[4]See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/
[5]See https://www.ishares.com/us/products/239482/ishares-cohen-steers-reit-etf
[6]As summarized in the Appendix.
[7]See Cetin, Jarrow and Protter (2004).
[8]See Protter (1990).

describing the relevant state of the economy. Markets are assumed to be complete and arbitrage free so that there exists a unique equivalent martingale probability measure $\mathbb{Q}$ under which discounted prices are martingales. The discount factor at time t is $e^{-\int_0^t r_s ds}$. In that earlier work, the objective was to value the market traded instrument (CMBS), and so most of the model formulation was conducted under the probability measure $\mathbb{Q}$.

The simulated risk partitions in Christopoulos and Jarrow (2018) are derived from the broader simulated economy and a set of transformations reconciling manifested theoretical risk neutral CMBX prices with observable market prices for CMBX in spread form as introduced in Christopoulos (2017). In Christopoulos and Barratt (2024) the PCA technique scales the monthly simulated risk partitions of Christopoulos and Jarrow (2018) very well to daily frequency (the 'Daily Model'). Given that scaling performance, scaling is further extended in Christopoulos and Barratt (2025a) to intraday frequency (the 'Intraday Model').

The Intraday Model estimates the projections which index a series of transformations, ex-post simulation, of projected fair value prices onto risk partitions for market spreads above the risk-free rate ('Spreads'). This results in risk partitioned Spreads for default, interest rates, liquidity and excess liquidity for individual CMBX series and tranches, which are then indexed across the CMBX sector for a set of sector-wide risk partition benchmarks. The pricing of residual risk premia identified in those two works are interpreted as distinct partitions of liquidity and excess liquidity availability which, unlike default and interest rate risks, are not explicitly modelled. Christopoulos and Barratt (2024) estimate the risk partitions daily from the monthly simulated risk partitions originally presented in Christopoulos and Jarrow (2018). A discussion of the Intraday Model as introduced in Christopoulos and Barratt (2025a) is provided in the Appendix. The techniques for EVT optimization introduced in this paper use the Intraday Model and the prior works as cited as the source for the CMBX signals which, in turn, are carefully interpreted with our EVT innovations as motivations for buying or selling specific REITs at specific times, intraday in all of testing. In so doing, we claim to exploit variations in the framing of the CMBX signals within cross-sectional risk terrains introduced in Christopoulos and Barratt (2025a)which are immediately revisited below in Section 3.2.

3.2 Risk terrains

One of the key findings of Christopoulos and Barratt (2025a) and intraday risk partitioning was the disclosure of cross-sectional risk partitions. The cumulative intraday change for each risk partition is defined as

$$W_{jkut} \equiv \sum_{t'=1}^{t} \Delta y_{jku}(t') \tag{1}$$

This is the second term in the Appendix Eq. (13), and is now also indexed for the u-th trading day, and so defined for j risk partitions, of k credit rating classes, for u trading days and t intraday trading times.

Figure 1 (taken from Christopoulos and Barratt (2025a)) depicts the cross-section for some 275370 observations computed for each of the intraday liquidity availability risk partition pricings in Year 1 of the Covid-era (April 7, 2020 to April 8, 2021). We use a double binning method to observe. The x-axes reflect 3 minute intervals binned from the fifteen-second interval values while the y-axes capture the log change of the VIX from the start of the trading day (with $t = 0$, 9:30am) until close. The y-axes are partitioned in increments of 0.01. The z-axes are the heat map renderings of W_{jkut} defined in Eq. (1)

[Insert Figure 1 about here]

Cumulatively, throughout the trading day, the capture of values intraday of Eq. (1) show the variations differ throughout the day, across credits and across decomposition types with concentration in the earlier part of the trading day. These so-called risk-terrains of CMBX ratings x risk decompositions, generated from our PCA technique, represent signals of value for the publicly traded REIT market.

In considering the risk partitions cross sectionally, some important facts emerge. One of the most interesting is an apparent regular 'spot' of volatility in the first fifteen minutes of trading in the cross-section. This repeats across all instruments and risk partitions in our sample. Figure 2 (taken from Christopoulos and Barratt (2025a)) zooms in on this interval for each of the risk partitions for all classes to revealing more detail of the phenomenon. There we see 'peaks' as indicated by the contour lines exceeding 1, and 'valleys' as indicated by contour lines less than one clustered about 9:39am. The subplots depict (clockwise) the risk pricing for default, liquidity, rates, and excess liquidity indices for all investment grade credit rating classes. Each of the six panels in the subplots reflects one of the six investment grade credit ratings from AAA thru BBB-.

[Insert Figure 2 about here]

The x-axes reflect 3 minute intervals binned from the fifteen-second interval values while the y-axes capture the log change of the VIX from the start of the trading day (with $t = 0$, 9:30am) until close. The y-axes are partitioned in increments of 0.01. The z-axes are the heat map renderings of W_{jkut} defined in Eq. (1). The plots represent the data for each of the CMBX classes with AAA in the upper left, AJ upper right, and so forth, with BBB- in the bottom right.

4 The Gumbel adaptation

This section discusses the Gumbel adaptation.

4.1 Motivation

While the previous work of Christopoulos and Barratt (2025a) provides a novel set of intraday benchmarks and compelling ICAPM and portfolio allocation results, the work says nothing about the intraday investment optimization of intraday risk estimation. This section resolves that issue with a key expansion to intraday optimization with a new strategy based on EVT. We do this with an adaptation of Gumbel (1958, 2004) and test with a trading strategy that is simpler and more realistic to the method by which portfolio managers seek to exploit intraday maxima and minimum in practice. In practice, to our knowledge, such maxima and minima are derived by 'feel' and various analytical techniques but, to our knowledge, do not use EVT or the Gumbel adaptation we present, which is a novel addition to the literature.

In contrast, our testing automates the REIT trading reasoning and decision-making process based on the probabilistic signals generated by our techniques which are informed by our intraday CMBX risk partitions at fifteen-second intervals.In thinking about the trading day, if our claim is correct, then these signals are not 'noise' and are, instead, signals predictive of intraday maximums and minimums vis a vis the Gumbel (1958, 2004) distribution and related hyperparameter techniques which we adopt for this study specifically to disclose whether such intraday extreme values may be exploited in portfolio management. We further claim, that by eliminating the open/close rebalancing restriction described in Christopoulos and Barratt

(2025a), and turning instead to the optimizing decision intraday it should be the case that choices with a better trading strategy sensitive to these intraday movements, will outperform standard techniques of long-only or even portfolio allocation techniques of mean variance optimization as introduced by Markowitz (1952, 1990) and Sharpe (1964, 1994). We find this to be true and provide support for both these claims in this section.

4.2 Innovation of intraday EVT

The fundamental challenge in developing a profitable high-frequency trading strategy is the inherent impossibility of generating deterministic ex-ante forecasts of the daily absolute maximum and minimum prices. Our work reframes this challenge by moving from absolute prediction to conditional probabilistic assessment of these extreme values using the framework of EVT. Specifically, we utilize EVT to model the conditional distribution of the daily maximum and minimum REIT prices. Our key innovation is to condition the parameters of this distribution on the continuously evolving intraday risk decomposition values derived from the related CMBX market. These risk decomposition values are interpreted as dynamic state variables, serving as direct signals for assessing the changing likelihoods of achieving new daily extrema. This methodology aims to identify and exploit the regular arrival of extreme events in the REIT market. By assessing the conditional EVT model at fifteen-second intervals, the model generates a high-confidence signal for a single optimal stopping time for an entry/exit trade: at most one for the predicted maximum ('short') and at most one for the predicted minimum ('long'), per REIT, per day.

4.3 Training Gumbel

The Gumbel distribution is a well-known distribution used to model the statistical likelihood of extreme events based upon historical evidence. The general form of the Gumbel distribution is,

$$P_{threshold} = \alpha - \beta \ln(-\ln(p)) \tag{2}$$

To operationalize the Gumbel adaptation for intraday decision-making, we employ the inverse Cumulative Distribution Function ('CDF') of the fitted distribution to bridge the gap between theoretical probabilities and actionable price levels. having predicted the location (α) and scale (β) parameters based on the out-of-sample input variables1, we select a specific probability threshold, p (e.g., 0.5, 0.7, etc.), representing the degree of confidence that a given value corresponds to the daily extremum. The inverse CDF, denoted as $G^{-1}(p)$, allows us to transform this confidence level into a specific numerical price threshold ($P_{threshold}$), such that there is a probability p that the day's actual maximum price will be less than or equal to this calculated level.

This computed threshold effectively functions as a dynamic boundary for generating trading signals within the so-called 'now-casting' platform. Throughout the trading day, in fifteen-second intervals, we continuously test the observed mid-market REIT price ($P_{observed}$) against the derived $P_{threshold}$. A signal is triggered precisely when the observed price equals or exceeds this threshold. In the context of EVT, this breach indicates that the current price has entered the extreme tail of the distribution defined by our predicted parameters, suggesting that the observed price is statistically likely to be the maximum value for the remainder of the trading session.

Consequently, the inverse CDF provides the mechanism for identifying the optimal stopping time adapted to the filtration of new information. By converting probabilistic assessments into concrete price levels, we automate the execution of contrarian trades; specifically, identifying these statistical extremes allows us to initiate short positions upon detecting a predicted maximum and long positions upon detecting a predicted minimum , thereby exploiting the intraday risk terrains revealed by our cross-sectional analysis. Each of the events is a Gumbel distributed random variable of maximum or minimum as described above. A numerical fitting of the past extremal events (maximum or minimum) is determined by two parameters: α (the 'location') and β (the 'scale').

To calibrate the model for intraday decision-making, we constructed a high-frequency training set spanning the first 231 trading days of the sample period. Rather than utilizing a single static maximum or minimum price for each day—which would discard valuable intraday variance—we defined the target extremum dynamically for each fifteen-second interval. Specifically, for every time step t within a trading day, the "observed high" used to train the distribution was defined as the maximum price occurring in the remaining trading window, from time t through the market close at 4:15 PM. Conversely, the "observed low" was defined as the minimum price observed over that same remaining interval $[t, T_{close}]$. This approach effectively treats every fifteen-second interval as a distinct observation with a shrinking look-ahead horizon, resulting in a robust training set of approximately 325944 discrete observations, per REIT in our sample. This granular structure allows the Gumbel adaptation to learn the conditional probability of an extremum occurring from the current moment onward, conditioned on the instantaneous state of the intraday risk partitions.[9] For tuning, it is often the case that historical means and standard deviations are used as starting points for α and β in the numerical iterations of Maximum Likelihood Estimations ('MLE') of the fitting parameters. With our computational resources, we achieved convergence with MLE between 60 and 90 seconds, per REIT.

The fitted parameters are then used in an OLS regression to determine the coefficients of the explanatory variables (the risk decompositions). The OLS coefficients are then used with the intraday CMBX risk decompositions from our PCA technology to predict maximums and minimums for the REITs fitted according to our EVT method in fifteen-second intervals. Predictions per REIT with OLS are essentially instantaneous but may lag by at much as fifteen-seconds due to latency. The location (α) and scale (β) parameter estimates and coefficients for the OLS[10] are reported in Table 2.

[Insert Table 2 about here]

5 Trading strategy

This section discusses the trading strategy and results used to validate the values produced by the Gumbel adaptation described in Section 4.

5.1 Motivation

Having trained the model using historical highs and lows, we are presented with the ability to predict values of α (location) and β (scale) based on novel values of the input variable from the out of sample sets. We also have a contemporaneous instantaneous mid-market price for each security. Using these, and under the assumption that the day's high and low follow the Gumbel distribution with the predicted parameters, we can then compute the probability that the day's high (maximum) will

[9] There is occasionally some latency in delivery and adjustments for early closes for holidays which affects the total signals captured per day. Latency is at most a full time interval of fifteen-seconds.

[10] Excess liquidity availability factors must be dropped at this stage for the Gumbel adaptation as they are deterministic functions of the other three risk decompositions. See Christopoulos (2017).

be equal to or less than the observed price, and reciprocally the probability that the day's low (minimum) will be greater than or equal to the observed price. By executing long/short trades, respectively at a given probability threshold, the price information generated by the model can be transformed into putative returns. As the frequency of our twenty-four CMBX risk decomposition signals, the VIX and US Treasuries arrive in fifteen-second intervals intraday, the theoretical framing of the problem is similar to an optimal stopping time adapted to the filtration of the arrival of new information content, where, in this case, the new information content are the CMBX risk decompositions.

5.2 Rules and assumptions

Our trading strategy is applied to the REIT sector to take advantage of optimized stopping times for predicted extreme values for the securities based on the Gumbel adaptation in response to intraday risk decompositions from the CMBX sector. Short positions are articulated through a margin account with the standard margin restrictions of thirty-percent capital set aside for such positions. Long positions are articulated through cash. No leverage is assumed. No overnight holdings are permitted. Aggregations at the portfolio level are equally weighted based on the n number of REITs in the portfolio with each REIT representing $1/n$ of the portfolio.

In the out of sample period and testing of the algorithm, six of the original REITs are censored. CLI, DRE, PSB and TCO are censored in this part of the study as they no longer exist. WYND is censored due to a name change in our data feed. SELF is censored because it has a market capitalization of less than $1B. This leaves the total number of REITs considered for testing to be $n = 19$.

On each day, for each fifteen-second interval, probabilistic signals of maximum and minimum REIT values are computed reflective of the PCA elements (VIX, US Treasuries, and REITs) and their relationship to predicted risk decompositions, fitted best with alphas and betas with the Gumbel distribution in Year 1 of Covid.

The nuance here is that we restrict our REITs to be the same representative sample of REITs used in the PCA model. This is deliberate and perfectly reasonable. REITs do not intrinsically report whether they have gotten to a level of conditional richness or cheapness in ordinary market practice. In contrast, our work with EVT, we claim, does precisely that. The work discerns these relative values of strength or weakness vis a vis the interaction between the PCA estimated theoretical CMBX signals (with training set of simulated CMBX risk partitions from Christopoulos and Jarrow (2018)) and the EVT methodology. When a REIT crosses a conditional maximum or minimum boundary the algorithm advises a long/short trading action, in near real time. Mechanically, in our algorithmic strategy, interpretations for trading with our algorithm are to sell a REIT upon receiving a signal of a maximum for that REIT and to buy a REIT upon receiving a signal of a minimum for that REIT.

1. For each REIT on each trading day, the algorithm provides at most a single hit of low (daily predicted minimum) and a single hit of high (daily predicted maximum) for each degree of confidence, intertemporally. If a low (high) signal is generated, then for the remainder of the day for that degree of confidence, no further low (high) signal will be generated for that REIT for that day. There is no guarantee, for any degree of confidence, that either a predicted maximum or minimum (or both) will arrive intertemporally for that trading day.

2. If a long (short) position is opened at any point in the day based upon a signal, then that long (short) position is closed upon the earlier of a.) receipt of an opposite signal for that REIT or b.) the closing price at the end of the trading day.

3. If both a minimum and a maximum predicted value for a given REIT at a given degree of confidence arrive at the exact same fifteen-second interval, at any point in the trading day, then no trading occurs for that REIT on that day.

4. For any days where only a low or a high is generated, the positions are closed out at the closing price at end of the trading day.

5. If no signal is generated prior to the close then no trading occurs on that day.

5.3 Example - October 20, 2025.

Table 3 provides an example of the output from our algorithm for October 20, 2025 with initialization of the algorithm at 9:30:00AM ET. There are a total of twenty-five trades signalled by our algorithm for this day and this initialization starting time. Column 1 provides the date; Column 2 the trade number, n; Column 3 the time, t, of the signal in 24 hour time notation; Column 4 is the direction of the signal as Buy or Sell at time t; Column 5 is the property type of the REIT; Column 6 is the REIT trading ticker; Column 7 is the market price for the REIT observed at time t corresponding to the signal time t; Column 8 is the directional inequality of the market price at time t relative to the boundary determined by the algorithm at time t (reported in Column 9).

[Insert Table 3 about here]

[Insert Table 4 about here]

In Table 4 we report the identical trades as in Table 3, but have sorted them by REIT ticker and signal time t. Additionally, we add values in Column 10 computed at the end of the trading which indicate a value equal to 1 if two opposite trade signals at distinct (non-overlapping) times were produced by the algorithm. We call these trades 'dual' trades or 'pairing' trades. We only know in hindsight if a trade was a dual as there is no guarantee that any signal will be produced for a REIT on any given day, much less a dual or pairing set of signals for a REIT.

We see on this day that of the twenty-five total trades, twelve of them were so-called 'dual' trades where two opposite signals were produced for the same REIT totaling six distinct REITs in this category. For these twelve 'dual' or 'pairing' trades, the corresponding sell/buy or buy/sell signal following the initial buy/sell or sell/buy signal at time t, unwinds the position originally taken. The remaining thirteen distinct (non-dual or non-pairing) trades are unwound at the closing price reported at 16:15:00 (4:15:00PM ET).

5.3.1 Returns for example

We define our percentage returns on each day for the i-th REIT, R_i, in terms of its market prices, $M_{i,\tau}$, at the time, τ, of its directional (buy/sell) signal driven by our algorithm as follows:

$$R_i = \begin{cases} \frac{M_{i,\tau_{sell}} - M_{i,\tau_{buy}}}{M_{i,\tau_{sell}}}, & \text{if } \tau_{sell} < \tau_{buy} \\ \frac{M_{i,\tau_{sell}} - M_{i,\tau_{buy}}}{M_{i,\tau_{buy}}} & \text{if } \tau_{buy} < \tau_{sell} \end{cases} \tag{3}$$

with the percentage returns converted to basis points ('bps') as in ordinary practice. Accepting these rules, restrictions, and our findings, it is *irrelevant* as to the sequence of which (or whether) a predicted maximum/minimum arrives first.

Consider again Tables 3 and 4 which show for October 20, 2025 trades 13 and 24 to be executed for BXP. Trade 13 is a sell-signal with $\tau_{sell} = $ 9:36:27AM at a market price for BXP $M_{i=BXP,\tau_{sell}=9:36:27AM} = \$71.78$ which is above the conditional boundary price for the sell-process of \$71.46. We short-sell on margin one share of BXP at a price of \$71.78 and thus receive proceeds of +\$71.78 in our trading account. No more sell signals are possible for the day for BXP. Later that day, as seen in Trade 24, our buy-process generates a buy-signal corresponding to time with τ_{buy} = 11:53:43AM, such that BXP $M_{i=BXP,\tau_{buy}=11:53:43AM}$ = \$70.71. Since, in this case we have an open short position, when we buy BXP, (-\$70.71 is withdrawn from our account), we cover that short and the position is closed. The resulting return for BXP for October 20, 2025 based on our algorithm in the top of Eq. (3)

$$R_{BXP} = \frac{M_{i,\tau_{sell}} - M_{i,\tau_{buy}}}{M_{i,\tau_{sell}}} = \frac{M_{BXP,\text{9:36:27AM}} - M_{BXP,\text{11:53:43AM}}}{M_{BXP,\text{9:36:27AM}}} = \frac{\$71.78 - \$70.71}{\$71.78} = 1.49066\% \tag{4}$$

or 149.07 bps for the daily return for BXP on October 20, 2025. This return for BXP, and the other returns for the other REITs in our sample are reported in Table 5 with all such trading returns for the nineteen REITs calculated as shown as in Eq (3), for October 20, 2025, in basis points.

[Insert Table 5 about here]

The remaining eighteen REITs all traded on this day with equal weighted allocation of portfolio funds equal to 1/19th of the then value of the portfolio.[11]

The equal weighted return for the portfolio spanning all nineteen REITs for this day is 18.27 bps. The returns restricted to the six dual-only trades (equal weighted within that category) was 74.73 bps ranging from 94.45 bps for WPC to 149.07 bps for BXP. In contrast, the returns restricted to the thirteen the non-dual trades (equal weighted within that category) was -7.78 bps ranging from -182.16 bps for PLD and 97.88 bps for MAR.

5.3.2 Margin account and transaction costs

The basic assumption of the use of a margin account for short selling REITs fully applies to all REITs in our trading strategies for our sample. This assumption is verifiably true with any (even retail) brokerage accounts[12]. All REITs in our study may be shorted with a margin account in place. All REITs in our sample require the

[11] On days in which no signal is produced for a given REIT, the return for that REIT is 0bps and still receives 1/19th of the weighting of the portfolio return for the day.

[12] See, for example, Charles Schwab, https://www.schwab.com/learn/story/shorting-stocks-your-investment-strategy?msockid=2956d820cb7363032ae2ce48cab16217; or even call their trading desk

standard 30% margin requirement, except Brookdale Senior Living ('BKD') which carries a 'special' 70% margin requirement. The margin requirement is cash (or marginable securities, if permitted) which is set aside (not tradable) and held in the brokerage account in addition to any principal (or notional principal) amounts of short positions taken by the trader. The margin account earns interest for the trader. Provided that the trading positions (long and short) taken by the trader are closed out ('covered') by the end of the trading day, the overnight interest fee of about 12.325% per annum is not charged to the trading account. Since by our rules, we carry no positions overnight the only transaction costs we would face would be bid/ask spreads and any special 'hard to borrow' fees which are announced ex-ante even through electronic brokerage APIs.

With respect to the bid/ask spreads, for the purpose of this analysis in the paper we assume them to be zero cost for comparative and academic purposes. Further, we do not have access to such data at the frequencies for which we have pricing through our API, nor do we have volumes traded. However, to put a finer point on the matter the reality is that the depth of the market for these publicly traded REITs appears to be quite good with bid/ask spreads ranging from 2bps to 12bps under the itself extreme assumption of 'suffering' the worst in bid-ask spread outcome ('buy' at full-offer, 'sell' at full-bid). Additionally, all REITs in our sample are well traded with average daily trading volumes of about hundreds of thousand of shares with bid/ask volume depth ranging from 10000 to 30000 shares from a recent snapshot in November 2025. As such, these assumption of zero cost appear to be reasonable for our methodological purposes of inquiry into a relationship between theoretical CMBX risk signals and REITs vis a vis PCA and EVT.

5.4 Results

Throughout the foregoing, we refer to our trading strategy consisting of executing a short/long trade based on an observed price occurring above/below a threshold corresponding to a given degree of confidence in the inverse cumulative Gumbel distribution function with α and β corresponding to the instantaneous observation of the predicted risk partitions and the security in question, as "for the given degree of confidence". We first calculate the predicted cumulative minimum and maximum for all REITs. This calculation occurs every fifteen-seconds during the trading day as described in the previous section.

5.4.1 Frequencies of predictions

For each degree of confidence there are 833 trading day classifications per REIT, one for each of the 833 out of sample trading days in our study.

[Insert Figure 3 about here]

First consider, in Figure 3, one REIT (SL Green, 'SLG') temporally for its maximum prices across the out of sample period, for different degrees of confidence for a 10:00:00am start time. Reading clockwise from the top left, for all plots the x-axis represents the times during the trading day beginning at 10:00am and ending at 4:15pm, ET; the y-axes reflect the dates in the out of sample period. The values depicted in the plots are thus optimal execution times for given dates in the sample period for maximums. We show the times for maximum (high) predictions for the SL Green REIT ('SLG') for the 833 trading days in the out of sample period, if they occur. What we see is in the upper left of the figure, at the 1% degree of confidence level (essentially a probability of 99% that the prediction is wrong), signals are generated almost immediately at the opening for the 10:00am start time cohort. In contrast, in the bottom right of the figure, at the 99% degree of confidence level, we see that maximum pricing signals are sparse and take place later in the trading day. This reflects the inherent discernment embedded within the Gumbel probability boundaries associated with the degrees of confidence selected. In between, we vary the degrees of confidence for the same sample period and REIT. These patterns repeat for all REITs in our sample for both 9:30:00am and 10:00:00am start times.

[Insert Figure 4 about here]

In Figure 4 we see that that for extreme degrees of confidence of 1 and 99, little trading occurs. In contrast more balanced trading occurs for middle degrees of confidence. This is as expected according to the trading rules. Looking at the classification of types of trades that come forth from the trading rules and probabilistic apertures the following pattern in the aggregate emerges. Recall, 'No trade' means that either no signal was generated for a REIT on a given day or that the signals for maximum and minimum were predicted at the exact time thereby indicating a flawed interpretation due to the independence of the distribution processes. 'Low only' indicates a day where only a minimum signal was predicted for a REIT. 'High only' indicates a day where only a maximum signal was predicted for the day for a REIT. 'Dual' indicates a day when *both* a minimum and a maximum was predicted for the day for a REIT. Table 6 shows the average allocation per classification of trade dates across all REITs in the out of sample period expressed as percentages of 833, across degrees of confidence. Panel A provides the percentage summaries for the 9:30am trading start time and Panel B provides the summaries for the 10:00am trading start time. These interim results report the differences which are helpful in portfolio selection, below.

[Insert Table 6 about here]

Why does this pattern matter? Because while intuition would suggest better returns with greater discretion of predicted maximums and minimums probabilistically, such discretion is itself a risk. Why? Because waiting for the perfect choice in a non infinite world with an artificial close of 4:15pm may never occur prior to the close. In this sense there is an inherent trade-off between risk and reward we address, putting on our hat of Portfolio Managers. Namely, 'What is the optimal degree of confidence in our trading strategy that admits trades that are profitable even if, in the limit, such trades must be suboptimal?' In this sense, we are putting ourselves on the clock of the trading day. This works quite well.

5.4.2 Annualized returns

To understand this issue better, we calculate the returns for all degrees of confidence applied to all REITs uniformly on a daily basis for all 833 out of sample trading days for trading strategy. We then aggregate these REIT objects into an equally weighted long/short REIT portfolio. We conduct testing for two strategies which restrict start times to 9:30:00am and 10:00:00am, respectively. This is purposeful and helps us to understand whether or not the first part of the trading day which exhibits considerable dislocation between market and model pricing as shown in Figure 2, represents a greater opportunity or greater risk, vis a vis our Gumbel adaptation and intraday extreme value signalling.

[Insert Figure 5 about here]

Figure 5 shows the annualized returns for the out of sample period of $n = 833$ trading days and the corresponding signal to noise ratio ('SNR')[13] for each degree of confidence for both 9:30:00am and 10:00:00am trading strategy starting times.

[13] The signal to noise ratio we use is μ^2/σ^2.

Higher SNR's suggest greater signal strength. Higher returns suggest greater exploitation of such signals in spotting trading opportunities of mispricing of REIT risks based on our Gumbel adaptation informed by intraday CMBX risk decompositions.

What we find is that at 50 degrees of confidence we secure annualized returns of about 95 percent, out of sample, for the 10:00:00am starting time. These returns correspond to the highest SNRs of about 1.25. The results favor using the 10:00:00am start time over the 9:30:00am start time at the 50 degrees of confidence level. While the 9:30:00am start time results are quite good, they peak at about 60% annualized returns, and at lower degrees of confidence. This may suggest that the 'mechanical' waiting for more information (inherent in the structure of our approach at higher degrees of confidence since we are not acting in the limit, but rather in real time) rewards our technique. In this sense, patience is a virtue, but only in the right measure, and this remains a (somewhat) open question for future research.[14]

5.4.3 Cumulative returns

With the above we now seek to determine if these profits earned by our strategies are demonstrative of skill. To answer this question we again turn to the ICAPM of Merton and Samuelson (1992). Preliminarily, for this comparison, we consider three portfolios: 1.) the 9:30:00am start time, 2.) 10:00:00am start time, and 3.) the Markowitz portfolio. The first two portfolios are equal weighted using out trading strategy under our adaptation of Gumbel. The third, is an implementation of the portfolio allocation techniques of mean variance optimization introduced by Markowitz (1952, 1990) and Sharpe (1964, 1994)with daily rebalancing of weights to maximize the Sharpe ratio, where such weights are then applied to the set of REITs in our sample at the start of each trading day. The Markowitz portfolio requires a rolling 1 year window for implementation. Ours do not. Nevertheless, for comparison, we have to restrict our out of sample period to accommodate. Additionally, as of this writing, the data from Ken French's website for ICAPM lag our sample period and so we must further restrict our analysis window. The end result for this analysis is

[14]Interestingly returns at the extremes of 99 and 1 degrees of confidence are not symmetric while the proportion of 'no trade' days is similar (see Figure 4). This suggests instances of infrequent trades at 99 degrees of confidence (waiting for more/better information) are more precise than similarly infrequent trades at the 1 degree of confidence level. This makes sense. It is noteworthy that all portfolios exhibit some positive returns out of sample, which represents a topic of future research into (possible) submartingale trading strategies and mini-bubbles.

a subset of $n = 438$ out of sample trading days from July 26, 2023 to August 29, 2025.

[Insert Figure 6 about here]

Figure 6 depicts the cumulative portfolio values for the three portfolios. The slightly smaller 2.05x (105% cumulative return, 10:00:00am start) vs. 2.11x (111% cumulative return, 9:30:00am start) cumulative portfolio values from our Gumbel adaptations are both much more robust than the Markowitz portfolio which shows cumulative values for this period of 1.17x (17% cumulative return). The fact that, in this truncated sample period, the 9:30:00am portfolio slightly outperforms the 10:00:00am start time portfolio is interesting and an area for future consideration.

5.4.4 ICAPM

Finally, turning to the ICAPM of Merton and Samuelson (1992) to complete the analysis at the portfolio levels of daily returns we again consider the three portfolios we consider three portfolios: 1.) the 9:30:00am start time, 2.) 10:00:00am start time, and 3.) the Markowitz portfolio. We capture the daily excess returns for each portfolio by deducting from those daily returns the corresponding daily returns for the long-only sector portfolios of our internal REITs ('Rindx') and also with iShares ICF REIT index ('ICF'), previously discussed.

[Insert Figure 7 about here]

In Figure 7 we depict the correlations amongst the three trading portfolios, the REIT sector long-only control portfolios (Rindx and ICF), and the standard ICAPM risk factors to evaluate equity based trading strategies introduced in Fama and French (1993) including: (i) the market portfolio, (ii) the small minus big ('SMB') equity index, and (iii) the high minus low ('HML') index, as well as the momentum ('MOM') risk factor introduced in Carhart (1997). The correlations are mostly as expected, in part reflecting the nature of the portfolio construction techniques. We see negative correlations between Markowitz and each of the Gumbel adaptation portfolio and positive correlations with the Market-Rf factor. We also observe positive correlations between the two Gumbel portfolios, and strong positive correlations between our two long-only REIT indices. The takeaway from this is that the returns results should presage an assessment of skill observable with positive and significant alphas under ICAPM testing. We find this to be true.

[Insert Table 7 about here]

In Table 7, Panel A we report the ICAPM results controlling for REIT sector risk with Rindx; Panel B shows results for controlling for REIT sector risk with ICF. We find positive and significant alphas for both Gumbel portfolios and insignificant alphas for the Markowitz portfolio implemented. Combined with the cumulative portfolio values depicted in Figure 6 and earlier findings, these results suggest skill in our trading strategy.

We further conduct the ICAPM analysis for each of the REITs underlying the two Gumbel adaptation portfolios to test to see if those results materially differed for different start time and different controls. These results are reported in Tables 8, 9, 10 and 11. What we find is further supporting evidence for choosing the 10:00:00am start time over the 9:30:00am start time. While all results represent substantial skill with significant and positive alphas per REIT, differences between 9:30:00am and 10:00:00am start times (holding sector control constant) show improvement in precision by waiting until 10:00:00am to start trading, This is evidenced by fewer insignificant alphas in the 10:00:00am cohort compared with the corresponding 9:30:00am cohort. For example, only one REIT in the 10:00:00am cohort for Rindx sector control does not exhibit positive and statistically significant alpha (NNN) while four REITs in the corresponding 9:30:00am cohort (also with Rindx sector control) do not exhibit positive and significant alpha (BKD, NNN, KIM and SPG). Additionally, holding start time constant and varying by sector control choice (Rindx vs. ICF), we see that controlling with ICF somewhat diminishes the assessment of skill at the individual REIT level for both time cohorts, but less so for the 10:00:00am cohort than the 9:30:00am cohort. Interestingly, NNN trading choices do not appear to demonstrate skill across all time and control cohorts. Thinking about it further, comparing across time cohorts with the Rindx sector control held constant, by waiting until 10:00:00am, more skilful choices are made for BKD, KIM and SPG REITs in the out of sample period. Overall, these results are excellent and provide further support for our research claim as to the validity of the relationship between intraday CMBX risk partitions and trading opportunities in the REIT market.

[Insert Table 8 about here]

[Insert Table 9 about here]

[Insert Table 10 about here]

[Insert Table 11 about here]

6 Conclusion

This paper is part of a growing inquiry into risk evaluation and portfolio rebalancing with enhanced and rapid information content. In this paper, we extend the work of Christopoulos and Barratt (2025a) to optimize long/short trading strategies intraday with EVT. We able to exploit intraday variation of the risk partitions as signals for the REIT market through our Gumbel adaptation. In this sense, this paper, at the more rapid pace of intraday estimation, expands on earlier inquiries in the literature into both equity and debt components of the real estate industry in a capital markets setting for securities linked to CRE property.

As noted by Ling, Wang and Zhou (2020), in their study of transmission time between risk at the CRE asset level within REITs and the responsiveness of the pricing of such publicly traded REITs, they provide evidence that the REIT market quickly incorporates such new information and translates investor expectations into updated REIT pricing reflecting investors' short-run and long-run expectations of the future cashflows of underlying REIT asset portfolios. By our work, while the updating frequency suggested in Ling, Wang and Zhou (2020) may be in place, the precision of investors sensibility with respect to future risks remains an open question, intraday. This may matter. As suggested by Shiller (2008), '*If people do not see any risk, and see only the prospect of outsized investment returns, they will pursue those returns with disregard for the risks.*' Our work, by disclosing risks in a new way, appears to provide investment outperformance and may provide empirical evidence to consider against the mathematics in mini-bubble/bubble formation noted by Fama (1965), Shiller (2008), Jarrow and Liu (2024), and others.

The work we perform, combines the theory manifested through simulation as found in Christopoulos and Jarrow (2018) with real time risk partition assessment as found in Christopoulos and Barratt (2025a) vis a vis the PCA techniques and then turns these insights into optimized portfolios through EVT techniques. The EVT techniques we focus to our investigation are motivated by finding a more elegant framework with which to rigorously spot inconsistencies between theoretical risk signals of CMBX risk partition and REIT pricing. In our trading strategy informed by our adaptation of Gumbel (1958, 2004), we are able to disclose intraday maximum and minimum values informed by the CMBX risk decomposition signals, intraday.

This exercise yields outstanding ICAPM results at the portfolio consolidated level of positive and significant alphas in the presence of 95% annualized returns for equal weighted constructions. It also yields impressive individual performance measures by our method for individual REITs with ICAPM positive and statistically significant alphas in a range of 69% to 95% of the REITs depending on the cohort. Finally it is a less cumbersome aggregation or trading exercise than the earlier work of found in Christopoulos and Barratt (2025a), with methodological improvements expanding that formative to work to a higher level of insights. The results in this paper validate the Intraday Model's crossover insights between theoretical intraday CMBX risk partition signals and the larger and more frequently traded REIT market, intraday.

Considering standard portfolio optimization techniques introduced in by Markowitz (1952, 1990) and Sharpe (1964, 1994) we also demonstrate that portfolios of REITs constructed by using our risk-signalled strategies perform better out-of-sample than REIT portfolios selected directly from REIT pricing histories as required in the mean variance approach of the prior literature and practice. There, our Gumbel adaptation portfolios exhibit positive and significant alphas in the presence of substantial excess returns, while the Markowitz portfolio does not. To be sure, there are many other comparisons that can be made even within the mean-variance approach to portfolio allocation. However, taking daily rebalanced long-short positions with reasonable assumptions demonstrated far worse cumulative returns, out of sample than those formed with our Gumbel adaptations with: -7.3% cumulative loss for the long/short Markowitz portfolio, 17.8% cumulative gain for long-only max Sharpe ratio approach, compared with cumulative gains of 106.4% and 113.4%, for the Gumbel adaptation portfolios of 9:30am and 10:00am start-times, respectively, in the out of sample period. As both the long-only and long/short mean-variance techniques are themselves still restricted to open and close prices for rebalancing, those findings further suggest that the intraday variation signals that we pick up with CMBX risk partitions within the Gumbel adaptations can be quite instructive to trading strategies for investors. Further inquiries into portfolio allocation along these lines are left to future work. Additionally, such work (under way) may consider the temporal clustering of predicted extrema compared with the actual extrema (hi/low) realized during the trading day juxtaposed with epsilons of predicted versus actual daily high/low values for REITs. This opens the door into further post-optimality analysis, finer tuning of the parameter estimates, and possibly incorporating additional techniques from the AI/ML ecosystem to refine further the trading decision-making process for investors.

Finally, the sample of 11% by count, 38% by market cap, and well distributed by major property types further supports the abstraction from transaction costs. While the sample of REITs is not exhaustive, the methodology could be more generalizable to a broader set of REITs and perhaps also to REIT ETF or options on REITs. This would entail re-estimation of the entire PCA technology of Christopoulos and Barratt (2024), further estimation of alpha and beta parameters for EVT in this work, and further backtesting. Additionally, in the case of consideration of options on REITs, such work presents a host of challenges related to strike prices and expiration dates, all of which may present challenges for optimization. This considerations of broader generalizations to other REITs and related derivativese, while interesting, are far outside the scope of this work.

For every fifteen-seconds, in each trading day of our study, we find intraday risk decompositions for CMBX represent strong signals for spotting intraday REIT mispricing with respect to risk across a broad array of market conditions. Our work, by framing risks in a new way, appears to provide investment outperformance and demonstrate skill. We claim this skill is based on our use of robust core signals (CMBX risk partitions) through our Gumbel adaptation and trading strategy techniques. Our work provides compelling support for our claims. Additionally, our findings expand beyond risk adjusted pricing of trillions USD of commercial real estate securities, and may provide insights into bubble/mini-bubble inquiries and facilitate technological advances in keeping with those of Federal Reserve Board (2025), and found elsewhere in policy and practice. This is left to future research.

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Appendix: PCA of Christopoulos and Barratt (2024, 2025a)

Christopoulos and Barratt (2024) contribute a technique of projection using PCA which they call the Daily Model, over the sample period of November 2007-April

2019. They implement a standard linear regression on the logs of the risk partitions reported in the monthly training set of Christopoulos and Jarrow (2018) against a digest of market data (twenty-five REITs, four US Treasuries, and the VIX volatility index). From ninety-two monthly observations in the training period over the period November 2007-June 2014[15] they create a lower-dimensional set of factors to explain 96% of the total variance at observed dates by performing a PCA retaining enough factors to preserve 96% of the total variance at the observed dates. For the PCA they, in general form, let $x_q(t)$ be the value of the q-th explanatory variable at time t. For PCA loadings $p_{iq},\ i \in [1,5], q \in [1,30]$ assuming all thirty factors, the elements of the i x q matrix of principal components of the observed explanatory variables $x_q(t)$ for all observed t, there exists a set of factors $f_i(t)$ such that

$$x_q(t) = \sum_{i=1}^{30} p_{iq} f_i(t) \tag{5}$$

with each explanatory variable a linear combination of the factors f_i at all times t. They reduce dimension because they have only ninety-two observations in the history of simulated risk partitions. The process reduced the number of components from thirty observable variables, to five variables. The factors are determined with matrix multiplication as

$$f_i(t) = \sum_{q=1}^{30} p_{iq} x_q(t),\ i \in \{1...5\} \tag{6}$$

The factors $f_i(t)$ are uncorrelated[16], such that the partial sum

$$x_q(t) = \sum_{i=1}^{5} p_{iq} f_i(t) + \varepsilon_n(t),\ \ \mathbb{E}[\varepsilon_n] = 0 \tag{7}$$

is an unbiased estimator of $x_q(t)$, where the error term $\mathbb{E}[\varepsilon_n] = \sum_{i=6}^{30} p_{iq} f_i(t)$, which is the minimal possible error that can be introduced in a 1:1 transformation with the technique. From the covariance matrix of the explanatory variables they calculate the 30×30 matrix of eigenvectors and their corresponding eigenvalues which are reported in their study. The first five eigenvalues have cumulative variance of 96.11%, supporting use of just the first five principal components. This allowed

[15] See Figure 9 in Christopoulos and Jarrow (2018).

[16] See Christopoulos and Barratt (2024) Online Appendix A.3.

the transformation of 30 variables into a digest of just 5 variables with $x_q(t)$ the value of the q-th economic variable at time t. The five-dimensional digest is used to construct factor volatility explanatory variables for the risk component estimates. The factor volatilities f_{it} are a function of the PCA loadings and the explanatory variables observed at time t.

For R^T the 5×30 PCA loadings matrix, and E^T the 30×92 matrix of the thirty variables over ninety-two observation dates, whose elements are $x_q(t)$, then the factor matrix, F, calculated using matrix multiplication as the product of R^T and E^T, is

$$\mathrm{F} = \mathrm{R}^T\mathrm{E}^T = \begin{bmatrix} f_{1,1} & \cdots & f_{t,5} \\ \vdots & \ddots & \vdots \\ f_{92,1} & \cdots & f_{92,5} \end{bmatrix} \tag{8}$$

which yields a 92×5 matrix, the elements of which are the factors, f_{ti} that they use to capture the volatility in their model. Switching notation $f_{ti} \equiv f_{it}$ for the remaining calculations, the factor volatility determined from the PCA is $v_i(t) \equiv [f_i(t) - f_i(t-1)]^2$. For each month, t, to estimate the risk partition they begin with an opening value based on the two previous one-month volatilities of the variables $v_i(t)$ and $v_i(t-1)$ and the CMBX indexed market spread $\mathbb{S}_k(t)$ for each credit rating class, as these were the values made available to them for training purposes.

The risk partitions are the proportional results from the ninety-two monthly simulated indexed risk decompositions of Christopoulos and Jarrow (2018) over the period November 2007 thru June 2015. The initial risk component $y_{jk}(t_0)$, $j \in \{\mathrm{def}, \mathrm{rate}, ...\}, k \in \{\mathrm{AAA}, \mathrm{AJ/AS}, ...\}$, is given by

$$y_{jk}(t) = \alpha_{jk} + \sum_{i=1}^{5} \beta_{ijk} v_i(t) + \gamma_{ijk} v_i(t-1) + \delta_{ijk}\left[v_i(t) - v_i(t-1)\right]^2 + \psi_k \mathbb{S}_k(t) + \varepsilon_{jk}(t) \tag{9}$$

The coefficients $\{\alpha_{jk}, \beta_{ijk}, \gamma_{ijk}, \delta_{ijk}, \psi_k\}$ were determined through OLS by minimizing the sum of the squared error $\sum_t \varepsilon_{jk}(t)$ with t indexed in months with $\mathbb{E}[\varepsilon_{jk}(t)] = 0$. In total, sixteen coefficients were estimated, one for each of the fifteen separate volatility components, and one for the indexed market spread corresponding to the credit rating class. The OLS captures ninety monthly observations over the period 12/2007 - 6/2015 with statistically significant results. In particular, the third principal component for all three volatilities $v_i(t)$, $v_i(t-1)$, and $[v_i(t) - v_i(t-1)]^2$ appears consistently more significant across all regressions compared with other principal components, with the VIX the largest value suggesting its large influence on the third principal component. After determining the estimates in Eq. (9) they then predict the daily spread risk decompositions using Eq. (10) combining the estimates and 2828 daily on the run observations, adjusting the lookback of the factor volatilities with twenty-two trading days equal to one month from the date of the daily observations for the updated calculations.

The estimation model re-expresses the daily predicted model with the following procedure. For all trading days, u, compute predicted values on the left hand side based on the principal component volatilities, market spreads and estimated coefficients on the right hand side as

$$\hat{y}_{jk}(u) = \alpha_{jk} + \sum_{i=1}^{5} \beta_{ijk} v_i(u) + \gamma_{ijk} v_i(u-22) + \delta_{ijk} \left[v_i(u) - v_i(u-22) \right]^2 + \psi_k \mathbb{S}_k(t) \quad (10)$$

with the final risk composition computed as a proportion of the total for the bond:

$$\bar{y}_{jk}(u) = \frac{\hat{y}_{jk}(u)}{\sum_j \hat{y}_{jk}(u)} \quad (11)$$

All four risk components are computed this way for the CMBX sector aggregated across all credits. The time series is a weighted average across all on-the run investment grade credit ratings classes with the weights the class subordination levels.

The Daily Model of Christopoulos and Barratt (2024) is based on changes in explanatory variables which capture the economy of REITs, US Treasuries and the VIX, not market pricing for CMBX. As such, nothing prevents increasing the frequency of estimation for all risk components from daily, to shorter intervals intraday. Specifically, Christopoulos and Barratt (2025a) introduce the Intraday Model for CMBX risk decomposition which adapts the Daily Model to higher frequency pricing intervals. In that study, all mathematics discussed above in the Daily Model apply to all trading days u, with time t the intraday time interval index with $t \in [1, 1560]$ representing one of the 1560 fifteen-second intervals from 9:30:15am to 4:15:00pm EST for each trading day u. Once the daily initial conditions have been determined, for each trading day, u, the intraday changes in risk composition are then modelled as a zero-centered function of the evolution of the factors

$$\Delta y_{jk}(t) = \sum_{i=1}^{5} \eta_{ijk} \Delta f_i(t) + \varepsilon^{\Delta}_{jk}(t) \tag{12}$$

for the j-th risk partition of the k-th bond at time t. They compute a covariance matrix such that η_{ijk} is the covariate of the i-th factor with the corresponding bond's corresponding risk component. The coefficients η_{ijk} are determined through OLS and $\varepsilon^{\Delta}_{jk}(t)$ has expected mean zero with standard deviation $\sqrt{\eta_{0jk}}$. They then normalize the sum of the proportions for the intraday risk decomposition to 1 as was done previously for daily observations in Eq. (11). The final risk composition is then calculated using the initial condition and the instantaneous changes:

$$y_{jk}(t) = y_{jk}(t_0) + \sum_{t'=1}^{t} \Delta y_{jk}(t') \tag{13}$$

where the intraday estimation of risk components $y_{jk}(t)$ is the natural log of the j-th component of the risk partition for bond k at time t on trading day u. The first term on the right-hand side, $y_{jk}(t_0)$, is the initial value of the risk component intraday and the second term $\sum_{t'=1}^{t} \Delta y_{jk}(t')$ the intraday sum of the changes in the risk component defined in Eq. (12). Importantly, these changes in the economy on the right hand side of Eq. (13) are independent of current market prices. Their relationship to estimated risk partitions on the left hand side is statistically driven vis a vis the coefficients, η_{ijk}, interacting with the change in the factor volatilities, $\Delta f_i(t)$, on the right hand side of the equation. The factor volatilities, $f_i(t)$, are determined with PCA as shown in Eq. (8) and related definitions, as discussed.

Tables

Table 1: Sample REITs

PropType	Ticker	Factor Name	REIT Name	Market Cap ($bn)
Industrial (IN)	DRE	IN_DRE	Duke Realty	$18.04
	FR	IN_FR	First Industrial Realty Trust	$6.90
	PLD	IN_PLD	Prologis, Inc.	$90.25
	SELF	IN_SELF	Global Self Storage, Inc.	$54.28
Hotel (LO)	HST	LO_HST	Host Hotels & Resorts, Inc.	$12.41
	MAR	LO_MAR	Marriott International, Inc.	$45.64
	WH	LO_WYND	Wyndham Hotels & Resorts, Inc.	$6.82
	MGM	LO_MGM	MGM Resorts International	$21.53
Multifamily (MF)	AVB	MF_AVB	Avalon Bay Communities, Inc.	$29.87
	ELS	MF_ELS	Equity LifeStyle Properties, Inc.	$13.81
	EQR	MF_EQR	Equity Residential	$29.39
	UDR	MF_UDR	UDR, Inc.	$14.80
Office (OF)	BXP	OF_BXP	Boston Properties, Inc.	$18.70
	CLI	OF_CLI	Mack-Cali Realty Corporation	$1.55
	HIW	OF_HIW	Highwoods Properties, Inc.	$4.85
	SLG	OF_SLG	SL Green Realty Corp.	$5.72
	VNO	OF_VNO	Vornado Realty Trust	$9.24
Mixed Use/Other (OT)	BKD	OT_BKD	Brookdale Senior Living Inc.	$1.54
	NNN	OT_NNN	National Retail Properties, Inc.	$8.41
	PSB	OT_PSB	PS Business Parks, Inc.	$4.15
	WPC	OT_WPC	W.P. Carey Inc.	$13.93
Retail (RT)	KIM	RT_KIM	KIMCO Realty Corporation	$9.14
	REG	RT_REG	Regency Centers Corporation	$11.05
	SPG	RT_SPG	Simon Property Group	$43.06
	TCO	RT_TCO	Taubman Centers Inc.	$3.40

This table summarizes the twenty-five REITs used in this study. The market capitalization of the REITs are $478.45 billion as of 6/27/2021. The first column provides the property type and groups the REITs by property type separated by borders. The six property types are Industrial (IN), Hotel (LO), Multifamily (MF), Office (OF), Mixed Use/Other (OT), and Retail (RT). The second column provides the stock market ticker symbol. The third column provides the factor name composite of the property type with the ticker. The fourth column provides the name of the REIT, with the fifth column the market capitalization.

Table 2: Parameter estimates of alpha and beta coefficients for explanatory variables under the Gumbel distribution

Panel A: Low Extremum (minimums)

Security	(Intercept) α	(Intercept) β	Default AAA α	Default AAA β	Default AJ α	Default AJ β	Default AA α	Default AA β	Default A α	Default A β	Default BBB α	Default BBB β	Default BBBm α	Default BBBm β
IN_FR	1E+01	6E+03	4E-03	8E-01	-4E-03	-1E+00	5E-03	2E+00	7E-03	1E+00	-4E-02	-1E+01	2E-02	5E+00
IN_PLD	2E+01	8E+03	4E-03	1E+00	-5E-03	-1E+00	8E-03	2E+00	1E-02	4E+00	-5E-02	-1E+01	3E-02	4E+00
LO_HST	3E+00	-3E+02	4E-04	-3E-01	-1E-03	3E-01	3E-03	-1E+00	8E-03	2E+00	-2E-02	-3E+00	2E-02	3E+00
LO_MAR	1E+01	4E+03	5E-03	7E-01	-5E-03	-7E-01	9E-03	8E-01	6E-03	2E+00	-4E-02	-9E+00	3E-02	5E+00
LO_MGM	1E+01	2E+03	5E-03	4E-01	-5E-03	-6E-01	6E-03	8E-02	1E-02	2E+00	-4E-02	-6E+00	3E-02	3E+00
MF_AVB	2E+01	4E+03	1E-03	2E-01	-3E-03	-6E-01	9E-03	2E+00	7E-03	8E-01	-3E-02	-4E+00	6E-03	-9E-01
MF_ELS	1E+01	3E+03	2E-03	5E-01	-3E-03	-7E-01	6E-03	9E-01	9E-03	2E+00	-3E-02	-6E+00	1E-02	2E+00
MF_EQR	2E+01	5E+03	1E-03	2E-01	-3E-03	-6E-01	8E-03	2E+00	4E-03	6E-01	-3E-02	-6E+00	1E-02	3E-01
MF_UDR	2E+01	5E+03	1E-03	4E-02	-9E-04	-3E-01	7E-03	2E+00	5E-03	-3E-01	-4E-02	-5E+00	1E-02	8E-01
OF_BXP	3E+01	5E+03	3E-03	6E-01	-2E-03	-3E-01	9E-03	2E-01	1E-02	3E+00	-6E-02	-1E+01	3E-02	7E+00
OF_HIW	2E+01	2E+03	-1E-04	-2E-01	-2E-03	-4E-01	1E-02	1E+00	7E-03	6E-01	-3E-02	-3E+00	9E-03	1E+00
OF_SLG	1E+01	2E+02	-1E-03	-8E-01	-2E-04	4E-01	7E-03	-1E-01	9E-03	1E+00	-3E-02	-4E-04	1E-02	4E-01
OF_VNO	2E+01	2E+03	4E-04	-6E-02	2E-03	2E-01	2E-03	-5E-02	8E-03	1E+00	-5E-02	-5E+00	3E-02	3E+00
OT_BKD	2E+01	7E+02	7E-03	4E-01	-1E-02	-6E-01	2E-02	8E-01	2E-02	1E+00	-5E-02	-3E+00	4E-02	3E+00
OT_NNN	3E+01	6E+03	5E-03	6E-01	-1E-03	-1E-01	4E-03	4E-01	1E-02	2E+00	-5E-02	-1E+01	1E-02	3E+00
OT_WPC	1E+01	3E+03	3E-03	3E-01	-2E-03	-5E-02	7E-03	7E-01	8E-03	1E+00	-3E-02	-3E+00	1E-02	-2E+00
RT_KIM	2E+01	2E+03	1E-03	-7E-02	-1E-04	5E-01	5E-03	-4E-01	6E-03	8E-01	-3E-02	-2E+00	8E-03	-4E-01
RT_REG	2E+01	3E+03	4E-03	4E-01	-3E-03	3E-02	8E-03	4E-02	1E-02	2E+00	-4E-02	-4E+00	1E-02	3E-01
RT_SPG	1E+01	9E+02	2E-03	-3E-02	2E-03	1E+00	-2E-04	-2E+00	1E-02	2E+00	-3E-02	-4E+00	2E-02	2E+00

Security	Rates AAA α	Rates AAA β	Rates AJ α	Rates AJ β	Rates AA α	Rates AA β	Rates A α	Rates A β	Rates BBB α	Rates BBB β	Rates BBBm α	Rates BBBm β
IN_FR	4E-03	1E+00	-1E-03	-1E+00	4E-03	2E+00	-2E-03	-7E-01	-2E-03	-4E-01	-2E-03	1E+00
IN_PLD	4E-03	1E+00	-3E-03	-1E+00	4E-03	1E+00	1E-03	-2E-01	-3E-03	-3E-01	4E-03	3E+00
LO_HST	-2E-03	-9E-01	-2E-03	-3E-01	-3E-04	-4E-01	3E-03	5E-01	-2E-03	-4E-01	1E-03	-5E-01
LO_MAR	5E-03	1E+00	-5E-03	-2E+00	4E-03	1E+00	2E-03	-3E-01	-8E-04	1E-01	8E-03	2E+00
LO_MGM	2E-03	-3E-01	-5E-03	-1E+00	3E-03	2E+00	4E-03	-2E+00	-2E-03	2E-02	6E-03	-2E-01
MF_AVB	5E-03	2E+00	-6E-03	-2E+00	1E-03	-4E-01	5E-03	1E+00	-2E-03	-5E-01	-3E-03	-4E-01
MF_ELS	8E-04	6E-01	-2E-03	-1E+00	6E-03	2E+00	-2E-03	-6E-01	-3E-03	-5E-01	-7E-03	-5E-01
MF_EQR	5E-03	2E+00	-4E-03	-2E+00	4E-03	2E-01	8E-04	6E-01	-2E-03	-3E-01	-6E-03	-1E-01
MF_UDR	2E-03	2E+00	-6E-03	-2E+00	3E-04	-3E-02	4E-03	7E-01	-2E-03	-2E-01	4E-03	6E-01
OF_BXP	1E-03	-3E-01	-7E-03	-2E+00	6E-03	2E+00	2E-03	-1E-01	-4E-03	-1E+00	3E-03	6E-01
OF_HIW	2E-03	6E-02	-5E-03	-1E+00	6E-03	2E+00	-4E-03	-2E+00	-4E-04	6E-02	-5E-03	-1E+00
OF_SLG	4E-03	6E-01	-8E-03	-1E+00	8E-03	8E-01	-2E-03	-3E-01	-3E-03	-5E-01	-9E-03	-3E+00
OF_VNO	1E-03	3E-01	-8E-03	-1E+00	-3E-03	-1E+00	1E-02	2E+00	-8E-03	-1E+00	5E-03	-2E-01
OT_BKD	6E-03	3E-02	-1E-03	-2E-01	8E-03	8E-01	3E-04	-5E-01	-5E-03	-2E-01	-2E-02	-1E+00
OT_NNN	3E-03	8E-01	-8E-03	-2E+00	-1E-04	4E-01	4E-03	7E-02	-2E-03	-5E-01	1E-02	2E+00
OT_WPC	1E-03	5E-01	2E-03	3E-01	8E-03	2E+00	-6E-03	-2E+00	-4E-04	3E-01	6E-04	-3E-01
RT_KIM	6E-03	9E-01	-9E-03	-2E+00	-1E-04	9E-02	4E-03	2E-02	-1E-03	5E-02	1E-02	4E-01
RT_REG	3E-03	4E-01	-5E-03	-1E+00	4E-03	9E-01	1E-03	-3E-01	-1E-03	-4E-02	7E-03	2E-02
RT_SPG	2E-03	-2E-01	-7E-03	-1E+00	-3E-03	5E-01	8E-03	-4E-01	-6E-03	-5E-01	-4E-03	-8E-01

Security	Liquidity AAA α	Liquidity AAA β	Liquidity AJ α	Liquidity AJ β	Liquidity AA α	Liquidity AA β	Liquidity A α	Liquidity A β	Liquidity BBB α	Liquidity BBB β	Liquidity BBBm α	Liquidity BBBm β
IN_FR	2E-03	3E-01	-6E-04	-7E-02	-3E-04	-1E-01	1E-03	2E-01	-1E-03	-5E-01	2E-03	2E-01
IN_PLD	5E-04	1E+00	-9E-04	-6E-02	-5E-04	-2E-01	1E-03	3E-01	-1E-03	-5E-01	2E-03	2E-01
LO_HST	1E-03	6E-01	-2E-04	-3E-02	-4E-05	3E-02	6E-04	-4E-02	4E-04	1E-01	3E-04	7E-02
LO_MAR	2E-03	1E+00	-5E-04	-1E-01	-6E-04	-3E-01	6E-04	2E-01	-1E-03	-3E-01	1E-03	3E-01
LO_MGM	3E-03	1E+00	-4E-04	-1E-01	-5E-04	-3E-01	6E-04	2E-01	-8E-04	-2E-01	9E-04	3E-01
MF_AVB	7E-04	9E-01	-6E-04	-8E-02	2E-05	-1E-01	1E-03	2E-01	4E-04	5E-02	2E-03	2E-01
MF_ELS	8E-04	6E-01	-6E-04	-9E-02	1E-04	-2E-01	1E-03	2E-01	2E-04	5E-03	2E-03	2E-01
MF_EQR	8E-04	1E+00	-9E-04	-9E-02	-2E-04	-1E-01	1E-03	3E-01	-4E-05	-9E-02	2E-03	3E-01
MF_UDR	2E-03	9E-01	-4E-04	-7E-02	3E-04	-6E-02	5E-04	1E-01	4E-04	7E-02	1E-03	2E-01
OF_BXP	2E-04	8E-01	-6E-04	-1E-01	3E-04	-1E-01	7E-04	1E-01	1E-04	-5E-02	1E-03	3E-01
OF_HIW	3E-03	8E-01	-4E-04	-6E-02	4E-05	-2E-01	1E-03	2E-01	-5E-04	-1E-01	1E-03	2E-01
OF_SLG	3E-03	1E+00	-6E-04	-8E-02	-7E-04	-1E-01	2E-03	3E-01	2E-03	3E-01	1E-03	2E-01
OF_VNO	1E-03	2E-01	-7E-04	-7E-02	5E-04	3E-02	4E-04	4E-02	3E-04	1E-01	2E-03	2E-01
OT_BKD	-5E-04	3E-01	-1E-03	-8E-02	-8E-04	-1E-01	4E-03	3E-01	-2E-03	-2E-01	4E-03	2E-01
OT_NNN	6E-03	2E+00	-5E-05	-4E-02	-6E-05	-2E-01	5E-04	1E-01	-1E-03	-4E-01	-4E-05	1E-01
OT_WPC	-2E-03	3E-01	-7E-04	-5E-02	-7E-04	-3E-01	2E-03	3E-01	2E-04	1E-01	2E-03	2E-01
RT_KIM	4E-03	1E+00	-2E-04	-4E-02	-4E-04	-2E-01	1E-03	2E-01	-5E-04	-2E-02	4E-04	1E-01
RT_REG	4E-04	9E-01	-6E-04	-7E-02	-4E-04	-1E-01	2E-03	2E-01	-9E-04	-1E-01	1E-03	2E-01
RT_SPG	8E-03	2E+00	-9E-04	-1E-01	1E-03	-3E-02	6E-04	1E-01	8E-04	1E-01	2E-03	3E-01

Panel B: High Extremum (maximums)

Security	(Intercept) α	(Intercept) β	Default AAA α	Default AAA β	Default AJ α	Default AJ β	Default AA α	Default AA β	Default A α	Default A β	Default BBB α	Default BBB β	Default BBBm α	Default BBBm β
IN_FR	7E+00	4E+03	-2E-03	-6E-01	3E-03	7E-01	-3E-05	9E-01	-3E-03	-1E+00	1E-02	-5E-01	-2E-02	-4E+00
IN_PLD	1E+01	5E+03	-3E-03	-9E-01	3E-03	6E-01	2E-03	1E+00	-5E-03	-1E+00	6E-03	1E-01	-2E-02	-6E+00
LO_HST	1E+01	2E+03	-2E-03	-7E-01	4E-03	9E-01	3E-03	2E-01	-8E-03	-1E+00	2E-03	1E+00	-1E-02	-3E+00
LO_MAR	1E+01	2E+03	-3E-03	-3E-01	6E-03	8E-01	-2E-03	-2E-01	-5E-03	-1E+00	2E-02	4E+00	-4E-02	-8E+00
LO_MGM	3E+01	6E+03	-2E-03	7E-02	5E-03	4E-01	4E-03	6E-01	-2E-03	4E-01	-2E-02	-6E+00	-2E-02	-1E+00
MF_AVB	4E+00	2E+03	-5E-04	-3E-01	2E-03	4E-01	2E-04	3E-01	-3E-03	-9E-01	8E-03	2E+00	-1E-02	-4E+00
MF_ELS	1E+01	4E+03	-1E-03	-7E-03	3E-03	4E-01	-2E-04	-1E-01	-4E-03	-1E-02	-4E-03	-5E+00	-1E-02	-3E-01
MF_EQR	8E+00	3E+03	-8E-04	-4E-01	4E-04	8E-02	4E-03	1E+00	-4E-03	-8E-01	1E-02	2E+00	-2E-02	-6E+00
MF_UDR	-4E-01	1E+03	2E-04	-6E-02	7E-04	2E-01	-1E-03	1E-01	-6E-04	-6E-01	1E-02	2E+00	-1E-02	-4E+00
OF_BXP	3E+00	2E+03	-1E-03	-3E-01	1E-03	5E-01	1E-03	1E-02	-5E-03	-7E-01	1E-02	1E+00	-2E-02	-4E+00
OF_HIW	9E+00	1E+03	-1E-03	-4E-01	3E-03	6E-01	-3E-03	-9E-01	-2E-03	-3E-01	9E-04	3E-01	-1E-02	-2E+00
OF_SLG	2E+01	3E+03	-2E-03	-7E-01	4E-03	1E+00	-2E-03	-8E-01	-2E-03	-4E-01	-4E-03	-6E-01	-1E-02	-3E+00
OF_VNO	1E+00	2E+03	-3E-03	-7E-01	3E-04	2E-01	4E-03	1E+00	-5E-03	-1E+00	3E-02	2E+00	-3E-02	-5E+00
OT_BKD	6E+01	7E+03	-7E-03	-2E-01	1E-02	4E-01	1E-02	2E+00	-3E-03	-4E-01	-6E-02	-9E+00	-1E-02	6E-01
OT_NNN	4E+00	1E+03	-4E-03	-9E-01	1E-03	3E-01	6E-03	1E+00	-6E-03	-1E+00	1E-03	-2E+00	2E-03	2E+00
OT_WPC	1E+01	5E+03	-2E-03	-3E-01	3E-03	7E-01	-6E-04	-4E-01	-1E-03	8E-01	-7E-03	-7E+00	-2E-03	3E+00
RT_KIM	1E+01	3E+03	-1E-03	-4E-01	1E-03	3E-01	8E-03	1E+00	-6E-03	-1E+00	-1E-03	-2E+00	-7E-03	-7E-01
RT_REG	1E+01	3E+03	-2E-03	-6E-01	6E-03	1E+00	-9E-04	2E-01	-5E-03	-1E+00	-1E-02	-3E+00	3E-03	3E-01
RT_SPG	3E+01	5E+03	6E-04	-5E-02	4E-03	5E-01	9E-03	1E+00	-4E-03	-4E-01	-3E-02	-6E+00	-2E-03	6E-01

Security	Rates AAA α	Rates AAA β	Rates AJ α	Rates AJ β	Rates AA α	Rates AA β	Rates A α	Rates A β	Rates BBB α	Rates BBB β	Rates BBBm α	Rates BBBm β
IN_FR	2E-03	5E-01	-4E-03	-2E+00	-7E-05	-4E-01	6E-04	1E+00	2E-03	5E-01	2E-04	2E+00
IN_PLD	3E-03	1E+00	-5E-03	-2E+00	4E-03	1E+00	-4E-03	-2E+00	2E-03	9E-01	-2E-03	-2E-01
LO_HST	7E-03	1E+00	-7E-03	-1E+00	1E-03	2E-02	5E-04	7E-02	1E-03	5E-01	4E-03	1E+00
LO_MAR	5E-03	2E+00	-3E-03	-1E+00	-6E-03	-2E+00	4E-03	2E+00	9E-04	4E-01	-2E-03	8E-02
LO_MGM	4E-03	1E+00	-5E-03	-2E+00	2E-03	-2E-01	5E-04	1E+00	9E-06	-2E-01	1E-02	4E+00
MF_AVB	5E-03	1E+00	-3E-03	-1E+00	9E-04	-2E-01	-4E-03	-6E-01	3E-03	9E-01	1E-03	1E+00
MF_ELS	5E-03	9E-01	-5E-03	-2E+00	-4E-04	-5E-01	2E-04	9E-01	3E-03	4E-01	1E-02	4E+00
MF_EQR	6E-03	1E+00	-5E-03	-1E+00	3E-03	7E-01	-4E-03	-7E-01	3E-03	8E-01	-2E-03	4E-01
MF_UDR	4E-03	1E+00	-1E-03	-6E-01	3E-03	2E-01	-4E-03	-3E-01	4E-03	1E+00	-5E-04	1E+00
OF_BXP	5E-03	1E+00	-2E-03	-9E-01	-2E-03	-2E+00	-4E-05	2E+00	2E-03	3E-01	-2E-03	1E+00
OF_HIW	4E-03	3E-01	-4E-03	-9E-01	-1E-03	-5E-01	7E-04	3E-01	2E-03	3E-01	3E-03	7E-01
OF_SLG	3E-03	6E-01	-5E-03	-1E+00	-7E-03	-2E+00	6E-03	2E+00	8E-04	2E-01	4E-03	2E+00
OF_VNO	5E-03	6E-01	2E-03	-8E-01	6E-03	-2E-01	-1E-02	-1E-01	5E-03	7E-01	-1E-02	-3E-01
OT_BKD	8E-03	1E+00	-1E-02	-2E+00	9E-03	9E-01	-5E-03	-3E-02	3E-03	2E-01	4E-02	5E+00
OT_NNN	9E-04	-4E-01	-1E-03	-7E-01	1E-02	2E+00	-1E-02	-2E+00	4E-03	8E-01	-4E-03	1E+00
OT_WPC	5E-03	1E+00	-8E-03	-3E+00	-4E-03	-2E+00	5E-03	3E+00	-8E-04	-6E-01	2E-03	2E+00
RT_KIM	4E-03	7E-01	-5E-04	-8E-01	7E-03	6E-01	-6E-03	-5E-01	4E-03	6E-01	3E-04	2E+00
RT_REG	3E-03	8E-01	-6E-03	-2E+00	-2E-03	-1E+00	3E-03	1E+00	7E-05	7E-02	6E-03	2E+00
RT_SPG	3E-03	5E-01	-7E-03	-1E+00	1E-02	1E+00	-4E-03	-4E-01	1E-03	2E-01	2E-02	3E+00

Security	Liquidity AAA α	Liquidity AAA β	Liquidity AJ α	Liquidity AJ β	Liquidity AA α	Liquidity AA β	Liquidity A α	Liquidity A β	Liquidity BBB α	Liquidity BBB β	Liquidity BBBm α	Liquidity BBBm β
IN_FR	1E-03	7E-02	2E-05	-7E-04	4E-04	2E-01	-3E-04	-7E-02	1E-05	-1E-01	-2E-04	-6E-02
IN_PLD	3E-03	1E+00	-3E-05	-3E-02	5E-04	4E-02	6E-04	2E-01	-5E-04	-2E-01	-1E-04	3E-02
LO_HST	4E-03	8E-01	-5E-04	-6E-02	4E-04	2E-02	-9E-06	-1E-02	-1E-03	-2E-01	1E-03	1E-01
LO_MAR	4E-03	1E+00	-2E-04	6E-03	1E-03	1E-01	-1E-04	-4E-02	5E-04	-2E-02	6E-05	-8E-02
LO_MGM	-7E-04	2E-01	-2E-04	-2E-02	2E-04	-8E-02	1E-03	1E-01	-1E-03	-3E-01	4E-07	-1E-02
MF_AVB	5E-03	1E+00	-1E-04	-1E-02	2E-04	6E-02	3E-04	9E-02	-8E-04	-1E-01	2E-04	-6E-03
MF_ELS	2E-03	3E-01	8E-05	3E-02	-2E-05	3E-02	3E-05	-4E-03	-9E-04	-2E-01	-2E-04	-1E-01
MF_EQR	5E-03	6E-01	-8E-05	7E-03	3E-04	6E-02	6E-04	1E-01	-1E-03	-1E-01	2E-05	-6E-02
MF_UDR	2E-03	7E-02	-1E-04	2E-02	4E-04	1E-01	4E-04	6E-02	-5E-04	1E-03	2E-04	-1E-01
OF_BXP	4E-03	1E+00	-2E-04	2E-02	9E-04	2E-01	2E-04	-7E-02	-1E-03	-3E-01	3E-04	-1E-01
OF_HIW	4E-03	1E+00	-2E-04	-2E-02	5E-04	1E-01	1E-04	-6E-02	3E-04	2E-01	3E-04	-2E-03
OF_SLG	7E-03	1E+00	-5E-04	-2E-02	1E-03	2E-01	-9E-04	-2E-01	-1E-03	-1E-01	1E-03	2E-02
OF_VNO	1E-03	2E-01	-3E-04	-1E-02	-8E-04	-3E-02	2E-03	2E-01	-6E-04	-2E-01	7E-04	1E-02
OT_BKD	-3E-03	-4E-01	-8E-04	-5E-02	7E-04	-3E-02	2E-03	2E-01	-2E-04	-2E-01	2E-03	1E-01
OT_NNN	-4E-03	-7E-01	-5E-04	-5E-02	9E-05	5E-02	1E-03	2E-01	3E-04	9E-02	1E-03	1E-01
OT_WPC	6E-03	2E+00	-3E-05	-2E-02	7E-04	2E-01	-2E-04	-7E-02	-3E-04	-1E-01	-9E-05	-7E-03
RT_KIM	-2E-03	-9E-02	-9E-04	-3E-02	6E-04	2E-02	1E-03	1E-01	6E-04	2E-01	2E-03	6E-02
RT_REG	4E-03	1E+00	-5E-04	-6E-02	2E-03	4E-01	1E-04	-6E-02	9E-05	3E-02	8E-04	8E-02
RT_SPG	-6E-04	-6E-02	-3E-04	-5E-02	4E-04	1E-02	2E-03	2E-01	-2E-03	-4E-01	2E-04	7E-02

This table shows the Gumbel distribution parameter estimates using the Maximum Likelihood Estimation numerical technique for fitting alpha and beta parameters estimated for each of the nineteen REIT securities considered in the trading strategy. Panel A shows the estimates for the low extremum (minimum) and Panel B shows the estimates for the high extremum (maximums).

Table 3: Trading signals produced on October 20, 2025 with algorithm start time of 9:30:00AM ET

date	trade #	signal time (t)	signal	proptype	reit_ticker	reitpx at (t)	direction	boundary at (t)
10/20/2025	1	9:30:21	BUY	MF	ELS	62.06	$<$	62.12
10/20/2025	2	9:30:21	SELL	IN	FR	55.49	$>$	55.36
10/20/2025	3	9:30:21	SELL	OF	VNO	39.5	$>$	39.48
10/20/2025	4	9:30:41	SELL	MF	AVB	188.03	$>$	187.87
10/20/2025	5	9:30:41	SELL	LO	MGM	31.85	$>$	31.83
10/20/2025	6	9:31:15	SELL	IN	PLD	124.89	$>$	124.66
10/20/2025	7	9:31:53	SELL	LO	HST	16.39	$>$	16.39
10/20/2025	8	9:31:53	SELL	LO	MAR	262.57	$>$	262.46
10/20/2025	9	9:31:53	SELL	MF	UDR	36.37	$>$	36.27
10/20/2025	10	9:32:54	SELL	MF	EQR	62.74	$>$	62.54
10/20/2025	11	9:33:12	SELL	RT	KIM	22	$>$	21.99
10/20/2025	12	9:33:51	SELL	OT	WPC	68.82	$>$	68.78
10/20/2025	13	9:36:27	SELL	OF	BXP	71.78	$>$	71.46
10/20/2025	14	9:36:27	SELL	RT	REG	72.75	$>$	72.65
10/20/2025	15	9:38:03	SELL	RT	SPG	179.4	$>$	179.35
10/20/2025	16	9:43:48	SELL	MF	ELS	62.74	$>$	62.71
10/20/2025	17	9:45:24	SELL	OF	HIW	30.24	$>$	30.21
10/20/2025	18	9:55:27	BUY	OF	SLG	52.23	$<$	52.23
10/20/2025	19	10:19:59	BUY	OF	VNO	38.95	$<$	38.98
10/20/2025	20	10:25:56	BUY	OT	NNN	42.53	$<$	42.56
10/20/2025	21	10:27:08	BUY	OT	WPC	68.17	$<$	68.19
10/20/2025	22	10:32:55	BUY	OF	HIW	29.88	$<$	29.9
10/20/2025	23	11:01:42	BUY	RT	REG	71.91	$<$	71.91
10/20/2025	24	11:53:43	BUY	OF	BXP	70.71	$<$	70.76
10/20/2025	25	14:04:46	SELL	OT	BKD	8.78	$>$	8.78

This table captures the set of twenty-five trades produced by our algorithm for October 20, 2025 with the initialization of our algorithm at 9:30:00AM ET. Column 1 provides the date; Column 2 the trade number, n; Column 3 the time, t, of the signal in 24 hour time notation; Column 4 is the direction of the signal as Buy or Sell at time t; Column 5 is the property type of the REIT; Column 6 is the REIT trading ticker; Column 7 is the market price for the REIT observed at time t corresponding to the signal time t; Column 8 is the directional inequality of the market price at time t relative to the boundary determined by the algorithm at time t (reported in Column 9).

Table 4: Sorted trading signals produced on October 20, 2025 with algorithm start time of 9:30:00AM ET and dual trade indicators

date	trade #, (n)	signal time (t)	signal	proptype	reit_ticker	reitpx at (t)	direction	boundary at (t)	dual=1
10/20/2025	5	9:30:41	SELL	MF	AVB	188.03	$>$	187.87	0
10/20/2025	27	14:04:46	SELL	OT	BKD	8.78	$>$	8.78	0
10/20/2025	14	9:36:27	SELL	OF	BXP	71.78	$>$	71.46	1
10/20/2025	26	11:53:43	BUY	OF	BXP	70.71	$<$	70.76	1
10/20/2025	1	9:30:21	BUY	MF	ELS	62.06	$<$	62.12	1
10/20/2025	17	9:43:48	SELL	MF	ELS	62.74	$>$	62.71	1
10/20/2025	11	9:32:54	SELL	MF	EQR	62.74	$>$	62.54	0
10/20/2025	2	9:30:21	SELL	IN	FR	55.49	$>$	55.36	0
10/20/2025	18	9:45:24	SELL	OF	HIW	30.24	$>$	30.21	1
10/20/2025	24	10:32:55	BUY	OF	HIW	29.88	$<$	29.9	1
10/20/2025	8	9:31:53	SELL	LO	HST	16.39	$>$	16.39	0
10/20/2025	12	9:33:12	SELL	RT	KIM	22	$>$	21.99	0
10/20/2025	9	9:31:53	SELL	LO	MAR	262.57	$>$	262.46	0
10/20/2025	6	9:30:41	SELL	LO	MGM	31.85	$>$	31.83	0
10/20/2025	22	10:25:56	BUY	OT	NNN	42.53	$<$	42.56	0
10/20/2025	7	9:31:15	SELL	IN	PLD	124.89	$>$	124.66	0
10/20/2025	15	9:36:27	SELL	RT	REG	72.75	$>$	72.65	1
10/20/2025	25	11:01:42	BUY	RT	REG	71.91	$<$	71.91	1
10/20/2025	19	9:55:27	BUY	OF	SLG	52.23	$<$	52.23	0
10/20/2025	16	9:38:03	SELL	RT	SPG	179.4	$>$	179.35	0
10/20/2025	3	9:30:21	SELL	RT	TCO	85.04	$>$	84.93	1
10/20/2025	20	10:02:05	BUY	RT	TCO	84.38	$<$	84.45	1
10/20/2025	10	9:31:53	SELL	MF	UDR	36.37	$>$	36.27	0
10/20/2025	4	9:30:21	SELL	OF	VNO	39.5	$>$	39.48	1
10/20/2025	21	10:19:59	BUY	OF	VNO	38.95	$<$	38.98	1
10/20/2025	13	9:33:51	SELL	OT	WPC	68.82	$>$	68.78	1
10/20/2025	23	10:27:08	BUY	OT	WPC	68.17	$<$	68.19	1

This table is an ex-post sort of the real time values reported in Table 3. It captures the set of twenty-seven trades produced by our algorithm for October 20, 2025 with the initialization of our algorithm at 9:30:00AM ET. Column 1 provides the date; Column 2 the trade number, n; Column 3 the time, t, of the signal in 24 hour time notation; Column 4 is the direction of the signal as Buy or Sell at time t; Column 5 is the property type of the REIT; Column 6 is the REIT trading ticker; Column 7 is the market price for the REIT observed at time t corresponding to the signal time t; Column 8 is the directional inequality of the market price at time t relative to the boundary determined by the algorithm at time t (reported in Column 9); Column 10 reports the ex-post indicator of a value equal to 1 if two opposite trade signals were produced by our algorithm for a REIT on this day and start time initialization.

Table 5: Algorithm driven returns for October 20, 2025 with initialization at 9:30:00AM ET

REIT ticker	daily ret (bps)	dual=1
AVB	54.78	0
BKD	11.39	0
BXP	149.07	1
ELS	109.57	1
EQR	60.57	0
FR	-102.72	0
HIW	119.05	1
HST	-61.01	0
KIM	0.00	0
MAR	97.88	0
MGM	-1.57	0
NNN	44.67	0
PLD	-182.16	0
REG	115.46	1
SLG	-99.56	0
SPG	49.05	0
UDR	27.50	0
VNO	-139.24	1
WPC	94.45	1
average traded ret (bps)	18.27	
average dual (bps)	74.73	
average non-dual (bps)	-7.78	

This table captures the daily returns per traded REIT for October 20, 2025 with an initialization time for the algorithm at 9:30:00AM ET. Returns are expressed in basis points (bps). Column 1 provides the REIT trading ticker; Column 2 provides the returns (bps) for the day; Column 3 provides a value of 1 if there were two opposite trades produced by the algorithm for the day and a value of 0 if the trade is unwound at the close of the trading day at 16:15:00PM ET. The three rows at the bottom provide aggregate statistics.

Table 6: Average trading day classification for all REITs (out of sample April 29, 2021 - October 20, 2025)

Panel A: 9:30AM start	Degrees of confidence										
Type of Day	1	10	20	30	40	50	60	70	80	90	99
No Trade	100.00%	43.73%	3.57%	3.10%	4.08%	5.53%	8.80%	14.76%	24.61%	40.07%	68.91%
Dual	0.00%	49.26%	66.94%	55.88%	44.45%	34.39%	25.36%	17.50%	11.19%	6.32%	1.64%
Low_Only	0.00%	5.72%	12.98%	18.42%	23.45%	27.30%	29.56%	29.96%	27.51%	21.41%	7.52%
High_Only	0.00%	1.30%	16.51%	22.60%	28.02%	32.78%	36.28%	37.77%	36.69%	32.20%	21.93%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Panel B: 10:00AM start	**Degrees of confidence**										
Type of Day	1	10	20	30	40	50	60	70	80	90	99
No Trade	99.91%	33.55%	3.95%	3.81%	4.90%	8.38%	14.90%	25.32%	38.93%	58.44%	87.97%
Dual	0.08%	60.44%	68.88%	52.52%	38.00%	26.06%	16.33%	9.63%	5.10%	2.01%	0.29%
Low_Only	0.00%	4.88%	14.29%	22.61%	29.55%	33.70%	35.64%	33.59%	29.15%	20.86%	6.38%
High_Only	0.00%	1.13%	12.89%	21.05%	27.54%	31.86%	33.13%	31.46%	26.83%	18.70%	5.36%
Total	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

This Table captures the average trade classification across all REITs in the out of sample period from April 29, 2021 - October 20, 2025 (n=833) for different degrees of confidence as percentages.Panel A captures these proportions for the 9:30am start time Gumbel adaptation, while Panel B captures these proportions for the 10:00am start time Gumbel adaptation,.

Table 7: ICAPM results, Gumbel and Markowitz portfolios (out of sample, July 26, 2023-August 29, 2025)

Panel A: REITs-Rindex	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
Markowitz	0.92	-4.44	23.85**	-6.24	-3.82	4.668	0.032	438
	(5.68)	(6.53)	(7.48)	(8.96)	(9.48)	0.001067		
50degGumbel_9:30am	19.83***	-64.96***	22.01***	-8.13	-17.23*	50.84	0.313	438
	(4.84)	(5.57)	(6.38)	(7.63)	(8.08)	2.2E-16		
50degGumbel_10:00am	19.35***	-64.46***	23.51***	3.55	-6.91	46.25	0.293	438
	(4.77)	(5.49)	(6.28)	(7.52)	(7.96)	2.2E-16		
Panel B: REITs-ICF	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
Markowitz	-1.3	-13.02*	24.37***	-24.44**	-40.96***	23.15	0.169	438
	(5.36)	(6.16)	(7.05)	(8.44)	(8.93)	2.2E-16		
50degGumbel_9:30am	17.61***	-73.54***	22.52***	-26.33***	-54.37***	84.37	0.433	438
	(4.87)	(5.6)	(6.41)	(7.68)	(8.12)	2.2E-16		
50degGumbel_10:00am	17.13***	-73.04***	24.02***	-14.65	-44.05***	72.57	0.396	438
	(4.82)	(5.54)	(6.35)	(7.6)	(8.04)	2.2E-16		

This table provides the results the ICAPM regressions of Merton and Samuelson (1992) of the out of sample period with the four factors introduced by Fama and French (1993) (the market portfolio (Mkt-Rf), high minus low (HML), and small minus big (SMB) and the fourth factor of momentum (MOM) introduced by Carhart (1997). The form of the regression is $R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u$ with the difference between the trading strategy portfolio minus the long only portfolio as the dependent variable, and the four factors as independent variables. Two long only portfolios acre considered. The iShares REIT index (ICF) and the internal long-only REIT index comprised of nineteen REITs in our sample (Rindx). Six portfolio strategies are tested. The top three adjust for the long only Rindx, while the bottom three adjust for the long only ICF. The portfolios considered are the Markowitz Sharpe maximiziing strategy, the Gumbel strategy beginning at 930am and the Gumbel strategy beginning at 10:00am The columns correspond to intercept alpha and each of the explanatory factors. The final three columns show the F-test value, the Adjusted R-squared value and the number of observations. The standard error of the estimates (in parentheses) are shown in the row immediately below the estimates. ***/**/*/. correspond to 0.1%, 1%, 5% and 10% levels of statistical significance.

Table 8: ICAPM Gumbel_9:30am-REIT Index (out of sample, July 26, 2023 - August 29, 2025)

PropType	Ticker	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
IN	FR	24.86***	-49.49***	19.93*	-11.42	-13.42	17.7	0.133	438
		(6.63)	(7.63)	(8.73)	(10.45)	(11.06)	1.822E-13		
IN	PLD	29.66***	-55.02***	17.87*	4.33	-31.44**	16.54	0.124	438
		(6.82)	(7.85)	(8.98)	(10.75)	(11.38)	1.278E-12		
LO	HST	15.42*	-47.13***	36.28***	-0.3	-12.21	19.02	0.142	438
		(6.4)	(7.36)	(8.43)	(10.09)	(10.68)	0.2027		
LO	MAR	18.47**	-55.55***	13.43	-3.79	-20.38	18.56	0.138	438
		(6.58)	(7.56)	(8.66)	(10.37)	(10.97)	4.324E-14		
LO	MGM	24.96**	-115.03***	47.78***	19.54	-8.69	35.18	0.238	438
		(9.57)	(11.01)	(12.6)	(15.08)	(15.96)	2.2E-16		
MF	AVB	24.33***	-59.22***	19.32*	-6.19	-12.17	22.06	0.162	438
		(6.63)	(7.62)	(8.73)	(10.45)	(11.06)	2.2E-16		
MF	ELS	18.36**	-49.30***	11.53	8.28	-12.16	15.93	0.12	438
		(5.82)	(6.69)	(7.66)	(9.17)	(9.7)	3.525E-12		
MF	EQR	22.84***	-58.89***	12.95	-1.7	-14.06	22.95	0.167	438
		(6.15)	(7.07)	(8.1)	(9.7)	(10.26)	2.2E-16		
MF	UDR	17.13**	-60.06***	23.56**	-0.91	-18.35	24.94	0.18	438
		(6.24)	(7.17)	(8.21)	(9.83)	(10.4)	2.2E-16		
OF	BXP	34.80***	-59.92***	25.62*	-12.33	-12.05	17.42	0.131	438
		(8.06)	(9.26)	(10.6)	(12.7)	(13.43)	2.9E-13		
OF	HIW	21.34**	-54.95***	4.76	-23.37	-8.02	15.52	0.117	438
		(8.03)	(9.24)	(10.57)	(12.66)	(13.4)	7.155E-12		
OF	SLG	33.82**	-37.12**	14.22	-45.24**	7.61	8.965	0.068	438
		(10.34)	(11.89)	(13.61)	(16.29)	(17.24)	5.797E-07		
OF	VNO	31.31**	-66.50***	7.38	-14.11	-31.14	13.15	0.1	438
		(9.7)	(11.15)	(12.76)	(15.28)	(16.17)	4.063E-10		
OT	BKD	9.01	-131.63***	36.70*	-46.33*	-30.39	40.28	0.264	438
		(11.9)	(13.68)	(15.66)	(18.75)	(19.84)	2.2E-16		
OT	NNN	7.51	-60.79***	9.8	1.7	-15.21	26.54	0.189	438
		(5.74)	(6.6)	(7.56)	(9.05)	(9.58)	2.2E-16		
OT	WPC	21.25**	-64.44***	25.45**	-1.57	-21.07	26.84	0.191	438
		(6.48)	(7.45)	(8.53)	(10.22)	(10.81)	2.2E-16		
RT	KIM	10.22	-52.36***	26.91**	-13.1	-12.05	21.66	0.159	438
		(6.6)	(7.59)	(8.69)	(10.4)	(11)	2.641E-16		
RT	REG	13.57*	-74.19***	35.31***	3.58	-28.64**	37.49	0.25	438
		(6.35)	(7.3)	(8.36)	(10.01)	(10.59)	2.2E-16		
RT	SPG	12.92	-82.58***	29.38***	-11.54	-33.56**	45.89	0.291	438
		(6.59)	(7.58)	(8.68)	(10.39)	(10.99)	2.2E-16		

This table provides results for the ICAPM regressions of Merton and Samuelson (1992) of the out of sample period with the four factors introduced by Fama and French (1993) (the market portfolio (Mkt-Rf), high minus low (HML), and small minus big (SMB) and the fourth factor of momentum (MOM) introduced by Carhart (1997). The form of the regression is $R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u$ with the difference between the trading strategy portfolio minus the long only portfolio (Rindx) as the dependent variable, and the four factors as independent variables. All nineteen REITs in our sample are tested using the Gumbel strategy beginning at 9:30am. The columns correspond to intercept alpha and each of the explanatory factors.

Table 9: ICAPM Gumbel_10:00am-REIT Index (out of sample, July 26, 2023 - August 29, 2025)

PropType	Ticker	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
IN	FR	22.63***	-82.98***	35.33***	25.00*	-8.31	39.22	0.259	438
		(6.33)	(7.28)	(8.33)	(9.98)	(10.56)	2.2E-16		
IN	PLD	16.79*	-87.64***	33.34***	19.18	-3.9	37.7	0.251	438
		(6.92)	(7.96)	(9.11)	(10.91)	(11.54)	2.2E-16		
LO	HST	20.77***	-59.57***	35.15***	2.75	-3.06	31.13	0.216	438
		(5.76)	(6.62)	(7.58)	(9.08)	(9.61)	2.2E-16		
LO	MAR	21.38***	-63.21***	31.39***	6.59	-7.15	29.45	0.207	438
		(5.98)	(6.87)	(7.87)	(9.42)	(9.97)	2.2E-16		
LO	MGM	33.19***	-67.16***	31.60**	1.9	-19.88	22.91	0.167	438
		(7.34)	(8.44)	(9.66)	(11.57)	(12.24)	2.2E-16		
MF	AVB	17.67**	-76.44***	32.16***	14.72	10.98	40.83	0.267	438
		(6.05)	(6.96)	(7.96)	(9.53)	(10.09)	2.2E-16		
MF	ELS	15.59**	-69.14***	26.44***	12.61	5.64	39.55	0.261	438
		(5.48)	(6.3)	(7.21)	(8.63)	(9.13)	2.2E-16		
MF	EQR	17.10**	-52.45***	21.57**	-1.25	12.37	24.37	0.176	438
		(5.78)	(6.65)	(7.61)	(9.11)	(9.64)	2.2E-16		
MF	UDR	11.51*	-54.23***	20.13**	1.45	2.43	23.7	0.172	438
		(5.75)	(6.62)	(7.57)	(9.07)	(9.59)	2.2E-16		
OF	BXP	24.47**	-62.69***	7.95	1.56	-22.14	16.22	0.122	438
		(7.53)	(8.66)	(9.91)	(11.87)	(12.56)	2.158E-12		
OF	HIW	21.93**	-61.60***	7.01	-7.01	-16.89	19.87	0.147	438
		(7.02)	(8.07)	(9.24)	(11.07)	(11.71)	4.922E-15		
OF	SLG	28.62***	-56.91***	20.19	-6.94	-17.48	12.45	0.095	438
		(8.61)	(9.9)	(11.33)	(13.57)	(14.36)	1.366E-09		
OF	VNO	26.31**	-46.70***	22.18	-18.29	-20.57	10.06	0.077	438
		(9.17)	(10.54)	(12.07)	(14.45)	(15.28)	8.55E-08		
OT	BKD	37.86***	-91.31***	46.53***	6.99	3.11	20.65	0.152	438
		(10.54)	(12.11)	(13.87)	(16.6)	(17.56)	1.377E-15		
OT	NNN	10.43	-56.79***	18.73*	-3.06	2.1	28.14	0.199	438
		(5.63)	(6.47)	(7.41)	(8.87)	(9.39)	2.2E-16		
OT	WPC	16.45*	-62.03***	4.82	-0.94	-11.5	23.01	0.168	438
		(6.38)	(7.33)	(8.39)	(10.05)	(10.63)	2.2E-16		
RT	KIM	12.66*	-51.47***	17.93*	-3.12	-11.09	20.69	0.153	438
		(5.89)	(6.77)	(7.75)	(9.28)	(9.81)	1.275E-15		
RT	REG	18.77***	-59.20***	17.97**	11.94	-13.05	28.67	0.202	438
		(5.23)	(6.02)	(6.89)	(8.25)	(8.72)	2.2E-16		
RT	SPG	14.76**	-63.37***	16.23*	3.49	-13.09	30.41	0.212	438
		(5.63)	(6.48)	(7.42)	(8.88)	(9.39)	2.2E-16		

This table provides results for the ICAPM regressions of Merton and Samuelson (1992) of the out of sample period with the four factors introduced by Fama and French (1993) (the market portfolio (Mkt-Rf), high minus low (HML), and small minus big (SMB) and the fourth factor of momentum (MOM) introduced by Carhart (1997). The form of the regression is $R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u$ with the difference between the trading strategy portfolio minus the long only portfolio (Rindx) as the dependent variable, and the four factors as independent variables. All nineteen REITs in our sample are tested using the Gumbel strategy beginning at 10:00am. The columns correspond to intercept alpha and each of the explanatory factors.

Table 10: ICAPM Gumbel_9:30am-ICF (out of sample, July 26, 2023 - August 29, 2025)

PropType	Ticker	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
IN	FR	22.63***	-58.08***	20.44*	-29.62**	-50.55***	34.36	0.234	438
		(6.65)	(7.65)	(8.75)	(10.48)	(11.09)	2.2E-16		
IN	PLD	27.44***	-63.60***	18.38*	-13.87	-68.58***	34.66	0.236	438
		(6.7)	(7.7)	(8.82)	(10.56)	(11.17)	2.2E-16		
LO	HST	13.2	-55.71***	36.80***	-18.5	-49.35***	32.53	0.224	438
		(6.86)	(7.89)	(9.03)	(10.81)	(11.44)	2.2E-16		
LO	MAR	16.25**	-64.14***	13.95	-21.99*	-57.51***	40.36	0.265	438
		(6.14)	(7.06)	(8.08)	(9.68)	(10.24)	2.2E-16		
LO	MGM	22.74*	-123.61***	48.30***	1.34	-45.82**	48.32	0.302	438
		(9.17)	(10.54)	(12.06)	(14.44)	(15.28)	2.2E-16		
MF	AVB	22.10***	-67.80***	19.84*	-24.39*	-49.30***	39.52	0.261	438
		(6.53)	(7.5)	(8.59)	(10.28)	(10.88)	2.2E-16		
MF	ELS	16.14*	-57.88***	12.04	-9.91	-49.29***	25.92	0.186	438
		(6.39)	(7.35)	(8.41)	(10.07)	(10.66)	2.2E-16		
MF	EQR	20.62***	-67.47***	13.46	-19.90*	-51.20***	39.39	0.26	438
		(6.21)	(7.14)	(8.18)	(9.79)	(10.36)	2.2E-16		
MF	UDR	14.91*	-68.65***	24.08**	-19.11	-55.48***	41.46	0.27	438
		(6.46)	(7.43)	(8.5)	(10.18)	(10.77)	2.2E-16		
OF	BXP	32.57***	-68.50***	26.14*	-30.53*	-49.18***	29.24	0.205	438
		(8.14)	(9.35)	(10.71)	(12.82)	(13.56)	2.2E-16		
OF	HIW	19.12*	-63.54***	5.28	-41.57**	-45.15**	24.83	0.179	438
		(8.27)	(9.51)	(10.88)	(13.03)	(13.78)	2.2E-16		
OF	SLG	31.60**	-45.70***	14.73	-63.44***	-29.52	16.38	0.123	438
		(10.17)	(11.7)	(13.39)	(16.03)	(16.96)	1.658E-12		
OF	VNO	29.09**	-75.09***	7.89	-32.30*	-68.28***	20.83	0.154	438
		(10.09)	(11.6)	(13.28)	(15.91)	(16.83)	1.013E-15		
OT	BKD	6.79	-140.22***	37.21*	-64.53***	-67.53***	55.69	0.334	438
		(11.39)	(13.09)	(14.98)	(17.94)	(18.98)	2.2E-16		
OT	NNN	5.29	-69.37***	10.31	-16.5	-52.34***	43.36	0.279	438
		(5.87)	(6.75)	(7.73)	(9.25)	(9.79)	2.2E-16		
OT	WPC	19.03**	-73.03***	25.96**	-19.77	-58.21***	43.75	0.281	438
		(6.67)	(7.66)	(8.77)	(10.5)	(11.11)	2.2E-16		
RT	KIM	7.99	-60.94***	27.42**	-31.30**	-49.19***	41.63	0.271	438
		(6.47)	(7.44)	(8.51)	(10.19)	(10.78)	2.2E-16		
RT	REG	11.35	-82.78***	35.82***	-14.62	-65.77***	55.02	0.331	438
		(6.68)	(7.67)	(8.79)	(10.52)	(11.13)	2.2E-16		
RT	SPG	10.7	-91.16***	29.90***	-29.74**	-70.70***	70.05	0.387	438
		(6.63)	(7.62)	(8.73)	(10.45)	(11.06)	2.2E-16		

This table provides results for the ICAPM regressions of Merton and Samuelson (1992) of the out of sample period with the four factors introduced by Fama and French (1993) (the market portfolio (Mkt-Rf), high minus low (HML), and small minus big (SMB) and the fourth factor of momentum (MOM) introduced by Carhart (1997). The form of the regression is $R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u$ with the difference between the trading strategy portfolio minus the long only portfolio (Rindx) as the dependent variable, and the four factors as independent variables. All nineteen REITs in our sample are tested using the Gumbel strategy beginning at 10:00am. The columns correspond to intercept alpha and each of the explanatory factors.

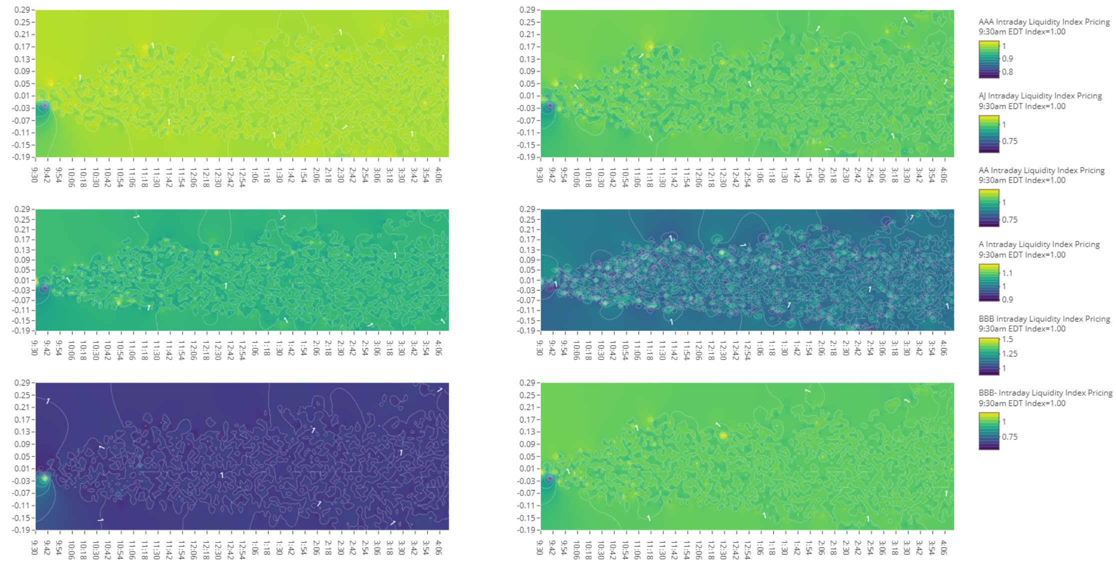
Table 11: ICAPM Gumbel_10:00am-ICF (out of sample, July 26, 2023 - August 29, 2025)

PropType	Ticker	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
IN	FR	14.28*	-91.55***	35.86***	6.77	-45.40***	56.77	0.338	438
		(6.21)	(7.14)	(8.17)	(9.78)	(10.35)	2.2E-16		
IN	PLD	14.56*	-96.19***	33.85***	1.01	-41.03***	51.52	0.316	438
		(6.86)	(7.89)	(9.03)	(10.81)	(11.44)	2.2E-16		
LO	HST	18.54**	-68.16***	35.64***	-15.48	-40.18***	50.22	0.311	438
		(5.83)	(6.7)	(7.67)	(9.18)	(9.71)	2.2E-16		
LO	MAR	19.18***	-71.79***	31.90***	-11.6	-44.27***	53.56	0.325	438
		(5.66)	(6.51)	(7.45)	(8.92)	(9.43)	2.2E-16		
LO	MGM	30.94***	-75.73***	32.13**	-16.31	-57.00***	37.12	0.248	438
		(7.45)	(8.57)	(9.81)	(11.75)	(12.43)	2.2E-16		
MF	AVB	15.46**	-85.02***	32.70***	-3.48	-26.11**	57.28	0.34	438
		(5.87)	(6.75)	(7.72)	(9.25)	(9.78)	2.2E-16		
MF	ELS	13.37*	-77.73***	26.95***	-5.61	-31.44***	54.14	0.327	438
		(5.55)	(6.39)	(7.31)	(8.75)	(9.26)	2.2E-16		
MF	EQR	14.83*	-61.00***	22.06**	-19.44*	-24.77*	37.72	0.252	438
		(5.78)	(6.65)	(7.61)	(9.11)	(9.64)	2.2E-16		
MF	UDR	9.32	-62.81***	20.65**	-16.74	-34.69***	36.54	0.245	438
		(5.96)	(6.85)	(7.84)	(9.39)	(9.93)	2.2E-16		
OF	BXP	22.23**	-71.25***	8.45	-16.64	-59.26***	29.01	0.204	438
		(7.42)	(8.53)	(9.76)	(11.68)	(12.36)	2.2E-16		
OF	HIW	19.67**	-70.15***	7.5	-25.21*	-54.01***	30.56	0.213	438
		(7.38)	(8.48)	(9.71)	(11.62)	(12.3)	2.2E-16		
OF	SLG	26.45**	-65.46***	20.66	-25.13	-54.66***	21.75	0.16	438
		(8.81)	(10.13)	(11.6)	(13.89)	(14.69)	2.269E-16		
OF	VNO	24.09*	-55.31***	22.72	-36.46*	-57.70***	19.65	0.146	438
		(9.34)	(10.74)	(12.29)	(14.72)	(15.57)	7.152E-15		
OT	BKD	35.68***	-99.90***	47.03***	-11.14	-34.03*	29.29	0.206	438
		(10.19)	(11.71)	(13.41)	(16.05)	(16.98)	2.2E-16		
OT	NNN	8.21	-65.38***	19.22**	-21.28*	-35.06***	46.81	0.295	438
		(5.55)	(6.38)	(7.3)	(8.74)	(9.25)	2.2E-16		
OT	WPC	14.25*	-70.62***	5.35	-19.12	-48.69***	37.33	0.25	438
		(6.36)	(7.31)	(8.37)	(10.02)	(10.6)	2.2E-16		
RT	KIM	10.44	-60.06***	18.44*	-21.32*	-48.23***	37.63	0.251	438
		(6.02)	(6.92)	(7.93)	(9.49)	(10.04)	2.2E-16		
RT	REG	16.54**	-67.75***	18.48*	-6.31	-50.16***	42.68	0.276	438
		(5.64)	(6.48)	(7.42)	(8.88)	(9.4)	2.2E-16		
RT	SPG	12.50*	-71.93***	16.74*	-14.71	-50.25***	44.98	0.287	438
		(5.97)	(6.86)	(7.85)	(9.4)	(9.95)	2.2E-16		

This table provides results for the ICAPM regressions of Merton and Samuelson (1992) of the out of sample period with the four factors introduced by Fama and French (1993) (the market portfolio (Mkt-Rf), high minus low (HML), and small minus big (SMB) and the fourth factor of momentum (MOM) introduced by Carhart (1997). The form of the regression is $R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u$ with the difference between the trading strategy portfolio minus the long only portfolio (ICF) as the dependent variable, and the four factors as independent variables. All nineteen REITs in our sample are tested using the Gumbel strategy beginning at 10:00am. The columns correspond to intercept alpha and each of the explanatory factors. The final three columns show the F-test value, the Adjusted R-squared value and the number of observations. The standard error of the estimates (in parentheses) are shown in the row immediately below the estimates. ***/**/*/. correspond to 0.1%, 1%, 5% and 10% levels of statistical significance.

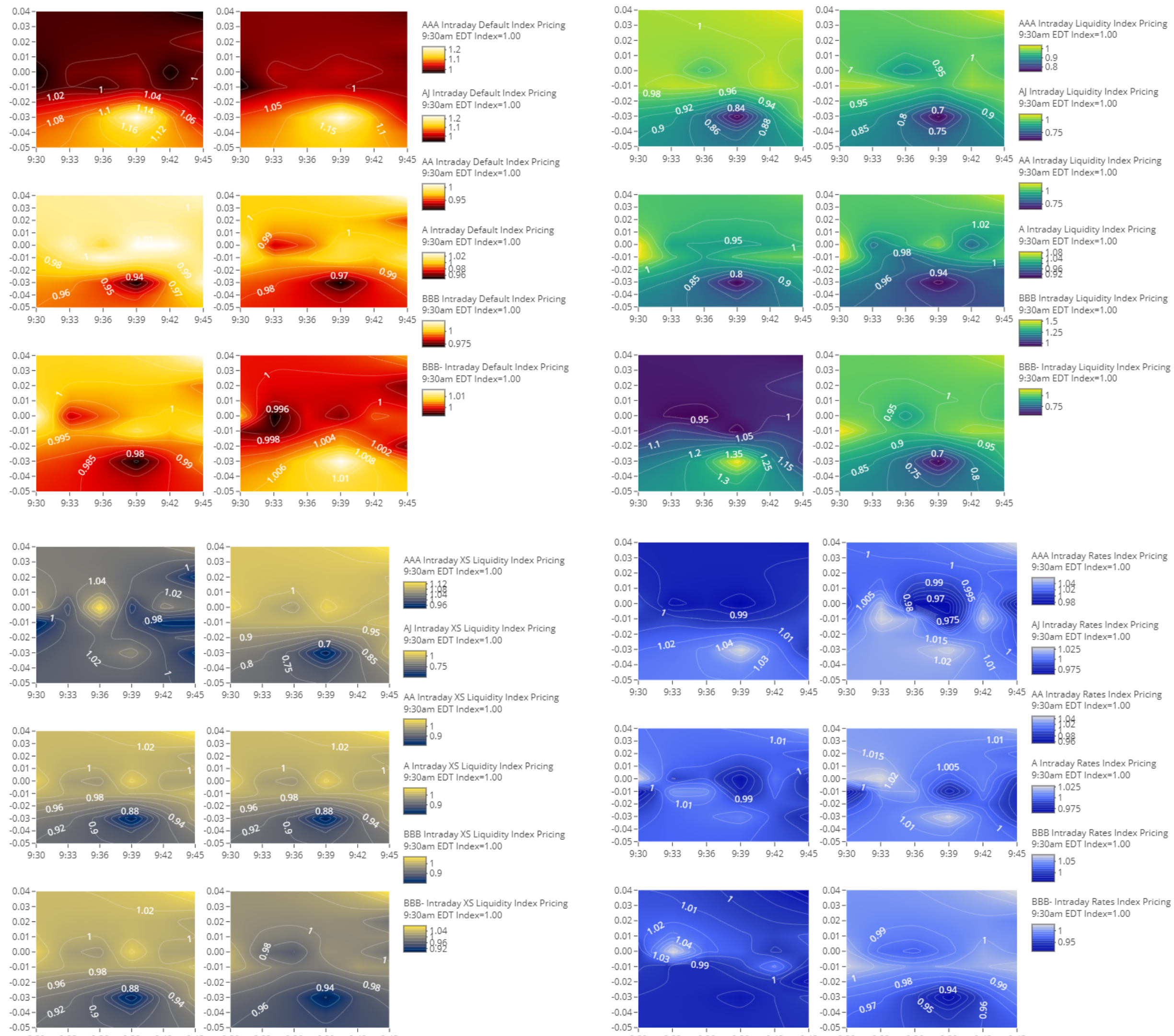
Figures

Figure 1: Liquidity cross-sectional risk terrains (April 7, 2020-April 8, 2021)



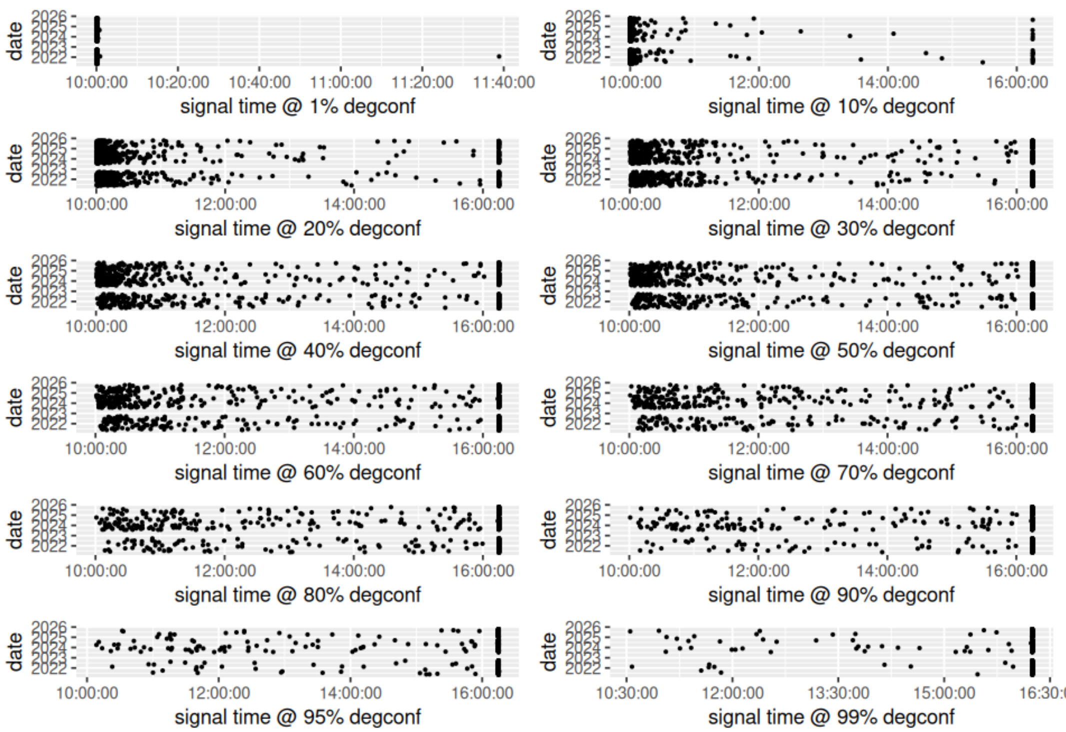
This figure provides the cross-section across all 275370 observations of liquidity risk composition for each of the investment grade CMBX tranches from AAA (top-left) to BBB- (bottom right). The x-axes reflect 3 minute intervals binned from the fifteen-second interval values while the y-axes capture the log change of the VIX from the start of the trading day (with $t = 0$, 9:30am) until close. The y-axes are partitioned in increments of 0.01. The z-axes are the heat map renderings of W_{jkut} defined in Eq. (1) for liquidity risk across all days in the sample period at identical times.

Figure 2: All risk terrains, 9:30:00am to 9:45:00am (April 7, 2020-April 8, 2021)



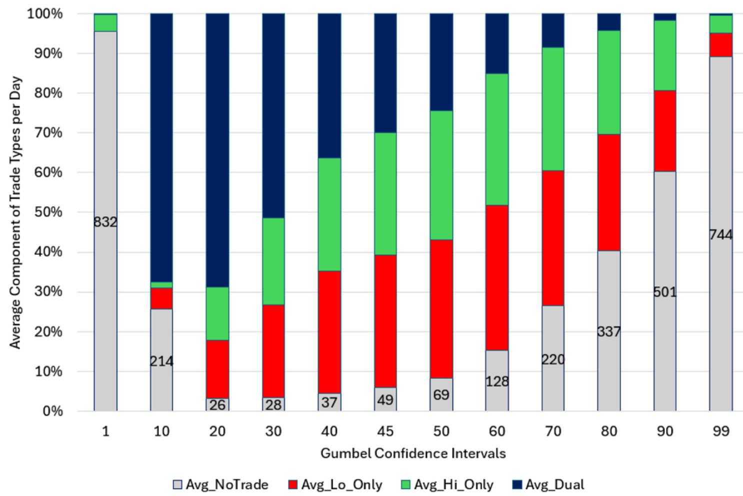
This figure provides the cross-section across all 275370 observations of risk composition for each of the four risk components (default, top left), liquidity (top right), excess (XS) liquidity (bottom left) and interest rates (bottom right). Each of the four risk component contain six charts depicting the investment grade CMBX tranches from AAA (top-left) to BBB- (bottom right). The x-axes reflect 3 minute intervals binned from the fifteen-second interval values from 9:30:15am to 9:45:00am EST. The y-axes capture the log change of the VIX from the start of the trading day (with $t = 0$, 9:30:15am) until 9:45:00am. The y-axes are partitioned in increments of 0.01. The z-axes are the heat map renderings of W_{jkut} defined in Eq. (1) for all four risk components and all six ratings with non-constant upper and lower boundaries, but identical colorscaling. The contour lines and hue of indicate higher or lower cumulative changes in liquidity risk across all days in the sample period at identical times.

Figure 3: Gumbel aperture for intraday highs SLG (out of sample, April 29, 2021 - October 20, 2025)



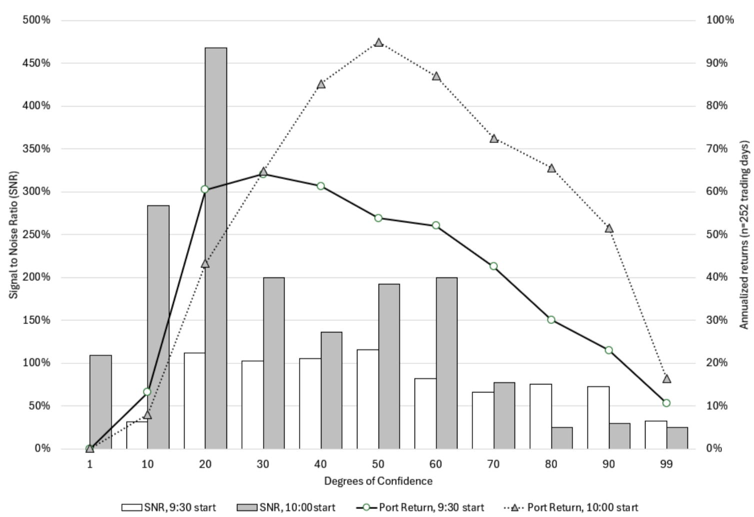
This figure presents the timing throughout the trading of predicted maximums for SLG in the out of sample period from April 29, 2021 - October 20, 2025 (n=833). The figure consists of twelve mini figures which capture the predicted times for different degrees of confidence.

Figure 4: Trade day classification all REITs, 10:00am Gumbel adaptation (out of sample, April 29, 2021 - October 20, 2025)



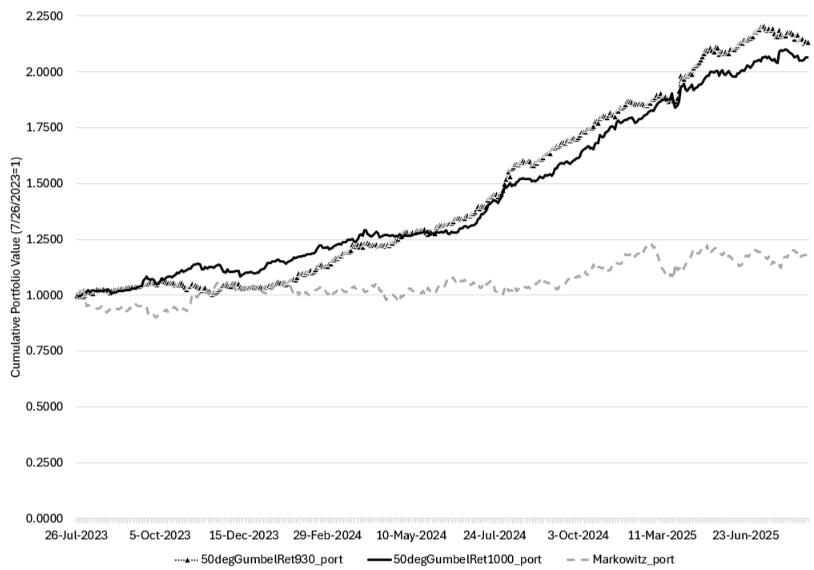
This figure captures the average trade classification across all REITs in the out of sample period from April 29, 2021 - October 20, 2025 (n=833) for different degrees of confidence for the 10:00am Gumbel adaptation.

Figure 5: Annualized Returns x Signal to Noise Ratios for Gumbel 9:30am and Gumbel 10:00am (out of sample April 29, 2021 - October 20, 2025)



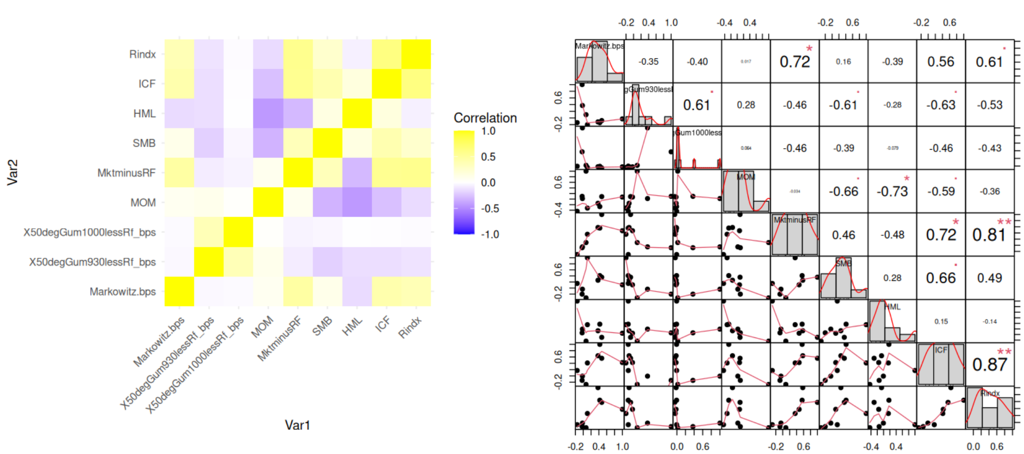
This figure captures the annualized return for the 9:30am and 10:00am start time Gumbel adaptations and their corresponding SNR's across varying degrees of confidence. The degrees of confidence are on the x-axis. The SNR's are captured on the left y-axis. The returns are captured on the right y-axis. The returns and SNR's are computed for the 833 days in the out of sample period April 29, 2021-October 20, 2025

Figure 6: Cumulative Portfolio Values for Markowitz, Gumbel 9:30am and Gumbel 10:00am (out of sample, July 26, 2023-August 29, 2025)



This figure captures the cumulative portfolio values from daily returns for the 9:30am, 10:00am start time Gumbel adaptations and the Markowitz portfolio for 472 days in the out of sample period July 26, 2023 - August 29, 2025.

Figure 7: Correlations of ICAPM factors, long REIT indices, and trading strategy portfolios (out of sample, July 26, 2023-August 29, 2025)



This figure captures the cross correlations for the returns for the Markowitz, the 9:30am, 10:00am start time Gumbel adaptations; the ICAPM factors (MOM, Mkt-Rf, SMB, and HML), and the long-only REIT sector portfolios (ICF and Rindx) for 472 days in the out of sample period July 26, 2023 - August 29, 2025.The left figure is a heatmap and the right figure reports the correlations with historgrams for visual effect.