15 SECONDS TO ALPHA: HIGHER FREQUENCY RISK PRICING FOR COMMERCIAL REAL ESTATE SECURITIES

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Abstract

In this paper we estimate risk decompositions at intraday frequency for commercial real estate securities in 1560 intervals of fifteen seconds for 240 days during the Covid pandemic. In cross-sectional analyses we discover stark patterns of price formation of risk. We articulate eighteen long-short trading strategies in the frequently traded, and related, REIT sector to exploit these aberrations. 84% of our risk signalled automated trading strategies produced significant alphas, with 75% of those generating strong positive abnormal returns. This is the first paper in the literature to estimate risk decompositions for commercial real estate securities at intraday frequencies.

Key Words: Credit ratings, High frequency trading, Liquidity, Microstructure, REITs, Risk decomposition, Securitization
JEL Codes: C58, E10, G17, R30

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Introduction

In November 2021, at the joint conference of the Cleveland Federal Reserve Bank and the Office of Financial Research, against the backdrop of the Covid pandemic, several prominent speakers emphasized the importance of increasing the pace of disclosure of risks posed to the financial system to increase transparency through technology. The emphasis on shifting focus from a crisis mode approach (reactive) to a more dynamically prescriptive mode oriented towards crisis prevention, more rapidly was also discussed. Revealing discontinuities in risk pricing vis a vis meaningful technological innovations may inform investing even more easily than they inform policy. Good technology and insightful risk monitoring may enhance transparency and make direct regulatory intercession less necessary, even if crises emerge. These insights in part motivate this study which focuses on commercial real estate ('CRE') securities risk pricing at higher frequencies.

Christopoulos and Barratt (2021a) provide a recent contribution to the microstructure literature with a model driven reconciliation between the classical effective bid-ask spread estimation of liquidity compared with reduced form driven risk decomposition estimates of liquidity and excess liquidity. Their inquiry was motivated by two strands of the literature pertaining to estimations of liquidity: work found in the classical microstructure literature associated with variants of Roll (1984) and work in the area of fixed income risk decomposition as found in Longstaff, Mithal and Neis (2005), Bao, Pan and Wang (2011), Gilchrist and Zakrajšek (2012), Christopoulos (2017) and Christopoulos and Jarrow (2018). They introduce a general model which is applied to commercial mortgage backed securities ('CMBS') indexed credit default swaps ('CMBX') on a daily basis. The method proxies for the direct two step approach of reduced form simulation and risk partitioning techniques introduced in Christopoulos (2017) and Christopoulos and Jarrow (2018), on a monthly basis. Through a combination of principal components analysis ('PCA') and ordinary least squares ('OLS'), Christopoulos and Barratt (2021a) create a projection model of risk partitions to increase risk partitioning for CMBX from monthly to daily frequency as informed by the monthly training set of risk partitions found in Christopoulos and Jarrow (2018) against a digest of market data. They find risk decomposition estimates to be significant in explaining effective bid-ask spreads historically over 12 years between 2007 and 2019, on a daily basis, and also in 20 day forecasts. The backdrop of high frequency trading seen in other markets is not addressed. Indeed one may question of what consequence is disclosure of risk decomposition at higher frequencies than observed trading?

In this paper we respond precisely to that question to show what type of information content may be disclosed to the market of approximately \$12.7 trillion[1] of credit sensitive fixed income products at higher frequencies with risk partitioning. To do this, we extend the generalizable model of Christopoulos and Barratt (2021a) and apply it to CMBX at intraday frequency, (the 'Intraday Model'). We produce estimated risk partitions in response to changing market variables in 15 second intervals for 240 trading days during the Covid-19 pandemic. Because these estimations are current market price independent, the values produced by our technique are more frequently observable than the actual market pricing for the sector which they evaluate. As such, this paper presents meaningful risk evaluation and monitoring measures in (near) real time and gives rise to two main results.

First, during the pandemic, we find considerably greater volatility in risk partition pricing with the Intraday Model at the start of each trading day for all risk partitions compared with the end of each trading day. We establish this result by conducting a cross-sectional evaluation of millions of cumulative intraday changes in risk partitions in 15 second intervals during the pandemic where we find stark patterns of risk decomposition price formation over the course of the trading day.

Since CMBX is quite large with nominal underlying collateral of \$600 billion[2], and ru-

[1] Outstanding debt issuance as of 2020 totalled \$9.8 trillion for US corporate bonds ('Corporates'), \$1.4 trillion for non-agency mortgage securities, and \$1.5 trillion for asset backed securities. Source: SIFMA (2021).

[2] See SIFMA (2021).

moured to trade more frequently than the underlying CMBS collateral reference assets, we turn to the $1.3 trillion[3] REIT sector. We do this to determine if intraday risk decompositions for CMBX have broader meaning to a more frequently traded sector that still shares similar fundamental risks. REITs fit this description. Like CMBX, REITs are also directly exposed to the risks of CRE and REITs also trade frequently on public exchanges. Investigating the relationship between CMBX risk partition signals and REIT pricing leads to our second main result.

Second, well constructed trading strategies using disclosures of CMBX risk partitions fused with REIT market pricing often result in substantial extraordinary returns. We establish this result by fusing the cross-sectional insights into CMBX risk partition estimation with the more frequently traded REIT sector in a set of 18 long-short day trading strategies during the Covid pandemic for each of the investment grade credit rating classes. The strategies exploit stark and systematic aberrations in risk decomposition price formation observed intraday which are then articulated into relative value long-short directional signals for REITs. Trades are executed at the beginning of the day based upon the trading signals and liquidated at the end of the trading day. The selection of these end points is directly supported by evidence from our cross-sectional analysis.

Using the Intertemporal Capital Asset Pricing Model ('ICAPM') of Merton (1990) we find 84% (16/18) of the strategies produced positive and statistically significant $\alpha's$. 75% (12/16) of the significant α strategies also exhibited positive cumulative returns over the Covid-19 crisis period ranging from 9.09% to 41.37% with very good Sharpe ratios ranging from about 2 to 5. As expected, the liquidity and excess liquidity risk partitions provide the greatest and most reliable insights. These two main results, and their supporting evidence, validate the Intraday Model. The intraday trading experiment establishes crossover insights between theoretical intraday CMBX risk partition signals and the larger and more frequently traded REIT market.

[3]See NAREIT (2020).

We make at least three contributions to the literature in this work. First, we provide to our knowledge the first, if only, intraday higher frequency estimates of risk partitions of default, rate volatility, liquidity and excess liquidity for the CMBX sector. This contributes to the strand of the literature focused on asset pricing and high frequency trading. Second, the investigations into cross sectional price formation contributes to the microstructure literature focusing on fixed income price formation. It also sets the stage for future investigation into 'bubbles' and their formation at early stages in these markets consistent with regulatory and microstructure literature aspirations. Finally, third, this work applies our approach to securities risk pricing within the CRE asset class and we thus contribute to the literature focusing on securitization and REITs with CRE exposure. As these some $2 trillion in securities, and underlying collateral, are broadly held in the portfolios and traded by investment managers, pension funds, insurance companies, mutual funds, hedge funds and banks, this paper should be of the general interest.

Our paper is the first to consider the theoretical price formation of risks for CRE securities at high frequency. The method and empirical implementation present a new perspective on the pricing of liquidity for two large and related sectors within US capital markets yielding insights across credit ratings and across related sectors. 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 introduces the Intraday Model describing it as an interesting extension to the Daily Model of Christopoulos and Barratt (2021a). Section 4 provides the results from cross-sectional analysis and trading strategy construction, thereby validating the Intraday Model. Section 5 summarizes with suggestions for future work.

1 Literature Review

This section discusses some of the literature and market development related to liquidity pricing at high frequency relevant to our study.

Many of the classical microstructure models that investigate into issues of illiquidity are based on both price and volume information content in equity markets.[4] As trading frequency and data reporting has increased, there have been studies in the literature addressing the phenomenon of the onset of high frequency trading as discussed in Chordia, Goyal, Lehmann and Saar (2013) and O'Hara (2015), with many focused on equity markets.[5]

Improved information however, is now available for more sectors, beyond equities, at much more rapid rates concomitant with the advent of high frequency trading in those sectors. For example, in addition to enhanced reporting through Trade Reporting and Compliance Engine ('TRACE') for fixed income securities as discussed in Kozora, et al (2020), and others[6], there have also been parallel developments in technology and electronic platforms to enhance the rate of trading in credit sensitive fixed income. According to Securities Industry and Financial Markets Association ('SIFMA'), the \$9.7 trillion US corporate market reported total average daily trading volumes of about \$28 billion with increasingly greater execution on electronic trading platforms. Average daily volumes on the electronic trading platforms of TradeWeb and MarketAxess[7] increased from about 25% of all US corporate bond trading in 2017 to about 41% in the first three quarters of 2021.[8] These changes align with the established presence of electronic trading as reported by TradeWeb and MarketAxess for non-credit sensitive areas of fixed income such as agency mortgage backed securities market and US Treasuries. Reflecting these improvements there have been more recent articles in the microstructure literature on the subject of liquidity in fixed income securities. For example, each of Benmelech and Bergman (2018), Haddad, Moreira and Muir (2020), and most recently Foley-Fisher, Gorton and Verani (2021) provide insightful studies on the characteristics of liquidity in Corporates and CLOs, and there are others, focused on

[4] See O'Hara (1997) and Foucault, Pagano and Röell (2013).

[5] See, for example, Budish, Cramton and Shim (2015).

[6] See for example earlier work by Hotchkiss and Ronen (2002), Bao, Pan and Wang (2011) and Ronen and Zhou (2013).

[7] See Wiltermuth (2021), among others.

[8] See Table 1 in Christopoulos and Barratt (2021a).

disclosures of risks in keeping with the frequency of trading.

Although there have been improvements in corporate bonds data availability, not all fixed income markets have equally benefited. Data for some credit sensitive securitizations has improved as discussed in Hollified, Nekyudov and Spatt (2017), but even with improvements in reporting which is uneven, we must still contend with the inherently less traded characteristic of credit sensitive securitizations compared with other fixed income sectors and equities.[9] CMBS and its derivative CMBX are OTC products which do not trade (meaningfully) on electronic exchanges. For CMBS and CMBX, communication between market makers (dealers) and investors in CMBX is still principally done through Bloomberg terminal posts and sporadically.[10] There is reliable recording of day-end mark-to-market values since 2007 for CMBX through IHS Markit, and some required posting intraday on TRACE.[11] However, the trading in this area of the market may still occur in minutes, days, weeks, months and even years for the most credit sensitive parts of the capital structure, rather than occurring in milliseconds as seen in other sectors. Average daily trading volumes ('ADV') for CMBS, for example, stand at $0.84 billion compared with $27.4 billion for Corporates as noted in Table 3.

Other areas of the literature focus on risk decomposition and disclosure of theoretical liquidity, which may differ from effective bid-ask spreads estimates of liquidity. For example, Amihud (2002) and Gilchrist and Zakrajšek (2012) each identify measures of liquidity for credit sensitive fixed income securities. Additionally, studies disclosing default and liquidity components such as Longstaff, Mithal and Neis (2005) find substantial concentration of default risk in corporate bond spreads that vary across credit ratings informed by implementing a theoretical model similar in class to Christopoulos and Jarrow (2018). Bao, Pan and Wang (2011) and Han and Zhou (2016) isolate factors apart from credit risk to be attributable to

[9]See Table 3 for a snapshot of multiple sector average daily trading volumes

[10]See the Christopoulos and Barratt (2021a) Appendix A.1. for greater detail on CMBX trading.

[11]Subject to 90 day SEC imposed reporting embargos with respect to volumes.

overall risk premia for that sector. They find illiquidity in corporate bonds increases with volatility and to be highly time varying. Bao, O'Hara and Zhou (2018) provide insights into deterioration of liquidity in the corporate bond market during times of distress and the potential for mischaracterization of risks of liquidity as default with implications for policy-making particularly for crisis mitigation. Gilchrist and Zakrajšek (2012) introduce the excess bond premium ('EBP') approach in excess of default risk estimated using firm specific variables and the distance to default framework of Merton (1974). Their results indicate significant explanatory power for both the isolated default partition and the excess bond risk premia for several economic indicators including the civilian unemployment rate ('UER'). Broto and Lamas (2016) use PCA to construct liquidity indices for US fixed income demonstrating an application of that technique in this area of the literature. In Christopoulos (2017) and Christopoulos and Jarrow (2018), the reduced form simulations introduced in those studies first allowed, and then restricted, simulation of default applied to about $400mm in CRE loans underlying the most actively traded CMBS which serve as collateral for CMBX over the 2007-2014 period. The state transition simulation informed by a rich history and well specified model approach allowed for isolation of implied risk neutral prices for default and interest rate risks, both of which were explicitly modelled.[12] Most recently, Christopoulos and Barratt (2021a) introduce the daily estimation risk decomposition approach for CMBX. Finally, Gilchrist et al (2021) consider the risk decompositions with the EBP approach for Corporates 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.

In the absence of rich data and well developed exchange traded markets, credit sensitive sectors in the fixed income market may remain silent with respect to the pricing of their underlying risks without the benefit of revealed intraday price formation indicators found in prices, bid-ask spreads, volumes or counterparties. This opacity in risk pricing disclosure motivates this paper into higher frequency risk decomposition estimation. It builds off the

[12]See Christopoulos and Barratt (2021a) for a more detailed summary of these two works.

prior literature into risk decomposistion. It also focuses the application onto CMBS and CMBX asset pricing and microstructure and addresses the inherently less frequent trading characteristic of that sector, despite its size. The potential impact of this sector on the financial markets in economic downturns has been seen in the Great Financial Crisis and, more recently, in the Covid pandemic.

2 Data

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

At the intraday level, during the Covid-19 pandemic period of April 2020-April 2021 we use prices for 25 representative publicly traded REITs obtained from Yahoo! Finance in the estimation of the Intraday Model obtained through through RapidAPI. We select these REITs due to their similarity to CMBX on a few dimensions. Table 1 lists the names of the 25 REITs used in this study along with their property type, ticker, factor name ('proptype_ticker'), and market capitalization as of June 27, 2021. The market capitalization of these 25 REITs selected 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[13], 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 is 223, and so by counts, our sample represents about 11% of the US REIT sector. Additionally, these REITs also are well distributed across multiple property types as shown in a further summary of the REIT sample in our study broken down by property type in Table 2. Finally, our estimated economy also captures most of the REITs used in the prior study of Christopoulos and Jarrow (2018) and for continuity with the simulation, we also use these REITs. The CMBX in our sample represent approximately $400 billion of CMBS underlying, the size of our REIT sample and our CMBX sample are of similar

[13]See NAREIT (2020).

market magnitude which is important in establishing a signal in one market as indicative of a condition in another market. We thus feel our sample is broadly representative of the US REIT sector. These 25 REITs are included in the training data and then used in the Daily and Intraday Models to estimate CMBX risk partitions.

[Insert Table 1 about here]

[Insert Table 2 about here]

We also captured the intraday values of the Chicago Board Options Exchange's CBOE Volatility Index (the 'VIX'), constant maturity ('CMT') US Treasury yields to maturity using the RapidAPI application with Yahoo! Finance. These factors are used in countless research studies. The choice of the VIX is particularly important for its broad usage in the market as a fear gauge as discussed in Carr (2017). These data are summarized later in Tables 5 and 6 at the start and at the end of the trading days during this period. We poll the data in 15 second time-stamped intervals and the average delay over this period is about 1.15 seconds. The data is always 'most-recent' and reflective of updates driven by trading in the marketplace. The data polling for each day starts at approximately 9:30:15am EST and ends at approximately 4:15:00pm EST. There were some delays in reporting due to electronic communication lags on the internet in the application of up to 2 seconds. Additionally, some delays in reporting can take up to 15 minutes for the VIX at the start of each trading day. All Federal holidays are excluded with trading in our studey only taking place on days when both bond and stock markets were open. Reporting terminates early with early market closings market circuit breaker triggers.

Finally, to put observable liquidity at a high level in context, using public data from SIFMA and NAREIT we see that REITs in the aggregate appear to be more liquid than CMBS. Table 3 indicates approximately 10x the dollar trading volume for REITs compared with CMBS with 4x the efficiency of turnover rates defined as average daily volume ('ADV') divided outstanding issuance. Because REITs and CMBX share similar risks to CRE and because REITs trade much more frequently than the underlying for CMBX derivatives, we use REITs to articulate our CRE risk pricing insights strategies based on CMBX trading signals in Section 4.

[Insert Table 3 about here]

Finally, for the trading strategies and related ICAPM testing conducted during the Covid-19 pandemic period (240 days between April 2020-April 2021) we obtain daily values of the market portfolio (Mkt-Rf, which consists of all NYSE, AMEX, and NASDAQ firms), small minus big ('SMB'), high minus low ('HML'), and momentum ('MOM') indices from Ken French's website.[14]

3 The Model

This section introduces the model used in this study

This model estimates the projections which index a series of transformations, ex-post simulation and project fair value prices of risk partitions onto 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 (2021a) estimate the risk partitions daily from the monthly simulated risk partitions of of Christopoulos (2017) and Christopoulos and Jarrow (2018) with what they call the 'Daily Model', over the sample period of November 2007-April 2019. In this paper we summarize the same mathematics introduced in that paper which we too use, extending them to handle intraday frequency.

[14]See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

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 (25 REITs, 4 US Treasuries, and the VIX volatility index). From 92 monthly observations in the training period over the period November 2007-June 2014 they create a lower-dimensional set of factors to explain 96% of the total variance at observed dates by performing a principal components analysis ('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 30 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

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

with each explanatory variable a linear combination of the factors f_i at all times t. They reduce dimension because they have only 92 observations in the history of simulated risk partitions. The process reduced the number of components from 30 observable variables, to 5 variables. The factors are determined with matrix multiplication as

$$f_i(t) = \sum_{q=1}^{30} p_{iq} x_q(t),\ i \in \{1...5\} \tag{2}$$

The factors $f_i(t)$ are uncorrelated[15], such that the partial sum

$$x_q(t) = \sum_{i=1}^{5} p_{iq} f_i(t) + \varepsilon_n(t),\quad \mathbb{E}[\varepsilon_n] = 0 \tag{3}$$

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

[15]See the proof in Christopoulos and Barratt (2021a) Appendix A.3.

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 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 30 variables over 92 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

$$\mathrm{F} = \mathrm{R}^T \mathrm{E}^T = \begin{bmatrix} f_{1,1} & \cdots & f_{t,5} \\ \vdots & \ddots & \vdots \\ f_{92,1} & \cdots & f_{92,5} \end{bmatrix} \tag{4}$$

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 previous two 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 92 monthly simulations and indexing of Christopoulos and Jarrow (2018) over the period November 2007 thru June 2015. The initial risk component $y_{jk}(t_0)$, $j \in \{\text{def}, \text{rate}, ...\}, k \in \{\text{AAA}, \text{AJ/AS}, ...\}$, is given by

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

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, 16 coefficients were estimated, one for each of the 15 separate volatility components, and one for the indexed market spread corresponding to the credit rating class. The OLS capture 90 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 $\left[v_i(t) - v_i(t-1) \right]^2$ 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. (5) they then predict the daily spread risk decompositions using Eq. (6) combining the estimates and 2828 daily on the run observations, adjusting the lookback of the factor volatilities with 22 trading days equal to one month from the date of the daily observations for the updated calculations. The estimation model is re-expressed for 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

$$\hat{y}_{jk}(u) = \alpha_{jk} + \sum_{i=1}^{5} \beta_{ijk} v_i(u) + \gamma_{ijk} v_i(u-22) + \delta_{ijk} \left[v_i(u) - v_i(u-22) \right]^2 + \psi_k \mathbb{S}_k(t) \quad (6)$$

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

$$\bar{y}_{jk}(u) = \frac{\hat{y}_{jk}(u)}{\sum_j \hat{y}_{jk}(u)} \quad (7)$$

All four risk components are computed this way as the proportions of Eq. (7) for the CMBX sector across all credits in Figure 1.

[Insert Figure 1 about here]

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 default, interest rate, liquidity availability and excess liquidity availability indices for the aggregate sector-wide CMBX found in Christopoulos and Barratt (2021a) is shown in Figure 1.

The Daily Model 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, there is nothing in principle that prevents us from increasing the frequency of estimation for all risk components from daily, to shorter intervals intraday. In this section we increase the frequency of linear estimation from daily to 15 second intervals, *intraday,* for each trading day in the Covid-19 pandemic in our sample (the 'Intraday Model'). This allows us to investigate into CMBX risk price formation at higher frequency than observed market pricing which is exogenous to the model.

Specifically, all mathematics 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 15 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

$$\Delta y_{jk}(t) = \sum_{i=1}^{5} \eta_{ijk} \Delta f_i(t) + \varepsilon_{jk}^{\Delta}(t) \tag{8}$$

for the j-th risk partition of the k-th bond at time t. We 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 $\varepsilon_{jk}^{\Delta}(t)$ has expected mean zero with standard deviation $\sqrt{\eta_{0jk}}$. We normalize the sum of the proportions for the intraday risk decomposition to 1 as was done previously for daily observations in Eq. (7).

The final risk composition is then calculated using the initial condition and the instantaneous changes:

$$y_{jk}(t) = y_{jk}(t_0) + \sum_{t'=1}^{t} \Delta y_{jk}(t') \tag{9}$$

where the intraday estimation of risk components $y_{jk}(t)$ is the j-th component of the risk partition for bond k at time t on trading day u. The first term on the righthand 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. (8). Importantly, these changes in the economy on the right hand side of Eq. (9) are independent of current market prices. Their relationship is 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. (4) and related definitions, as previously discussed. In conjunction, these mathematics are the 'Intraday Model'.

4 Results

This section presents the results for this study.

4.1 Intraday decomposition time series

Although the time scales for the training data and intraday time steps of 15 seconds are vastly different, they appear to scale well. What we see in Figure 2 is the intraday evolution of risk decompositions, $y_{jk}(t)$ as defined in Eq. (9) for CMBX over two trading days for all $j \in [1, 4]$ risk partitions and $k \in [1, 6]$ credit ratings. The risk partitions are observed for $t \in [1, 1560]$ consecutive 15 second intervals in length per trading day. The first estimation occurs at or after 9:30:15 seconds following the market open; the last estimation occurs at or about 4:15:00pm. The variability at the open occurs because the implementation requires the information released at 9:30:00am, the variability at the close is due to reporting delays which may occur slightly before or slightly after 4:15:00pm. The risk partitions at the tranche level and for the aggregate composite ('Christopoulos and Jarrow (2018) Composite') are projections based on the training set of simulated and indexed risk partition primitives in Christopoulos and Jarrow (2018).

[Insert Figure 2 about here]

The risk composites vary considerably across credit rating classes, days, and intraday. The rank order results by credit ratings are similar to findings of Longstaff, Mithal and Neis (2005) in the corporate bond sector regarding the proportion of the risk of default embedded in spreads varying by credit rating. The intraday decompositions reflect updated live data for 25 REITs, 4 US Treasuries, and the VIX index as previously described. Figure 2a shows the evolution for u = April 17, 2020 in the early stages of the Covid-19 global pandemic with the Dow Jones Industrial Average ('DJIA') closing 23537, while Figure 2b shows the evolution of the risk decomposition indices on u = December 4, 2020 with the DJIA closing at 30217. The sum of all compositions on all intervals are normalized to 1. The values are different. Although we show only two trading dates, these evolutions differ on different trading days The values are captured intraday in 15 second intervals for all 240 trading days between April 7, 2020 and April 8, 2021 in this study.

As noted in Christopoulos (2017), model estimated liquidity of CMBX vary considerably across credit ratings and time. AAA CMBS securities make up about 80 percent of the CMBS market due to the senior/subordinate capital structure as noted in An, Deng, Nichols and Sanders (2015) and Riddiough and Zhu (2016) while subordinate BBB- CMBS make up less than 5 percent of the market. As BBB- securities are more immediately exposed to loss manifestation following a default event than AAA securities a smaller proportion of the risk compensation above the risk free rate for BBB- securities should be associated with liquidity availability when compared with AAA. This dynamic is confirmed in Christopoulos (2017) and Christopoulos and Jarrow (2018) in indexed form from 2007-2015 in monthly simulations and is confirmed again in this paper with bid-ask comparisons daily (as previously discussed), and now as evident, intraday.

4.2 Statistical summary of time series

[Insert Table 4 about here]

Table 4 provides a statistical summary across all observations intraday for default, rates, liquidity and excess liquidity risk partitions. The summary results generally follow intuition with some new insights and we exhibit all investment grade classes. Focusing first on intraday default risk pricing, we observe AAA CMBX appear to exhibit substantially greater volatility than BBB-, with only the AJ exhibiting greater volatility. Rates volatility pricing intraday is much calmer than default intraday pricing across most credits with the exception of the BBB class. Again, as with default, the AJ class appears to exhibit higher volatility than the AAA class. This relatively higher volatility for the AJ class compared with the AAA class repeats across all four risk measures. Finally, as we are concentrating on liquidity, the low nominal amounts of both liquidity and excess liquidity in BBB- classes should result in higher volatility estimates reflective of scarce liquidity availability. Min and max values follow intuition suggesting that the capital structure allocation concentrates mispricing in the mid-section with the endpoints of AAA and BBB- exhibiting more regular behaviour.

4.3 Cross sectional visualizations

While the summary information in Table 4 is interesting from an academic perspective, it is fundamentally limited for two reasons. First, the values estimated intraday still must use an initial set of simulated values and market spreads. The simulated risk decomposition studies of Christopoulos (2017) and Christopoulos and Jarrow (2018), reflecting actual cashflow and updated credit and prepayment profiles, end in 2015.

Second, the initialized spread value informing these evolutions are restricted to only March 18, 2020 because no additional daily CMBX pricing data was made available to us after that date. In this sense, the intraday results depicted are essentially cross-sectional intraday stress tests of the response of risk decompositions holding market spreads as of March 18, 2020 held constant. Although the limitations of the initialization restrict the validity of the intraday time series across dates, they will reveal insights in cross sectional analysis. Each day is a valid time series and the collection of all dates represents the set for cross section evaluation. At the same time, because the real time estimations are price independent, observing their changes over time yields some unique insights. One way to approach the evaluation of cross section of daily time series is through the heat map approach using binning. We want to cast the daily risk pricing data against both time and a relevant variable. The VIX provides such a variable as a dominant explanatory variable in the previous daily historical analysis.

[Insert Figure 3 about here]

[Insert Figure 4 about here]

To simplify the notation for the remainder of the paper, we define the cumulative intraday change for each risk partition as

$$W_{jkut} \equiv \sum_{t'=1}^{t} \Delta y_{jku}(t') \tag{10}$$

This is the second term Eq. (9), 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 3 shows 275370 observations computed for each of the intraday default risk partition pricings. We use a double binning method to observe. The x-axes reflect 3 minute intervals binned from the 15 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. 10. The depiction have non-constant upper and lower boundaries, but identical colorscaling . This is purposeful, as each of the classes may have inherently different sensitivities to market indicators. 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. The color saturation produced for each plot is interesting during the Covid period. Together they suggest somewhat lower intraday default risk pricing for AAA, AJ and BBB- classes compared with the AA, A and BBB classes. In Figure 4 we take the same vantage point but for liquidity availability. Here, we see somewhat greater intraday liquidity availability for AAA with the least liquidity available for A and BBB classes as indicated by the color palettes and contour lines.

These perspectives document some important facts in theoretical observation of CMBX risk pricing during the Covid period, one of the most interesting being an apparent regular 'spot' of volatility in the first 15 minutes of trading in the cross section. This repeats across all instruments and risk partitions in our sample. Figure 5 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 risk pricing for default, liquidity, excess liquidity and rates indices for all investment grade credit rating classes. For example, consider in Figure 5 the case of intraday liquidity availability pricing in the second composite of six plots on the top right. At about 9:39am we observe considerable cross-sectional deterioration in liquidity availability for AAA, AJ, AA and BBB- classes with contour labels in 'valleys' ranging from 0.70 to 0.84. In contrast class A class shows relatively more modest deterioration in liquidity availability at about 0.94 while the BBB class shows expansion of liquidity availability of about 1.35. These types of comparisons can be made for all credit ratings classes and all estimated risk partitions generated by the Intraday Model.

[Insert Figure 5 about here]

In Tables 5 and 6 we observe summary values across 246 trading days, two times during the trading day: the opening (9:30:15) and the closing (4:15:00).

[Insert Table 5 about here]

[Insert Table 6 about here]

Opening volatilities for the cumulative changes in proportions of all risk partitions are categorically higher than the closing volatilities for those values. Additionally, looking at the modelled economy, the VIX and interest rates also exhibit categorically higher opening volatility compared with closing volatility. Finally, REITs also exhibit mostly higher volatility at the open than the close, but not categorically with only 18 of the 25 REITs exhibiting higher volatility at the open in the cross-section with and 7 of the 25 exhibiting lower volatility at the open in the cross-section. The differences in magnitude between the theoretical risk partitions and the publicly traded securities and indices are not completely surprising. The risk partition measures represent cumulative changes in proportions from the start of the day. In contrast, the pricing for the publicly traded objects are just prices and not changes of prices. The cross-sectional insights across all intervals and at the open and close give us our *third main result*: During the pandemic, we find considerably greater volatility in risk partition pricing at the start of each trading day for all risk partitions compared to the end of each trading day. This finding of higher volatility of signals at the open compared with the close prompts further investigation into liquidity across the CMBX and REIT sectors.

4.4 Trading strategies

4.4.1 REITs liquidity and trade frequency

REITs, like CMBS and CMBX, have similar underlying exposure to CRE risk, and so estimated CMBX risk partitions may carry relevance to REIT pricing in the marketplace. As previously mentioned, CMBX as an OTC product does not trade electronically. That means that the estimated risk partitions in this study update more rapidly than the pricing of actual CMBX securities and the pricing of their underlying CMBS collateral. In earlier studies the CMBX risk partitions gave many profitable insights into the buy/sell decision-making within the CMBX market. Publicly traded REITs trade on electronic equity exchanges and thus have a similar frequency of price updates as our intraday risk measures.

4.4.2 Trading signal

We focus our trading strategies on REITs due to their better liquidity in the market and their observable pricing. We use the risk partitions of default, liquidity and excess liquidity. The interest rate risk partition is a more complex interpretation in the trading context with respect to REITs. Higher interest rate risk compensation for higher future rate volatility may affect REITs differently, depending on leverage and asset composition. As such inquiry into trading signals based on the rate risk partition is left to future research. To keep things tractable we present one trading signal, $L_{\iota jkut}$, defined as

$$L_{\iota jkut} = \frac{\Delta R_{\iota ut}}{W_{jkut}} \tag{11}$$

$\Delta R_{\iota ut}$ is defined for $\iota \in [1, 25]$ REITs in our sample as

$$\Delta R_{\iota ut} = \frac{R_{\iota ut}}{R_{\iota t=4:15:00pm,u-1}} \tag{12}$$

and represents the proportion of cumulative changes in REIT prices from the close of the prior trading day t =4:15:00 pm to the time of trade execution for the ι-th REIT. W_{jkut} is defined in Eq. (10) as the cumulative intraday change in the theoretical price of the CMBX risk partition for j risk partitions, of k credit rating classes, for u trading days and t intraday trading times.

The trading signal $L_{\iota jkut}$ has been carefully selected from among others considered in the development of this study. It has several interesting properties and provides clear theoretical and trading directional (long-short) interpretations that correspond to intuition. As noted earlier, the liquidity and excess liquidity measures have the interpretation of liquidity availability. Large values for those measures suggest that compensation in market spreads exceeds (wider than) what is required fair compensation for the risks of default and interest rate risks. In this paper, which does not benefit from market prices to project onto, the risk composition is theoretical, and estimates reflect cumulative intraday changes in the measures from the opening bell. As such, higher values for cumulative changes intraday in the liquidity and excess liquidity pricing measures, suggest more attractive pricing (liquidity) or enhanced safety of liquidity to spread shocks (excess liquidity) for CMBX. This would suggest, temporally, a healthier than expected CRE environment than is being priced by the market in theory. The opposite interpretation is true for default risk pricing where higher cumulative values for the theoretical pricing of default risk indicates greater default risk (more compensation required) while lower cumulative values suggest lower default risk (less compensation required). We summarize some of these interpretation with examples in Table 7 which capture all changes in the components of the signal and the trading interpretation. The statistical analysis shows the mean and median for the $L_{\iota jkut}$ ratios to be strongly clustered about 1, thereby justifying this value to be the center point about which the for direction of trading (long-short) is determined.

[Insert Table 7 about here]

Specifically, for liquidity and excess liquidity measures, higher values of $L_{\iota jkut} > 1$ correspond to 'sell' signals while lower values of $L_{\iota jkut} < 1$ correspond to 'buy' signals. Values of $L_{\iota jkut} = 1$ indicate no trade signal. It is important to see that the relative rate of change between the numerator and denominator come into play and the signal picks up these subtleties. For example, consider in Table 7 Examples 3 and 13, $\Delta R \uparrow, W\uparrow$. Both instances correspond to simultaneous increases in both the numerator and the denominator, indicated by the upward pointing arrows. In Example 3, the cumulative proportional liquidity measure W is increasing more slowly (1.20) than the cumulative proportional REIT price change ΔR (1.25). Since liquidity availability is lagging price increases, the trade signal suggests 'sell' as prices are moving higher than justified relative to the liquidity measure ($L = 1.25/1.20 = 1.0417 > 1 \rightarrow$ 'sell'). In contrast, in Example 13, also $\Delta R \uparrow, W\uparrow$, since liquidity (1.10) is increasing more rapidly than the cumulative price increases in the REIT (1.02), the trade signal suggests a buying opportunity ($L = 1.02/1.10 = 0.9273 < 1 \rightarrow$ 'buy'). Finally, while liquidity and excess liquidity availability generate the same directional signalling, the default risk measure generates exactly the opposite signal, because higher default risk decompositions correspond to higher default risk as noted in Christopoulos (2017).

4.4.3 Automated trading strategies

The purpose of the automated trading strategies is primarily oriented towards discerning the value of the trading signals to understanding the related REIT market pricing of CRE risks at higher frequencies. On each day we consider the set of all 25 REITs with the Trading Signal $L_{\iota jkut}$ for all risk partitions for all credits. We 'buy' securities into the long portfolio and 'sell' securities into the short portfolio. We assume execution at mid-market prices for the REITs when we enter and exit trades and do not, in this initial study, make adjustments for bid/ask spreads of REITs which were not provided. We execute all our trading (long and short positions) at the first trade of the day at approximately t =9:30:15 am EST. We unwind all positions at end of the day at the close of the day approximately t =4:15:00pm EST.[16] For all strategies we rank order the REITs based on the values $L_{\iota jkut}$ and buy or sell them instantaneously into their respective portfolios at the price which contributes to the signals. In this paper, long and short portfolios are assumed to make price weighted contributions to the long-short portfolio components with the daily returns on long-short components equally weighted. We consider the rank order of the REITs based on the signals with interpretations given in Table 7. For liquidity and excess liquidity risk availability portfolios, for those REITs with values of $L_{\iota jkut} > 1$ we 'sell' those securities in the short portfolio; and for those REITs with values $L_{\iota jkut} < 1$ we 'buy' those securities into the long portfolio. In the case of the default risk partition portfolio we buy (long) REITs with values of $L_{\iota jkut} < 1$ and sell (short) REITs with values of $L_{\iota jkut} > 1$. Values of $L_{\iota jkut} = 1$ indicate no trade signal in all cases.

It is certainly the case in this strategy that on any given day we may be 100% directionally long or short, but we are never more than 50% weighted long-short. In the instances where 100% of the values $L_{\iota jkut}$ are in the same direction (Eg. all > 1 or all< 1), then the corresponding portfolio is allocated 50% to the direction given by the uniform signal on that day and 50% into cash (0% Return). For example, if all 25 REITs had a buy-signal based on $L_{\iota jkut}$ then all 25 would be purchased into the long position. The return for the day would be calculated based on the change in value between 9:30:15am (when they were purchased) and 4:15:00pm (when they were sold). However, in such cases 50% of the portfolio is said to have been moved to cash with assumed 0% return for that day. On all other days, when the signals are mixed 50% of the returns are generated by the long leg of the portfolio and 50% are generated by the short leg of the portfolio, regardless of how many signals indicate long and short on such date. The risk management of the portfolio is enforced in cases where only one direction is signalled, with a 50% allocation to cash imposed. Additionally, the

[16] On occasion there are small differences of a few seconds due to latency. All trading times are time stamped.

time horizon of mandatory unwind of all positions by the end of the day ensures that each portfolio horizon is only one trading session. The obvious artifice is the forcing trades to close at the end of the day instead exploiting the intraday changes observable in Figures 2, 3, 4 and 5. Investigation of such tactical intraday exploitation of CMBX risk partition pricing is outside the scope of this paper and left to future work.

4.5 Trading strategy results

4.5.1 Returns

The trading strategies were implemented for excess liquidity, liquidity and default risk measures for all ratings classes 12 month cumulative returns, Sharpe ratios and standard deviations for the portfolios were calculated. Sharpe ratios, H_ω, for the ω-th different trading strategies[17] with $\omega \in [1, 18]$ trading strategies were calculated as

$$H_\omega = \frac{R_\omega - R_\lambda}{\sigma_\omega \times \sqrt{240}} \tag{13}$$

The standard deviation of the daily returns for the day trading strategy portfolio is denoted as σ_ω. The square root of the 240 trading days is the required adjustment for daily standard deviations for 240 trading days in our sample period. The cumulative trading return for the specific day trading strategy is denoted, R_ω, while R_λ is the cumulative return for the long-only portfolio. The long-only portfolio (with 100% allocation to the 25 REITs), like the day trading strategies, is also a day traded portfolio executed with buys and sells at 9:30am and 4:00pm, respectively, on each trading day contemporaneous with the long-short portfolio. For the long-short trading strategies, the same credit rating x risk partition cohort drove the buy sell decisions, with updated values for $L_{\iota jkut}$ at each time t over the sample period.

[17] See Sharpe (1994).

The return on the long-only day traded portfolio over the sample period was -14.97% during the 240 days during the Covid pandemic making up our sample period. Table 8 summarizes the results over 240 trading days for the long-short portfolios during the Covid pandemic. The best results were found with the excess liquidity risk strategy returns of 41.37% for AJ (Panel A). The worst result was found with the default risk strategy of -34.67% for BBB (Panel C). For portfolios with positive returns, the portfolio Sharpe ratios were quite strong with values ranging from 1.99 to 5.09; For excess liquidity and liquidity trading strategies we see categorically positive returns ranging from 9.09% to 41.37% for all credit rating classes. For the default pricing driven signals, positive returns of 11.08% and 17.08% are captured only for the AAA and AJ classes, respectively. To put these ratios and returns into context, consider the survey of Lo (2002) which reports 12-month estimated Sharpe ratios for 10 mutual funds and 12 hedge funds in the range of 0.49 to 3.83, after adjusting for serial correlation. More recently, Investment News (2020) report the top 10 hedge funds at year end 2020 demonstrating Sharpe ratios of 0.72 to 1.68, with annual returns of 17.8% to 37.4%. The results of our automated trading strategies appear to be in line with, if a bit better than, these top professional performances.

As the measures produced are theoretical for CMBX and updated more frequently than that market trades, the reverse application of going from REIT pricing to CMBX intraday pricing, is not possible. Unlike two funds that recently exploited mispricing of risk in CMBX as described in Tempkin (2021), we do not have access to intraday trading information for CMBX, which is not regularly reported. This maintains our focus on the relationships between CMBX risk measures and the larger ($1.3 trillion) and more liquid (see Table 3) REIT market. While there may be some conflicting directional signals across different trading signals, the returns during considerably different periods of volatility during Covid suggest that the signals within cohorts are reliable. While the overall levels of returns and Sharpe ratios could be lower if executed, they could also be considerably higher. The calculation of Sharpe ratios is done with the returns on the trading strategies and with the long-only returns which are both subject to the same transaction costs (they are both REITs), and thus the transactions costs are internally consistent. This internal consistency in trading horizon supports analysis using ICAPM.

[Insert Table 8 about here]

4.5.2 ICAPM

To test for skill in the trading strategies we use the ICAPM of Merton (1990). We choose this approach as a standard approach for equity asset pricing tests of skills. An alternative approach was introduced by Acharya and Pedersen (2005) which includes the Amihud (2002) ILLIQ measure. However, ILLIQ is dependent on observed volumes. Since no observed volumes were provided for CMBX, ILLIQ cannot be implemented as an ICAPM factor in this study. However, the key findings of Acharya and Pedersen (2005) concerning flight to liquidity do appear to be confirmed in this study, in particular in our trading strategies that exploit the estimated reduced form measures of liquidity and excess liquidity.

Following Christopoulos and Jarrow (2018) the final regression model to test for abnormal returns in our trading strategies is given by:

$$R_{\omega u} - R_{\lambda u} = \alpha + \sum_{i=2}^{M} \beta_{\omega i}(R_{iu} - r_u) + \varepsilon_u \tag{14}$$

with $u \in [1, 240]$ trading days, $R_{\omega u}$ the daily returns of the trading strategy portfolio, $R_{\lambda u}$ the returns of the long-only trading portfolio, R_{iu} the i-th portfolio equity risk factor, and r_u the risk-free rate. Positive and significant α implies these trading strategies generate abnormal returns. We use the standard risk factors to evaluate equity based trading strategies introduced in Fama and French (1993) including: (i) the market portfolio, (ii) the SMB equity index, and (iii) the HML index as well as the MOM risk factor introduced in Carhart (1997). We test the trading strategies with results summarized in Table 9. For each of the six credit rating classes our trading strategies span 240 trading dates from $u = 4/8/2020$ thru $u = 3/31/2021$. The results are quite strong. All of the strategies were statistically significant overall based on the F-test. Adjusted R-squared values ranged from 0.3187 to 0.4760. 84% (16/18) of the strategies produced positive and significant $\alpha's$ ranging from 0.01 to 0.100 levels significance. In all strategies the market portfolio was statistically significant at the 0.001 level and negative. The MOM risk factor was generally insignificant and negative. SMB varied in sign and was insignificant across all strategies. HML was categorically negative and highly significant at the 0.001 level. 75% (12/16) of the significant strategies also exhibited positive abnormal returns ranging from 9.09% to 41.37%.

[Insert Table 9 about here]

This comparatively greater proportion of positive returns coupled with positive and significant α is echoed when we break down returns by credit rating class as seen in Figure 6. The plots are read from left to right by descending credit rating class beginning with AAA (blue) in the top left and BBB- (red) in the bottom right. Across all strategies and credits, the strategies for the AJ class (green) appear to perform best. The capital structure differences are consistent with the earlier literature[18] and discussion. Interestingly, as noted in An, Deng, Nichols and Sanders (2015) the pricing of credit risk alone is insufficient to explain subordination impact on pricing. While W_{jkut} values in Eq. (11) are picking up risk tranching effects, and differentiating across different risks, they are not directly pricing the idiosyncratic risks of CMBX bond collateral due to data restrictions at this time. Thus we provide evidence of idiosyncratic risk of collateral in CMBX to be comparatively more important for lower credit rated tranches than higher rated tranches and, as such signals with respect to default x REITs to be weakest in the absence of updated current loan level default data, which was not available for this study.

[18] See for example Riddiough and Zhu (2016).

[Insert Figure 6 about here]

This is an excellent result. If there is a systematic mispricing of liquidity and excess liquidity in CMBX capital structure informed by broader market misspecification of state transitions and their impact on credit tranches, then those CMBX risk partitions should provide the best signals to the related REIT market. Further, if the liquidity and excess liquidity availability in the capital structure is not accurately priced, as found under risk neutral simulation in Christopoulos (2017) and Christopoulos and Jarrow (2018), then those signals from the bottom of the capital structure should provide the best of the best signals in the cohort. This is exactly what we see. The liquidity and excess liquidity trading signals with respect to REIT relative value provide more consistent and positive insights than default at the bottom of the capital structure. While there are some differences at the BBB- level the results still are consistent with a mispricing of liquidity and excess liquidity in CMBX and establish a relationship of similar mispricing in REITs.[19] As shown in the cross-sectional analysis, we find considerably greater volatility in risk partition pricing at the start of each trading day for all risk partitions compared to the end of each trading day, which contrast with the much more muted volatility for REITs from the start to end of the trading day. This suggests that the monthly and daily analyses provided by the theoretical liquidity risk partitions persist at the intraday level, which is our *first main result.* Finally, the success of the trade strategies and their significance confirm that CMBX risk partitions bring valuable insights to the related REIT sector and to CMBX at higher frequencies which is our *second main result,* completing the Intraday Model validation.

[19] Tables of all trades for all trading strategies are available upon request.

5 Summary

The estimation of risk partitions at intraday frequency for CMBX is conducted in this study. Our estimations are conducted for all investment grade credits in 15 second intervals over 240 days during the Covid pandemic. We find stark and regular volatility pockets of risk partition pricing in the cross-section over the sample period April 2020-April 2021. If broader real estate risk sentiments of investors are embedded within the CMBX residual risk partitions of liquidity and excess liquidity, it would make sense if those measures also revealed pricing insights into real estate risk in securities apart from CMBX. We find this to be true. By fusing the CMBX risk partition signals with REIT pricing in 18 trading strategies over 240 trading days, we achieved significant ICAPM $\alpha's$ in 84% of the strategies and positive cumulative returns ranging from 9.09% to 41.37% in 75% of those strategies during the Covid pandemic. By our results, the fusion of CMBX risk partition signals with REIT pricing appears to exploit rapid changes in investor sentiment with respect to the pricing of real estate securities risks. We find that intraday CMBX risk partitions reveal insights into the related REIT sector intraday, with matching trading frequency.

The intraday estimation of reduced form risk partitions, as we have done in this work, is general. It can be applied to all fixed income securities, with particular benefit to those securities that are credit sensitive and trade with less frequency than more mature sectors. To be sure, a training set for the economy and reduced form simulated risk partitions is required. This necessarily requires the simulation of those reduced form risk partitions directly as introduced in Christopoulos (2017) and Christopoulos and Jarrow (2018). With that, and by our method, the intraday estimations can be conducted. Further, it should be noted that what we execute utilizes the same initial condition date of March 18, 2020, for the market spreads, which allows for our cross-sectional analysis to be especially meaningful. However time series analyses in subsequent work could be conducted if end-of-day mark-to market pricing were provided. This would allow for two sets of estimations to take place intraday: one based on the March 18, 2020 initial market spread and the other based on the market spread reported from the previous close. Again, these estimates are proxies for the simulation based and loan and bond level data intensive simulations of Christopoulos (2017) and Christopoulos and Jarrow (2018), but early work on that technology suggest that computational time could be achieved with the same frequency as these estimations. And so future studies, could compare estimate to direct simulation liquidity assessments.

Additionally, consideration of dynamic intraday strategies would be interesting in that it would further clarify the meaning of the signals at higher frequencies instead of only exploiting them at pre-defined fixed points at the beginning and end of the trading day. This could foster better sensitivity analysis and optimization across different signals at different points in time and could improve trading selection into portfolios. This sets the stage for investigation into 'bubbles' in these markets diagnosing price formation and testing theories surrounding these phenomena.

Finally, from a risk policy perspective, investigating into a longer term relationship between intraday signals of risk partitions and manifestation of actual hazards in the real estate asset classes would be an interesting area for exploration. This would be fostered by the rapid estimation of risk partitions in this work and, in parallel, the simulation of those reduced form risk partitions directly as introduced in Christopoulos (2017) and Christopoulos and Jarrow (2018). Interesting analyses and comparisons between ratings upgrades and downgrades and mark-to-model estimations of risk could be juxtaposed with near real time risk decomposition estimation. Since lending criteria, risk retention, and capital constraints all have links to capital markets, research into the evolution of those links, with our intraday approach, before hazards manifest, seems a natural next level of inquiry. This is left to future research.To our knowledge, this is the first paper to investigate into the risk decomposition and price formation of commercial real estate securities at higher frequencies. This paper contributes to the literature on price formation and highlights the role of risk partitioning in enhancing transparency in credit sensitive US fixed income securities, rapidly.

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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	Wyndam 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 25 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: Aggregate Summary of Sample REITs

Property Type	Market Cap ($bn)	% Market Cap	Count	US Count	% of US
Industrial (IN)	$169.47	35.42%	4	13	30.77%
Hotel (LO)	$86.39	18.06%	4	13	30.77%
Multifamily (MF)	$87.86	18.36%	4	20	20.00%
Office (OF)	$40.06	8.37%	5	19	26.32%
Mixed Use/Other (OT)	$28.02	5.86%	4	126	3.17%
Retail (RT)	$66.65	13.93%	4	32	12.50%
Total	$478.45	100.00%	25	223	100.00%

This table aggregates values related to the 25 REITs used in this study. The first column gives the property type and total labels. 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 market capitalization (Market Cap). The third column provides proportion of each property type Market Cap compared to the total Market Cap in the sample. The fourth column provides the counts of the REITs by property type in the sample. The fifth column the number of REITs by property type in the US. The sixth column captures the proportion of the sample count to the US count of REITs.

Table 3: Liquidity summary for several sectors

Sector	ADV ($bn)	Outstanding ($bn)	Turnover	Turnover % Tsy
US Tsys	$565.00	$19,300.00	2.9275%	100.0000%
US RMBS (Agency)	$289.80	$9,900.00	2.9273%	99.9936%
US REITs	$8.70	$1,300.00	0.6692%	22.8604%
US Corporates	$27.46	$10,600.00	0.2590%	8.8480%
US CMBS	$0.84	$596.40	0.1408%	4.8112%

This table provides summary issuance and trading volume for US Treasuries, US Agency backed mortgage backed securities, US REITs, US Corporate Bonds and US CMBS. The columns report the average daily trading volume (ADV) at of Q1 2021 and the outstanding issuance, in $billions. The Turnover is the ratio of ADV/Outstanding issuance. The Turnover % of Tsy is the ratio of Turnover/Turnover of US Treasuries. Source: SIFMA (2021) and NAREIT (2020).

Table 4: Summary statistics of cumulative changes of intraday CMBX risk partitions

Panel A: Default	AAA	AJ	AA	A	BBB	BBB-
min	0.483416	0.338351	0.494514	0.609670	0.717165	0.823893
max	1.820368	8.403204	6.036482	6.121692	1.913765	1.400509
mean	1.000102	1.000104	1.000046	1.000039	1.000012	1.000005
median	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
variance	0.000212	0.000380	0.000156	0.000147	0.000020	0.000006
stdev	0.014562	0.019491	0.012485	0.012127	0.004425	0.002384
obs	275370	275370	275370	275370	275370	275370
Panel B: Rate risk	**AAA**	**AJ**	**AA**	**A**	**BBB**	**BBB-**
min	0.702365	0.610945	0.530693	0.583500	0.476037	0.599777
max	1.518098	1.742393	2.244835	1.871355	1.976362	1.469975
mean	1.000010	1.000137	1.000058	1.000042	1.000061	1.000024
median	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
variance	0.000019	0.000281	0.000123	0.000086	0.000123	0.000041
stdev	0.004340	0.016768	0.011092	0.009273	0.011089	0.006433
obs	275370	275370	275370	275370	275370	275370

Panel C: Liquidity	AAA	AJ	AA	A	BBB	BBB-
min	0.735970	0.330755	0.030144	0.016780	0.275537	0.134313
max	1.707165	8.456980	9.348418	27.908990	2.411473	6.462325
mean	1.000036	1.000466	1.000559	1.000738	1.000176	1.000397
median	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
variance	0.000078	0.001217	0.001370	0.007370	0.000361	0.000976
stdev	0.008806	0.034890	0.037017	0.085848	0.019004	0.031240
obs	275370	275370	275370	275370	275370	275370
Panel D: XS liquidity	**AAA**	**AJ**	**AA**	**A**	**BBB**	**BBB-**
min	0.346666	0.136986	0.508825	0.508825	0.508825	0.140683
max	3.379393	7.812876	2.413748	2.413748	2.413748	6.325317
mean	1.000147	1.000329	1.000074	1.000074	1.000074	1.000184
median	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
variance	0.000333	0.000868	0.000152	0.000152	0.000152	0.000719
stdev	0.018239	0.029465	0.012328	0.012328	0.012328	0.026816
obs	275370	275370	275370	275370	275370	275370

This table provides summary statistics of intraday CMBX risk partitions. The columns show the investment grade credit rating class and the rows the summary statistics of minimum (min), maximum (max), mean, median, variance, standard deviation (stdev), kurtosis and the number of observation (obs). Panel A summarizes for default risk, Panel B summarizes for interest rate risk, Panel C summarizes for liquidity, while Panel D summarizes for excess (XS) liquidity.

Table 5: Open Summary during Covid

variable	mean	median	min	max	variance	stdev	n
VIX	26.7659	25.6000	16.5500	47.3400	31.88860	5.6470	246
IN_DRE	37.9874	38.5400	30.4000	43.0600	6.83532	2.6144	246
IN_FR	41.0038	41.5825	33.1700	47.3700	8.22299	2.8676	246
IN_PLD	98.7801	99.5750	81.4700	109.7950	35.65076	5.9708	246
IN_SELF	4.0519	4.0000	3.5200	5.0500	0.08360	0.2891	246
LO_HST	12.8944	11.8875	9.1400	18.4200	4.94857	2.2245	246
LO_MAR	109.4389	100.5550	72.7600	155.7419	495.52655	22.2604	246
LO_WYND	37.0577	33.4700	21.0900	51.7500	93.63226	9.6764	246
LO_MGM	24.6343	22.3325	12.1100	41.7300	63.82471	7.9890	246
MF_AVB	162.0976	159.2000	133.1000	193.5300	145.65429	12.0687	246
MF_ELS	62.7243	62.7025	55.8600	68.2900	5.18841	2.2778	246
MF_EQR	60.1919	59.3700	46.0100	75.9600	37.04669	6.0866	246
MF_UDR	37.7456	37.4550	29.9100	45.6700	11.21798	3.3493	246
OF_BXP	91.4597	91.0200	70.7300	108.5900	74.19748	8.6138	246
OF_CLI	14.0493	13.8825	10.4000	18.5100	2.23470	1.4949	246
OF_HIW	37.9485	38.0200	29.4500	45.1700	10.21290	3.1958	246
OF_SLG	54.5778	50.6400	36.8300	77.1200	93.46684	9.6678	246
OF_VNO	38.3335	37.5750	29.9550	49.0300	16.31488	4.0392	246
OT_BKD	3.8272	3.3900	2.4400	6.7500	1.36962	1.1703	246
OT_NNN	37.3254	36.8075	27.1050	45.8552	17.25113	4.1534	246
OT_PSB	133.0409	131.7250	110.3200	159.8700	106.10071	10.3005	246
OT_WPC	67.5772	68.2300	54.5500	75.0000	12.15876	3.4869	246
RT_KIM	13.6444	12.6550	8.3400	19.7200	8.91863	2.9864	246
RT_REG	45.0055	44.4750	34.0300	59.8800	38.80736	6.2296	246
RT_SPG	78.3857	69.6225	49.7200	120.4975	364.88435	19.1019	246
RT_TCO	40.0019	40.4050	28.1450	46.8000	13.19712	3.6328	246
TSY_3MO	0.0854	0.0880	0.0030	0.2350	0.00149	0.0386	246
TSY_5YR	0.4095	0.3600	0.2060	0.9710	0.02983	0.1727	246
TSY_10YR	0.8936	0.7735	0.5260	1.7490	0.10170	0.3189	246
TSY_30YR	1.6290	1.5460	1.1380	2.4960	0.11141	0.3338	246
AAA_def	1.0131	1.0015	0.6218	1.8204	0.01493	0.1222	246
AAA_rates	1.0015	1.0001	0.8004	1.5181	0.00313	0.0560	246
AAA_reglq	1.0046	0.9995	0.7360	1.3345	0.00616	0.0785	246
AAA_xslq	1.0118	0.9994	0.3467	3.1465	0.04744	0.2178	246
AJ_def	1.0457	1.0008	0.5545	8.4032	0.23584	0.4856	246
AJ_rates	1.0023	0.9998	0.8048	1.3263	0.00365	0.0604	246
AJ_reglq	1.0303	0.9959	0.3308	2.8615	0.10486	0.3238	246
AJ_xslq	1.0308	0.9975	0.1370	4.5724	0.11270	0.3357	246
AA_def	1.0277	1.0000	0.5937	6.0365	0.10726	0.3275	246
AA_rates	1.0082	1.0003	0.6064	2.2448	0.01458	0.1207	246
AA_reglq	1.0092	0.9982	0.0301	3.0219	0.07331	0.2708	246
AA_xslq	1.0087	0.9992	0.5088	2.4137	0.02058	0.1435	246
A_def	1.0219	0.9997	0.6108	6.1217	0.11167	0.3342	246
A_rates	1.0084	0.9995	0.7212	1.8714	0.00939	0.0969	246
A_reglq	1.0013	1.0004	0.0168	3.4114	0.05614	0.2369	246
A_xslq	1.0087	0.9992	0.5088	2.4137	0.02058	0.1435	246
BBB_def	1.0050	0.9999	0.7172	1.9138	0.00514	0.0717	246
BBB_rates	1.0101	1.0001	0.6726	1.4887	0.00836	0.0914	246
BBB_reglq	0.9934	0.9982	0.3555	1.9290	0.02679	0.1637	246
BBB_xslq	1.0087	0.9992	0.5088	2.4137	0.02058	0.1435	246
BBBm_def	1.0029	1.0001	0.9184	1.4005	0.00095	0.0308	246
BBBm_rates	1.0012	1.0000	0.5998	1.3887	0.00533	0.0730	246
BBBm_reglq	1.0430	0.9956	0.1343	5.0141	0.15543	0.3942	246
BBBm_xslq	1.0062	0.9992	0.3763	2.7905	0.03548	0.1884	246

This table summarizes the observations of intraday data at the open of the trading day 9:30:15ET for 246 trading days during the pandemic April 2020 - April 2021). The first column provides the abbreviation for the variable name. The VIX is the CBOE volatility index. This is followed by the prices of 25 REITs with the name a composite made up of the property type (industrial (IN), hotel/lodging (LO), multifamily (MF), mixed use/other (OT), office (OF) and retail (RT)) and the REIT's stock market ticker. Following the REITs are US Treasury yields with ticker representing the 4 maturities of 3 month, 5 year, 10 year and 30 year. The remaining values are the simulated risk partitions indexed in Christopoulos and Jarrow (2018) in cumulative change form. The ticker is a composite of the 4 types of risk partitions default (def), interest rates (rates), liquidity (reglq) and excess liquidity (xslq) combined with the credit rating class names of AAA, AJ, AA, A, BBB and BBB- (BBBm). Each of the columns to the right of the ticker report statistics across all 246 observations.

Table 6: Close Summary during Covid

variable	mean	median	min	max	variance	stdev	n
VIX	26.6096	25.6550	16.9900	45.4300	29.64890	5.4451	246
IN_DRE	38.0191	38.4550	30.4000	43.0300	6.75872	2.5998	246
IN_FR	41.0291	41.6200	33.3500	47.4500	8.21028	2.8654	246
IN_PLD	98.7703	99.6100	82.8500	109.5300	36.53448	6.0444	246
IN_SELF	4.0505	4.0000	3.5622	5.0500	0.08343	0.2888	246
LO_HST	12.8848	11.9275	9.4500	18.4200	4.91837	2.2177	246
LO_MAR	109.2835	100.3450	75.2600	157.5000	492.77623	22.1986	246
LO_WYND	37.0491	33.2800	21.3900	51.7500	92.64766	9.6254	246
LO_MGM	24.6201	22.0400	12.6800	42.2000	63.62672	7.9766	246
MF_AVB	161.9634	159.0800	132.7800	193.6100	143.79254	11.9914	246
MF_ELS	62.7417	62.6450	56.1500	68.2900	5.27037	2.2957	246
MF_EQR	60.1311	59.3700	46.2300	74.9600	37.29848	6.1072	246
MF_UDR	37.7246	37.5050	29.6000	45.5600	11.21592	3.3490	246
OF_BXP	91.4361	91.2000	71.1500	108.6600	73.53062	8.5750	246
OF_CLI	14.0223	13.8000	10.4100	18.6900	2.24609	1.4987	246
OF_HIW	37.9085	38.0250	29.7050	45.2300	10.27220	3.2050	246
OF_SLG	54.5360	51.1750	36.8200	77.7900	92.16894	9.6005	246
OF_VNO	38.2630	37.4800	30.1900	49.0100	16.01428	4.0018	246
OT_BKD	3.8215	3.4050	2.4350	7.0500	1.37638	1.1732	246
OT_NNN	37.3067	36.7350	27.6000	45.6000	16.87934	4.1084	246
OT_PSB	133.0165	131.8750	110.3100	159.9100	107.41229	10.3640	246
OT_WPC	67.5539	68.1400	54.5600	74.3100	11.90968	3.4510	246
RT_KIM	13.6380	12.7100	8.3000	19.7000	8.91577	2.9859	246
RT_REG	44.9848	44.4500	34.0500	59.6500	38.49700	6.2046	246
RT_SPG	78.2918	69.4800	51.2000	121.1400	363.46241	19.0647	246
RT_TCO	40.0404	40.4700	32.8700	46.6900	12.51065	3.5370	246
TSY_3MO	0.0850	0.0880	0.0030	0.2100	0.00149	0.0386	246
TSY_5YR	0.4094	0.3620	0.1950	0.9410	0.02932	0.1712	246
TSY_10YR	0.8942	0.7630	0.5150	1.7460	0.10130	0.3183	246
TSY_30YR	1.6306	1.5450	1.1620	2.4760	0.11075	0.3328	246
AAA_def	0.9997	0.9999	0.9806	1.0272	0.00002	0.0039	246
AAA_rates	1.0001	1.0000	0.9971	1.0066	0.00000	0.0010	246
AAA_reglq	1.0001	1.0001	0.9745	1.0138	0.00001	0.0032	246
AAA_xslq	1.0006	1.0000	0.9696	1.0326	0.00004	0.0060	246
AJ_def	1.0001	1.0000	0.9913	1.0217	0.00001	0.0026	246
AJ_rates	1.0002	1.0001	0.9666	1.0247	0.00002	0.0040	246
AJ_reglq	1.0001	1.0000	0.9176	1.0409	0.00009	0.0092	246
AJ_xslq	0.9988	1.0000	0.9528	1.0172	0.00006	0.0079	246
AA_def	1.0000	1.0000	0.9866	1.0188	0.00000	0.0018	246
AA_rates	1.0004	1.0003	0.9775	1.0225	0.00002	0.0043	246
AA_reglq	0.9992	1.0000	0.9347	1.0215	0.00004	0.0066	246
AA_xslq	0.9995	1.0000	0.9776	1.0071	0.00001	0.0033	246
A_def	1.0000	1.0000	0.9870	1.0065	0.00000	0.0014	246
A_rates	1.0003	1.0002	0.9824	1.0169	0.00001	0.0034	246
A_reglq	0.9998	1.0000	0.9441	1.0294	0.00003	0.0054	246
A_xslq	0.9995	1.0000	0.9776	1.0071	0.00001	0.0033	246
BBB_def	0.9999	1.0000	0.9952	1.0030	0.00000	0.0009	246
BBB_rates	1.0001	1.0000	0.9827	1.0273	0.00002	0.0042	246
BBB_reglq	1.0000	0.9999	0.9785	1.0248	0.00002	0.0047	246
BBB_xslq	0.9995	1.0000	0.9776	1.0071	0.00001	0.0033	246
BBBm_def	1.0000	1.0000	0.9953	1.0029	0.00000	0.0008	246
BBBm_rates	0.9999	1.0000	0.9877	1.0059	0.00000	0.0012	246
BBBm_reglq	0.9993	1.0000	0.9467	1.0170	0.00003	0.0056	246
BBBm_xslq	0.9996	1.0000	0.9665	1.0092	0.00001	0.0033	246

This table summarizes the observations of intraday data at the close of the trading day 4:15:00ET for 246 trading days during the pandemic (April 2020 - April 2021). The first column provides the abbreviation for the variable name. The VIX is the CBOE volatility index. This is followed by the prices of 25 REITs with the name a composite made up of the property type (industrial (IN), hotel/lodging (LO), multifamily (MF), mixed use/other (OT), office (OF) and retail (RT)) and the REIT's stock market ticker. Following the REITs are US Treasury yields with ticker representing the 4 maturities of 3 month, 5 year, 10 year and 30 year. The remaining values are the simulated risk partitions indexed in Christopoulos and Jarrow (2018) in cumulative change form. The ticker is a composite of the 4 types of risk partitions default (def), interest rates (rates), liquidity (reglq) and excess liquidity (xslq) combined with the credit rating class names of AAA, AJ, AA, A, BBB and BBB- (BBBm). Each of the columns to the right of the ticker report statistics across all 246 observations.

Table 7: Trade Signal Examples

Ex #	type	ΔR	W	$L = \Delta R/W$	W = XSLQ	W= LQ	W= DEF
1	$\Delta R\uparrow$, $W\uparrow$	1.250	1.250	1.0000	no trade	no trade	no trade
2	$\Delta R\downarrow$, $W\downarrow$	0.990	0.990	1.0000	no trade	no trade	no trade
3	$\Delta R\uparrow$, $W\uparrow$	1.250	1.200	1.0417	sell	sell	buy
4	$\Delta R\downarrow$, $W\downarrow$	0.990	0.980	1.0102	sell	sell	buy
5	$\Delta R\uparrow$, $W0$	1.500	1.000	1.5000	sell	sell	buy
6	$\Delta R\uparrow$, $W\downarrow$	1.200	0.999	1.2012	sell	sell	buy
7	$\Delta R0$, $W\downarrow$	1.000	0.900	1.1111	sell	sell	buy
8	$\Delta R0$, $W0$	1.000	1.000	1.0000	no trade	no trade	no trade
9	$\Delta R0$, $W\uparrow$	1.000	1.500	0.6667	buy	buy	sell
10	$\Delta R\downarrow$, $W\uparrow$	0.800	1.500	0.5333	buy	buy	sell
11	$\Delta R\downarrow$, $W0$	0.900	1.000	0.9000	buy	buy	sell
12	$\Delta R\downarrow$, $W\downarrow$	0.960	0.970	0.9897	buy	buy	sell
13	$\Delta R\uparrow$, $W\uparrow$	1.020	1.100	0.9273	buy	buy	sell
14	$\Delta R\downarrow$, $W\downarrow$	0.960	0.960	1.0000	no trade	no trade	no trade
15	$\Delta R\uparrow$, $W\uparrow$	1.020	1.020	1.0000	no trade	no trade	no trade

This table summarizes the logic underlying the direction (long/buy or short/sell) for the Trading Signal, $L_{\iota jkut}$. The 15 examples show possible trading signal impact, numerically, for different cumulative changes in REIT prices, ΔR, and different cumulative changes in the risk partition, W. The rows capture the different examples and the columns the combination of changes (type), the individual changes ($\Delta R$and W) the signal ($L = \Delta R/W$), and the different types of risk partition tested in the trading strategies: excess liquidity (W = XSLQ), liquidity (W = LQ), and default (W = DEF). The rowwise indication of 'no trade' indicates that no valid trade signal is observed for L at that time. The indication of 'sell' is a signal to allocate the REIT corresponding to R into the short portfolio, while an indication of 'buy' is a signal to allocate to the REIT correspond to R into the long portfolio.

Table 8: Cumulative returns for Trading Strategies

	AAA	AJ	AA	A	BBB	BBB-
Panel A: Excess Liquidity						
Return	9.09%	41.37%	37.62%	37.62%	37.62%	15.09%
Stdev	0.78%	0.71%	0.78%	0.78%	0.78%	0.76%
Sharpe	1.99	5.09	4.37	4.37	4.37	2.57
Panel B: Liquidity						
	AAA	AJ	AA	A	BBB	BBB-
Return	37.69%	22.80%	14.34%	34.89%	39.95%	21.03%
Stdev	1.09%	1.09%	0.74%	0.75%	0.77%	0.72%
Sharpe	3.12	2.23	2.57	4.30	4.63	3.24
Panel C: Default						
	AAA	AJ	AA	A	BBB	BBB-
Return	11.08%	17.08%	-5.23%	-13.02%	-34.67%	-32.53%
Stdev	0.80%	0.72%	0.79%	0.73%	0.84%	0.86%
Sharpe	2.11	2.87	0.80	0.17	-1.52	-1.31

This table provides the cumulative returns over 240 consecutive trading days over the sample period for the Trading Strategies using the three different risk partitions of Excess Liquidity (panel A), Liquidity (panel B), and Default (panel C) as embedded within Eq. (11). Each of the panels A, B and C provide the 12 month cumulative returns (Return), the standard deviation (Stdev) and the Sharpe Ratio (Sharpe) for each of the credit cohort trading strategy portfolios denoted AAA, AJ, AA, A, BBB and BBB- in the columns.

Table 9: ICAPM Results

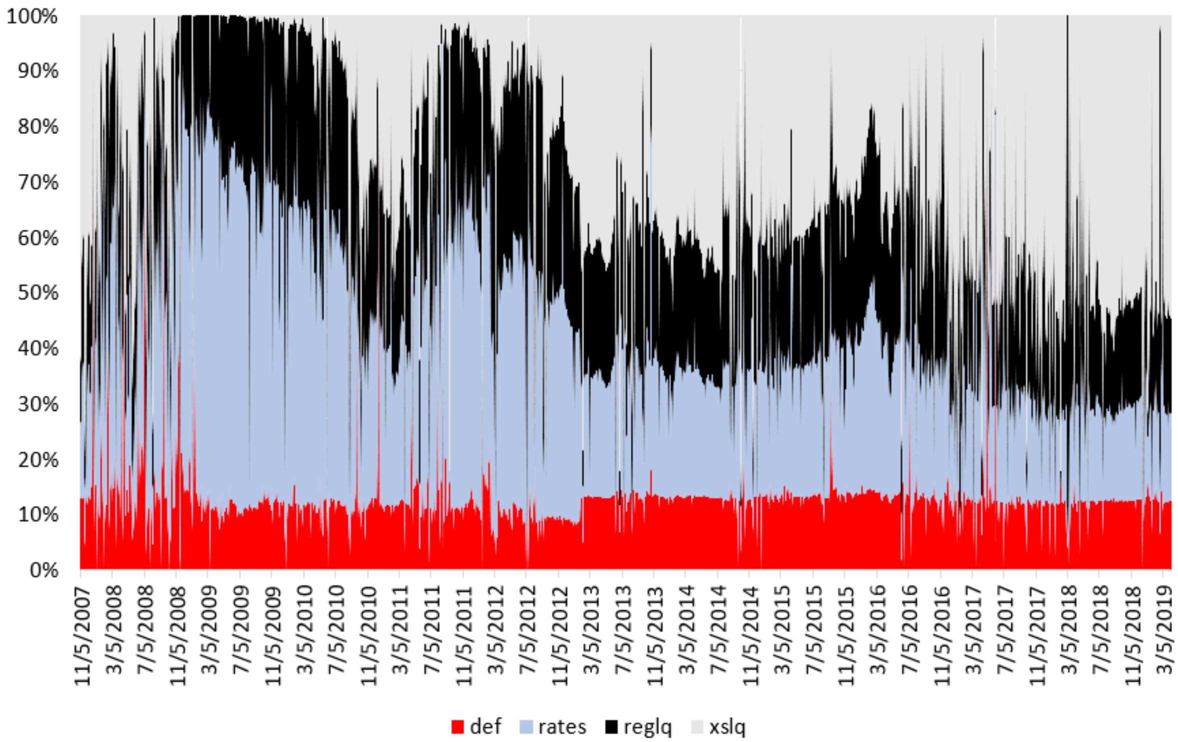
Panel A, AAA	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.004437**	-0.011797***	-0.001651	-0.00105	-0.008825***	39.87	0.3187	240
	(0.001599)	(0.001355)	(0.001589)	(0.002011)	(0.002176)	0.00		
Liquidity	0.0038399*	-0.0137208***	-0.0012093	0.0007149	-0.0092415***	54.21	0.476	240
	(0.0015339)	(0.0013006)	(0.0015248)	(0.0019296)	(0.0020874)	0.00		
Default	0.003991*	-0.015079***	-0.001129	0.00106	-0.009997***	52.45	0.4191	240
	(0.001714)	(0.001454)	(0.001704)	(0.002157)	(0.002333)	0.00		
Panel B, AJ	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.004683**	-0.011807***	-0.002287	-0.001453	-0.009541***	41.04	0.3391	240
	(0.001586)	(0.001345)	(0.001576)	(0.001995)	(0.002158)	0.00		
Liquidity	0.004194**	-0.01331***	-0.0009555	0.00002154	-0.008433***	53.18	0.4646	240
	(0.0015)	(0.001272)	(0.001491)	(0.001887)	(0.002041)	0.00		
Default	0.004079*	-0.01402***	-0.001466	-0.00004531	-0.008893***	45.21	0.3462	240
	(0.00167)	(0.001416)	(0.00166)	(0.002101)	(0.002273)	0.00		
Panel C, AA	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.0038622*	-0.0125738***	-0.0021869	-0.0009717	-0.0098577***	41.67	0.3486	240
	(0.0016568)	(0.0014047)	(0.0016469)	(0.0020842)	(0.0022547)	0.00		
Liquidity	0.004194**	-0.01331***	-0.0009555	0.00002154	-0.008433***	53.18	0.4646	240
	(0.0015)	(0.001272)	(0.001491)	(0.001887)	(0.002041)	0.00		
Default	0.004079*	-0.01402***	-0.001466	-0.00004531	-0.008893***	45.21	0.3462	240
	(0.00167)	(0.001416)	(0.00166)	(0.002101)	(0.002273)	0.00		
Panel D, A	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.003497*	-0.012009***	-0.002309	-0.001462	-0.010016***	42.67	0.3593	240
	(0.00161)	(0.001365)	(0.0016)	(0.002025)	(0.002191)	0.00		
Liquidity	0.004194**	-0.01331***	-0.0009555	0.00002154	-0.008433***	53.18	0.4646	240
	(0.0015)	(0.001272)	(0.001491)	(0.001887)	(0.002041)	0.00		
Default	0.004079*	-0.01402***	-0.001466	-0.00004531	-0.008893***	45.21	0.3462	240
	(0.00167)	(0.001416)	(0.00166)	(0.002101)	(0.002273)	0.00		
Panel E, BBB	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.0025332	-0.0120336***	-0.0023626	-0.0006994	-0.0098406***	38.99	0.3121	240
	(0.0016395)	(0.0013901)	(0.0016297)	(0.0020625)	(0.0022311)	0.00		
Liquidity	0.004575**	-0.0128342***	-0.0006617	-0.0003317	-0.0079207***	52.7	0.459	240
	(0.0014701)	(0.0012464)	(0.0014613)	(0.0018493)	(0.0020005)	0.00		
Default	0.005056**	-0.0134311***	-0.0003629	-0.0002725	-0.0077591***	51.39	0.4141	240
	(0.0015477)	(0.0013123)	(0.0015385)	(0.001947)	(0.0021063)	0.00		
Panel F, BBB-	α	Mkt-Rf	MOM	SMB	HML	F	Adj-Rsq	N
XSLiquidity	0.002663	-0.012487***	-0.003047.	-0.001407	-0.010772***	40.39	0.3351	240
	(0.001682)	(0.001426)	(0.001672)	(0.002116)	(0.002289)	0.00		
Liquidity	0.0066207**	-0.0180265***	-0.0027309	-0.0004056	-0.0140932***	46.3	0.4231	240
	(0.0022618)	(0.0019177)	(0.0022483)	(0.0028453)	(0.003078)	0.00		
Default	0.0078028***	-0.0181336***	-0.0023276	-0.0000474	-0.0137304***	43.97	0.3912	240
	(0.0023297)	(0.0019753)	(0.0023158)	(0.0029307)	(0.0031704)	0.00		

This table provides the results the ICAPM regressions of Merton (1990) 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. Three strategies are tested for each credit rating class captured in the panels. Each panel presents excess liquidity (XSLiqudity), Liquidity and Default 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 estimates, the F-test value, the Adjusted R-squared value and number of observations are in the row labelled with the trading strategy. The standard error of the estimates (in parentheses) are shown in the row immediately below the estimates and the p-value for the F-test immediately below the F-test statistics. Panel A, shows the results for AAA, Panel B shows the results for AJ, Panel C shows the results for AA, Panel D shows the results for A, Panel E shows the results for BBB and Panel F shows the results for BBB-. ***/**/*/' correspond to 0.1%, 1%, 5% and 10% levels of significance.

Figure Captions

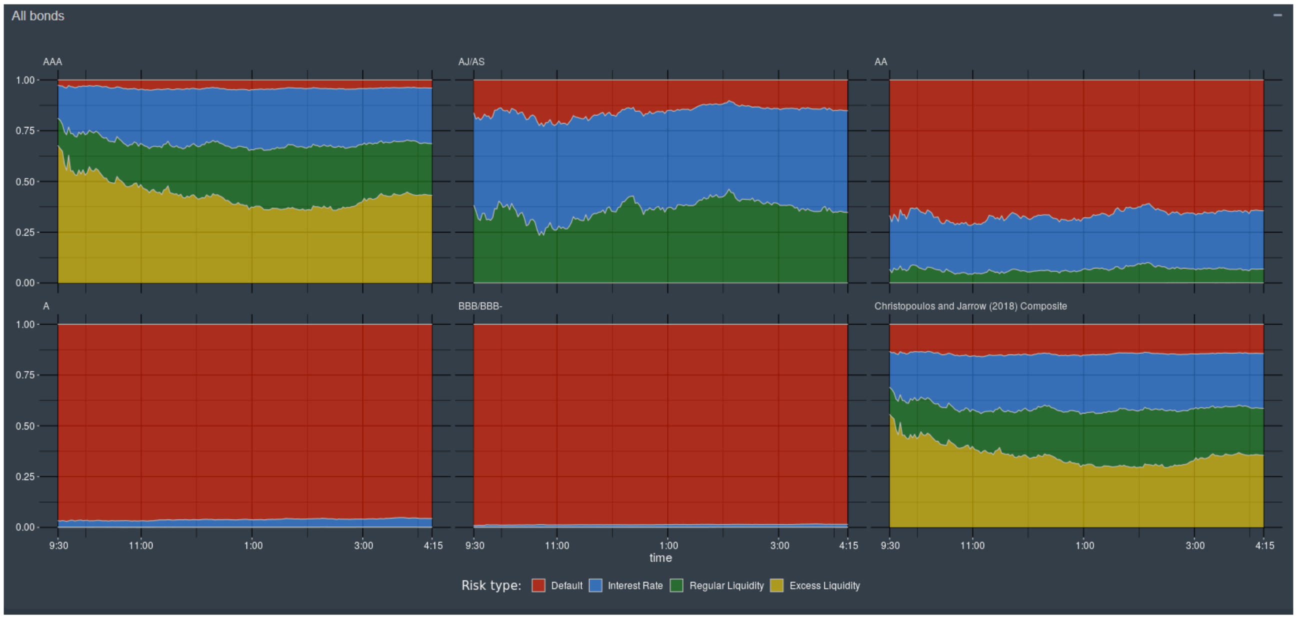
Figures

Figure 1: Daily Indexed CMBX Risk Partitions



This figure depicts the estimated risk partitions defined in Eq. (7) for all four risk components of default, interest rates, liquidity and excess liquidity on a daily basis in the plot on the left from November 2007 thru April 2019. These estimates are based on the monthly training set of 92 weighted observations of risk partitions for the CMBX sector overall across all credits as depicted in Fig. (9) in Christopoulos and Jarrow (2018). The x-axis capture the trading days over the sample period and the y-axis captures the proportions of risk. Source: Christopoulos and Barratt (2021a).

Figure 2: CMBX intraday risk decomposition (15 second intervals)

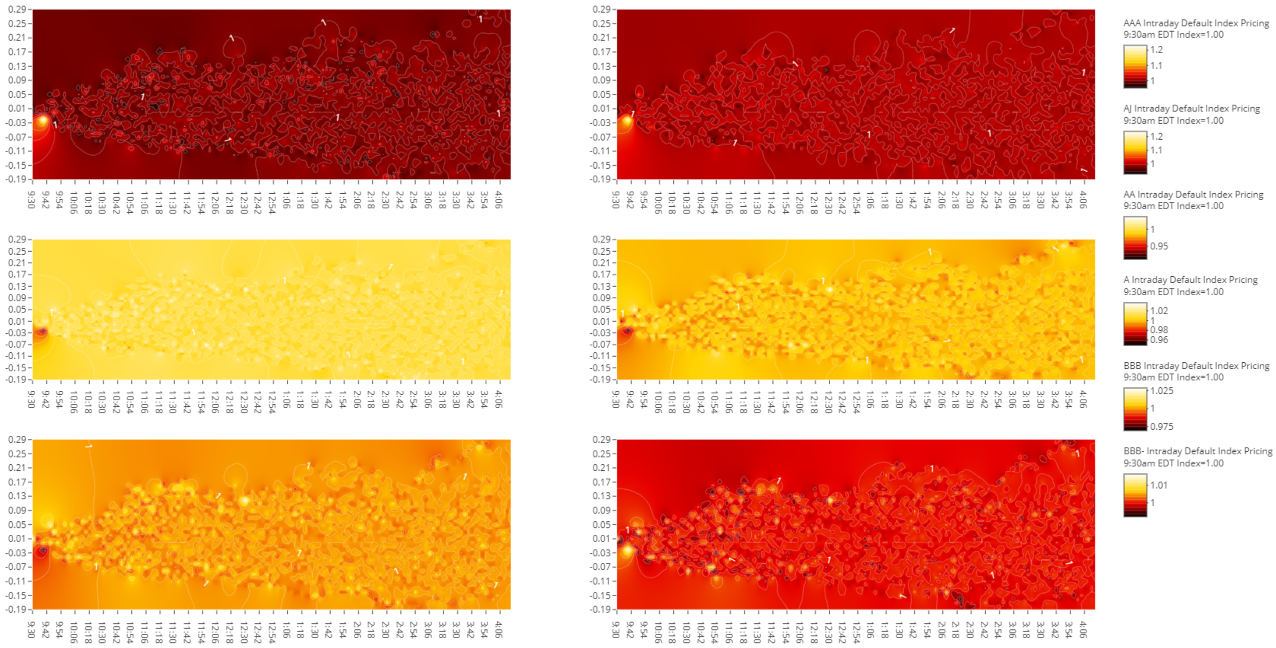


(a) CMBX intraday, 20200417

(b) CMBX intraday, 20201204

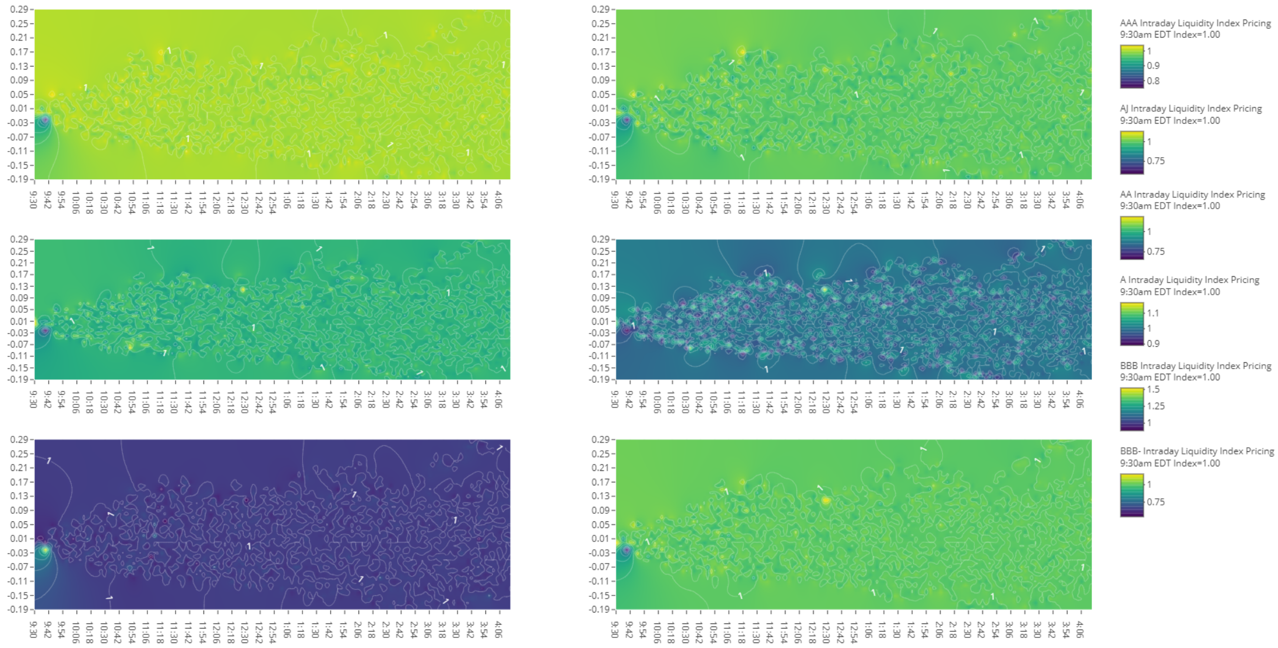
This figure provides proportional intraday CMBX risk decomposition in 1560, 15 second intervals. The four components of risk modelled are default, interest rates, liquidity and excess liquidity. The x-axis capture the time intervals from 9:30:15am to 4:15:00pm.EST The y-axis captures the estimated proportion of CMBX risk embedded within CMBS spreads as determined in Eq. (7). Fig. (2.a) captures the intraday evolution of CMBX proportional risk decompositions on April 17, 2020 and Fig. (2.b) captures the intraday evolution of CMBX proportional risk decompositions on December 4, 2020. Separate evolutions are provided for each of the investment grade CMBX tranches, as well as for the weighted average composite index across all investment grade CMBX as shown monthly in Christopoulos and Jarrow (2018).

Figure 3: Default cross section (all observations)



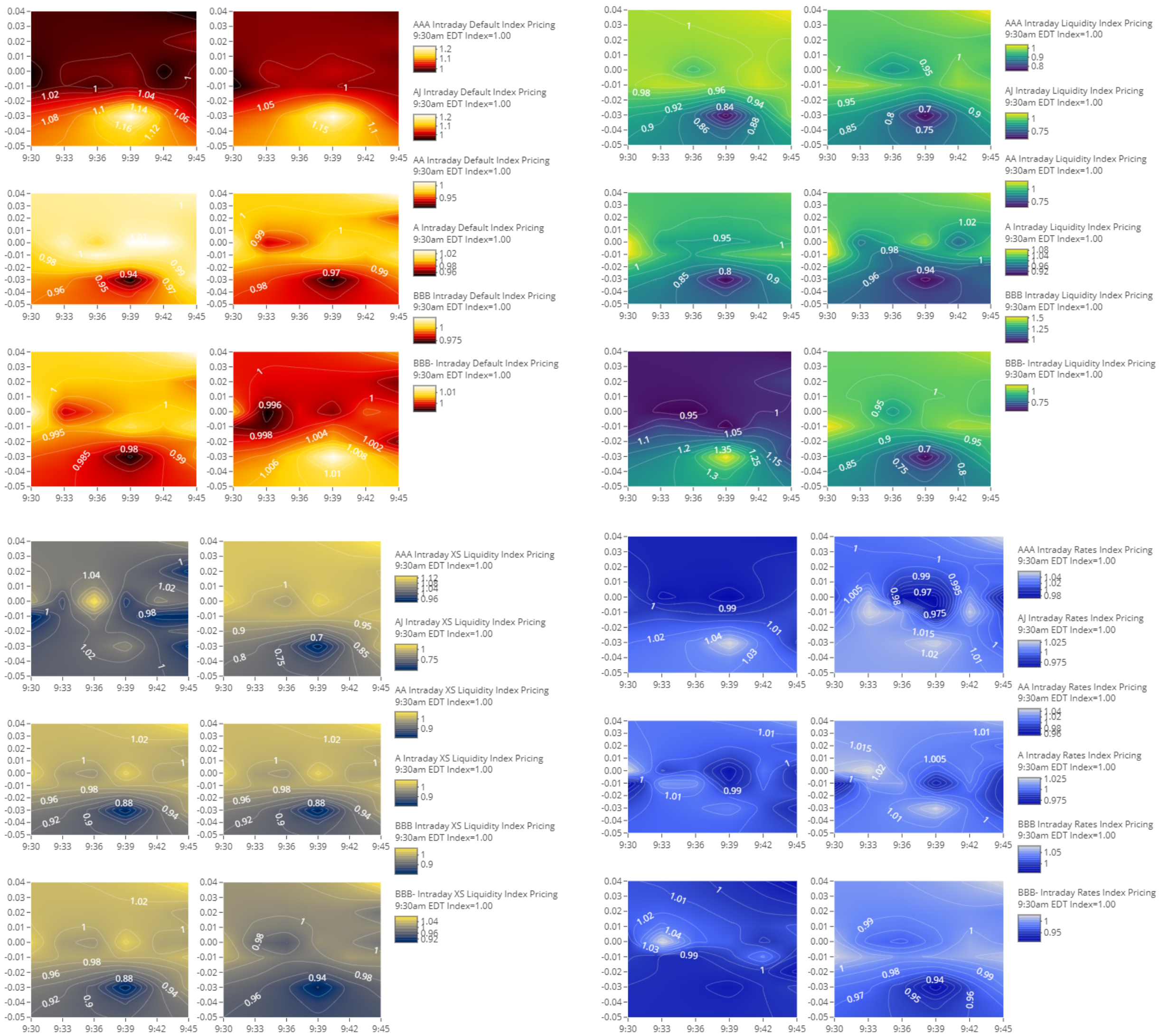
This figure provides the cross section across all 275370 observations of default risk composition for each of the investment grade CMBX tranches from AAA (top-left) to BBB- (bottom right). The x-axes reflect 3 minute intervals binned from the 15 second interval values while the y-axes capture the log 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. 10 for default risk across all days in the sample period at identical times.

Figure 4: Liquidity cross section (all observations)



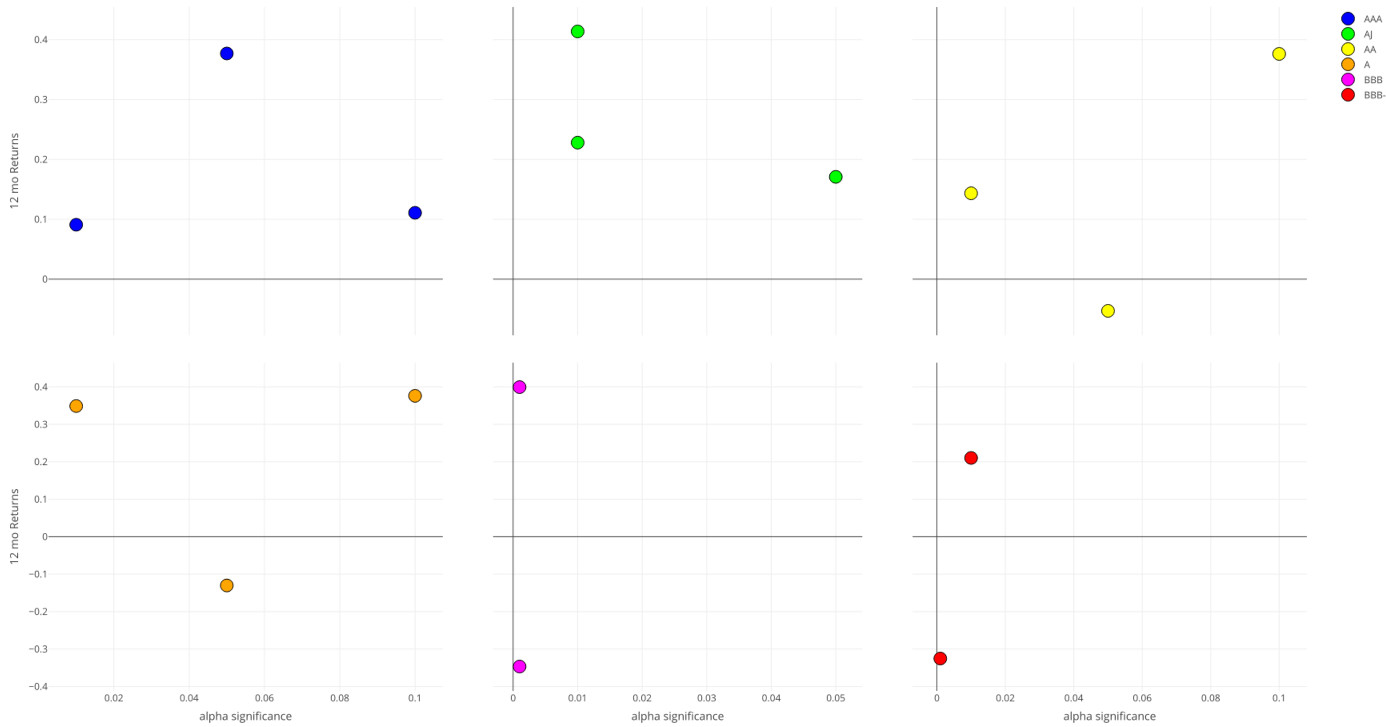
This figure provides the cross section across all 275370 observations of liquidity risk composition for each of the investment grade CMBX tranches from AAA (top-left) to BBB- (bottom right). The x-axes reflect 3 minute intervals binned from the 15 second interval values while the y-axes capture the log 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. 10 for liquidity risk across all days in the sample period at identical times.

Figure 5: All partitions, all dates, 9:30:00am to 9:45:00am



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 15 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. 10 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 6: Trading strategy returns and alpha significance levels by ratings



This figure depicts the 16 (of 18 total) trading strategy returns with statistically significant and positive α's showing their α significance and the returns for those strategies, broken out by credit rating class. The x-axes show α significance levels and the y-axes show the cumulative returns over the sample period. The credit ratings begin with AAA in the upper left corner and descend rowwise from left to right ending with BBB- in the bottom right corner.