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The composition of CMBS risk

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ABSTRACT

This paper identifies the put-option, liquidity availability proportion, and shadow liquidity risk premia embedded within commercial mortgage backed securities (CMBS) using reduced form and structural generalization models. These risk values are then interpreted as trading signals which are tested with automated trading strategies that buy undervalued and sell overvalued CMBS from November 2007 through June 2015. All three signals generate substantial positive trading profits in testing for the reduced form model but not for the structural generalization. The risk signals constructed independently of market pricing provide more profitable automated trading insights than those constructed from interactions between modeled risk measures and market spreads. In my tests of the information content of the risk signals with respect to future macroeconomic indicators, I find statistically significant evidence in keeping with recent studies. While I cannot reject CMBS efficiency, this paper's disclosure of new risk measures, the profitability of automated strategies based on those risk measures, and the statistical significance of their forward guidance capabilities, together contributes to our understanding of CMBS risk and the credit spread puzzle debate.

1. Introduction

The purpose of this paper is to quantify the risks facing investors in commercial mortgage backed securities (CMBS) determined empirically using both the reduced form and structural generalization models over the period November 2007 through June 2015. To begin, I first isolate the embedded put-option of default within CMBS, following Jarrow (2007). I then introduce a novel approach to construct risk proportions of default, market and liquidity risks implied by the put-option and other factors solely from modeled prices. From there, I then propose and implement a method to further refine identification of the compositional structure of observable risk premia (aka 'spreads') by interacting risk neutral measures of risk with said observable risk premia. To validate the merits of the informational content of these newly disclosed risk measures, I implement three automated long/short trading strategies which use the different risk measures with respect to market efficiency I have disclosed as the basis for investment strategy *signals*. Motivated by the work of Fama and Malkiel (1970) and Fama (1991) and prompted by the good performance of these automated trading strategies, I then conduct tests of the efficiency of the CMBS market by utilizing the intertemporal capital asset pricing model (ICAPM) introduced by Merton (1990).

The findings of the three automated trading strategies in this study are promising and demonstrate substantial outperformance across all three measures with the reduced form model but not with the structural generalization (see Fig. 1). The reduced form strategies using the pure risk neutral measures of the put option[1] and the liquidity proportion[2] performed better than the strategy using the shadow liquidity signal[3] which interacts risk neutral proportions with observed market spreads. This distinction in the performance secured by pure model versus market/model interaction signals, serves as further support for claims that the CMBS market may not be actively pricing risks in as precise manner as it could given the techniques introduced in this paper.

I perform ICAPM testing to test whether the returns associated with the trading strategies are abnormal. While the results of the ICAPM do not permit a rejection of CMBS market efficiency, they do provide empirical support for the debate on the merits of structural and reduced form models. In Jarrow and Protter (2004) they posit the locus of the distinction between the two approaches to be found within the differing information sets used by the approaches. My study suggests that differing methods for absorbing information in the default mechanisms is important. I observe worse performance in the structural generalization on both the

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[1] Noted as $\mathring{p}_{j,k}(s)$ and defined in Eq. (11).
[2] Noted as $\mathring{l}_{j,k}(s)$ and defined in Eq. (17).
[3] Noted as $\bar{\mathbb{S}}_{j,k}(t)$ and defined in Eq. (33).

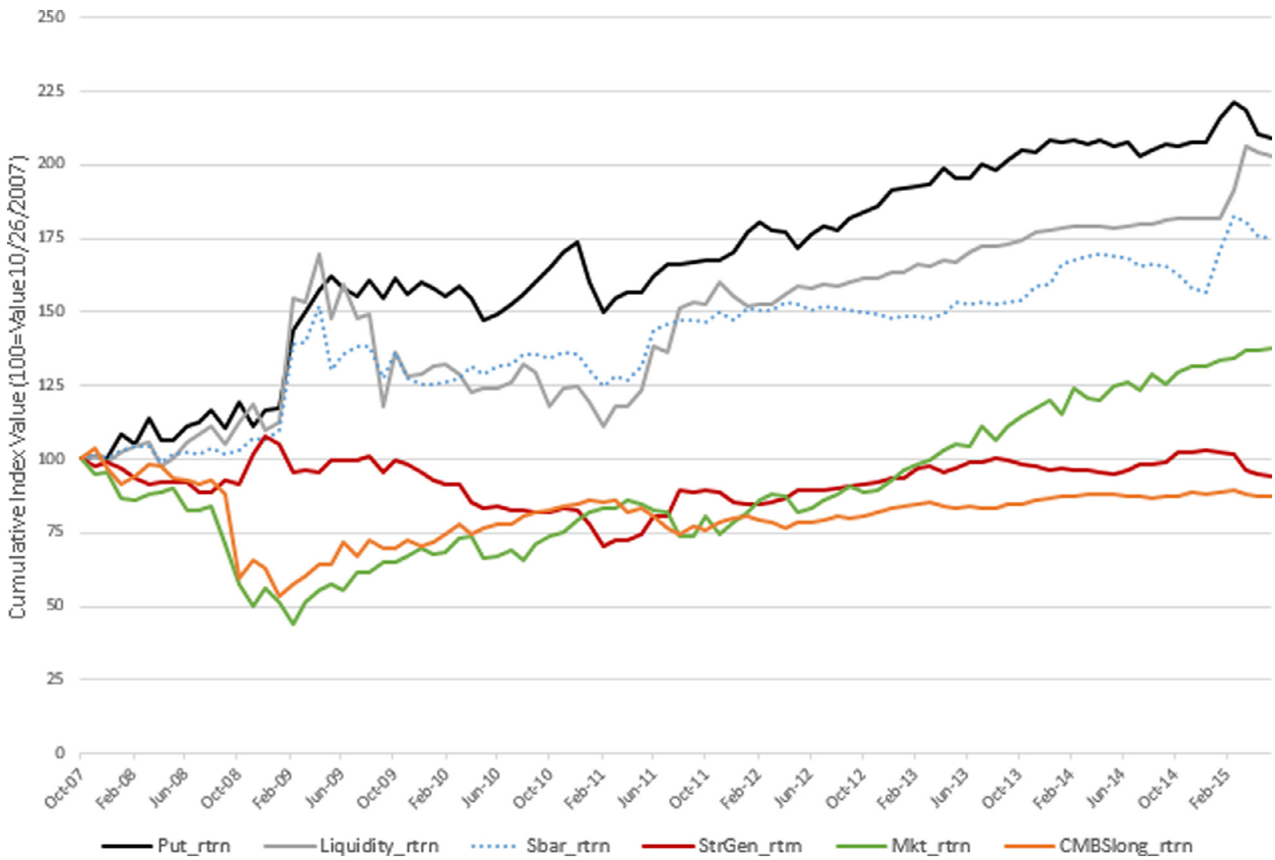

Fig. 1. Cumulative portfolio returns. This figure shows the cumulative returns for six portfolios. The first four portfolios were constructed with the automated trading strategies informed by the risk measures: (i.) the put option using the reduced form, $\dot{p}$(*Put_rtrn*); (ii.); the liquidity proportion, $\mathring{l}$(*Liquidity_rtrn*); (iii.) the shadow liquidity premia, $\bar{\mathbb{S}}$(*Sbar_rtrn*); and (iv.) the put option using the structural generalization, $\mathring{p}$(*StrGen_rtrn*). The fifth portfolio (v.) is the Market Portfolio (*Mkt_rtrn*); while the sixth portfolio (vi.) is the CMBS long-only portfolio (*CMBSlong_rtrn*). The portfolios are indexed to a value of 100 on a start date of 10/26/2007. The cumulative returns are determined over 92 consecutive trading intervals comprised of 21 consecutive business days between 10/26/2007 and 6/15/2015.

trading results using the put option and on the statistical tests applied to the default estimates. These results echo the findings of Arora et al. (2005), and others, who also find relatively worse risk navigation ability in the structural approach compared with the reduced form.

This area of inquiry in the literature with recent works by Collin-Dufresne et al. (2001), Driessen (2005) and Pavlov and Wachter (2006) and others, seeks to reconcile portions of observed credit spreads above risk free rates that cannot be fully ascribed to the health of the issuer, the collateral heterogeneity, or the structural aspects of the securities. More recent developments in the 'credit spread puzzle' literature have advanced to identification of liquidity factors and research into illiquidity broadly defined as the unaccounted for compensation beyond the credit risk of such securities. For example, Chen et al. (2007) use three different proxies for liquidity[4] to test for liquidity pricing identification; while An and Riddiough (2015) study the determinants of subprime mortgage loan spreads, and the impact of liquidity funding and its interaction with default. To be sure, in my study, the predictive content of my risk compositions is evidenced by profitable automated trading strategies based on those innovative risk measures. For further support, however, I also perform preliminary testing of the value of the informational content of my risk measures along the lines of Gilchrist, Zakrajšek (2012) who consider the informational content of bond spreads in predicting changes in macroeconomic activity in the US over 6–12 month horizons. Specifically, in keeping with this area of the literature, I too test the informational content of my risk measures using vector autoregressions (VARs) with respect to the *forward guidance* for US unemployment. My results in this area provide evidence that some of the risk measures introduced are statistically significant indicators of future changes in the US unemployment rate up to five quarters forward.[5]

The recent related CMBS literature can be split into four categories: (i) work on commercial real estate loans related to lender incentives, securitization, and the origination process (e.g., Titman and Tsyplakov, 2010, and Ghent and Valkanov, 2015), (ii) work on credit risk ratings and the misclassification of loan and bond risk (e.g., Crouhy et al., 2008; Stanton and Wallace, 2012, and Buschbom et al., 2015), (iii) analyses of loan and bond credit spread risk premia (e.g., Titman et al., 2005; Nichols and Cunningham, 2008, and Ambrose et al., 2014), and (iv) studies investigating commercial real estate loan collateral, derivative pricing, and CMBS market efficiency (e.g., Christopoulos et al., 2008; Kau et al., 2009, and Driessen and Van Hemert, 2012). This paper adds to the CMBS literature in both (iii.) and (iv.) in its isolating of key risks facing CMBS bondholders and its disclosure of the compositional profile of such risks facing investors. Given CMBS is a member of the 'spread product' family of US fixed income, this paper's focus on discerning the composition of CMBS risks necessarily also expands its applicability beyond CMBS.

[4] Namely the bid/ask spread, the proxy of zero returns, and the LOT liquidity estimator attributed to Lesmond et al. (1999).

[5] See Section 9.

An outline of the remainder of this paper is as follows. Section 2 discusses the data and Section 3 summarizes the models used with key statistical validations. Section 4 describes the risk-neutral valuation procedure. Section 5 describes the identification of the embedded put-option through the use of the interim price and Section 6 describes the construction of the proportional risk profile independent of market prices. Section 7 introduces the interactions between market spreads and model risk measures and constructs the risk compositions in market spread form. Section 8 presents the results of my trading strategy tests and the analysis of CMBS market efficiency while Section 9 discusses alternative approaches to evaluating market efficiency and testing of the informational content and forward guidance embedded within the disclosed risk measures examining variation across ratings. Section 10 provides a summary of conclusions and direction for future work.

2. The data

Throughout this paper, the analysis of loans and bond pricing and risk values is based upon loan and bond cashflows which have monthly payment frequencies underlying CMBS. The period of this study is November 2007 through June 2015. This data provided to me by an anonymous institutional investor with approximately $0.5 trillion assets under management (AUM) includes: (a.) monthly payment status and descriptive characteristics of the loans and securing property data as captured by Intex; (b.) daily pricing for CMBX as captured by Markit; and (c.) quarterly National Council of Real Estate Investment Fiduciaries (NCREIF) property x regional indices. All such data are available to researchers with the means to secure such data directly or who have also benefited from the generosity of institutional investor(s) and/or data vendor(s). Studies by Titman et al. (2005),Yildirim (2008),Christopoulos et al. (2008),Stanton and Wallace (2012),Driessen and Van Hemert (2012),Buschbom et al. (2015), and Piskorski et al. (2015), were made possible by access to costly non-public data and my study also falls into that proprietary data category of research. The other data were obtained from public sources and Wharton Research Data Services (WRDS) as further described in detail below.

Although a longer sample period would be ideal, securing a longer sample is simply not possible at this time. The period November 2007 through June 2015 represents the nearly exhaustive set of observables of specialized and costly data[6] limited to the generous donations of a single institutional investor in an important period in finance. Additionally, CMBX did not begin trading until 2006 and the data prior to November 2007 was not made available and stated to be 'spotty'. As such any comparisons prior to November 2007 would be suspect for CMBX pricing comparisons. The data subsequent to June 2015 has not been made available. While it is true that the time series of seven years and eight months is shorter than some recent studies investigating the informational content of Corporate bond prices and yields,[7] the data in this study, is nevertheless comparable other studies[8] adjusting for the scarcity of data in the evolution of a sector at its point in history. My data is quite robust and at the highest standards of industry and sufficient to achieving the objectives of this study and is comparable to others in the literature.

[6] Subscriptions to data providers such as Intex and Trepp can cost upwards of one-hundred thousand US dollars per annum for current, which does not include historical data, which is upwards of multiples of that figure.

[7] See O'Hara et al. (2016), among others.

[8] See Katz (1974); Gehr and Martell (1992); Hotchkiss and Ronen (2002), and Bariviera et al. (2012).

Finally, I split the sample in a few places in this study between what I characterize as the *crisis* and *recovery* periods to determine if there are distinctions associated with the two periods compared with the sample overall. I set the end of the crisis period at June 2010 and the beginning of the recovery period immediately following in July 2010.

2.1. Commercial real estate loans

The most granular object considered in this study are commercial real estate loans (CRELs) that represent the underlying collateral for the CMBS bonds found within the CMBX indices. In this study, 25019 loans underlying the CMBX Series 1–8, have been provided from Intex's monthly loan level information from November 2007 through June 2015. This loan sample serves as the collateral of 200 CMBS transactions ("deals"). With an original principal balance of $389 billion, my sample represents approximately 1/3 of the entire CMBS universe outstanding at any point in time over the sample period.[9] Fig. 2 gives a summary of the CMBX loans and tranches included in my study. I take the loan characteristic information at origination and model the promised (and *actual*) principal and interest cashflows for all 25,019 loans in my sample and allocate such loan level cashflows to Trust and bond structures as described in the Appendix. Within the monthly time series data it is noted if the loan has paid off in the period considered. If the loan has paid off, it is removed from all subsequent simulation dates.

2.2. CMBX derivatives

Additionally, I have the daily mark-to-market prices released by Markit for the 57 priced tranches of CMBX Series 1–8 for this same period. All of the licensed market-makers in CMBX provide daily closing prices to Markit. Markit then aggregates these prices and distributes them to its customers at the end of each trading day (4:15PM EDT). I only determine fair prices for the CMBX tranches (not underlying reference tranches) under the assumption that the loan collateral securing the CMBS tranches serves as the cashflow generating collateral for the CMBX tranches. The simplification here is that I view the collateral pool as the loans themselves, and not the CMBS bond tranches.[10]

Each CMBX index has six to seven tranches. I model the top six tranches for each CMBX:

$k \in \{AAA, AJ/AS, AA, A, BBB, BBB-\}$ which are the most actively traded. The first four CMBX Series (Series 1,...,4) were issued prior to 11/2007; Series 5 was issued in 5/2008; Series 6, 7, and 8 were issued annually in the month of January between 2013 and 2015. Therefore, the total number of bonds available to construct my trading strategies is $6 \cdot J$ where

$$J = \begin{cases} 4, & time: \ 10/2007 - 5/2008 \\ 5, & time: \ 5/2008 - 12/2012 \\ 6, & time: \ 1/2013 - 12/2013 \\ 7, & time: \ 1/2014 - 12/2014 \\ 8, & time: \ 1/2015 - 6/2015 \end{cases} \tag{1}$$

Since the object of inquiry is ultimately the derivative of bonds which, at the most granular level, are still collateralized by loan

[9] Estimates vary. According to the Federal Reserve Board as of Q2 2015 there were approximately $602 billion outstanding while Securities Industry and Financial Markets Association (SIFMA) estimated $627 billion, down from more than $800 billion. Additionally an unknown portion of the outstanding balance of ABS CDOs is associated with CREL and CMBS collateral which would increase the representation of CMBS and CREL collateral in the US spread product fixed income family of securities.

[10] This follows from Driessen and Van Hemert (2012) and Christopoulos and Jarrow (2016).

	CMBX Series								
	1	2	3	4	5	6	7	8	Total
Number of Loans	4004	3890	4422	4418	3145	1587	1667	1886	25019
Industrial	*547*	*529*	*613*	*581*	*447*	*200*	*189*	*249*	*3355*
Lodging	*256*	*401*	*437*	*446*	*283*	*238*	*225*	*230*	*2516*
Multifamily	*701*	*387*	*378*	*347*	*162*	*251*	*482*	*496*	*3204*
Office	*834*	*809*	*933*	*974*	*634*	*269*	*192*	*290*	*4935*
Other	*107*	*158*	*228*	*248*	*205*	*85*	*88*	*99*	*1218*
Retail	*1559*	*1606*	*1833*	*1822*	*1414*	*544*	*491*	*522*	*9791*
Loan Balance ($ billions)	$ 57.8	$ 55.1	$ 71.9	$ 72.2	$ 49.9	$ 29.9	$ 27.5	$ 25.1	$ 389.4

Fig. 2. Summary of CMBX underlying loans. This figure shows the number of loans within each CMBX Series 1–8 in my sample with a property type specific breakdown within each CMBX Series. The total balance at origination for all loans is provided for each CMBX Series 1–8.

level cashflows, and since my simulation is at the loan level, the direct allocation of simulated loan cashflows to the bond capital structure can be compared to observable CMBX prices.

2.3. The economy

Interest rates were obtained from the Federal Reserve Board public data. Real Estate Investment Trusts (aka 'REITs') prices were aggregated by Yahoo! Finance from primary pricing data provided by the stock exchanges associated with such REITs (New York Stock Exchange, aka 'NYSE', NASDAQ, and American Stock Exchange, aka 'AMEX') as the primary source. REIT debt levels and 90-day volatilities for REITs and the Standard & Poor's 500 (S&P500) were provided by Wharton Research Data Services (WRDS). Property value indices were provided by the National Council of Real Estate Investment Fiduciaries (NCREIF). NCREIF indices are updated quarterly and correspond to 8 regions: (i.) East-north-central, (ii.) Mid-east; (iii.) Mountain; (iv.) North-east, (v.) Pacific, (vi.) South-east, (vii.) South-west, and (viii.) West-north for each of the 6 property types: (i.) Multifamily; (ii.) Retail; (iii.) Office; (iv.) Hotel; (v.) Industrial; and (vi.) Other. This gives a total of 48 different (property $\times$ regional) indices.

NCREIF indices are reflective of actual sale prices and marked-to-market valuations by the largest commercial real estate property holders in the United States including: all pension funds, all commercial banks, all investment banks, and all life insurance companies, among others holders. Holding property values constant, aggregated REITs exhibit greater volatility than corresponding NCREIF indices at the national level. NCREIF represents an industry standard for CRE value monitoring and has been widely used in thousands of academic studies over the past twenty-five years, and more than 1000 since 2015 alone.

The REITs selected are a representative sample that expand on those selected by Driessen and Van Hemert (2012) to account for the greater number of property types considered in my structural generalization (discussed below). To be sure the 25,019 loans in my sample will have property specific idiosyncrasies that outstrip my attempts to capture such idiosyncrasies. At the same time, by considering both slower moving property values captured in the NCREIF series as well as more volatile REIT values, a richer tracking to historically realized risk events in real estate has been demonstrated and statistically validated in two studies considering more than four-million loan life observations, before the crisis, during the crisis, and after the crisis.[11] Because of that validated relationship in other studies, I too adopt the same economy to develop the literature and to isolate the effects of the default mechanism in this paper.

3. Summary of models used

This section discusses the two different models used in this study to disclose the composition of risks in CMBS: the reduced form and the structural generalization. The justification for the use of the reduced form approach introduced by Jarrow and Turnbull (1992); 1995) is found in Christopoulos et al. (2008) and Christopoulos et al. (2014) and their exploration of the benefit of the implementation of the Cox Process in CMBS evaluation motivated more generally by Lando (1998). The justification for the use of the structural generalization attributed to Merton (1974) is found in applications to CMBS in each of Kau et al. (2009) and Driessen and Van Hemert (2012).

Other more recent works include Christopoulos (2017) and Christopoulos and Jarrow (2016) which use the reduced form and the structural hybrid models to evaluate CMBS default and loss risks under simulation. The methods implemented in those two recent papers are justified with the discussion above and prior literature. The data set and technology used in those studies are also used in this study.

To be thorough, I provide the essential crossover synopses and important statistical validations from those two studies to ensure that the arguments in this paper are made clear to readers unfamiliar with those two studies which are unpublished at this time. In the former, a reduced form model is presented to test CMBS market efficiency. In the latter, a structural generalization is presented for the same purpose and to investigate comparative empirical results across both modeling approaches. The primary difference between the approaches is the default trigger.[12]

The Monte Carlo simulation implemented for the models in this study uses the standard approach for simulating correlated random variables using the Cholesky decomposition as described in Glasserman (2003). 10000 scenarios were selected because the standard error of a simulation converges to zero at the rate $1/\sqrt{N}$. For $N = 10000$, the error will be approximately 1% of the resulting values. In the case of Driessen and Van Hemert (2012), 50 scenarios were run; while in the case of Christopoulos et al. (2008), 2500 scenarios were run. After performing convergence tests showing little difference between 2500 and 1000 scenarios, the final number of scenarios run in this paper was 1000 for each loan, at each time, on each simulation date, giving an error of approximately 3%. As such, my scenarios are in line with scenarios provided in the earlier works in the literature.

[11] See Christopoulos et al. (2008), and Christopoulos and Jarrow (2016).

[12] See Christopoulos (2017).

Additionally, a substantial effort was made to secure realism in the models to ensure proper treatment of loan level idiosyncrasies related to timing and amounts of payments and the macro economy which influence them. Specifically, I capture: (i.) loan level principal and interest cashflows whose amounts and timing are accurately modeled; (ii.) accurate allocation of loan level cashflows to tranched bond structures[13]; (iii.) categorization of all commercial real estate property types; (iv.) term *and* balloon defaults, pathwise; and (v.) a robust multi-factor economy consisting of interest rates, property values and REITs. The cashflow modeling reflects accurate implementation of loan level characteristics such as coupon, balloon timing, amortization schedule, loan balance, and maturity (among others) to generate promised cashflows. As loans age through time their payment status is reported and may change and this updated information is also incorporated into the reduced form, but is necessarily absent from the structural generalization. When loans are observed to have matured, prepaid, or defaulted in the data then they are removed from all future simulation dates. These developments allow for rigorous evaluation of the comprehensive data set of 25,019 CRELs across the crisis and the recovery.

3.1. Synopsis of reduced form approach to CMBS

Christopoulos and Jarrow (2016, CJ), provide us with a reduced form CMBS valuation model. A reduced-form model is selected because they value CMBS from the market' s perspective and not the borrower' s (e.g. Duffie and Lando, 2001, and Cetin et al., 2004). CMBS face market (interest rate), credit, prepayment, and liquidity risks and in the initial formulation, they abstract from prepayment and liquidity risk. The exclusion of liquidity risk is common in asset pricing models where bond markets are assumed to be frictionless and competitive. Prepayment risk is excluded for two reasons. *First*, a 'credit-only' model is preferred for ease of comparison with other credit-only modeling approaches and consistent with regulatory requirements in light of the significant default realizations during the financial crisis.[14] *Second*, defeasance and other prepayment penalties impose explicit disincentives for refinancing activity in commercial real estate mortgages and these disincentives are highly effective. For example, in the sample for their study of 25,019 loans which reflect the collateral of the actively traded CMBS universe, categorically all loans had some form of prepayment restriction. Of these loans only approximately 1% of the sample loan balance (representing 201 loans) prepaid for any reason with approximately another 1% of the sample loan balance (representing 181 loans) prepaying during either free prepayment periods[15] or cum-defeasance penalties, and much less than 1% of the sample loan balance (representing 20 loans) prepaying with fixed penalties or yield maintenance. As neither regulators nor the market/ratings community actively considers prepayment risk as being significant in the risk evaluation or market pricing of these securities and in keeping with earlier studies such as Titman and Torous), implementing a competing risk of prepayment[16] is reasonably omitted.

The state variables that constitute the simulated economy in their model correspond to various indices related to the property values underlying the CMBS trusts. All indices are assumed to correspond to the prices of actively traded assets (e.g., such as values of different portfolios of properties). There are three levels of property value indices. The first set of state variables correspond to the price of a particular type of property located in a particular region of the country, e.g. hotels in New York City. The second set of state variables correspond to an index for a particular property type (but across the entire country), e.g. hotels. Last, the third state variable is an index across all property types across the entire country, e.g. a REIT general stock price index. This borrows from portfolio theory, where the first state variable is an individual stock price, the second state variable is an industry index, and the third state variable is the market index. This construction is formulated to facilitate the simulation of the state variable processes.

CJ model interest rate risk using a multi-factor Heath et al. (1992, aka HJM) model. Credit risk is captured using a reduced-form model first introduced by Jarrow and Turnbull (1992, 1995). The statistically determined transition intensities articulate payment state transitions of current to delinquent (CD), delinquent to current (DC) and delinquent to default (DF), so $g \in \{(C \to D), (D \to C), (D \to F)\}$. The intensity estimates are determined from a multinomial logistic regression for hazard rate transitions utilizing approximately two-million historical loan life transition observations from the Intex database of all loans underlying CMBX 1–8. Default is thus modeled as an intensity process. Each commercial loan i has a current, delinquency, and default intensity process that depends upon its payment status N_t, the state variable vector X_t, a vector of loan specific characteristics U^i that are deterministic (non-random), e.g. the net operating income of the underlying property at the loan origination, and time dependent loan characteristics V_t^i, e.g. the age of the loan. The current, delinquent, and default intensity processes for each loan have the same functional form, differing only in the loan specific variables used.

Consider the discrete time interval $[t, t+\Delta]$, CJ assume that:

$$\lambda_c(t, U^i, X_t, V_t^i, N_t)\Delta = 1/(1 + e^{-(\varphi_c + \phi_c U^i + \psi_c X_t + \xi_c V_t^i)}), \tag{2}$$

$$\lambda_d(t, U^i, X_t, V_t^i, N_t)\Delta = 1/(1 + e^{-(\varphi_d + \phi_d U^i + \psi_d X_t + \xi_d V_t^i)}), \tag{3}$$

$$\lambda_f(t, U^i, X_t, V_t^i, N_t)\Delta = 1/(1 + e^{-(\varphi_f + \phi_f U^i + \psi_f X_t + \xi_f V_t^i)}), \tag{4}$$

where

φ_c, ϕ_c, ψ_c, ξ_c, φ_d, ϕ_d, ψ_d, ξ_d, φ_f, ϕ_f, ψ_f, ξ_f are vectors of constants,

$\lambda_c(t, U^i, X_t, V_t^i, N_t)\Delta$ is the probability of jumping to current from delinquent,

$\lambda_d(t, U^i, X_t, V_t^i, N_t)\Delta$ is the probability of jumping to delinquent from current, and

$\lambda_f(t, U^i, X_t, V_t^i, N_t)\Delta$ is the probability of jumping to default from delinquent.

Estimation of these intensities is under the statistical measure and given the assumption that delinquency and default risk are conditionally diversifiable, these intensity functions will be equivalent under both the empirical and martingale measures.[17] They then estimate these intensities using a multinomial logistic regression of the form:

$$F_g(v) = \frac{1}{(1 + e^{-(\beta_0 + \sum_{i=1}^{m} \beta_i v_i)})} \tag{5}$$

where $F_g(v)$ represents the probability of a transition event for each of the three transition categories $g \in \{(C \to D), (D \to C), (D \to F)\}$, β is a constant vector, and v is the vector of independent variables. The method of implementation is Monte Carlo simulation with estimates informed by approximately two-million loan life observations between November 2007 and June 2015.

[13] I use subordination levels provided by vintage as discussed in Stanton and Wallace (2012).

[14] See *Appendix B* of Board of Governors of The Federal Reserve System (2015).

[15] Free prepayment periods are observed typically in the last six to twelve months of a loan's life and are specifically included in the loan terms to allow borrowers time to secure financing which is not as readily available for CRELs as it is for residential mortgage borrowers.

[16] See Ciochetti et al. (2002) and Christopoulos et al. (2008), among others.

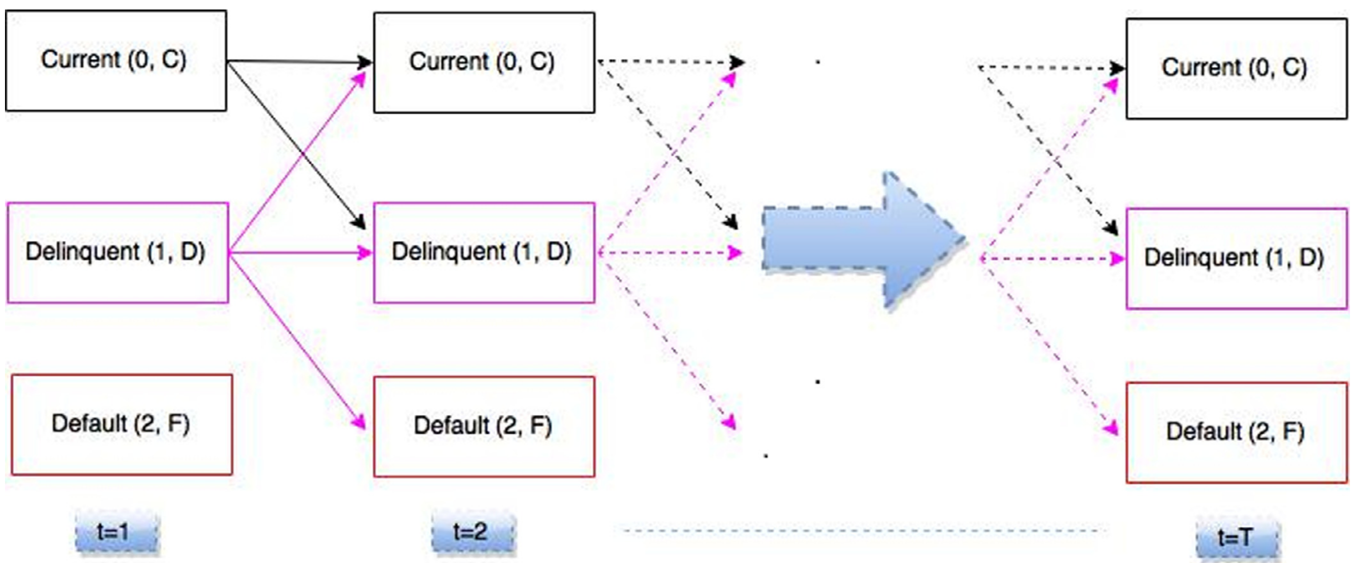

Fig. 3. Loan state transition profile (reduced form). This figure provides a visual description of the possible loan payment state transitions within a simulation possible under the reduced form approach. Loans may remain current, may transition from current to delinquent, may transtion from delinquent to current or from deliquent to default, or may remain delinquent over the time interval $[t, t + \Delta]$. Default is an absorbing state.

Fig. 3 shows a transition schematic for a loan in the reduced form model. The static loss severity assumptions by property type are: Multifamily (36%), Retail (47%), Office (37%), Hotel (48%), and Industrial (38%), and Other (50%)[18] with three months to disposition for all loans that transition to default under simulation. The static time of three months to disposition of a property is consistent with restrictions and tax penalties associated with disposition of properties contemplated as prohibited transactions within a Real Estate Mortgage Investment Conduit (REMIC) structure as discussed in Peaslee and Nirenberg (2001). Certain exceptions of extension provisions were made available to trustees by the Internal Revenue Service (IRS) during the crisis to ensure the preservation of the tax status of certain REMICs and other structured investment vehicles (SIVs) under extreme distress as discussed in the report of the law firm Sullivan and Cromwell LLP (2010). These provisions were implemented to accommodate the practicalities of disposition times longer than ninety days during the crisis for properties underlying qualified mortgages as well as to allow for loan modification as an alternative to foreclosure, both of which actions had the potential to have been deemed prohibited transactions in REMICs and other SIVs. Notwithstanding these rare exceptions, the simplifications are reasonable and consistent with standard tax laws and well regarded works in the prior literature.

The assumptions above are applied to all loans in the property type cohort across all regions. For τ_g a random transition time on the ith loan and its point process denoted by $N_t^i(t) \equiv 1_{\tau_g \le t}$ the point process follows a Cox process with an intensity $\lambda_g^i(t, N_t^i, U^i, V_t^i, X_t)$ under the martingale measure where $(X_t)_{t\in[0,\,T])}$ represents a vector of state variables, adapted to the filtration, describing the relevant economic state of the economy, N_t^i is the payment status (or 'state') of the ith loan (current C, delinquent D, or default F), U^i are the ith loan's immutable characteristics (e.g. loan to value (aka 'LTV') at origination), and V_t^i are ith loan's time dependent loan characteristics (e.g. age of loan, remaining loan balance). All stochastic processes for the state variables are specified under the martingale measure. Default is an absorbing state and current/delinquency are repeating states for the loan. These intensity processes are given under the martingale measure for inclusion in the CREL valuation equations in the Appendix. This assumption is reasonable if the intensity processes, through the state variables employed, include all relevant systematic risks in the economy. This inclusion leaves only idiosyncratic risk to determine the actual occurrence of delinquency and default.

3.2. Synopsis of structural generalization approach to CMBS

In Christopoulos (2017), a structural generalization is presented that uses the identical simulated economy and data set that is used in Christopoulos and Jarrow (2016) for valuation and testing of CMBS risk measures. The distinctions of the structural generalization approach[19] are summarized below in three steps, where the important default mechanism of inverse LTV is captured in Step 3.

Step 1 determines calibrated parameters following Merton (1974) and as suggested by Driessen and Van Hemert (2012). In Step 1, a parametrization is implemented where such parameters are the outputs of a numerically solved non-linear system of six equations of Black-Scholes-Merton which calibrate to daily S&P 90-day option volatility, REIT pricing covariances and other observable market metrics relevant to simulation and CREL valuation.

Step 2 simulates the economy informed the parameters estimated in Step 1. In this step, the calibrated parameter outputs interact with other values as inputs for use in simulation of REIT prices using multivariate correlated Wiener processes. The method is Monte Carlo simulation.

Step 3 links the loan level characteristics to the simulated economy to simulate default events and, in turn, to value bonds for which the loan sample serves as collateral. In this step, the random cashflows to the bonds, $\nu_k(j)$, are determined. Simulated default is triggered by the condition that if the normalized property value, $\widetilde{V}_{t,j}^i < 1$ then the loan defaults, otherwise the loan pays as expected in accordance with the promised cashflow schedule; if the debt obligation is greater than the property value, the borrower no longer has an incentive to make debt payments.

[17] See Jarrow et al. (2005).

[18] These compare well with Moody's historical loss severities for CRELs across all vintages of Multifamily (35%), Retail (49%), Office (40%), Hotel (46%), and Industrial (39%) as reported in Banhazl and Halpern (2015) and also correspond to similar values reported by Frerich and van Heerden (2015).

[19] Based in part on Merton (1974) and then expanded on by Driessen and Van Hemert (2012) with application to CMBS.

From the set of simulated loan states for all loans i, corresponding cashflows are generated allowing construction of synthetic tranche level CMBX prices under risk neutral conditions independent of actual CMBX prices. In this last step the risk event for CRELs is default (and associated losses) that may occur at any simulation time $t \leq T$. The losses generated at the portfolio level in the simulation are the result of linking the loans underlying the tranches (which collateralize the CMBX Series) to the simulated REIT values.

Beginning with the simulated REIT value $\bar{V}_{j,t}$ where $\bar{V}_{j,0}$ is the initial value of the REIT at the date of initialization of the simulation, the equation capturing the property value evolution is:

$$\tilde{V}^i_{t,k} = \frac{1}{LTV^i_{0,k}} \times \frac{\bar{V}_{j,t}}{\bar{V}_{j,0}} \times e^{-0.5\sigma_j^2 t + \sigma_j \sqrt{t} dZ_i} \tag{6}$$

where $\frac{1}{LTV^i_{0,k}}$ which represents the historical (at origination) inverse of the loan to value ratio for the ith loan in the kth CMBX Series. For example, for $k = 1,\ i \in (1, \ldots, 4004)$. Necessarily the entire sample of each of the $i \in (1, \ldots, 25019)$ loans are partitioned amongst the $j \in (1, \ldots, 6)$ indexed property types and $k \in (1, \ldots, 8)$ CMBX Series. The i independent Brownian idiosyncratic shocks, dZ_i, are associated with the individual loan risks captured in the discrete representation of the Brownian random walk in the remaining terms. Importantly the volatility, σ_j, is determined in the calibration step (Step 1). The value $\tilde{V}^i_{t,k}$ represents the ith simulated property value.[20]

3.3. Comparative statistical validation of both models

In the credit ratings literature two well established methods for validating the predictive ability of model default probabilities are i.) the Receiver Operating Characteristic Area Under the Curve (ROC AUC) and ii.) the Brier Score. Briefly, a ROC AUC value of 0.50 indicates a random model with no predictive ability, while a ROC AUC value of 1.00 indicates perfect forecasting. In the case of the Brier Score, B, which is the average mean square error of a predictor with a binary event[21] it holds that lower Brier Scores indicate better predictive power.[22]

The ROC AUC and Brier Score are determined from the sample of approximately two-million loan life observations from November 2007 to June 2015. The predictive value of the default probabilities in associated with the sample correspond to a ROC AUC of 0.76 for the reduced form model while the corresponding ROC AUC determined for probabilities associated with the structural generalization is 0.71. In the case of the Brier Score, the reduced form approach yields a Brier Score of 0.05 while the structural generalization yields a Brier Score of 0.10. This is consistent with Bauer and Agarwal (2014) who also find better predictive power for hazard rate models.

The ROC AUC and Brier Scores for both the reduced form and the structural generalization are consistent with those reported in the credit ratings literature. As documented in Güttler's (2005) study based on four-year default frequencies for Corporate debt, the ROC AUC is 0.83 for Moody' s and 0.82 for S&P. Similarly, reported Brier Scores in the same study of 0.07 for Moody's and also 0.07 for S&P are both in-line with the CMBS results. Finally, the corresponding ROC AUC for CMBS as reported by Christopoulos et al. (2008), pre-crisis, was 0.83.

There are many additional tests related to ROC and interesting expansions for weighted Brier Scores[23] that could expand the discussion in future work. Together, however, these test results validate the predictive ability of both models, and seem to indicate better predictive power with the reduced form approach compared with the structural generalization.

4. CMBS valuation

We are given a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\in[0,\mathcal{T})}, \mathbb{P})$ satisfying the usual conditions[24] with $\mathbb{P}$ the statistical probability measure. The trading interval is [0, T]. Traded are default free bonds of all maturities $T \in [0, T]$ with time t prices denoted $p(t, T)$, and various property indices, REITs, CRELs, CMBS bonds, and CMBX indices. The default-free spot rate of interest at time t is denoted r_t. I assume markets are complete and arbitrage free so that there exists a unique equivalent martingale probability measure $\mathbb{Q}$ under which discounted prices are martingales. The discount factor at time t is $e^{-\int_0^t r_s ds}$. Because I am interested in valuing CMBS, most of the model formulation is under the probability measure $\mathbb{Q}$.

The market price $m_{j,\,k}(t)$ for the kth bond in the j-th CMBX Series depends on the principal and interest cashflows from the N loans that are allocated to the kth bond from the Trust cashflows, $\hat{\mathbb{T}}_{j,k}(t) = \sum_{i=1}^N [\hat{\mathbb{A}}_{j,k}(t) + \hat{\mathbb{I}}_{j,k}(t)]$ where $\hat{\mathbb{A}}_{j,k}(t)$ are the promised principal payments and $\hat{\mathbb{I}}_{j,k}(t)$ are the promised interest payments (a complete description of the trust allocation rules for senior-subordinated structures is found in the Appendix). The CMBX bonds are then valued in the standard fashion using the corollary *actual* cashflows for N loans are allocated to the kth bond from the Trust cashflows, $\mathbb{T}_{j,k}(t) = \sum_{i=1}^N [\mathbb{A}_{j,k}(t) + \mathbb{I}_{j,k}(t)]$ where $\mathbb{A}_{j,k}(t)$ are the actual principal payments and $\mathbb{I}_{j,k}(t)$ are the actual interest payments.

Letting the random cash flows that contemplate loan level risks of default, loss, and interest rate risks, at time t to bonds $k = 1, \ldots, K$ be denoted $\nu_k(t)$, the time t value of these bonds is given by the following expression

$$b_k(t) = E_t\left[\sum_{j=t+1}^{T_k} \nu_k(j) e^{-\int_t^j r_s ds}\right] \text{ if } t < T_k \tag{7}$$

Substituting promised cashflows held constant pathwise, valuation that contemplates only loan level interest rate risks (prohibiting pathwise loan level defaults and losses) at time t to bonds $k = 1, \ldots, K$ is denoted by $\hat{\nu}_k(t)$, and the time t value of these bonds is given by

$$\tilde{b}_k(t) = E_t\left[\sum_{j=t+1}^{T_k} \hat{\nu}_k(j) e^{-\int_t^j r_s ds}\right] \text{ if } t < T_k \tag{8}$$

In the empirical process then, the *fair value price* of a bond at date s as a percent of par for the kth bond in the jth CMBX Series is

$$b_{j,k}(s) = \frac{E_s\left[\sum_{t=s}^T \mathbb{T}_{j,k}(t) e^{-r_t t}\right]}{\hat{\mathbb{F}}_{j,k}(s)} \tag{9}$$

where $\hat{\mathbb{F}}_{j,k}(s) = \sum_{t=1}^T \hat{\mathbb{A}}_{j,k}(t)$ is the face value of the bond and $\hat{\mathbb{A}}_{j,k}(t)$ are the promised principal payments. Additionally, the theoretical price I refer to as the *interim price* reflecting interest rate

[20] The index notation for the entire correlated economy is $\iota = 1, \ldots, 73$. There are $j = 1, \ldots, 6$ property specific REIT indices and $j \in \iota$ The volatility σ_j is determined only for the j subset objects.

[21] Expressed for simplicity as $B = \frac{1}{N}\sum_i^N \left(\hat{p}_i - Y_i\right)^2$ where $\hat{p}_i$ is the estimated probability of an event.

[22] See Grunert et al. (2005); Christopoulos et al. (2008); Krämer and Güttler (2008); Medema et al. (2009), and Bauer and Agarwal (2014), among others.

[23] See Young (2010).

[24] See Protter (1990).

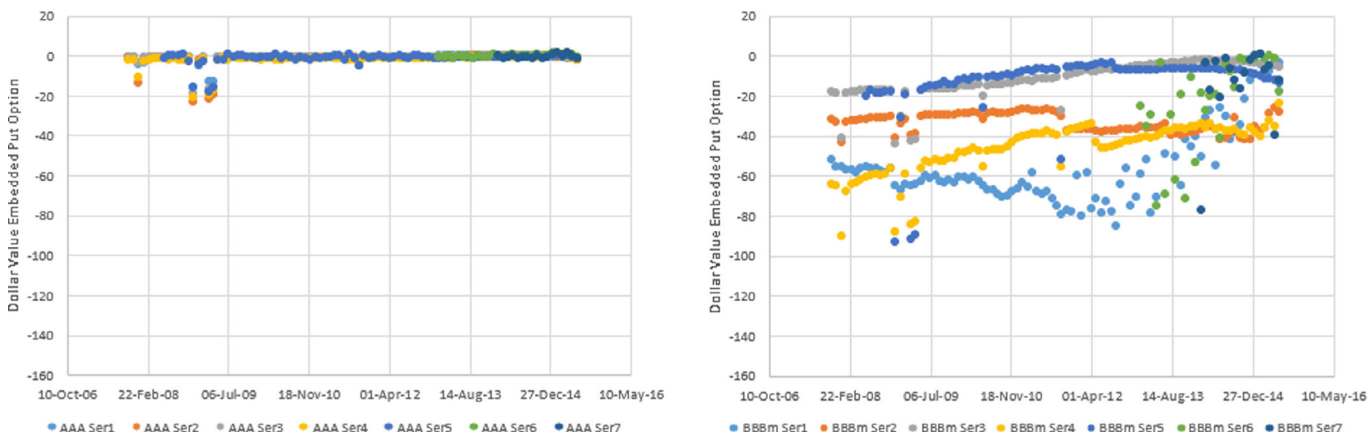

Fig. 4a. Dollar value of reduced form embedded put options by rating. This figure shows the dollar value of the embedded put options under the reduced form model. In the plot to the left the put option is captured for AAA rated CMBX, while in the plot to the right the put option is captured for BBB-minus rated CMBX. The figures show the values for CMBX Series 1–7 over the period November 2007 through June 2015.

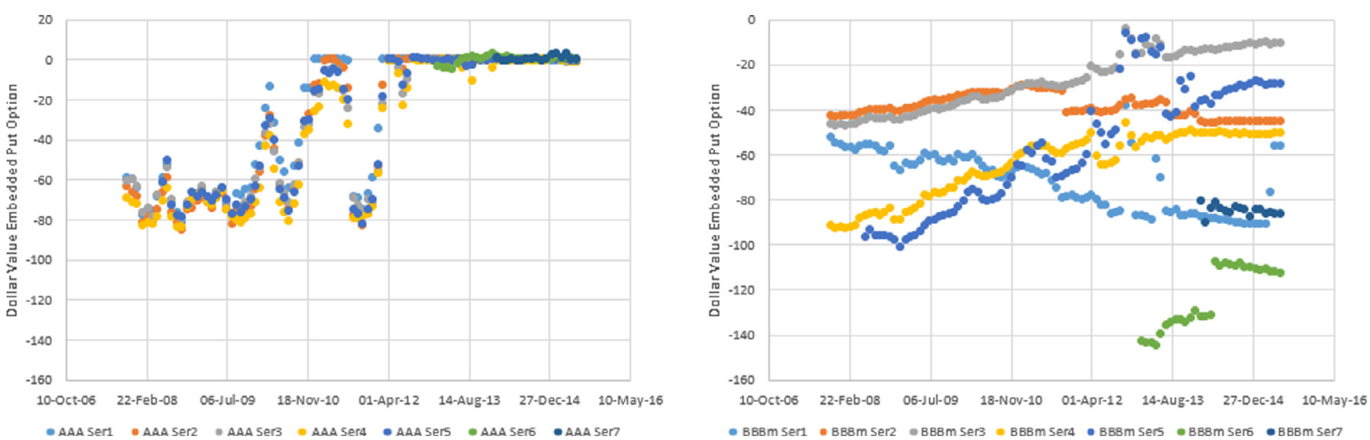

Fig. 4b. Dollar value of structural generalization embedded put options by rating. This figure shows the dollar value of the embedded put options under the structural generalization model. In the plot to the left the put option is captured for AAA rated CMBX, while in the plot to the right the put option is captured for BBB-minus rated CMBX. The figures show the values for CMBX Series 1–7 over the period November 2007 through June 2015.

risk only (and *no* default) is given by

$$\tilde{b}_{j,k}(s) = \frac{E_s\left[\sum_{t=s}^{T} \hat{\mathbb{T}}_{j,k}(t)e^{-r_t t}\right]}{\hat{\mathbb{F}}_{j,k}(s)} \tag{10}$$

The expectations in Eqs. (9) and (10) are evaluated using Monte Carlo simulation[25] and correspond to expressions Eqs. (7) and (8) above, respectively. Necessarily, the values of Eqs. (9) and (10) will reflect the implementation of the default mechanisms of either the reduced form as described in Eq. (4) or the structural generalization as described in Eq. (6).

5. Identifying default risk (the put-option)

Only default and loss risk are modeled directly. Following Jarrow (2007), I observe that the dollar value of the CMBS embedded put-option of default $\mathring{p}$ is defined as

$$\mathring{p}_{j,k}(s) = b_{j,k}(s) - \tilde{b}_{j,k}(s) \tag{11}$$

If the bondholder is long an embedded option, then the bond's fair value as defined in Eq. (9) will exceed (or be equal to) the interim price as defined in Eq. (10) such that $b_{j,k}(s) - \tilde{b}_{j,k}(s) \geq 0$. Conversely, as in the case of embedded default risk exposure, if the bondholder is short an embedded option, then $b_{j,k}(s) - \tilde{b}_{j,k}(s) < 0$. In the above definitions, both $b_{j,\,k}(s)$ and $\tilde{b}_{j,k}(s)$ represent the fair value or arbitrage-free value of the bonds given a particular cash flow pattern. These are the bond prices in markets with no mispricings and these values are entirely independent of the market prices $m_{j,\,k}(t)$ of securities traded. This characterization is intuitive. The differences between fair value and the interim price can only be attributed to default/loss risk in the risk neutral framework as implemented here.

Fig. 4a and 4b show the plots of the time series of dollar values of the embedded put-option defined in Eq. (11) for the triple-A (AAA) and triple-B minus (BBB-) rated tranches for the reduced form and structural generalization approaches.[26] As contemplated in the theory, across both model approaches, the vast majority of the put values are negative, implying a short position for the bondholder exposed to the risk of default. In the instances where the value of the put-option is positive, it indicates that the bondholder is long the option. This arises empirically in tranched structures where the physical default driven prepayment and concomitant recovery results in greater value to the bondholder through the receipt of cashflows sooner than expected. Depending on the path profile of forward rate evolutions and timing of cashflows,

[25] A discussion of the simulation procedure is available by request as a technical appendix.

[26] These patterns are consistent across all CMBX Series, varying with ratings.

this condition may indicate a trading opportunity. Nevertheless, positive embedded put option values are in the minority across the observed dollar values of the embedded put-option as defined in Eq. (11). Tranching of risk influences the risk of default to the bondholders with increased credit deterioration associated with simulated defaults in fair value $b_{j,\,k}(s)$ compared with the no-default interim price $\tilde{b}_{j,k}(s)$. As expected, this difference is much larger during the crisis period than in the recovery for the combined reasons of lower volatility and lower risk of default due to survivorship as well as convergence in bond prices to par due to maturity.

One standout pattern of the charts is the observable differences between the put-option values generated in the reduced form (Fig. 4a) compared with those generated using the structural generalization (Fig. 4b). It is apparent that the default mechanism of the structural generalization casts a more severe outlook than the reduced form during the crisis. As consequence, the impact of such defaults are manifested through the capital structure more extensively in the structural generalization compared with the reduced form. Additionally, there is greater disparity exhibited through the crisis. Christopoulos (2017) argues that the default trigger in the structural generalization described in Eq. (6) is too coarse to the task of estimating default and related risk neutral valuation compared with the reduced form approach described in Eq. (4). These comparisons in Fig. 4a and 4b support that perspective.

6. Constructing the risk proportions

Liquidity risk is a key focal point for institutional investors, dealer liquidity providers, risk managers, regulators, and scholars in the academic community. In an efficient market, investors should not be unduly penalized for executing trades in *any* market environment. Indeed, in an efficient market the prices of securities should accurately reflect all risks embedded within the securities at *any* point in time. By partitioning the total risk facing CMBS investors into its components, I attempt to identify clearly the composition associated with warranted risks of default, loss and interest rate volatility, versus those resulting from insufficient or excessive liquidity manifested possibly by investor panic, improper risk controls, insufficient dealer balance sheet flexibility, inappropriate leverage ratios, ill conceived regulatory restriction, ineffective research valuation methods, and human error, among others.

Having previously isolated the default option, I now seek to use it in conjunction with standard estimates of market risk to solve for the component of liquidity risk such that the components of total risk, Ψ, in CMBS (*default risk* $\mathring{d}$, *interest rate risk* $\mathring{r}$, and*liquidity risk* $\mathring{l}$),[27] sum to 1, or:

$$\Psi_{j,k}(s) \equiv \mathring{d}_{j,k}(s) + \mathring{r}_{j,k}(s) + \mathring{l}_{j,k}(s) = 1 \tag{12}$$

The direct approach presented in this paper is different than other approaches in the literature[28] and thus a few important points should be expanded upon. *First*, I want to disclose the trading and risk opportunities independent of market prices to track the exposure to credit and market risk. This approach is different than the one taken in the option-adjusted spread (OAS) literature. In the case of conforming residential mortgage backed securities (RMBS), the default option is still present at the collateral level resulting in default driven prepayments by mortgage borrowers even though the principal is guaranteed by the US government at the bond level. As such, in conforming RMBS an OAS for the bonds can always be calculated because the simulated cashflows will never be insufficient to map to the market price and a positive root always determined.[29]

The same cannot be said, however, for non-conforming RMBS and CMBS, and this observation is important to discussions of spread composition later in this paper. Specifically, for tranched credit sensitive securities, traditional OAS can in certain extreme cases (like those in the crisis) fail to be determined when simulated cashflows reflecting losses are insufficient to map to market price. As such, fair value pricing estimates and comparisons to exogenous market prices, is a more reliable approach than OAS.[30]

Second, the CMBS market itself is still in development. There are no actively traded options such as the put-option described in Eq. (11) and no consensus as to effective best practices for risk management. Unlike RMBS where market prices, at minimum, reflect constant (aka 'conditional') prepayment rate (CPR) assumptions and generally carry OAS valuations as described in Boyarchenko et al. (2015), CMBS market prices categorically do not reflect any such sector-wide consensus of standardized stress scenarios be it conditional default rate (CDR) assumptions, OAS, or fair value. As such, there is an educational aspect to the disclosure of the risk composition proposed here to assist in reconciling model driven signals of risk with practical intuition. The proportions, if effective, will provide a framing of the risk based largely on risk-neutral valuation that is both a.) self-evident to traders and portfolio managers and b.) *proactively* useful in conjunction with the disclosed put-option and other fair value measurements in the areas of investments, risk management, and policy. In this way the proportional compositions serve as barometers of risks embedded *within* CMBS rather than pricing estimators *of* CMBS.

6.1. The default risk proportion

Based on Eqs. (9) and (10) I define the proportion of risk associated with default and loss, $\mathring{d}_{j,k}(s)$, facing bondholders as:

$$\mathring{d}_{j,k}(s) = \max\left(1 - \frac{b_{j,k}(s)}{\tilde{b}_{j,k}(s)},\ 0\right) \tag{13}$$

This characterization of risk neutral proportional default risk is intuitive. If the fair value *cum* default risk, $b_{j,\,k}(s)$, exceeds the fair value *ex* default risk, $\tilde{b}_{j,k}(s)$, then the default risk to bondholders is zero (bondholders are *long* the default option). The upper bound of 1 applies when the fair value *cum* default risk, $b_{j,\,k}(s)$, of the bond has *no* value and thus 100% of the risk facing the bondholder is associated with default in the risk neutral framework.

6.2. The market risk proportion

I need to make a modeling choice regarding the relative influence of market versus credit risk in the construction of the Market Risk Proportion. To inform this choice, I first compress individual CMBX prices by ratings into a set of *price ratings indices,* $m_k(t)$, defined as

$$m_k(t) = \frac{1}{J}\sum_j m_{j,k}(t) \tag{14}$$

which is the arithmetic average of prices for a given credit rating, k, across J CMBX Series, for a given time, t. I compute these values for 1912 daily prices provided by Markit over the sample period November 2007 through June 2015 for $k = AAA$ and $k = BBB-$

[27] In the notation, the designating mark ˚ indicates a risk measure informed by risk neutral values.

[28] Schwarz (2015), for example, offers a perspective on disentangling credit and liquidity risk premia by constructing an industry liquidity index to isolate Eurobond liquidity risk and impute default risk from a regression based approach; while Nichols and Cunningham (2008) consider a regression approach for CMBS credit spreads.

[29] See Jarrow (2007).

[30] Discussions on broad disparity among OAS measures across dealer firms can be found in Hayre (2002), and Boyarchenko et al. (2015), among others.

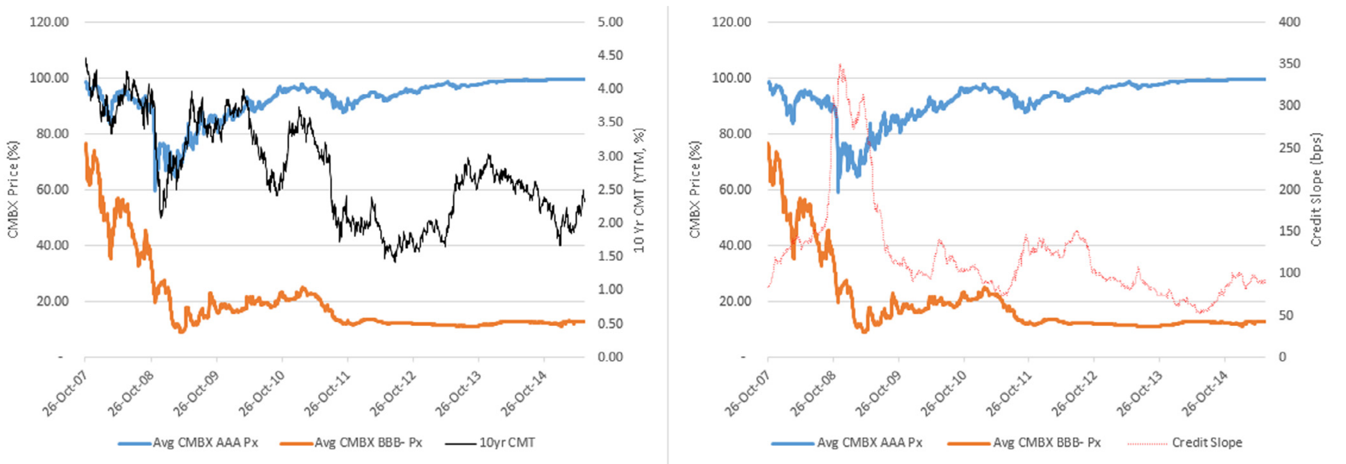

Fig. 5. Historical analysis of credit risk and risk free yield sensitivity for CMBX. This figure shows the time series for the average 1912 AAA and BBB- prices across CMBX Series 1–4 which are observed across the entire sample period. In the plot to the left, the CMBX prices are compared to the 10-year constant maturity treasury (CMT) yield to maturity. In the plot to the right, the CMBX prices are compared to the credit slope defined as the difference between the yield to maturity for Baa and Aaa corporate bonds. The sample period is 10/26/2007 through 6/15/2015.

ratings and for $J = 4$ CMBX which are observed across the entire sample period. I then compare these two price series with the 10 year constant maturity treasury (CMT) yield to maturity and the corporate credit slope defined as the difference between BBB and AAA corporate bond yields.[31] In Fig. 5, it is apparent that while both types of CMBX exhibit price declines due to deterioration in corporate credit in the crisis, only AAA securities respond positively to subsequent declines in the 10 year CMT. In contrast, BBB- securities exhibit virtually no improvement in pricing due to declines in the risk free rate and subsequent, improvement in corporate credit during the recovery.

While not the most complex approach, I use a simple ordinary least squares regression (OLS) that regresses CMBX prices against 10 year CMT and the credit slope to develop some intuition. In Fig. 6, Panel A we observe the results for the entire sample period. In the case of the AAA analysis, the familiar relationships hold. The regression is significant overall at the 1% significance level and has a high adjusted R-squared of 0.72. The explanatory variables on the right hand side are significant and the signs are intuitive for less credit sensitive securities where higher prices are associated with lower risk free yields and a tighter credit slope. After adjusting the standard errors for bias by bootstrapping in the generalized linear model (GLM) and performing ordinary robustness checks for standard error biases, the standard errors of the estimates are quite stable resulting in stable upper and lower bounds of the 95% confidence interval that vary approximately 1/100th of 1% across tests.

In contrast, the same exercise regressing BBB- CMBX on the left-hand side indicate higher CMBX BBB- prices associated with higher treasury yields and wider credit slopes. Again the regression overall is significant as are the explanatory variables at the 5% level of significance. The adjusted R-squared of 0.44 is worse than what was observed in the AAA case. The same robustness checks for standard error biases performed in the AAA regression were performed for the BBB- regression with similarly stable results.

In Fig. 6 panels B and C I split the sample between the crisis and the recovery, respectively. Consistent with the regression found in Fig. 6, Panel A both subset regressions are significant as are the t-stats at the 95% confidence interval. In the crisis (Fig. 6, Panel B) the pattern observed for observations generally repeats what was seen in Fig. 6, Panel A. There appears to be a better explanatory relationship as measured by the adjusted R-squared between AAA CMBX securities and macro factors than there is for BBB- securities. In contrast, during the recovery (Fig. 6, Panel C), this relationship changes with the explanatory relationship as measured by the adjusted R-squared exhibiting similar explanatory power.

The takeaway from this is that during the crisis the impact of credit deterioration was so severe that market risk measures for lower credit rated securities were inconsequential, consistent with default risk dominating price in the lower credit rated securities. During the crisis, the lowest credit ratings exhibited patterns in the regression consistent with sustained panic. During the recovery period, this pattern seemed to switch in lockstep with lower volatility. In such periods, broadly, default risk should recede although not categorically.

Given the above I propose that credit concerns dominate the composition of risks facing CMBS bondholders and I define the proportion of market risk, $\mathring{r}_{j,k}(s)$, facing CMBS bondholders as:

$$\mathring{r}_{j,k}(s) = \min\left(1 - \mathring{d}_{j,k}(s),\, D_{j,k}(t)\right) \tag{15}$$

where $D_{j,\,k}(t)$, is the Macaulay Duration of the kth bond in the jth CMBX Series, representing the weighted average time to receipt of the bond's promised cashflows divided by the sum of the bond's promised cashflows as shown in Hull (2015) and defined as:

$$D_{j,k}(t) = \frac{t \times \sum_{j=t+1}^{T_k} \hat{\mathbb{T}}_{j,k}(t) e^{-r_t t}}{\sum_{j=t+1}^{T_k} \hat{\mathbb{T}}_{j,k}(t) e^{-r_t t}} \tag{16}$$

$D_{j,\,k}(t)$, is a reasonable proxy for the proportion of market risk facing investors and provides a measure of the sensitivity of bond prices to changes in interest rates as indicated by Pacific Investment Management Company (2016) and Fabozzi (1993). Market risk is generally defined as the risk incurred in the trading of assets and liabilities due to changes in interest rates, exchange rates and other asset prices as described in Saunders and Cornett (2014). Changes in interest rates dominate the market risk exposure of investors due to the direct relationship between so-called risk free rates, r_t, and the pricing of all such fixed income securities as discussed in Federal Deposit Insurance Company (2015). Since CMBS are fixed income securities, the use of $D_{j,\,k}(t)$ is a meaningful first approximation of market risk partitioned from credit and liquidity

[31] Source: Markit and FRB H.15 Interest Rates.

Dependent Variable	cons	10yr CMT	creditslope	Pr >F	AdjR2 (%)	N
Panel A: All Observations (Crisis and Recovery, November 2007 - June 2015)						
avgAAApx	109.5444***	-1.6270***	-0.1017***	0.00	0.7270	1912
	295.62	-13.44	-67.24			
avgBBB-px						
	-14.5764***	11.7867***	0.0131***	0.00	0.4419	1912
	-15.29	37.83	3.36			
Panel B: Crisis Only (November 2007 - June 2010)						
Dependent Variable	cons	10yr CMT	creditslope	Pr >F	AdjR2 (%)	N
avgAAApx	59.2785***	9.5700***	-0.0436***	0.00	0.7031	676
	26.36	18.24	-13.91			
avgBBB-px						
	-68.2779***	26.0325***	0.0390***	0.00	0.3129	676
	-9.33	15.24	3.82			
Panel C: Recovery Only (July 2010 - June 2015)						
Dependent Variable	cons	10yr CMT	creditslope	Pr >F	AdjR2 (%)	N
avgAAApx	109.7170***	-1.3600***	-0.1046***	0.00	0.6233	1236
	263.57	-12.69	-44.40			
avgBBB-px						
	-6.7088***	6.1107***	0.6580***	0.00	0.6165	1236
	-12.59	44.56	21.82			

Fig. 6. OLS analysis of credit risk and risk free yield sensitivity of CMBX. This figure shows the summary results for the ordinary least squares (OLS) regressions with the average CMBX price by rating as the dependent variable and each of (i.) the 10-year CMT yield and (ii.) the credit slope as the independent variables. The entire sample period is 10/26/2007 to 6/15/2015. There are 1912 daily observation for each of the dependent and independent variables. Coefficients are shown on the first line for each regression and t-stats on the second line for each regression. Each panel shows two regressions with the first OLS using the average AAA CMBX price as the dependent variable and the second using average BBB-minus CMBX price as the dependent variable. Panel A gives summary results for entire sample. Panel B gives summary results for the crisis only. Panel C gives resuls for the recovery only. ***/**/* indicate significance at the 1%, 5% and 10% level.

risks as proposed in the discussion above.[32] Additionally, if default risk $\mathring{d}_{j,k}(s)$ as a component of total risk $\Psi_{j,\,k}(s)$ begins to dominate the profile, the market risk measure captured by $D_{j,\,k}(t)$ will diminish, resulting in smaller $\mathring{r}_{j,k}(s)$ as indicated in Eq. (15).

6.3. The liquidity risk proportion

Given that prepayment risk is excluded for the reasons previously discussed, the only remaining composite risk confronting CMBS bondholders is liquidity risk, the proportion of which I define as:

$$\mathring{l}_{j,k}(s) = 1 - \mathring{d}_{j,k}(s) - \mathring{r}_{j,k}(s) \tag{17}$$

The interpretation of the liquidity proportion is interesting. One should expect that in times of distress the composition of securities risk exposure will be dominated by default risk with a declining proportional presence associated with liquidity ('liquidity drying up'). Framed this way, the liquidity proportion can be thought of as *liquidity availability*. In contrast, in periods of declining volatility, the default risk proportion should decline and the liquidity proportion should increase. This is exactly the pattern observed with differences amongst credits (and model approaches) completely in line with intuition.

Consider Fig. 7a which depicts the time series of proportional risk composition described in Eqs. (13), (16), and (17) for the AAA and BBB tranches for CMBX Series 1 using the reduced form approach. As expected, the higher rated AAA tranche exhibited a greater proportion of liquidity than the lower rated BBB tranche. Additionally, during the crisis period, the default risk proportion, $\mathring{d}_{j,k}(s)$, increases while the liquidity proportion, $\mathring{l}_{j,k}(s)$, decreases. As the crisis abates and the recovery ensues, this trend reverses. The general pattern repeats in the structural generalization as shown Fig. 7b. However, it is clear that the default risk proportion is generally much larger across all credits compressing much less over time than observed in the reduced form plots.[33]

7. Spreads and the risk management of CMBS

In the previous section I introduced risk compositions informed by risk measures determined independently of market pricing. This parsing of risks into proportions is unique in the literature related to CMBS valuation. At the same time, because the proposed proportional measures are independent of observed market prices (and corresponding observed risk premia, aka 'spreads'), we don't learn anything about the transformation of embedded risks into spread form.

In this section, I seek to address this issue and to disclose the implied composition of market perception of risks of default, rate volatility and liquidity availability as captured in observed risk premia above the risk free rate, $\mathbb{S}_{j,k}(t)$, for the kth bond in the j-th CMBX Series. I seek to *project* the risk neutral components previously described onto observed spreads in the market.

The most thorough and successful of my investigations into spread interaction with risk neutral risk assessments requires a fairly complex set of transformations and the introduction of the

[32] As indicated in Fabozzi (1993), there are many different duration measures are used in practice including modified duration, dollar duration, effective duration. All relate in varying degrees to the duration described in Eq. (16) which is a good first approximation for the price sensitivity of CMBS to changes in risk premia.

[33] These patterns are consistent across all CMBX Series, varying with ratings, and are available upon request.

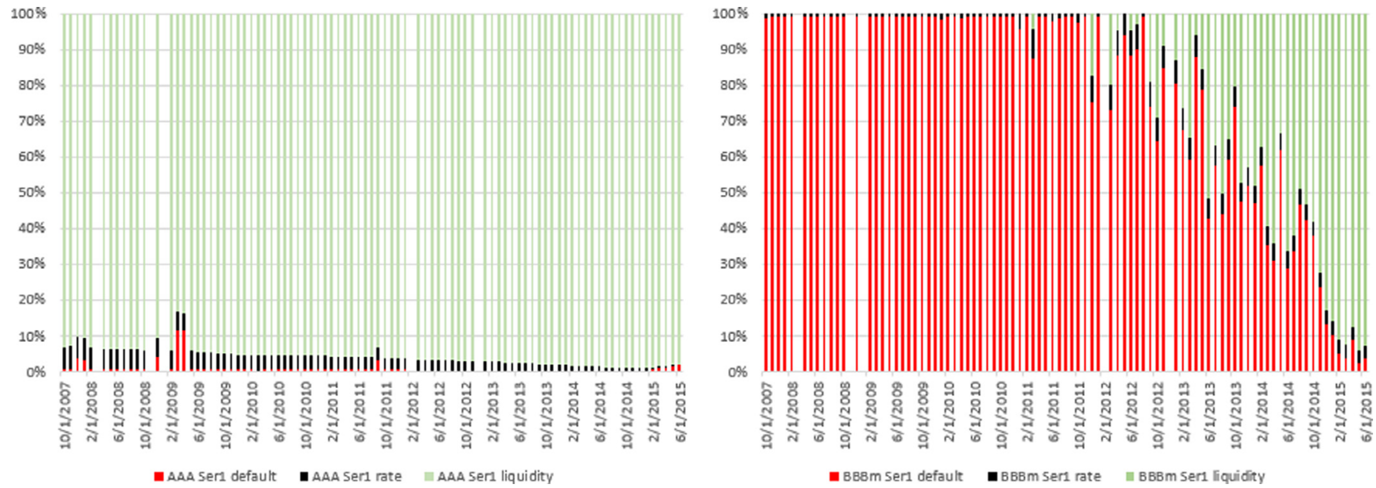

Fig. 7a. CMBX Series 1 risk neutral proportional risk composite using reduced form. This figure shows the risk composition for CMBX Series 1 with default ($\mathring{d}$), rate ($\mathring{r}$), and liquidity ($\mathring{l}$) risk proportions as determined under the reduced form. In the plot to the left, the risk composition is shown for the AAA class and the plot to the right show the risk composition is shown for the BBB-minus. The proportions are shown for 92 consecutive simulation dates separated by intervals of 21 consecutive business days. The sample period is 10/26/2007 to 6/15/2015.

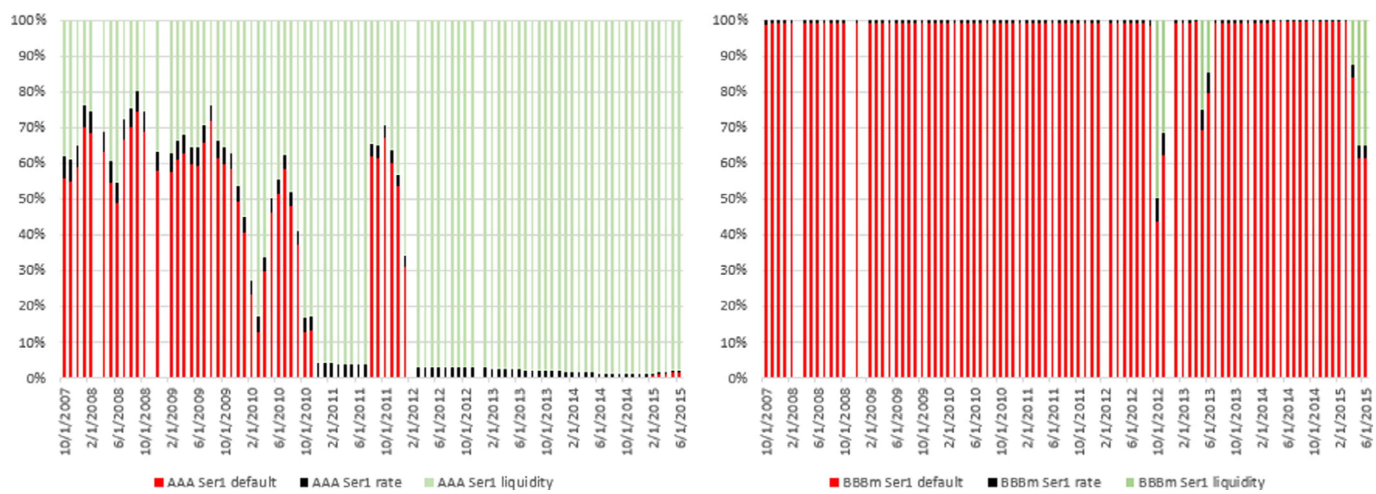

Fig. 7b. CMBX Series 1 risk neutral proportional risk composite using structural generalization. This figure shows the risk composition for CMBX Series 1 with default ($\mathring{d}$), rate ($\mathring{r}$), and liquidity ($\mathring{l}$) risk proportions as determined under the structural generalization. In the plot to the left, the risk composition is shown for the AAA class and the plot to the right show the risk composition is shown for the BBB-minus. The proportions are shown for 92 consecutive simulation dates separated by intervals of 21 consecutive business days. The sample period is 10/26/2007 to 6/15/2015.

concept of *shadow liquidity*. The methodology for projection described below articulates one way to transform the embedded risk neutral option values into risk premia and how to then disclose the proportional representation of such risk premia *within* observed market risk premia as shown in Fig. 8a and 8b for CMBX Series 3 (AAA and BBB classes). The approach appears to work well and the steps, arguments and statistical support are described below.

7.1. Embedded rate risk and total option value

Recall that in the risk neutral framework the interim price, $\tilde{b}_{j,k}(s)$, provides the upper bound for the value of the security without default while the fair value, $b_{j,\,k}(s)$, provides the risk neutral value of the security reflecting the risks default/loss. In the marketplace, there is a corresponding value for the risk neutral interim price called the *market interim price*, $\tilde{m}_{j,k}(t)$, which, like the risk neutral interim price also has a corresponding risk premium above the risk free rate equal to zero. It then follows that the market interim price is greater than or equal to the observed market price,[34] $\tilde{m}_{j,k}(t) \geq m_{j,k}(t)$.

I now follow the method described in Eq. (11) to determine the embedded put option. The difference between the interim price and the market interim price is the dollar value of embedded interest rate volatility or *market risk* facing CMBS investors, $\mathring{y}_{j,k}(s)$, defined as

$$\mathring{y}_{j,k}(s) = \tilde{b}_{j,k}(s) - \tilde{m}_{j,k}(t) \tag{18}$$

As discussed previously and following Jarrow (2007) and Fabozzi (1993), I have now isolated two embedded options facing investors: default risk, $\mathring{p}_{j,k}(s)$, and interest rate risk, $\mathring{y}_{j,k}(s)$, with their sum defined as the total embedded option value, $\Xi_{j,\,k}(s)$, such that

$$\Xi_{j,k}(s) = \mathring{p}_{j,k}(s) + \mathring{y}_{j,k}(s) \tag{19}$$

[34] The expressions for the market and market interim prices are found in the Appendix in Eqs. (49) and (50).

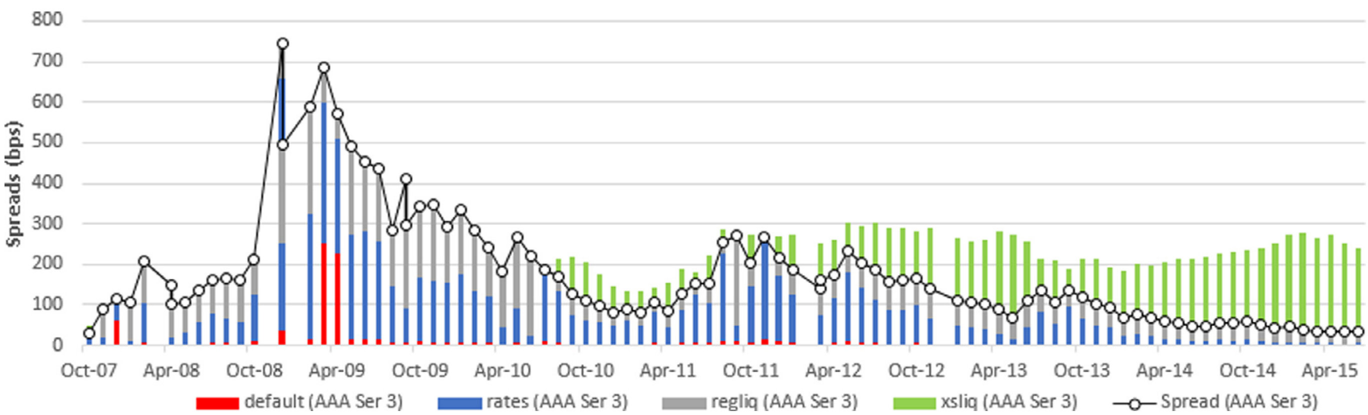

Fig. 8a. Implied spread risk composition for the AAA class of CMBX Series 3 under reduced form. This figure shows the implied risk composition for the AAA class of CMBX Series 3 on a spread basis reflecting the interaction between risk neutral proprotions and observed risk premia (*Spread AAA Ser-3*) determined under the reduced form. The spread composition is attributed to default $C^{p}_{j,k}$(*default (AAA Ser-3)*), rate $C^{y}_{j,k}$ (*rates (AAA Ser-3)*), regular liquidity $C^{l}_{j,k}$(*regliq (AAA Ser-3)*), and excess liquidity $C^{\tilde{l}}_{j,k}$(*xsliq (AAA Ser-3)*), risk premia expressed in basis points (bps). The proportions are shown for 92 consecutive simulation dates separated by intervals of 21 consecutive business days. The sample period is 10/26/2007 to 6/15/2015.

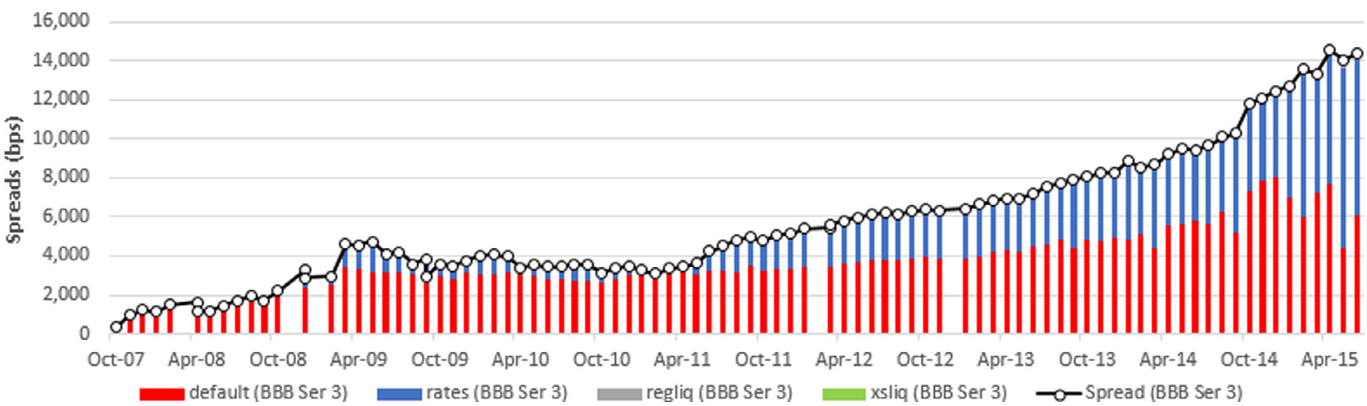

Fig. 8b. Implied spread risk composition for the BBB class of CMBX Series 3 under reduced form. This figure shows the implied risk composition for the BBB class of CMBX Series 3 on a spread basis reflecting the interaction between risk neutral proprotions and observed risk premia (*Spread BBB Ser-3*) determined under the reduced form. The spread composition is attributed to default $C^{p}_{j,k}$(*default (BBB Ser-3)*), rate $C^{y}_{j,k}$ (*rates (BBB Ser-3)*), regular liquidity $C^{l}_{j,k}$(*regliq (BBB Ser-3)*), and excess liquidity $C^{\tilde{l}}_{j,k}$(*xsliq (BBB Ser-3)*), risk premia expressed in basis points (bps). The proportions are shown for 92 consecutive simulation dates separated by intervals of 21 consecutive business days. The sample period is 10/26/2007 to 6/15/2015.

To determine the spread composition corresponding to risks within the market price, I first need to construct a *hybrid price*, $\ddot{m}_{j,k}(t)$, that reflects elements of *both* the market price and elements of the risk neutral option values. The hybrid price linearly adjusts the market price with the proportional representation of total option value, $\Xi_{j,k}(s)$, to the interim price, $\tilde{b}_{j,k}(s)$, and is defined as

$$\ddot{m}_{j,k}(t) = \left(1 + \frac{\Xi_{j,k}(s)}{\tilde{b}_{j,k}(s)}\right) \times m_{j,k}(t) \tag{20}$$

This makes intuitive sense. Because the total option value $\Xi_{j,k}(s)$ may be positive or negative, the hybrid price, $\ddot{m}_{j,k}(t)$, may take on values greater than, less than, or equal to, $m_{j,k}(t)$.

7.2. Risk components embedded in CMBS spreads

With the hybrid price, $\ddot{m}_{j,k}(t)$, I compute the percentage price change between the market price $m_{j,k}(t)$ and the hybrid price $\ddot{m}_{j,k}(t)$ defined as

$$\triangle m_{j,k}(t) = \frac{\ddot{m}_{j,k}(t) - m_{j,k}(t)}{m_{j,k}(t)} \tag{21}$$

Next, I take the product of $\triangle m_{j,k}(t)$ with the negative of its duration (adjusting for basis points) to get the corresponding estimated directional change in market spreads, $\triangle\mathbb{S}_{j,k}(t)$, defined as

$$\triangle\mathbb{S}_{j,k}(t) = -\frac{1}{D_{j,k}(t)} \times \triangle m_{j,k}(t) \tag{22}$$

which corresponds to the move from the market price $m_{j,k}(t)$ to the hybrid price $\ddot{m}_{j,k}(t)$. From here I define the *total theoretical risk premium*, $\mathring{\mathbb{S}}_{j,k}(t)$, as

$$\mathring{\mathbb{S}}_{j,k}(t) = \triangle\mathbb{S}_{j,k}(t) + \mathbb{S}_{j,k}(t) \tag{23}$$

which reflects the adjustment for the optionality. The baseline difference between the actual and theoretical spreads is then given by the *shadow liquidity*, defined as

$$\bar{\mathbb{S}}_{j,k}(t) = \mathbb{S}_{j,k}(t) - \mathring{\mathbb{S}}_{j,k}(t) \tag{24}$$

which is used in the final spread calculations for risk composition below and in the trading strategy. As the risk measures $\mathring{\mathbb{S}}_{j,k}(t)$ and $\bar{\mathbb{S}}_{j,k}(t)$ are informed by the interaction value $\triangle m_{j,k}(t)$, either risk measure may take on value greater than, less than, or equal to zero. The assumption is that there exists a *shadow liquidity value*, informed by theoretical and market constructs. If the total theoretical risk premia $\mathring{\mathbb{S}}_{j,k}(t)$ implied by risk neutral prices exceeds the observed risk premia $\mathbb{S}_{j,k}(t)$ implied by market prices then, there will be a condition of excess liquidity. Alternatively, liquidity can be subsumed within observed risk premia, implying excess liquidity equal to zero.

Referring back to the option values $\mathring{p}_{j,k}(s)$ and $\mathring{y}_{j,k}(s)$ and expressing each of them as percentages of the interim price, $\triangle\mathring{p}_{j,k}(s) = \mathring{p}_{j,k}(s)/\tilde{b}_{j,k}(s)$ and $\triangle\mathring{y}_{j,k}(s) = \mathring{y}_{j,k}(s)/\tilde{b}_{j,k}(s)$, I capture the proportion of the optionality in terms of the theoretical interim price. These relationships between the options and the baseline theoretical interim price can also be expressed in spread form using the duration measure, $D_{j,k}(t)$. This interaction gives theoretical spread values[35] for the put, $\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t)$, and the interest rate, $\mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)$, embedded options, as defined below as

$$\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) = -\frac{1}{D_{j,k}(t)} \times \triangle\mathring{p}_{j,k}(t) \tag{25}$$

and

$$\mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t) = -\frac{1}{D_{j,k}(t)} \times \triangle\mathring{y}_{j,k}(t) \tag{26}$$

From here I capture the total distance between the two spreads which I will use to determine the options' relative contributions (in percentage form) to the observed market spreads. To do this, I compute the distance as

$$|\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) - \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)| = \max\left(\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t),\, \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)\right) - \min\left(\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t),\, \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)\right) \tag{27}$$

because we do not know the signs of the option values which may vary across observation period and across the capital structure. With the total distance of the option spread as defined in Eq. (27) I then express the composition of that distance for the put spread, $\frac{\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t)}{|\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) - \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)|}$, and the interest rate spread, $\frac{\mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)}{|\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) - \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)|}$, which necessarily[36] sum to one. These *initial proportions* do not contemplate liquidity premia directly.

In the final step I map the theoretical risk relationships to the market observed risk premia. The conceptual assumption of shadow liquidity requires that liquidity be divided into two types: excess liquidity or regular liquidity. The *initial excess liquidity spread*, $\widehat{\widehat{C^{l}_{j,k}}}(t)$, is given by

$$\widehat{\widehat{C^{l}_{j,k}}}(t) = \begin{cases} -\mathring{\mathbb{S}}_{j,k}(t), & \forall\ \mathring{\mathbb{S}}_{j,k}(t) < 0 \\ \text{otherwise}, & 0 \end{cases} \tag{28}$$

The *initial regular liquidity spread,* $\widehat{C^{l}_{j,k}}(t)$, is given by

$$\widehat{C^{l}_{j,k}}(t) = \begin{cases} \bar{\mathbb{S}}_{j,k}(t), & \forall\ \widehat{\widehat{C^{l}_{j,k}}}(t) = 0 \\ \text{otherwise}, & \max\left(\bar{\mathbb{S}}_{j,k}(t),\, 0\right) \end{cases} \tag{29}$$

At this stage liquidity risk premia *cannot* be distributed to both excess and regular liquidity characterizations. In the final mapping below, allocation to both characterizations of liquidity is possible and readily apparent.

From here, I simply do the remaining adjustments to get the *final regular liquidity spread*,

$$C^{l}_{j,k}(t) = \begin{cases} \frac{\widehat{\widehat{C^{l}_{j,k}}}(t)}{\mathbb{S}_{j,k}(t)} \times \mathbb{S}_{j,k}(t), & \forall\ \widehat{\widehat{C^{l}_{j,k}}}(t) > 0 \\ \text{otherwise}, & \widehat{C^{l}_{j,k}}(t) \end{cases} \tag{30}$$

the *final default spread*,

$$C^{p}_{j,k}(t) = \max\left(\left(\mathbb{S}_{j,k}(t) - C^{l}_{j,k}(t)\right) \times \frac{\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t)}{|\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) - \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)|},\, 0\right) \tag{31}$$

the *final rate spread*,

$$C^{y}_{j,k}(t) = \max\left(\left(\mathbb{S}_{j,k}(t) - C^{l}_{j,k}(t)\right) \times \frac{\mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)}{|\mathring{\mathbb{S}}^{\mathring{p}}_{j,k}(t) - \mathring{\mathbb{S}}^{\mathring{y}}_{j,k}(t)|},\, 0\right) \tag{32}$$

and the *final excess liquidity spread,* $C^{\check{l}}_{j,k}(t)$,

$$C^{\check{l}}_{j,k}(t) = \max\left(\widehat{\widehat{C^{l}_{j,k}}}(t),\, 0\right) \tag{33}$$

These spreads are constructed to ensure that observed risk premia in the market, $\mathbb{S}_{j,k}(t)$, equates to the sum of the components previously defined in this paper and as expressed below

$$\mathbb{S}_{j,k}(t) \equiv C^{l}_{j,k}(t) + C^{p}_{j,k}(t) + C^{y}_{j,k}(t),\ \forall j, k, t \tag{34}$$

with *total liquidity* reflecting the sum of regular liquidity and excess liquidity, as given by:

$$C^{\ddot{l}}_{j,k}(t) = C^{l}_{j,k}(t) + C^{\check{l}}_{j,k}(t) \tag{35}$$

As mentioned previously, Figure 8, provides a time series of risk composition. Fig. 8a shows the composition for CMBX AAA Series 3 while Fig. 8b shows the composition CMBX BBB Series 3 using the method described above. As is evident, the AAA security contains excess liquidity availability and regular liquidity availability components, with a muted exposure to default risk and sizable exposure to market risk. In contrast, the BBB class exhibits solely default and rate risk components, with virtually no liquidity availability. This compositional breakdown is reflective of the combination of the market's and the model's assessment of risks embedded within the securities as discussed above.

Fig. 9 provides a set of tables which allow the reader to walk through several numerical examples to validate the calculations of the risk spread composition using the equations in this paper from the primitives of (i.) observed market spread, (ii.) market price, (iii.) interim market price, (iv.) interim price, (v.) fair value price and (vi.) duration, for three trading dates (10/26/2007 - Panel A, 7/15/2011 - Panel B, and 6/10/2015 - Panel C). Fig. 10 provides the componentwise transformation of the risk that was previously displayed in spread form into unity (100%) for easy risk management evaluation. In Fig. 10A I show the composition of all risks for the AAA Series 3 CMBX and in Fig. 10B the corresponding plot for BBB Series 3 CMBX. These graphs visually describe the risk composition of spreads in a manner that is easily understood in the fixed-income community. Upon review one may readily express the relative risks embedded within a bond in spread or percentage terms. As the 'language' of spreads is immediately familiar to the entire fixed-income community, it is hoped that the proposed discussion advances intuition on risks embedded within CMBS spreads.

8. Model driven strategies and testing market efficiency

To validate the relevance of the newly disclosed risk measures I construct three trading strategies in this section to jointly test my model and CMBS market efficiency using historical data and market prices for the CMBX bonds from November 2007 to June 2015. I consider the entire sample period and then two sub-periods: the crisis and the recovery. I use the embedded put-option, $\mathring{p}_{j,k}(s)$, and the liquidity availability proportion, $\mathring{l}_{j,k}(s)$, as *signals* constructed independent of market prices for the first two automated trading strategies. As the measure $\mathring{l}_{j,k}(s)$ relies on identification of $\mathring{p}_{j,k}(s)$, a priori, the returns driven by both measures should be similar for each measure, but may differ across the separate reduced form and structural model approaches previously discussed. In the third trading strategy I use the shadow liquidity value, $\bar{\mathbb{S}}_{j,k}(t)$ which measures the difference between theoretical and observed risk premia and thus in contrast to the first two trading strategies is not constructed independently of market pricing.

[35] I introduce superscript notation here to keep track of the association of the different spreads with their primitives.

[36] In instances where the ratios exceed 1, an upper bound of 1 is imposed.

Panel A: 10/26/2007														
		Primitives						Eq(11)	Eq(17)	Eq(18)	Eq(19)	Eq(20)	Eq(21)	Eq(22)
Date	Security	S	mktpx	mxpx_0	i_px	fairval_px	Dur	put px	rate px	totoptpx	hybrid px	dpx_m:mhyb	dS_m:mhyb	S_hyb
10/26/2007	AAASer3	31.59	98.11	100.54	104.88	104.43	7.86	-0.45	4.33	3.89	101.74	0.04	-47.15	-15.56
10/26/2007	BBBSer3	330.65	76.19	108.53	92.02	32.35	12.84	-59.67	-16.51	-76.18	13.12	-0.83	644.74	975.39
								Eq(23)			Eq(24)	Eq(25)	Eq(26)	
								Sbar_S-Shyb	d_putpct	d_ratepct	Sput	Srate	dist_Sp:Srate	Sput/dist
10/26/2007	AAASer3							47.15	0.00	0.04	5.45	-52.60	58.05	0.09
10/26/2007	BBBSer3							-644.74	-0.65	-0.18	505.02	139.72	365.30	1.00
									Eq(27)	Eq(28)	Eq(29)	Eq(30)	Eq(31)	Eq(34)
								Srate/dist	Cxslqinit	Creglqinit	Creglq	Cdef	Crate	Ctotlq
10/26/2007	AAASer3							0.91	15.56	0.00	10.43	1.99	19.17	25.99
10/26/2007	BBBSer3							0.00	0.00	0.00	0.00	330.65	0.00	0.00
Panel B: 7/28/2011														
		Primitives						Eq(11)	Eq(17)	Eq(18)	Eq(19)	Eq(20)	Eq(21)	Eq(22)
Date	Security	S	mktpx	mxpx_0	i_px	fairval_px	Dur	put px	rate px	totoptpx	hybrid px	dpx_m:mhyb	dS_m:mhyb	S_hyb
7/28/2011	AAASer3	152.89	92.79	98.85	109.85	109.24	4.27	-0.61	11.00	10.39	101.57	0.09	-221.47	-68.58
7/28/2011	BBBSer3	4490.73	13.48	69.08	96.10	26.95	9.18	-69.15	27.02	-42.13	7.57	-0.44	477.28	4968.01
								Eq(23)			Eq(24)	Eq(25)	Eq(26)	
								Sbar_S-Shyb	d_putpct	d_ratepct	Sput	Srate	dist_Sp:Srate	Sput/dist
7/28/2011	AAASer3							221.47	-0.01	0.10	13.04	-234.52	247.56	0.05
7/28/2011	BBBSer3							-477.28	-0.72	0.28	783.41	-306.13	1089.54	0.72
									Eq(27)	Eq(28)	Eq(29)	Eq(30)	Eq(31)	Eq(34)
								Srate/dist	Cxslqinit	Creglqinit	Creglq	Cdef	Crate	Ctotlq
7/28/2011	AAASer3							0.95	68.58	0.00	47.35	5.56	99.99	115.93
7/28/2011	BBBSer3							0.28	0.00	0.00	0.00	3228.97	1261.76	0.00
Panel C: 6/10/2015														
		Primitives						Eq(11)	Eq(17)	Eq(18)	Eq(19)	Eq(20)	Eq(21)	Eq(22)
Date	Security	S	mktpx	mxpx_0	i_px	fairval_px	Dur	put px	rate px	totoptpx	hybrid px	dpx_m:mhyb	dS_m:mhyb	S_hyb
6/10/2015	AAASer3	34.57	99.62	100.12	105.47	103.80	1.46	-1.67	5.35	3.68	103.10	0.03	-239.22	-204.65
6/10/2015	BBBSer3	14339.76	7.83	56.02	99.66	66.84	4.29	-32.82	43.64	10.82	8.68	0.11	-253.07	14086.69
								Eq(23)			Eq(24)	Eq(25)	Eq(26)	
								Sbar_S-Shyb	d_putpct	d_ratepct	Sput	Srate	dist_Sp:Srate	Sput/dist
6/10/2015	AAASer3							239.22	-0.02	0.05	108.67	-347.89	456.56	0.24
6/10/2015	BBBSer3							253.07	-0.33	0.44	767.64	-1020.72	1788.36	0.43
									Eq(27)	Eq(28)	Eq(29)	Eq(30)	Eq(31)	Eq(34)
								Srate/dist	Cxslqinit	Creglqinit	Creglq	Cdef	Crate	Ctotlq
6/10/2015	AAASer3							0.76	204.65	0.00	29.58	1.19	3.81	234.23
6/10/2015	BBBSer3							0.57	0.00	253.07	253.07	6046.63	8040.06	253.07

Fig. 9. Six spread compostion examples with equation references for AAA and BBB classes of CMBX Series 3. This figure shows six numerical examples that calculate the spread decomposition values for two securities AAA Series 3 and BBB Series 3 on three trading dates (Panel A: 10/26/2007, Panel B: 7/15/2011, and Panel C: 6/10/2015). The primitives are in the center. To the right the Equations and non-numbered intermediate calculations are provided stacked and labled. With the primitives and the equations provided in the text, the reader can recreate each of the values in the equations. S is observed risk premia; mktpx is the market price; mxpx_0 is the market price at 0bps; i_px is the interim price; fairval_px is the fairvalue price; Dur is the duration. Equations (Eq (#) are clearly marked. Other equations follow the text and are located in between equations d_putpct and d_ratepct are the ratios of the option to the interim price, while Sput/dist is the min(Eq(24)/Eq(26),1), while Srate/dist is the min(Eq(25)/Eq(26),1). All spreads are in basis points (bps) and all prices expressed as percents of par.

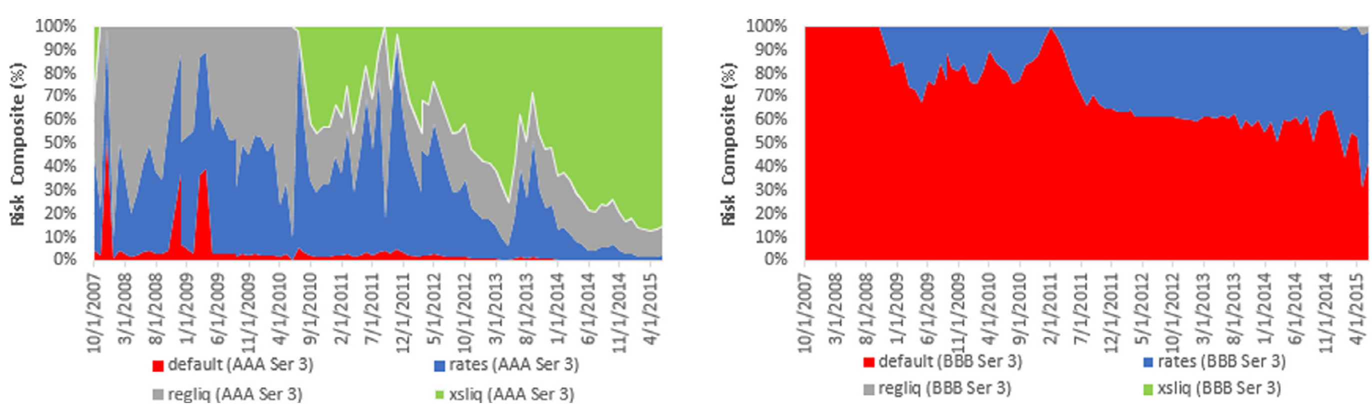

Fig. 10. Percentage risk composition for AAA and BBB classes of CMBX Series 3. This figure provides the componentwise transformation of the risk that was previously displayed in spread form into unity (100%). In the plot to the left (Fig. 10A) we show the composition of all risks for the AAA Series 3 CMBX. In the plot to the right (Figure 10B) we show the composition of all risk for the BBB class of CMBX Series 3. The spread composition normalized to unity is attributed to default $C^{p}_{j,k}$(*default (BBB Ser-3)*), rate$C^{y}_{j,k}$ (*rates (BBB Ser-3)*), regular liquidity $C^{l}_{j,k}$(*regliq (BBB Ser-3)*), and excess liquidity $C^{\tilde{l}}_{j,k}$(*xsliq (BBB Ser-3)*), risk components. The sample period is 10/26/2007 to 6/15/2015.

For the trading tests, the beginning value of the entire long/short portfolio is indexed to a value of 100 as of November 26, 2007. The cumulative value of the long/short portfolio is determined at the end of each trading interval using continuous compounding of periodic returns with the last trading interval terminating on June 10, 2015. A *trading interval* in my study is defined as consisting of 21 consecutive business days. Long/short portfolios are constructed, held, and unwound on the 21st business day of each trading interval. A portfolio is formed by identifying under- and overvalued securities using one of the risk measures $\mathring{p}_{j,k}(s)$, $\mathring{l}_{j,k}(s)$, or $\bar{\mathbb{S}}_{j,k}(t)$. The portfolio long and short positions have equal weightings with 50% weighting in the long and 50% weighting in the short positions. On the first business day of each trading interval equally weighted long (50%) and short (50%) positions are identified and taken into the portfolio with trades executed at the end of day observed market price as provided by Markit. The identification procedure of trading opportunities using the measures described in Eqs. (11), (17), and (24) are executed by the purchase and sale of positions at the market price at simulation date *s*.

Specifically, I select from the available CMBX the top two and bottom two bonds from the set of all available bonds in my sample. I select using the put option, $\mathring{p}_{j,k}(s)$, for Trading Strategy 1; the liquidity proportion, $\mathring{l}_{j,k}(s)$, for Trading Strategy 2; and the shadow liquidity premium, $\bar{\mathbb{S}}_{j,k}(t)$, for Trading Strategy 3. These selections of two bonds for the long position and two bonds for the short position are also equally weighted, such that each bond's weight contribution to the total portfolio represents 25% of the portfolio within each trading interval. I consider trading opportunities across all credit ratings and tenors in the sample. Given the limitation of the number CMBX bonds, partitioning the sample further by rating or vintage is not possible in this study. This automated process is repeated across the sample period divided into 91 consecutive trading intervals.

Loan information is updated monthly and NCREIF property indices are updated quarterly. The information on loans and property indices is held constant until such time as it is updated and made available. Prices may adjust within an interval due to the release of new loan or price information as well as for other reasons that change market participants expectations related to risks. The approach is thus conservative to the information release dates.

Additionally, transaction costs as contemplated in bid/ask spreads are excluded from this study. The CMBX prices used in this study are mid-market. Such mid-market prices for CMBX are provided to Markit by the entire dealer community at the close of each business day and they are consistent with the entire risk community's CMBS daily evaluations. The monitoring of such quotes by internal risk management groups and regulatory oversight authorities provide support for the veracity of these prices. CMBX were created to provide more liquidity and exposure to the underlying cash CMBS assets. Although cash CMBS trade, they are limited in number. Some information on CMBS bid/ask spreads have been tracked on the Trade Reporting and Compliance Engine (TRACE) platform of Financial Industry Regulatory Authority (FINRA) since 2011[37] as described in Hollifield et al. (2014). Importantly, however, FINRA explicitly excludes synthetic CMBX transactions from its monitoring activities. Since I use CMBX as the pricing object in my study, and not cash CMBS and since CMBX prices are explicitly not included in TRACE monitoring, there is no shortcoming in my study with the use of synthetic CMBX pricing provided by dealers to Markit and no need to provide an exogenous adjustment for transaction costs in this study. The prices in my study reflect information digested through the interval, and thus it is reasonable to assume that bid/ask spreads at the beginning of the period and the end of period will reasonably cancel each other out. This assumption is empirically supported by findings in West (2012) related to patterns of abnormal returns surrounding catastrophe events of ± 25 days, as well as other studies. Given that this study does not utilize daily trading intervals, further adjustment for transaction costs is not required.

8.1. Trading strategy 1 (the embedded put-option strategy)

In Trading Strategy 1, the most undervalued j CMBX Series and k rating cohort ("cheapest of the cheap"), e.g., $\max_{j,k}(\mathring{p}_{j,k}(s))$ indicates the bond to be selected for the long position. This corresponds to the least negative (or, in some instances, actually positive) values from the available set (recall Fig. 4a and 4b). The most overvalued j CMBX Series and k rating cohort ("richest of the rich"), e.g., $\min_{j,k}(\mathring{p}_{j,k}(s))$ indicates the bond to be selected for the short position. This corresponds to the most negative values from the available set. The thinking is that although there are a small number of $\mathring{p}_{j,k}(s) > 0$, the ranking of the option values may be interpreted as a long/short signal that communicates trading opportunities which may result in extraordinary portfolio returns in testing.

The embedded put-option strategy produced outstanding results for the reduced form model. Over the sample period, the reduced form portfolio earned positive cumulative returns of 109% with 46% coming from the crisis period and 63% from the recovery period. In contrast, employing the same strategy informed by the embedded put-option generated using the structural generalization exhibited a cumulative loss of approximately −6% over the sample period. Given this negative performance for the structural generalization there is no need to construct or test further risk measures for the structural generalization in this paper.

8.2. Trading strategy 2 (the liquidity proportion strategy)

For Trading Strategy 2, I simply substitute $\mathring{l}_{j,k}(s)$ for $\mathring{p}_{j,k}(s)$ used in Trading Strategy 1. In Trading Strategy 2 the most undervalued j CMBX Series and k rating cohort ("cheapest of the cheap"), e.g., $\max_{j,k}(\mathring{l}_{j,k}(s))$ indicates the bond to be selected for the long position. This corresponds to the largest liquidity proportion values from the available set (recall Fig. 7a and 7b). The most overvalued j CMBX Series and k rating cohort ("richest of the rich"), e.g., $\min_{j,k}(\mathring{l}_{j,k}(s))$ indicates the bond to be selected for the short position. This corresponds to the smallest liquidity proportion values from the available set. Since $\mathring{l}_{j,k}(s) \geqslant 0$, the interpretation is that the liquidity proportion is a valuable commodity, supporting its framing as liquidity availability as previously noted.

8.3. Trading strategy 3 (the shadow liquidity strategy)

To test the validity of the spread interaction risk composition, I turn to the shadow liquidity measure risk measure, $\bar{\mathbb{S}}_{j,k}(t)$, defined in Eq. (24) which can take on positive or negative values. In Trading Strategy 3 the most undervalued j CMBX Series and k rating cohort ("cheapest of the cheap"), e.g., $\max_{j,k}(\bar{\mathbb{S}}_{j,k}(t))$ indicates the bond to be selected for the long position. This corresponds to the largest shadow liquidity values from the available set. The most overvalued j CMBX Series and k rating cohort ("richest of the rich"), e.g., $\min_{j,k}(\bar{\mathbb{S}}_{j,k}(t))$ indicates the bond to be selected for the short position. This corresponds to the smallest shadow liquidity values from the available set. In Fig. 11, the plots show comparisons between the actual observed spreads, $\mathbb{S}_{j,k}(t)$, and corresponding theoretical spreads, $\mathring{\mathbb{S}}_{j,k}(t)$ defined in Eq. (23) for a AAA and BBB subset of available securities. The columns represent the shadow liquidity, $\bar{\mathbb{S}}_{j,k}(t)$. In Fig. 11A we see the plot for the AAA class of CMBX Series 3. Generally the shadow liquidity measure, $\bar{\mathbb{S}}_{j,k}(t)$ takes on positive values, but not always. From a trading strategy perspective, the implication is that observed spreads $\mathbb{S}_{j,k}(t)$ are higher than the theoretically justifiable spread, $\mathring{\mathbb{S}}_{j,k}(t)$. In such conditions, there would appear to be a buying opportunity. When $\bar{\mathbb{S}}_{j,k}(t)$ takes on negative values, the implication is that the investor is due more compensation in spread than is currently observed in the market and as such the investor should short such bonds which are relatively expensive compared with the theoretical risk measure. This is observed in the BBB class of CMBX Series 3 in Fig. 11B.

8.4. Profitability of trading strategies

Recall the time series cumulative returns for each of the four portfolios corresponding to the different trades strategies (and models) as previously provided in Fig. 1. The best performing of the portfolios tested is the reduced form embedded put-option strategy. A summary of the portfolio choices and trading history

[37] See http://www.finra.org/industry/trace/structured-product-activity-reports-and-tables.

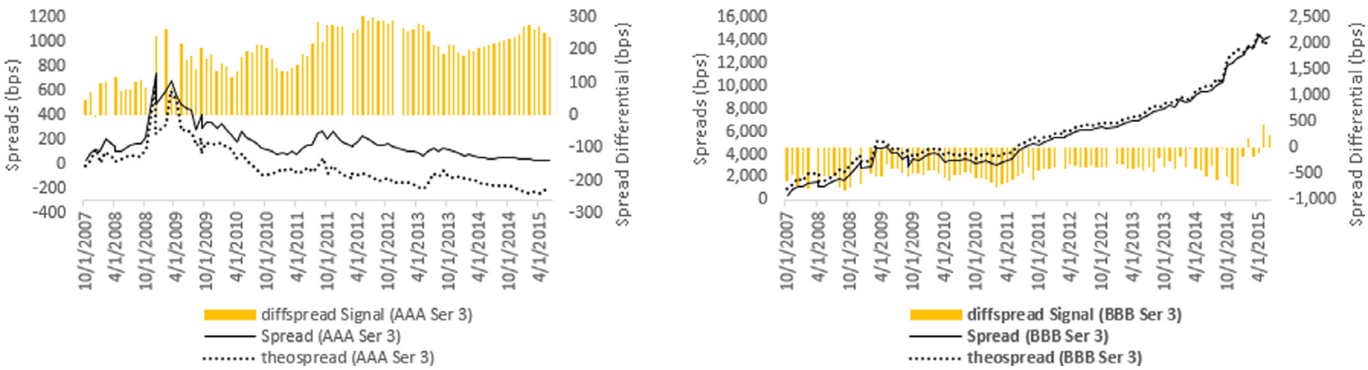

Fig. 11. Shadow liquidity signal and its components for the AAA and BBB classes of CMBX Series 3. This figure depicts the shadow liquidity measure $\bar{\mathbb{S}}_{j,k}$(*diffspread Signal (AAA Ser-3)*), the observed risk premia in the market $\mathbb{S}_{j,k}$ (*Spread (AAA Ser-3)*), and the theoretical risk premia $\mathring{\mathbb{S}}_{j,k}$ (*theospread (AAA Ser-3)*) for the AAA Fig. 8bA) and BBB (Figure 11B) classes of CMBX Series 3. All risk premia and differentials are expressed in basis points (bps). The risk premia are shown for 92 consecutive simulation dates separated by intervals of 21 consecutive business days. The sample period is 10/26/2007 to 6/15/2015.

	Panel A				Panel B				Panel C				Panel D				Panel E					Panel F
	Put Signal				Bonds Selected				Market Trade Prices (Initiated)				Market Trade Prices (Unwind)				Interval Returns					Cumulative
Date	short1	short2	long1	long2	short1	short2	long1	long2	pxshort1	pxshort2	pxlong1	pxlong2	pxshort1	pxshort2	pxlong1	pxlong2	short1	short2	long1	long2	Portfolio	Portfolio Value
Oct-07	-106.25	-94.21	4.21	-0.45	BBB Ser4	A Ser1	AJ Ser4	AAA Ser3	85.92	91.98	98.26	98.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00
Nov-07	-109.75	-93.93	4.77	-0.41	BBB Ser4	A Ser1	AJ Ser4	AJ Ser3	76.91	88.39	91.16	99.00	76.91	88.39	91.16	94.79	-0.11	-0.04	-0.07	-0.03	0.01	101.03
Dec-07	-139.31	-128.13	-3.52	-4.09	BBB Ser4	A Ser4	AAA Ser3	AAA Ser1	81.02	94.57	96.15	97.44	81.02	91.69	94.81	100.00	0.05	0.04	0.04	0.01	-0.01	100.03
Jun-11	-101.32	-89.54	3.01	-0.23	BBB Ser4	BBB Ser2	AJ Ser4	AJ Ser3	23.12	20.69	65.73	71.81	23.12	20.69	65.73	68.21	-0.10	-0.28	-0.12	-0.12	0.03	161.89
Jul-11	-107.66	-94.44	2.23	2.20	BBB Ser4	A Ser4	AJ Ser4	AJ Ser5	22.63	35.79	67.85	69.79	22.63	19.58	67.85	72.31	-0.02	-0.06	0.03	0.01	0.03	166.55
May-15	-78.34	-39.43	1.23	1.16	BBB Ser5	BBB- Ser7	BBB Ser1	AJ Ser6	16.65	99.06	35.58	100.14	16.65	7.54	99.43	100.44	0.02	0.12	0.00	0.00	-0.03	210.69
Jun-15	-51.08	-32.82	1.22	0.22	BBB Ser5	BBB Ser3	BBB Ser1	A Ser1	17.33	7.83	35.92	68.08	17.33	98.76	35.92	99.76	0.04	0.00	0.01	0.00	-0.01	209.05

Fig. 12. Reduced form embedded put-option long/short trading strategy cumulative returns. This table shows a summary of selected 21 day trade intervals for the automated Put strategy for date in the leftmost column. Panel A shows the value of the two smallest and two largest put values. Panel B shows the bonds for those put signals on that trading date. Panel C shows the prices at which trades for the short and long positions were executed and brought into the portfolio. Panel D shows the prices for bonds when they were taken out of the portfolio (unwound) at the end of the interval. Panel E shows the log returns for each of the short and long positions over the interval and the interval return for the portfolio comprised of the two short and two long components. Panel F shows the cumulative return on the portfolio initiated at a value equal to 100 on October 26, 2007 and with an ending cumulative value equal to 209.05 on June 15, 2015.

for the put-option portfolio[38] which earned cumulative returns of 109% is provided in Fig. 12. Fig. 12, Panel A shows the value of the two smallest and two largest put values. Fig. 12, Panel B shows the bonds for those put signals on that trading date. Fig. 12, Panel C shows the prices at which trades for the short and long positions were executed and brought into the portfolio. Fig. 12, Panel D shows the prices for bonds when they were taken out of the portfolio (unwound) at the end of the trading interval. Fig. 12, Panel E shows the log returns for each of the short and long positions over the interval and the interval return for the portfolio comprised of the two short and two long components. Fig. 12, Panel F shows the cumulative return on the portfolio initiated at a value equal to 100 in November 2007 and which shows a cumulative value equal to 209 as of June 2015.

The results for the liquidity proportion strategy, while not quite as strong as the put option portfolio, were still impressive. Over the sample period, the reduced form portfolio earned positive cumulative returns of approximately 103% and the structural generalization earned positive cumulative returns of about 10%. The comparatively worse navigation capability using the liquidity proportion (versus the embedded put-option) as signal is not entirely surprising. The embedded put-option reflects a risk neutral valuation of a pathological risk of loss in the marketplace. As such, if modeled correctly, the embedded put-option should articulate sources of value in advance of the default events occurring. In contrast, the liquidity proportion is an analytical construct based upon the put-option. While evidently useful, and intuitively appealing, it does not directly reflect pricing of a pathological risk, only the relative proportion compared with other risks facing bondholders. This small comparative weakness in trade strategy nevertheless has significant strengths in providing forward guidance for US unemployment as discussed below in Section 9.

Finally, the shadow liquidity strategy exhibited a cumulative return of 75% over the entire sample period with evenly split returns in the crisis and recovery periods. It is interesting to note that this result based on this newly introduced measure corresponds well to the returns documented in Christopoulos et al. (2008) and more recently Christopoulos and Jarrow (2016) who use the measure Theta to compare market and risk neutral model prices. As Theta also interacts market and model prices as a risk measure, this observation adds weight to the validity of the proportional risk characterizations proposed in this paper. Although this signal $\bar{\mathbb{S}}_{j,k}(t)$ is presented in a form that is generally more familiar to investors who trade on a spread versus price basis, the measure nevertheless still produces results relatively worse than the pure model measures $\mathring{p}_{j,k}(s)$ and $\mathring{l}_{j,k}(s)$ used in Trading Strategies 1 and 2 respectively. As such, this comparative underperformance adds further support to the earlier claim of a disconnect in the CMBS market's ability to evaluate risks and as further documented in Christopoulos et al. (2014). The interaction between the market and model assessment appears to dilute the effectiveness of the signal $\bar{\mathbb{S}}_{j,k}(t)$ in trade strategy navigation compared with market price independent measures $\mathring{p}_{j,k}(s)$ and $\mathring{l}_{j,k}(s)$. This is very interesting and is further considered in Section 9, below.

8.5. Testing abnormal returns with ICAPM

To test CMBS market efficiency, I need to determine if my cumulative positive trading profits represent abnormal returns. For this purpose, I utilize a standard ICAPM[39] where, briefly, the expected returns on the portfolios follow a multi-beta model. With

[38] The trade histories for the other three portfolios are available upon request.

[39] See Merton (1990) for greater detail.

Panel A: All Periods

Dependent Variable	cons (α)	Mkt-Rf	F	AdjR2	N
Put (StrGn)	-0.0001	-0.2448	5.51*	0.0477	91
	(-0.02)	(-2.35)**			
Put (RdFrm)	0.0088	-0.2167	3.56*	0.0276	91
	(1.34)	(-1.89)*			
Liq (RdFrm)	0.0118	-0.6529	31.90***	0.2556	91
	(1.79)*	(-5.65)***			
S (RdFrm)	0.0078	-0.3827	13.81***	0.1246	91
	(1.33)	(-3.72)***			

Panel B: All Periods

Dependent Variable	cons (α)	Mkt-Rf	SMB	HML	F	AdjR2	N
Put (StrGn)	0.0054	-0.1961	-0.3425	0.1058	2.34*	0.0427	91
	(0.09)	(-1.44)	(-1.16)	(0.44)			
Put (RdFrm)	0.0090	-0.0823	-0.4535	-0.1395	1.95	0.0306	91
	(1.36)	(-0.55)	(-1.40)	(-0.53)			
Liq (RdFrm)	0.1167	-0.4226	-0.6155	-0.3808	13.12***	0.2877	91
	(1.79)*	(-2.87)***	(-1.93)**	(-1.48)			
S (RdFrm)	0.0077	-0.2936	-0.2244	-0.1593	4.91**	0.1153	91
	(1.30)	(-2.18)**	(-0.77)	(-0.67)			

Panel C: Crisis

Dependent Variable	cons (α)	Mkt-Rf	F	AdjR2	N
Put (StrGn)	-0.0063	-0.2402	1.6	0.0189	32
	(-0.41)	(-1.26)			
Put (RdFrm)	0.0117	-0.3369	2.41	0.0435	32
	(0.67)	(-1.55)			
Liq (RdFrm)	0.0046	-0.7653	13.3***	0.2841	32
	(0.27)	(-3.65)***			
S (RdFrm)	0.0069	-0.4793	6.45**	0.1495	32
	(0.27)	(-3.65)***			

Panel D: Crisis

Dependent Variable	cons (α)	Mkt-Rf	SMB	HML	F	AdjR2	N
Put (StrGn)	-0.0027	-0.1765	-0.7626	0.3375	1.15	0.0147	32
	(-0.17)	(-0.65)	(-1.25)	(0.73)			
Put (RdFrm)	0.0181	-0.1409	-1.0017	0.0993	1.49	0.0456	32
	(1.00)	(-0.46)	(-1.44)	(0.19)			
Liq (RdFrm)	0.0133	-0.4345	-1.1029	-0.2434	5.73***		32
	(0.78)	(-1.49)	(-1.67)	(-0.49)			
S (RdFrm)	0.0108	-0.3545	-0.6191	0.0502	2.41*	0.1204	32
	(0.67)	(-1.30)	(-1.00)	(0.11)			

Panel E: Recovery

Dependent Variable	cons (α)	Mkt-Rf	F	AdjR2	N
Put (StrGn)	0.0041	-0.3104	7.14***	0.0098	59
	(0.90)	(-2.67)***			
Put (RdFrm)	0.0994	0.1211	1.48	0.0083	59
	(0.57)	(1.22)			
Liq (RdFrm)	0.1222	-0.4233	11.39***	0.1519	59
	(2.48)**	(-3.38)***			
S (RdFrm)	0.0047	-0.1401	1.68	0.0116	59
	(1.12)	(-1.3)			

Panel F: Recovery

Dependent Variable	cons (α)	Mkt-Rf	SMB	HML	F	AdjR2	N
Put (StrGn)	0.0042	-0.3485	0.1940	-0.0872	2.58*	0.0757	59
	(0.88)	(-2.43)**	(0.69)	(-0.32)			
Put (RdFrm)	0.0014	0.1441	0.0116	-0.2285	0.85	-0.0076	59
	(0.33)	(1.18)	(0.05)	(-1.00)			
Liq (RdFrm)	0.0115	-0.4084	0.0279	-0.1925	3.87**	0.1293	59
	(2.21)**	(-2.63)**	(0.09)	(-0.66)			
S (RdFrm)	0.0042	-0.1533	0.1593	-0.2312	1.12	0.0061	59
	(0.94)	(-1.16)	(0.62)	(-0.93)			

Fig. 13. Intertemporal CAPM regressions. This table shows the coefficients and t-stats (in parentheses) for the constant α and explanatory variables used in the ICAPM tests of CMBS market efficiency. The table also include the F-stat, adjusted R-squared, and number of observations. The dependent variables shown in the left column of each panel and are labeled: *Put (StrGn)* which is the put option, $\mathring{p}_{j,k}(s)$, for the structural generalization; *Put (RdFrm)* which is the put option, $\mathring{p}_{j,k}(s)$, for the reduced form; *Liq (RdFrm)* which is the liquidity proportion, $\mathring{l}_{j,k}(s)$, for the reduced form; *S(RdFrm)*which is the shadow liquidity premia, $\bar{\mathbb{S}}_{j,k}(t)$, for the reduced form. The two sets of independent variables are (i.) the market portfolio (Mkt-Rf); and (ii.) the Fama and French (1993) 3-factor model consisting of the market portfolio (Mkt-Rf), the small minus big index (SMB), and the high minus low index (HML). Panel A and B consider the entire sample period varying by independent variable (i) in Panel A and independent variables (ii) in Panel B. Panel C and D consider the crisis period varying by independent variable (i) in Panel C and independent variables (ii) in Panel D. Panel E and F consider the recovery period varying by independent variable (i) in Panel E and independent variables (ii) in Panel F. The form of the ICAPM is $R_t^p - R_t^1 = \alpha + \sum_{i=2}^{M} \beta_{pi}(R_t^i - r_t) + \varepsilon_t$ with R_t^p the p portfolio's return over $[t, t+1]$, R_t^i is the return over $[t, t+1]$ on a portfolio perfectly correlated to the i^{th} systematic risk component, and β_{pi} is the beta of portfolio p to the i^{th} risk component portfolio for M possible risk factors. A positive and significant α implies that these trading strategies generate abnormal returns. The entire sample period is November 2007 to June 2015. The crisis period is November 2007 to June 2010. The recovery period is July 2010 to June 2015. ***/**/* indicate significance at the 1%, 5% and 10% level.

R_t^p the p portfolio's return over $[t, t+1]$, R_t^i is the return over $[t, t+1]$ on a portfolio perfectly correlated to the i^{th} systematic risk component, and β_{pi} is the beta of portfolio p to the i^{th} risk component portfolio. For M possible risk factors the final regression model to test for abnormal returns is given by

$$R_t^p - R_t^1 = \alpha + \sum_{i=2}^{M} \beta_{pi}(R_t^i - r_t) + \varepsilon_t. \qquad (36)$$

A positive and significant α implies that these trading strategies generate abnormal returns. The market portfolio is a portfolio consisting of all assets in the market where the weights of the assets are proportional to the size of the assets in the market. The empirical returns for the market portfolio used in this study were secured from the portfolio constructed by Professor Ken French which includes all New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ firms.[40]The long-only CMBX portfolio is comprised of all CMBX classes weighted by the principal balance outstanding of each of the classes.

To estimate this model, I use the following specifications of Eq. (36): (i) market portfolio, and (ii) the Fama-French 3-factor model[41] consisting of the market portfolio, the SMB index (small minus big), and the HML index (high minus low). For the portfolio R_t^1 I use a long-only sector portfolio consisting of all CMBX bonds weighted by the representation of each of the tranches within the CMBX Series. The returns for the trading strategy net of the risk-free rate and net of the long only CMBX portfolio are regressed against the explanatory variables.

The panels in Fig. 13 summarize the results for the ICAPM procedure. Fig. 13 is split into 6 panels (A through F) with four ICAPM regression results within each panel, one corresponding to each portfolio trading strategy. I only test the structural generalization with the put-option risk measure (Trading Strategy 1); the reduced form approach is tested with to all three trading strategies (put, liquidity availability proportion, and shadow liquidity). The four dependent variables found in each panel that correspond to different risk measure are: The put option, $\mathring{p}_{j,k}(s)$ for the structural generalization, labeled "*Put (StrGn)*" for Trading Strategy 1; the put option, $\mathring{p}_{j,k}(s)$, for the reduced form, labeled "*Put (RdFrm)*" for Trading Strategy 1; the liquidity proportion, $\mathring{l}_{j,k}(s)$, using the reduced form, labeled as "*Liq (RdFrm)*" for Trading Strategy 2; and the shadow liquidity premia, $\bar{\mathbb{S}}_{j,k}(t)$, for the reduced form, labeled as "*S (RdFrm)*" for Trading Strategy 3.

8.5.1. Results for the market portfolio

In Fig. 13 I present results for the ICAPM with the Market Portfolio (Mkt-Rf) as the sole explanatory variable and vary across four different dependent variables. In Fig. 13, Panel A we see that the regression with *Put (StrGn)* as the dependent variable is significant at the 5% level as measured by the F-stat. We observe also that the independent variable of the Market Portfolio (Mkt-Rf) exhibits a statistically significant t-stat. Coupled with the negative sign and statistical insignificance of the constant α we conclude that there is no support for abnormal returns for the portfolio formed with the put as captured by the structural generalization model.

Immediately following, within the same panel, I show the results for the regression with *Put (RdFrm)* as the dependent vari-

[40] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[41] As introduced by Fama and French (1993).

able. For this portfolio, the overall regression is insignificant at the 5% level as measured by the F-stat. The t-stat for the Market Portfolio is insignificantly different from zero at the 5% level. Although the sign for α is positive, it is insignificantly different from zero. As such, there is no conclusive support for abnormal returns for the portfolio formed with the put, $\mathring{p}_{j,k}(s)$, as captured by the reduced form model.

Next, within the same panel, we consider the results for the regression with *Liq (RdFrm)* as the dependent variable. This regression overall is significant at the 1% level as indicated by the F-stat. The t-stat for the Market Portfolio is also significant at the 1% level. Interestingly, we see a positive and significant α but only at the 10% level. However, this indication of abnormal returns is only found within a regression that is statistically significant and one which also exhibits a highly significant explanatory variable of the Market Portfolio. As such, the abnormal return corresponding to the positive and significant α found in the portfolio formed with the liquidity proportion, $\mathring{l}_{j,k}(s)$, is nevertheless insufficient to reject CMBS market efficiency.

Finally, the last regression within Panel A shows *S (RdFrm)* as the dependent variable. The regression overall is highly significant at the 1% level as indicated by the F-stat. The Market Portfolio carries a negative sign and is also significant at the 1% level. This is not surprising for *S (RdFrm)* given its direct interaction between market spreads and the risk neutral risk measure informing that portfolio. Although the sign for α is positive, it is insignificantly different from zero. As such, there is no conclusive support for abnormal returns for the portfolio formed with the shadow liquidity measure, $\bar{\mathbb{S}}_{j,k}(t)$.

8.5.2. Results for the Fama-French 3-factor model

In Fig. 13, Panel B I present the results for the ICAPM with the Fama French 3-factor model with each of the Market Portfolio, the small minus big (SMB) and the high minus low (HML) as the set of three explanatory variables and vary across four different dependent variables. In this set of results I observe a general repetition of the patterns exhibited in the previous results reported in Fig. 13, Panel A. Focusing on *Put (RdFrm)* I see that the regression for the Fama-French 3-factor model overall is statistically insignificant. None of the predictive variables are significant. Although the sign for α is positive, it is statistically insignificant. As in the earlier results, there is no conclusive support for abnormal returns for the portfolio formed with the put, $\mathring{p}_{j,k}(s)$, as captured by the reduced form model.

This contrasts (as before), with the *Liq (RdFrm)* portfolio which, again, exhibits significance overall for the regression at the 1% level and significance in the predictive variables for the Market Portfolio with a negative sign at 1%, SMB with a negative sign at 5%, and positive α significantly different from zero at the 10% level. However, as before, this indication of abnormal returns is only found within a regression that is statistically significant and one which also exhibits a highly significant explanatory variable of the Market Portfolio (Mkt-Rf). As such, as in the earlier results, the abnormal return corresponding to the positive and significant α found in the portfolio formed with the liquidity proportion, $\mathring{l}_{j,k}(s)$, is nevertheless insufficient to reject CMBS market efficiency with similar results for the shadow liquidity measure, $\bar{\mathbb{S}}_{j,k}(t)$.

8.5.3. Results for split sample

To study the impact of the crisis and recovery events on CMBS market efficiency, I split my sample into two sub-periods: the crisis (period ending June 2010) and the recovery (beginning July 2010) as previously discussed. Fig. 13, panels C and D summarizes the crisis regressions while and Fig. 13, panels E and F summarize the recovery regressions.

With respect to the crisis-only (in Fig. 13, panels C and D) there is no indication of abnormal performance (α) across any of the strategies. While the signs of α are positive for all the reduced form portfolios and negative for the structural generalization, they are categorically insignificantly different from zero. The *Put (RdFrm)* continues to exhibit no significance for the regressions overall and no significance amongst the explanatory variables nor α. The signs for all the reduced form portfolios correspond to intuition. Interestingly, while the during the crisis the regression for the *Liq (RdFrm)* portfolio again exhibits significance overall at the 1% level as seen across the entire sample period (in panels A and B), the constant α is insignificantly different from zero (in panels C and D) during the crisis which contrasts with the entire sample period results previously discussed.

From the reporting of the regression results restricted to the recovery-only (in Fig. 13, panels E and F) we see some differences between the two sub-periods of the crisis and recovery. Although, the signs for α are positive and insignificant in the recovery, the signs for the explanatory variables within the *Put (StrGn)* portfolios change between the crisis and recovery periods. Additionally, the significance in *S (RdFrm)* for the Market Portfolio at the 1% vanishes during the recovery with insignificance for each of the explanatory variables in both the Market and Fama-French 3-factor regression examples. While the *Put (RdFrm)* portfolio exhibited statistical consistency across the crisis and the recovery, the statistical profile of the Liq *(RdFrm)* portfolio changes somewhat, with α insignificantly different from zero during the crisis but α significant at the 5% level during the recovery implying abnormal returns. Nevertheless, due to the significance of the explanatory variables and the regression overall for the Liq *(RdFrm)* portfolios, I am still unable to reject CMBS market efficiency.

9. Alternative approaches and expansions

9.1. Numeraire discussion

A different approach to detecting abnormal returns in portfolios has been seen in the literature through the normalization of asset returns with the numeraire portfolio first introduced by Long (1990). Briefly, following Carr and Yu (2012), the numeraire portfolio is a self-financing portfolio whose price is always positive. If any set of assets is arbitrage free then there always exists a numeraire portfolio comprising these assets. Platen (2005) suggests that *any* well diversified benchmark portfolio (aka the ‘growth optimal portfolio’ or ‘GOP’) which is combination of the market portfolio and the savings account with expected returns equal to zero could provide insights into abnormal returns of specific assets in a real world setting. This work was empirically tested by West (2012) who uses the All Ordinaries Index comprising 99% of the market capitalization of the Australian Market. In the context of my paper, two candidates for the numeraire portfolio would include the long-only CMBX portfolio and the Market Portfolio combined with the savings account, in a multivariate diffusion setting. As noted by Carr and Yu (2012) however, in order to correctly identify the unique numeraire portfolio one must first determine that it is positive, self financing and stationary.

Although I don't adopt the formalism of the numeraire analysis discussed above, I do provide summary benchmarking statistics based upon the actual returns of the portfolios. As stated the reduced form long/short portfolios constructed using the trading navigation measures of $\mathring{p}$ *and* $\mathring{l}$ independent of market prices both substantially outperform the Market Portfolio and the Long-Only CMBS cumulatively across the entire sample as well as severally in the split sample of the crisis and the recovery as previously discussed in Fig. 1. Interestingly there is clear indication of sensitivity to changing market conditions with respect to the pricing of such risks *in advance* of the substantial declines in the Market Portfolio and the CMBS Long Only Portfolio reaching troughs in mid-2009. The portfolio returns benefit from use of both long and short positions, which is absent from the two benchmark portfolios (Market and CMBS). It is also the case, however, that during the recovery in a period of relatively muted volatility compared with the crisis, the long/short portfolios informed by the trading navigation measures of both $\mathring{p}$ *and* $\mathring{l}$ also outperform.

9.2. Preliminary credit spread puzzle analysis

Up to this point we have seen differences in navigation precision from using the pure model values of $\mathring{p}$ *and* $\mathring{l}$ that contrast with the use of $\bar{\mathbb{S}}$. The general reasoning thus far has been that if the risks of a market or sector have been incorrectly specified by market participants, then the pricing in the market (as may be observed in spreads) will sully the accuracy of risk assessment presented in pure model measures. The results of the trading strategies above support this perspective with respect to CMBS. But is there further support for this perspective to found in methods applied in the recent credit spread puzzle literature?

9.2.1. Short discussion of Gilchrist, Zakrajšek (2012)

One area that has been recently considered of interest to the credit spread puzzle area of research is the validation of the meaningfulness of risk measures with respect to the future values of macroeconomic indicators. In particular, Gilchrist, Zakrajšek (2012) test the information content of their excess bond premium (EBP) with respect to a number of macroeconomic indicators. Briefly, they first construct a credit quality index, or "GZ credit spread", S_t^{GZ}, from the Corporate bond risk premia over the risk free rate, $S_{it}[k]$, of the form $S_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k S_{it}[k]$ which they state is "arithmetic average of credit spreads on outstanding bonds in any given month". From there, they seek to explain statistically using OLS the observed Corporate bond risk premia in terms of a firm specific expected default estimate DFT_{it} determined using the distance to default framework of Merton (1974) and a vector of explanatory variables,[42] $\mathbf{Z}_{it}[k]$, taking the form in their Equation 3 of $\ln S_{it}[k] = \beta DFT_{it} + \gamma'\mathbf{Z}_{it}[k] + \epsilon_{it}[k]$ from which they are then able to calculate the predicted level of spread for the kth bond, of firm i at time t as $\hat{S}_{it}[k] = \exp[\hat{\beta} DFT_{it} + \hat{\gamma}'\mathbf{Z}_{it}[k] + \frac{\hat{\sigma}^2}{2}]$. This then allows them to determine[43] the excess bond premium as $EBP_t = S_t^{GZ} - \hat{S}_t^{GZ}$. The interpretation of their EBP_t is the amount of risk premia above the statistically predicted risk premia based on the default estimate and the independent explanatory variables specific to the bond. This has a similar interpretive meaning to my shadow liquidity measure, $\bar{\mathbb{S}}_{j,k}(t) = \mathbb{S}_{j,k}(t) - \mathring{\mathbb{S}}_{j,k}(t)$ noted previously in Eq. (24), which represents the baseline difference between the observed spread in the market and the theoretical spread, where the theoretical spread reflects sensitivities in bond pricing converging to the hybrid price as described in Eq. (20).

Despite similarities, however, there are some important distinctions. *First*, in the construction of EBP_t Gilchrist, Zakrajšek (2012) statistically relate the default estimator DFT_{it} to the vector of bond level characteristics $\mathbf{Z}_{it}[k]$. In contrast, in my construction, no such statistical relationship is estimated. Instead a direct relationship is constructed to form a composition of risks from implementation of the theory to identify default and rate risk components through differencing of simulation results and then interacting such priced values with characteristics such as duration. In this sense, my study and Gilchrist, Zakrajšek (2012) share a similar goal, but the method is different. My simulation which captures a statistically robust economy and cashflow specification for the loans and bonds in my sample address many of the idiosyncracies sought to be captured in the vector $\mathbf{Z}_{it}[k]$.

Second, because my risk measures $\mathring{\mathbb{S}}_{j,k}(t)$ and $\bar{\mathbb{S}}_{j,k}(t)$ are informed by the interaction value $\triangle m_{j,\,k}(t)$, either risk measure may take on value greater than, less than, or equal to zero. The assumption is that there exists a *shadow liquidity value*, informed by theoretical and market constructs. If the total theoretical risk premia $\mathring{\mathbb{S}}_{j,k}(t)$ implied by risk neutral prices exceeds the observed risk premia $\mathbb{S}_{j,k}(t)$ implied by market prices then, there will be a condition of excess liquidity. Alternatively, liquidity can be subsumed within observed risk premia, implying excess liquidity equal to zero. In contrast it would appear that $EBP_t > 0$. We know from Carr et al., (2012) and Jarrow (2007) that excessive risk premia which have the effect of depressing market prices such that fair value is greater than the market price presents a relative buying opportunity. Similarly, insufficient risk premia corresponding to market prices such that they exceed fair value, present a relative selling opportunity. Given that the put option and liquidity availability measures are constructed from the fair value price, they too appear to have been effective in describing embedded risks and assessing relative buying/selling opportunities in the CMBS sector. The spread interaction risk measure of shadow liquidity, informed by fair value is also effective in this endeavor, though less so than the pure model values.

9.2.2. Testing the forward guidance of risk measure information content and US unemployment

To test whether this distinction between pure model and market/model interaction persists, I turn again to the methods employed by Gilchrist, Zakrajšek (2012) who test whether movements in EBP_t provide independent information about future economic activity. In their study they do this by using a forecasting specification using OLS for macroeconomic indicators, $\nabla^h Y_{t+h}$, regressed on lag lengths of such indicators determined by the Akaike Information Criteria (AIC), and also include independent variables of the term spread (aka the 'treasury slope'), the Fed funds rate, and a credit spread component. The credit spread component are identified as the independent variables of the GZ spreads and EBP_t.[44] The results in their *Table 6* indicate significant explanatory power for both the GZ spreads and EBP_t for several economic indicators including the civilian unemployment rate (UER). Motivated by their results and my findings discussed in the trading strategy section of this paper, I in turn perform a similar analysis to test the forward guidance capabilities of my risk measures with respect to unemployment in the US.

I first test for the time series stationarity of each of my risk measures: $\mathring{p}$, $\mathring{l}$, and $\bar{\mathbb{S}}$ and the US unemployment rate (UER) obtained from the Bureau of Labor Statistics.[45] Over the sample period each of the put, $\mathring{p}$, and liquidity proportion,$\mathring{l}$, time series are stationary for each of the credit rating categories as determined with Dickey-Fuller unit root tests. The risk measure time series for the put and liquidity proportion are constructed as arithmetic averages for a given credit rating, k, across J CMBX Series, for a given time, t. The indexed put risk measure is given by

$$\mathring{p}_k(t) = \frac{1}{J}\sum_j \mathring{p}_{j,k}(t) \tag{37}$$

and the indexed the liquidity proportion is given by

$$\mathring{l}_k(t) = \frac{1}{J}\sum_j \mathring{l}_{j,k}(t) \tag{38}$$

[42] This vector includes things like the bond's duration and coupon, and the issuer's associated NAIC industry code, among others.

[43] $\hat{S}_t^{GZ}$ is the indexed predicted component of the GZ credit spreads given by $\hat{S}_t^{GZ} = \frac{1}{N_t}\sum_i\sum_k \hat{S}_{it}[k]$.

[44] See Equation 2 in Gilchrist, Zakrajšek (2012).

[45] See http://data.bls.gov/timeseries/LNS14000000.

Although each of $\mathring{p}_k(t)$ and $\mathring{p}_k(t)$ are stationary, in contrast, the shadow liquidity premia, $\bar{\mathbb{S}}$ and UER time series are not stationary. Therefore, I must take first differences for each of $\bar{\mathbb{S}}$ and UER to construct corresponding stationary time series. The corresponding indexed difference time series for the shadow liquidity premia is then given by

$$\Delta\bar{\mathbb{S}}_k(t) = \frac{1}{J}\sum_j \Delta\bar{\mathbb{S}}_{j,k}(t) \tag{39}$$

where the first difference in the shadow liquidity premia is given by $\Delta\bar{\mathbb{S}}_{j,k}(t) = \bar{\mathbb{S}}_{j,k}(t) - \bar{\mathbb{S}}_{j,k}(t-1)$. The first difference in the US unemployment rate is given by $\Delta UER(t) = UER(t) - UER(t-1)$. From rating-specific values, I then compute the index risk measure across all K ratings such that the time series of the total put index for all ratings is given by

$$\mathring{p}(t) = \frac{1}{K}\sum_k \mathring{p}_k(t) \tag{40}$$

the liquidity index across all K ratings is given by

$$\mathring{l}(t) = \frac{1}{K}\sum_k \mathring{l}_k(t) \tag{41}$$

and the first differenced shadow liquidity premium index (to account for stationarity) across all K ratings is given by

$$\Delta\bar{\mathbb{S}}(t) = \frac{1}{K}\sum_k \Delta\bar{\mathbb{S}}_k(t) \tag{42}$$

Since I want to test the value of independent information embedded in my risk measures concerning future economic indicators such as UER, I need to lead the comparative UER quarterly. For each of $Q = 1, \ldots, 8$ forward quarters with a monthly time index, t, I express the value for the US unemployment rate Q quarters forward as $UER_Q(t) = UER(t + Q \times 3)$, with the corresponding first differenced US unemployment rate then expressed as

$$\Delta UER_Q(t) = UER_Q(t) - UER_Q(t-1) \tag{43}$$

From here I construct a basic VAR with an n period lag that includes as an independent exogenous explanatory variable equal to one of the indexed risk measures defined above in Eqs. (37), (38), or (39). The expression for my VAR is

$$\Delta UER_Q(t) = \alpha + \beta\Delta UER_Q(t-n) + \gamma RM_i(t) + \epsilon \tag{44}$$

with $RM_i(t)$ the time t value of the i-th exogneous risk measure (namely, $\mathring{p}$, $\mathring{l}$, and $\bar{\mathbb{S}}$). I assume a value of $n = 1$ for ΔUER_Q instead of allowing n lags to be determined by AIC for a few reasons. *First*, I have less than 100 observations and adding additional lags would compress the number of observations in an unreliable way. *Second*, AIC's may indicate using from 1 to as many as 4 period lags, and would introduce several new layers of complexity. These include: differences in AIC's across forward guidance periods for the same risk measure, differences across risk measures, and discussions as to whether for $n > 1$ a single lagged independent variable versus a vector of lagged unemployment variables was more appropriate. *Finally*, many of the VARs have $n = 1$ lag determined with AIC. Performing checks of many other VARs allowing AIC to select the lag yielded results that were essentially the same as my assumed value of $n = 1$. Since I only want to determine if my risk measures are statistically significant and do not seek to fully explain $\Delta UER_Q(t)$, my choice of $n = 1$ is reasonable. This resonableness is validated in the confirmed stability of each of my VARs determined with Eigenvalue stability tests. As such, my VAR tests isolate the marginal contributions of the risk measures in providing forward guidance as intended.

9.2.3. Results of macroeconomic testing of risk measures for US unemployment

I calculate the VAR in Eq. (44) for $Q = 1, \ldots, 8$ forward quarters for each of the across ratings risk measures, $\mathring{p}(t)$, $\mathring{l}(t)$, and $\Delta\bar{\mathbb{S}}(t)$ as well as for the rating-specific measures $\mathring{p}_k(t)$, $\mathring{l}_k(t)$ and $\Delta\bar{\mathbb{S}}_k(t)$ for $k = AAA$ and $BBB-$. In all, I test $i = 9$ risk measures, RM_i, using the VAR expressed in Eq. (44). The results of the VARs are reported in Fig. 14, Panels A, B, and C. Each panel is divided into 3 parts reporting: (i.) the put, $\mathring{p}$; (ii.) the liquidity proportion, $\mathring{l}$; and (iii.) the shadow liquidity measure, $\bar{\mathbb{S}}$. Fig. 14, Panel A captures the results for the three risk measures across credit ratings, while Fig. 14, Panel B and Fig. 14, Panel C each capture the results for the three risk measures for each of the AAA credit rating and BBB- credit rating, respectively. The values of interest are the R-squared for each VAR, the coefficient for the exogenous risk measure, and its significance. There are four important results that can be gleaned from this table.

First, many of my risk measures demonstrate statistical significance at the 1% and 5% level in providing forward guidance to US Unemployment. This is observed in many instances across the 'all' credit ratings category in Fig. 14, Panel A, and in the credit rating specific measures in Fig. 14, Panel B and Fig. 14, Panel C. The relatively low R-squareds for those VARs in which the risk measures demonstrate statistical significance is not of concern considering that no other factors other than my risk measures and the one period lagged value are included as explanatory variables. As such, the primary inquiry of determining whether the risk measures are statistically significant measures of forward guidance for macroeconomic variables is answered in the affirmative. The qualification that it is but one macroeconomic variable is noted and expansions to other analysis in the future can be performed in a broader treatment.

Second, the model measures perform better than market/model risk measures. The earlier observations of distinctions in trading strategy results between model only versus market/model interacted risk values holds true in the testing of the ability of my risk measures sensitivity to changes in future economic indicators. In Fig. 14, Panel A we see very good forward guidance capability for all quarters $Q = 1, \ldots, 5$ at the 1% and 5% significance levels for both the put (i.) and the liquidity proportion (ii.) which are both pure model values. The negative signs are intuitive indicating higher put valuation and greater liquidity availability associated with lower unemployment. In contrast, within the same panel, we observe essentially no forward guidance capability for the excess liquidity spread (iii.) with the sole exception of statistically significant forward guidance at the 5% significance level forward $Q = 7$ quarters. In that instance, the positive sign may be interpreted as the greater/lower difference between theoretical and observed market spreads occurs in periods of higher/lower unemployment. The schism between the pure model compared with market/model measures is consistent with the earlier results from the trading strategies and consistent across the credit rating specifications in Fig. 14, Panel B and Fig. 14, Panel C, for AAA and BBB- credit ratings, respectively.

Third, the interaction of the structural attributes of the securities and the formation of the risk measures provides more subtle information about unemployment going forward. Specifically, in the senior/subordinated tranched capital structure implemented for all CMBX in my sample, the lower rated credit tranches will be first in line to experience losses. Given this, one would expect that the put option, for relatively more credit protected AAA rated securities, would give little indication as to changes in the economy compared with the more credit exposed BBB- rated securities. This is exactly what we observe. In the Fig. 14, Panel B, we see no statistical significance for the AAA rated put option while, just below in Fig. 14, Panel C, we see statistical significance for the

Panel A: Risk Measures across all credit ratings									
	(i.) Average Put (all credits)			(ii.) Average Liquidity % (all credits)			(iii.) Excess Liquidity Spread (all credits)		
UE forward	R-sq	coeff	p-value	R-sq	coeff	p-value	R-sq	coeff	p-value
difUE_+1q	0.1950	-0.0028**	0.0270	0.2100	-0.3410***	0.0100	0.1606	0.0001	0.3030
difUE_+2q	0.2129	-0.0028**	0.0220	0.2273	-0.3460***	0.0090	0.1676	0.0001	0.5760
difUE_+3q	0.2258	-0.0032***	0.0070	0.2368	-0.3730***	0.0030	0.1605	-0.0001	0.5240
difUE_+4q	0.1812	-0.0031***	0.0100	0.1971	-0.3768***	0.0040	0.1265	-0.0001	0.2750
difUE_+5q	0.0607	-0.0022**	0.0500	0.0770	-0.2884**	0.0220	0.0131	0.0000	0.9660
difUE_+6q	0.0203	-0.0012	0.2520	0.0295	-0.1580	0.1780	0.0055	0.0000	0.9500
difUE_+7q	0.0141	0.0005	0.6680	0.0116	0.0103	0.9350	0.0842	0.0002**	0.0180
difUE_+8q	0.0270	0.0003	0.2400	0.0262	-0.0032	0.9800	0.0502	0.0001	0.1930
Panel B: Risk Measures for AAA credit rating									
	(i.) Average Put (AAA credits)			(ii.) Average Liquidity % (AAA credits)			(iii.) Excess Liquidity Spread (AAA credits)		
UE forward	R-sq	coeff	p-value	R-sq	coeff	p-value	R-sq	coeff	p-value
difUE_+1q	0.1521	-0.0028	0.6840	0.1876	-1.3181**	0.0450	0.1772	0.0008	0.0910
difUE_+2q	0.1723	-0.0058	0.3750	0.2127	-1.4146**	0.0230	0.1648	0.0001	0.8900
difUE_+3q	0.1713	-0.0076	0.2240	0.2067	-1.3243**	0.0220	0.1693	-0.0005	0.2580
difUE_+4q	0.1269	-0.0069	0.2690	0.1611	-1.2562**	0.0340	0.1206	-0.0004	0.4200
difUE_+5q	0.0228	-0.0050	0.3850	0.0528	-0.9627*	0.0740	0.0426	-0.0006	0.1260
difUE_+6q	0.0055	0.0004	0.9330	0.0104	-0.3015	0.5450	0.0700	0.0008**	0.0240
difUE_+7q	0.0369	0.0072	0.1740	0.0156	0.2793	0.5870	0.0382	0.0005	0.1630
difUE_+8q	0.0331	0.0036	0.4880	0.0270	0.1215	0.8110	0.0413	0.0004	0.3050
Panel C: Risk Measures for BBB- credit rating									
	(i.) Average Put (BBB- credits)			(ii.) Average Liquidity % (BBB- credits)			(iii.) Excess Liquidity Spread (BBB- credits)		
UE forward	R-sq	coeff	p-value	R-sq	coeff	p-value	R-sq	coeff	p-value
difUE_+1q	0.1889	-0.0046**	0.0410	0.1872	-0.2852**	0.0460	0.1508	0.0000	0.8580
difUE_+2q	0.2071	-0.0051**	0.0330	0.2030	-0.3047**	0.0430	0.1664	0.0000	0.6660
difUE_+3q	0.2217	-0.0062***	0.0090	0.2098	-0.3665**	0.0190	0.1564	0.0000	0.9690
difUE_+4q	0.1947	-0.0070**	0.0050	0.1830	-0.4345***	0.0090	0.1352	0.0001	0.1570
difUE_+5q	0.0573	-0.0046**	0.0590	0.0641	-0.3532**	0.0420	0.0141	-0.0000	0.7770
difUE_+6q	0.0402	-0.0036	0.1040	0.0408	-0.2765	0.1010	0.0100	-0.0000	0.5600
difUE_+7q	0.0182	0.0016	0.4870	0.0125	0.0507	0.7890	0.0869	0.0002**	0.0160
difUE_+8q	0.0268	0.0005	0.8380	0.0262	-0.008	0.9670	0.0429	0.0001	0.2800

Fig. 14. Vector autoregressions for risk measures. This table shows the significance of the risk measures in the vector autoregressions (VAR) of the form $\Delta UER_Q(t) = \alpha + \beta \Delta UER_Q(t-n) + \gamma RM_i(t) + \epsilon$ with $RM_i(t)$ the time t value of the i-th exogeneous risk measure (namely, $\mathring{p}$, $\mathring{l}$, and $\mathring{\mathbb{S}}$). I assume a value of $n = 1$ for ΔUER_Q. difUE+#q is the dependent variable of the change in the unemployment lead by # quarters. The statistics of the coefficient and its p-value for each of the exogenous risk measures as well as the R-squared for the VAR are captured in each of the subpanels. From left to right, the first subpanel (i) shows the VAR statistics for the put option $\mathring{p}$; the second subpanel (ii) shows the VAR statistics for the liquidity proportion $\mathring{l}$; and the third subpanel (iii) shows the VAR statistics for the shadow liqudity premia $\mathring{\mathbb{S}}$. Panel A uses the average form of each of the risk measures taken across all ratings. Panel B uses the risk measures averaged within the AAA rating class. Panel C uses the risk measures averaged within the BBB-minus credit rating. The entire sample period is November 2007 to June 2015. ***/**/* indicate significance at the 1%, 5% and 10% level.

BBB- put option for all quarters $Q = 1, \ldots, 5$. The conclusion to be drawn from this observation is that while the put option may be the best measure for discerning trading opportunities across the capital structure, from a pure economic forecasting perspective, the senior subordinated capital structure necessarily obfuscates the macroeconomic forward guidance capability of senior tranches.

Finally, *fourth*, unlike the put option, the liquidity proportion performs extremely well for both AAA and BBB- securities for all quarters $Q = 1, \ldots, 5$ as seen in Fig. 14, Panel B and Fig. 14, Panel C, respectively. Recall from Eq. (17) that the construction of the liquidity proportion necessarily normalizes to 1 for total risk. This construction was intended to build intuition about the relative risks associated with the securities. It would appear that one by-product of this normalization is that it enhances the forward guidance on unemployment in a manner which is not the case in the price bound variable of the put option. As such, while the liquidity proportion performed slightly worse in the automated trading strategy than the portfolios informed by the put option (cumulative returns of 103% versus 109%, respectively), the proportional liquidity measure has the dual benefit of intuition building and solid forward guidance performance of one of the most widely watched macroeconomic indicators of the health of the US economy.

10. Summary

This paper focuses empirically on the composition of CMBS risk and makes a contribution to both the asset pricing literature in CMBS and, more broadly, to the credit spread puzzle debate through the introduction and testing of several innovative risk measures. While a singular focus on a specific product type is typical in the literature as previously noted, my paper's scope nevertheless extends beyond CMBS. The risk measures in my study are applicable to all spread products.

It is important to recognize that the trading results are a function of the compositional risk measures. These risk measures which I introduce also provide insights into thinking about risk in general, beyond CMBS, entering the fray of the 'credit spread puzzle' debate. By definition, all credit sensitive securities have observed credit spreads above risk free rates. Subject to making adjustments for risks of prepayments and government guarantees, the approach to partitioning of risks introduced in my paper can be applied to all fixed income spread products. As such, my quantification of risks and disclosure of their proportional representation within CMBS pricing is general enough for broader use beyond CMBS. My study thus also contributes to the more general discussion on credit spread composition in the literature.

Although I do not apply my risk composition to the entire spread product subset of the US fixed income universe this in fact could be done with minor adjustments and data. According to SIFMA, spread products in US fixed income represent, on average, 27% of the total fixed income universe[46]. At roughly \$10 trillion, this set of investments represent an important area of capital markets of which CMBS itself represents between 6% and 10% of the overall universe of spread products.

The testing of the risk measures I introduce in the trading strategy section accomplish two goals. *First*, the results indicate stronger performance in the disclosure of the put under the reduced form model compared with the structural generalization which provides empirical support for the claims of Jarrow and Protter (2004), and others involved in the structural versus reduced form debate. *Second*, across the compositional risk measures there are substantial distinctions in the precision of risk evaluation.

From the ICAPM tests of the automated trading strategies, the inconclusive nature of the results with respect to the efficiency of the CMBS sector is indicated by the insignificance of the $\alpha's$ across the entire sample and in both sub-periods for Trading Strategies 1 and 3 as well as in the changing behavior of the liquidity availability in Trading Strategy 2 across the crisis and recovery periods. This could be due to the fact that there are less than 100 trading intervals in this study, making the sampling errors too large to indicate significance. Although I cannot reject the hypothesis that the CMBS market is efficiently priced, the results are consistently positive across the worst financial crisis since the Great Depression and during the following recovery and show noticeable differentiation in the results between model approaches and across compositional risk measures.

To further test the predictive value of the information content contained in my risk measures, I turn to the credit spread puzzle literature focusing on the work of Gilchrist, Zakrajšek (2012). They disclose an excess bond premium (EBP) value which captures the portion of credit spreads not explained by default probabilities. In testing, they find EBP to be a predictor of the business cycle. In my study, I identify the shadow liquidity premia, $\bar{\mathbb{S}}(t)$, which is somewhat more restrictive than EBP. My results from the VAR regressing unemployment against its one period lag and each of the aggregated risk measures $\mathring{p}(t)$, $\mathring{l}(t)$, and $\Delta\bar{\mathbb{S}}(t)$ as well as for the rating-specific measures $\mathring{p}_k(t)$, $\mathring{l}_k(t)$ and $\Delta\bar{\mathbb{S}}_k(t)$ for $k = AAA$ and $BBB-$ are in line with the earlier findings in the literature. I find important new distinctions, including contrasts across ratings categories and across risk measures. Perhaps due to the restrictiveness of the construction of my shadow liquidity measure, I find little evidence of forward guidance. In contrast, I find statistically significant forward guidance capabilities from each of the put and the liquidity proportion measures. My findings suggest that guidance determined from purely model driven risk is more insightful than guidance informed with spread interaction. An additional observation supporting the use of the model risk measures in providing forward guidance for US unemployment can be found in the evaluation of the information content of the credit slope (Baa-Aaa). Adjusting for stationarity by taking first differences and then substituting the differenced credit slope for RM_i in the VAR expressed in Eq. (44) I observe statistical significance only for the $\Delta UER_{Q=4}$ with a 10% confidence level.[47] No other statistically significant forward guidance for US unemployment was observed for the credit slope for any forward quarter. As such, the trade navigation and the business cycle forward guidance provided with my risk compositions appears to provide good insights compared with the market's expression of risk.

Of the risk measures disclosed, the liquidity availability proportion, $\mathring{l}(t)$, seems most interesting. One interpretation of this measure is that it is a barometer of investor fear. Liquidity availability is a by-product of excessive risk premia where what is meant by *excessive* is risk premia in excess of the risk of default/loss as determined by the model approach in risk neutral pricing. When we observe large liquidity availability it is thus unjustified from the perspective of the simulation model. In contrast, when the liquidity availability is compressed or even zero, it indicates justified fear with default and loss risk imminent. This is suggested initially in the theoretical compositions independent of market prices and then further supported through the discussion on interacting risk neutral values with market observed risk premia in both trade strategy testing as well as testing the forward guidance capability of the information content of these measures with respect to the unemployment.

These observations seem especially relevant given the growing interest in the literature and practice over the impact of risk estimation on financial institutions and influence of such estimates on liquidity. Inquiries into the role of Dodd-Frank and risk retention in the academic literature is increasing. As the work of Pavlov and Wachter (2011) indicates, one of the unifying features between lending and asset markets is that asset-backed loans are mispriced and that underpricing of default risk appears to exacerbate asset market crashes as evidenced by the recent financial crisis. If default risk is incorrectly evaluated by the market and further if there is a relationship between the mispricing of default risk and the assessment of liquidity availability, then policy restrictions placed on liquidity providers may be misplaced. This seems to be confirmed in part from a market microstructure perspective in the recent work of Bao et al. (2016) which concludes that the impact of the Volcker Rule on liquidity at dealer firms for Corporate bonds has been overly restrictive and may have decreased liquidity in Corporate bonds at times when it was most needed.

One area of future research related the compositional risk profiles introduced in this study would be to consider the use of the Aitchison geometry which is often used in mining research to discern the statistical significance of compositional data. Additionally, one could also consider further testing and forecasting methods employed in the credit spread puzzle literature with multiple factors and test the impulse response functions and to perhaps apply those techniques in the market/credit risk debate area of the literature. Finally, considering the specific economic meaning and differences amongst macroeconomic variables compared with risk measures also may provide insights as one risk measure may not fit all economic variables. These expansions lie outside of the scope of this paper and are left to future research. The disclosing of the composition of embedded risks facing CMBS investors presented in this study thus carry promise for future academic research in CMBS and other fixed income spread products.

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[46] Fixed income issuance overall has increased from \$30 trillion to \$40 trillion from 2006 to 2015 with spread products maintaining a fairly steady outstanding amount of \$10 trillion to \$11 trillion. See http://www.sifma.org/research/statistics.aspx.

[47] The VAR had an R-squared of 0.15, a coefficient of 0.0022 and a corresponding *p*-value of 0.0547.

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Appendix A

A.1. Bond cash flow allocation

For the promised cashflows, let the Trust Principal of the jth CMBX Series be defined for N-loans as $A_j(t) = \sum_{i=1}^{N} a_{j,i}(t)$ with $a_{j,\,i}(t)$ representing the ith loan's promised principal payment due at time t for the jth CMBX Series. The corresponding Trust Interest is defined for N-loans as $C_j(t) = \sum_{i=1}^{N} c_{j,i}(t)$ with $c_{j,\,i}(t)$ representing the ith loan's promised interest payment due at time t for the jth CMBX Series. At the end of each monthly payment period there is an outstanding principal balance for each of the loans, trust, and bonds reflecting monthly payments. The allocation of principal at the beginning of each monthly payment period, t, is made from $A_j(t)$ and such payments are said to be sequential pay, senior/subordinate with 'top-down' priority payment of principal for K total rated classes are paid first to AAA class, then to AJ/AS class, then to the AA class,..., and then to the Unrated class until each of the kth bond's outstanding principal balance is reduced to zero.

In each monthly payment period, t, the beginning balance of the bond, trust and loan objects are adjusted for the principal payment made in the prior period, $t-1$. Let $\mathbb{O}_{j,k}(t)$ represent the outstanding principal balance at the end of the payment period and $\hat{\mathbb{A}}_{j,k}(t)$ represent the promised principal payment to the kth bond at the beginning of the payment period so $\mathbb{O}_{j,k}(t) = \mathbb{O}_{j,k}(t-1) - \hat{\mathbb{A}}_{j,k}(t)$ with

$$\hat{\mathbb{A}}_{j,k}(t) = \begin{cases} \max(0,\ \min(\mathbb{O}_{j,1}(t-1),\ A_j(t)), & \text{for } k=1; \\ \max(0,\ \min(\mathbb{O}_{j,k}(t-1),\ A_j(t) \\ \quad -\sum_{k=1}^{K} \hat{\mathbb{A}}_{j,k-1}(t)), & \text{for } k>1 \end{cases}$$

representing the promised principal payments to the kth bond at the beginning of the payment period for all k-tranches. Any excess principal remaining is then allocated to the next most senior tranche in the capital structure. Similarly for the interest paid to each of the k bond classes is paid from the trust interest collected from the loans, $C_j(t)$, as defined above. The expression for the promised interest payment $\hat{\mathbb{I}}_{j,k}(t)$ with bond coupons, $i_{j,\,k}$ is:

$$\hat{\mathbb{I}}_{j,k}(t) = \begin{cases} \max\left(0,\ \min\left(\mathbb{O}_{j,1}(t-1) \times \frac{i_{j,k}}{12},\ C_j(t)\right)\right), & \text{for } k=1; \\ \max\left(0,\ \min\left(\mathbb{O}_{j,k}(t-1) \times \frac{i_{j,k}}{12},\right.\right. & \text{for } k>1 \\ \quad \left.\left. C_j(t) - \sum_{k=1}^{K} \hat{\mathbb{I}}_{j,k-1}(t)\right)\right), & \end{cases}$$

with total promised payment for the kth bond in the jth series in month t as:

$$\hat{\mathbb{T}}_{j,k}(t) = \hat{\mathbb{A}}_{j,k}(t) + \hat{\mathbb{I}}_{j,k}(t) \tag{45}$$

A2. Valuation of commercial real estate loans (CRELs)

CRELs are issued against commercial properties. My sample are exclusively fixed-rate mortgages issued to borrowers based on the quality (economic earning power) of the securing property. If the property loses value, the borrower may decide to default on the loan. As such, CRELs face both market (interest rate) and credit risk.

Fixed-rate CRELs are similar to straight Corporate bonds with the exception that the loan' s principal is partly amortized over the life of the loan. While some CRELs are fully amortizing level pay mortgages, most typical CRELs have a (T/n) balloon payment structure. In the (T/n) balloon payment structure, the loan has a fixed maturity date T, a principal payment F, scheduled payments P paid at equally spaced intervals over the life of the loan (usually monthly) and a coupon rate per payment period $c = C/F$ where C is the dollar coupon payment. The payments P are determined as if the loan would be completely amortized in n periods. But instead of lasting n periods, a balloon payment occurs at time $T < n$ representing the remaining principal balance at that time, denoted B_T.

The Cox process assumption implies that conditional upon the information set generated by$(N_t,\ U_t,\ V_t,\ X_t)_{t\,\in\,[0,\,T]}$, $N_f(t)$ behaves like a Poisson process. If default occurs, the recovery on the loan is assumed to be $\delta_{\tau_f}(B_{\tau_f} + P)$. The trust receives δ_{τ_f} percent of the remaining principal balance plus the prorated scheduled principal payment.[48] I assume that the recovery rate is a constant.

Under this intensity process, the probability that default occurs on the loan' s balloon payment date $(T-dt, T]$ is approximately $\lambda_f(T,\ N_T,\ U_T,\ V_T,\ X_T)dt$. Allowing for default on the balloon payment date captures what is often called "extension risk" in the CMBS literature.[49] Given the previous notation, as viewed from time t, the cash flow to a CREL at time T is:

$$\sum_{j=t+1}^{T} P 1_{\{j<\tau_f\}} e^{\int_j^T r_s ds} + (B_T + P) 1_{\{T<\tau_f\}} + \delta_{\tau_f}(B_T + P) 1_{\{\tau<T\}} e^{\int_{\tau_f}^T r_s ds}. \tag{46}$$

The first two terms in expression (46) give the promised payments on the CREL if there is no default. The third term gives the accumulated payment up to time T if a default occurs.

Given the martingale measure $\mathbb{Q}$, the time t present value of these cashflows is:

$$E_t\left[\sum_{j=t+1}^{T} P 1_{\{j<\tau_f\}} e^{\int_j^T r_s ds} + (B_T + P) 1_{\{T<\tau_f\}} + \delta_{\tau_f}(B_T + P) 1_{\{\tau<T\}} e^{\int_{\tau_f}^T r_s ds}\right] \tag{47}$$

where $E_t(\cdot)$ denotes the expectation under the martingale measure. Under the Cox processes, standard techniques yield:

$$E_t\left[\sum_{j=t+1}^{T} P e^{-\int_t^j (r_s + \lambda_f(s))ds} + (B_T + P) e^{-\int_t^T (r_s + \lambda_f(s))ds} \right. \\ \left. + \delta_{\tau_f}(B_T + P) e^{-\int_t^s (r_u + \lambda_f(u))du}\right]. \tag{48}$$

For the reduced form, I calculate the expectation in expression (48) using Monte Carlo.

A3. Market price and market interim price

In the empirical process recall that price of the bond is determined using the promised cash flows of the principal and interest cashflows from the N loans, $\hat{\mathbb{T}}_{j,k}(t) = \sum_{i=1}^{N} [\hat{\mathbb{A}}_{j,k}(t) + \hat{\mathbb{I}}_{j,k}(t)]$

[48] For notational simplicity, I assume that the prorated portion of the loan payment is the entire payment P. However, in my valuation software, I compute the exact prorated portion of the loan payment.

[49] Extension risk is the risk that on the balloon payment date, the borrower will not be able (or willing) to make the balloon payment but will be able (or willing) to continue making the coupon and amortization payments P. The belief is that, by extending the loan, the balloon payment will be made at a later date.

where $\hat{\mathbb{A}}_{j,k}(t)$ are the promised principal payments and $\hat{\mathbb{I}}_{j,k}(t)$ are the promised interest payments which are allocated through the capital structure. The *market price*, expressed as a percent of par, for the kth bond in the jth CMBX Series for date s is expressed as:

$$m_{j,k}(s) = \frac{\sum_{t=s}^{T} \mathbb{T}_{j,k}(t) e^{-(r_t+\mathbb{S}_{j,k}(t))t}}{\hat{\mathbb{F}}_{j,k}(s)} \tag{49}$$

where $\hat{\mathbb{F}}_{j,k}(s) = \sum_{t=1}^{T} \hat{\mathbb{A}}_{j,k}(t)$ is the face value of the bond, $r_t$is the risk free rate, and $\mathbb{S}_{j,k}(t)$ is the observed nominal risk premium above the risk free rate. When$\mathbb{S}_{j,k}(t) = 0$, Eq. (49) yields the *market interim price*:

$$\tilde{m}_{j,k}(s) = \frac{\sum_{t=s}^{T} \mathbb{T}_{j,k}(t) e^{-r_t t}}{\hat{\mathbb{F}}_{j,k}(s)} \tag{50}$$

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