Information in Financial Contracts: Evidence from Securitization Agreements

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Abstract

We introduce a novel application of machine learning to compare pooling and servicing agreements (PSAs) that govern commercial mortgage-backed securities. In contrast to the view that the PSA is largely boilerplate text, we document substantial variation across PSAs, both within- and across-underwriters and over time. A part of this variation is driven by differences in loan collateral across deals. Additionally, we find that differences in PSAs are correlated with ex post loan and bond performance. Collectively, our analysis suggests the importance of examining the entire governing document, rather than specific components, when analyzing complex financial securities.

I.   Introduction

Securitization is the process of pooling assets and issuing new securities tied to the cash flows generated by the pool (hence the term asset-backed security or ABS). This process is one of the major advances in modern finance and promotes greater

efficiency and liquidity in both capital and asset markets.[1] However, the process of securitization is complex and requires a governing document, called a pooling and servicing agreement (PSA), which explicitly identifies the rights and responsibilities of each party involved with the operation of the deal. In detailing the design and operation of the security, the PSA fulfills different purposes. For example, the PSA is drafted by the underwriter to reflect the risk of the underlying assets; and thus, it may communicate both hard information about the underlying collateral, and soft information that may be more difficult to quantify.[2] The PSA may also reflect information about the agents (the master servicer, special servicer, and sub-servicers, as well as the trustee) employed to oversee the daily ex post operation of the deal. This information is often critical for investors to assess how the securitization will perform. For example, Ambrose, Sanders, and Yavas (2016) document how the relationships between servicers can impact their incentives to maximize investor cash flows. In addition, as the governing document, the PSA provides investors with detailed information about actions various agents are required to take in managing the assets in the securitization. For example, Jacob and Fabozzi (2003) discuss how the PSA memorializes the actions required by the special servicer in resolving a loan default.

While the economics and finance literature recognizes the complexity inherent in securitization structures (Jacob and Fabozzi (2003), DeMarzo (2005), Demiroglu and James (2012), An, Deng, Nichols, and Sanders (2015), Ambrose et al. (2016), and Begley and Purnanandam (2017)), studies often completely abstract away from the contents of the underlying governing contracts to focus on observable characteristics of the underlying assets (see, e.g., Ambrose and Sanders (2003), Chen and Deng (2013), and Buschbom, Kau, Keenan, and Lyubimov (2021), in the context of commercial mortgages). To the extent that studies do consider the role of the PSA, they focus on small sections of the contract, such as the representation and warranties or the role of servicing institutions (e.g., Agarwal, Chang, and Yavas (2012), Kruger (2018)). However, the legal profession has established the principle that a contract should be read as a whole and its interpretation should be based on all the clauses read together (Epstein (1984), DiMatteo and Morant (2010)). Thus, the challenge faced by finance researchers lies in summarizing and characterizing the contents and meanings of the PSAs, which are lengthy legal documents.

We look to shed light on three aspects of the PSAs. First, we document the degree of heterogeneity in PSAs across securitization deals. To the best of our knowledge, we are the first to undertake such a systematic comparison of PSAs. Second, we investigate whether differences in PSAs reflect observed differences across securitization in their underlying collateral. Third, we examine whether PSAs reflect unobservable information about collateral quality and risk, either as a signaling device or as a means of outlining ex post contingencies to reduce agency

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[1]In 2018, the U.S. debt market comprised approximately $11.3 trillion in securitized assets, or about one-third of all debt outstanding – second only to U.S. Treasury securities in size, and over the period from 2008 to 2018 securitized debt accounted for approximately one-quarter of all fixed-income new issuance volume (SIFMA (2019)).

[2]See Agarwal and Hauswald (2010) for a discussion of the differences in hard and soft information in the context of bank lending.

frictions. We do so by considering the ex post differences in collateral and deal performance, controlling for observable deal and loan characteristics.

The empirical setting for our analysis is the conduit commercial mortgage-backed securities (CMBS) market.[3] The typical CMBS PSA is a lengthy legal document filed with the Securities and Exchange Commission (SEC). It is a multi-party agreement written at deal inception that outlines the rights, duties, and responsibilities of the securitization issuer, the servicers, and the loan originators. The PSA governs the selection of mortgages into the collateral pool, the subsequent monitoring of the loans, and the actions to be taken if a mortgage becomes seriously delinquent. As such, it may reflect the risk characteristics (both observable and unobservable) of the underlying assets.

To analyze the contents of the CMBS PSAs, we apply a machine-learning, natural language processing (NLP) algorithm. This method recognizes the connections among the words and sentences within the document and then converts these patterns into a multidimensional numerical vector representation that can then be analyzed.[4] A particular document's vector has analytical content when compared to that of another document. Therefore, the algorithm ultimately delivers a N-by-N symmetric matrix of uniqueness scores, which measure the distance between a pair of vectors.[5] The larger the distance, the more unique is one document compared to the other, and the more differences there are in their contents. In this context, machine learning is advantageous because the algorithm is capable of comparing entire legal documents, rather than specific words or sentences (Li, Mai, Shen, and Yan (2021)).

The article's first contribution is to use these uniqueness scores to document heterogeneity in PSAs across CMBS deals, which counters the perception that these documents are largely boilerplate legal contracts. We also show that this degree of heterogeneity varies depending on whether we compare a deal to others underwritten by the same entity, or to those underwritten by another entity. Specifically, we find that PSAs from deals originated by the same underwriter are more likely to be similar to each other. To the extent that the PSAs reflect the underlying mortgage pool, this finding implies specialization by underwriters in creating the mortgages that comprise the CMBS deal. We also find that, regardless of the underwriter, PSAs are more likely to be similar for deals originated in the same year cohort. This suggests that underwriters tailor the governing documents to reflect the macroeconomic environment prevailing at the time of origination.

Our second contribution is to document the extent to which the underlying collateral can explain differences in CMBS PSAs. We show that differences across CMBS deals with respect to average loan-to-value (LTV) ratios, average interest rates, and the variance of loan size distributions correspond to greater differences in the governing documents. Therefore, similar to other aspects of security design,

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[3]Conduit CMBS deals typically comprise large pools of commercial real estate loans that were originated explicitly for inclusion in mortgage-backed securities.

[4]This represents an innovation from the standard "bag-of-words" approach used in the seminal applications of textual analysis in the finance literature (Tetlock (2007), Loughran and McDonald (2011)).

[5]We retain the portion of the matrix that lies above the diagonal to conduct our analysis.

such as subordination levels, the PSA reflects observable differences in the underlying collateral. However, the differences in the deals' collateral characteristics do not fully explain variation in the PSAs.

Third, our analysis lends insight into whether PSAs provide economically meaningful information beyond that captured by observable hard information. We do so by examining differences in loan and security performance. Since our primary independent variable, the uniqueness score, is a pairwise measure of distance and the dependent variables measure the pairwise variations in the loan performance of deals, our analysis relates differences in PSAs to differences in deal performance. We find that a greater distance between two PSAs correlates with a larger difference in loan performance across the two securitization deals, even after conditioning on differences in collateral characteristics. This holds true both when comparing deals originated by the same underwriter, or by different underwriters, and controlling for a host of observable characteristics and fixed effects. We also find only weak evidence that PSA uniqueness appears to be priced in the average deal coupon but uniqueness is reflected in the ex post bond internal rates of return, particularly for medium- and lower-rated bonds. These results suggest that variation in PSAs may, in fact, reflect or signal differences in deal quality, or be tailored to various ex post contingencies to overcome agency frictions.

Finally, we consider the question of whether analyzing the complete PSA document lends insight beyond restricting attention to specific sections, or articles, of the PSA. We show that deal-pair uniqueness increases as the totality of the governing document is considered, rather than only specific articles. Additionally, uniqueness scores correlate with differences in loan performance only when they are based on the entire PSA document. This suggests the necessity of examining the entire document rather than specific components of it, such as the representations and warranties section.

Our study contributes to three strands of the literature. First, we provide novel evidence showing how securitization facilitates information creation and destruction among issuers (DeMarzo and Duffie (1999), Ambrose and Sanders (2003), Ambrose, LaCour-Little, and Sanders (2005), DeMarzo (2005), Titman and Tsyplakov (2010), An, Deng, and Gabriel (2011), Gaur, Seshadri, and Subrahmanyam (2011), Bougheas (2014), Guo and Wu (2014), and Hartman-Glaser (2017)). For example, An et al. (2011) demonstrate how conduit CMBS lenders mitigate asymmetric information and adverse selection in the sale of loans to the secondary market versus securities created by portfolio lenders. Yet, even within the set of conduit CMBS deals An et al. (2011) document heterogeneity in origination spreads. Thus, our results provide additional evidence on how CMBS originators signal deal quality beyond observable characteristics, that is, through differences in PSAs.

Second, we provide new insights into the role of various entities involved in the securitization process (Demiroglu and James (2012), Chen and Deng (2013), Liu and Quan (2013), Ambrose et al. (2016), and Mooradian and Pichler (2018)). For example, in discussing the differences in performance between portfolio loans and CMBS loans, Black, Krainer, and Nichols (2017) note how CMBS PSAs' prescribe servicer actions when dealing with loans in default. However, these restrictions are not monolithic and our study provides evidence that PSAs do vary across CMBS deals in meaningful ways.

Third, we demonstrate the application of a new tool rooted in artificial intelligence and machine learning to study complex economic and financial problems (Boudoukh, Feldman, Kogan, and Richardson (2018), Buehlmaier and Whited (2018), Chen, Wu, and Yang (2019), Bellstam, Bhagat, and Cookson (2020), Cong, Liang, Yang, and Zhang (2020), Huang, Tan, and Wermers (2020), Liu, Nowak, and Smith (2020), Brogaard and Zareei (2023), Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022), and Shen and Wilkoff (2022)). However, in contrast to most textual analysis of financial contracts that focus on specific words, which necessitates word selection by the researcher, our focus is on the contents of the entire document.

II.   Data

To study the information content of CMBS PSAs, we begin with data on a sample of CMBS deals collected by Trepp.[6] These data contain extensive loan-level information about the underlying mortgages (including detailed loan terms and property characteristics) and data on the cash flows to each of the deals' tranches.

Given data quality issues for deals and loans originated before 2000, we restricted the sample to the period from 2000 to 2019. To ensure, we are analyzing deals that are similar in their legal structure and tax treatment, we further restrict attention to conduit CMBS deals which were all structured as Real Estate Mortgage Investment Conduits (REMICs) under U.S. Federal income tax law for the purpose of pooling and securitizing mortgage loans.

We then obtain each deal's PSA by searching SEC's EDGAR database for the deal name (https://www.sec.gov/edgar.shtml). Each PSA obtained from EDGAR is cleaned by removing the nomenclature chapter and exhibits contained in Appendix B.[7] After dropping duplicate and erroneous documents, we are left with a sample of CMBS data merged with the PSAs for 692 conduit deals.

III.   Empirical Method

Our analysis relies on a NLP model to characterize the contents of the PSAs. We adopt the document vectorization (DV) algorithm introduced and implemented in Le and Mikolov (2014), Shen and Ross (2021), and Shen and Springer (2022) to convert each PSA into a high-dimensional numerical vector. Appendix A provides a brief overview of the methodology and discusses the document-specific vectors (v_j) produced by the DV algorithm. We note that these vectors preserve the meaning of the document, unlike supervised learning algorithms that attempt to make predictions based on training samples. Thus, the vector produced by the algorithm for a given document has analytical content when compared to vectors for other documents. As a result, PSAs with similar content are closer to each other in the vector space.

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[6]Trepp tracks over 1,500 CMBS deals comprising over 200,000 mortgages. More information about Trepp is available at http://www.trepp.com/about-us.

[7]To clean the documents, we employ an automated documenting screening method that uses a regular expression matching technique, which is subsequently validated by trained research assistants.

FIGURE 1

3–D Representation of Vector Space for CMBS PSAs

Figure 1 offers a 3D demonstration of the vector space for the PSA files. In reality, our vector space has more than 100 dimensions. Every dot represents a unique PSA document. Each axis in the vector space does not hold a physical meaning in human language; the relative distance between two dots indicates the relative semantic distance between the corresponding PSAs.
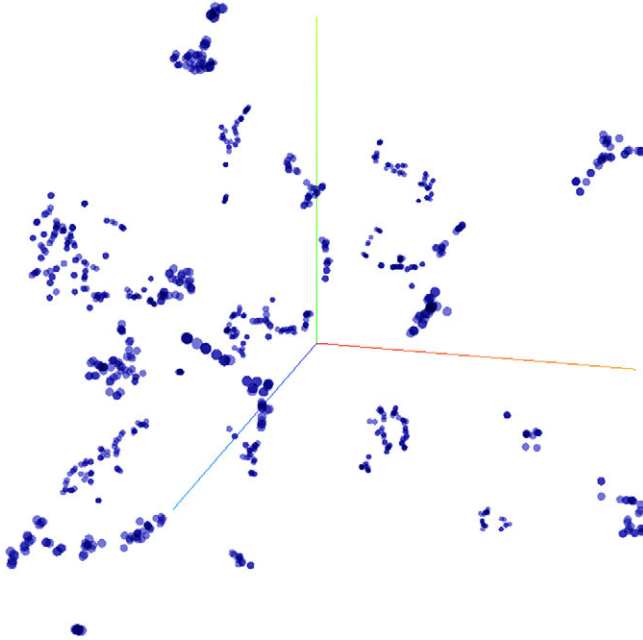
To demonstrate the output delivered by the algorithm, we estimate vectors for each PSA, reduce their dimensionality to three dimensions and plot them in Figure 1.[8] Although we do not force the axes to represent a designated word or the meaning of a sentence in a PSA, the relative distance between vectors captures the distance between the content of corresponding PSAs. As evident in Figure 1, even in this relatively simple demonstration, we can identify clusters of similar documents. This vector representation approach provides the basis for the creation of a numerical measure which captures the differences in content and meaning between a pair of deal documents. Since the precision of our measure increases as the number of dimensions increases, we construct our PSA uniqueness scores by employing a 150 dimension vector space.[9]

The content and semantic deviations across PSA documents are easily calculated using their vector representations. The pairwise distance between the vectors of two PSA documents increases as their semantic meanings deviate from each

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[8]To demonstrate the intuition of the methodology, we reduce the dimensionality of the v_j vectors using principal component analysis (PCA).

[9]Note that each dimension does not associate with the meaning of a specific word or sentence. As the dimension increases, the representation of the document becomes more detailed. Correspondingly, the computational complexity increases exponentially in the number of dimensions.

other. For example, suppose that we are comparing documents d_i and d_j represented by vectors v_i and v_j, then the corresponding deviation between the two documents can be defined as

$$U(d_i, d_j) = 1 - cos(v_i, v_j)$$
$$= 1 - \frac{v_i \cdot v_j}{\|v_i\| \cdot \|v_j\|}.$$

(1)

$U(d_i, d_j)$, which we term the uniqueness score, is bounded between 0 and 1. A distance score of 1 means the two PSAs are completely different from each other, whereas a distance score of 0 indicates an exact match. Therefore, the distance from a PSA to itself ($U(d_i, d_i)$) will always be 0. By reducing the semantic meaning and content of each document into a single vector, the DV methodology provides a substantial improvement over other algorithms based on keywords or word frequencies. This is particularly advantageous when studying lengthy legal documents such as PSAs.

A. An Example

To provide more context on how the algorithm works, we demonstrate the methodology on a smaller scale by calculating pairwise uniqueness scores only for a given subsection from five representative PSAs. The subsection we analyze is "Section 2.1, subsection (a)." This section identifies the "Conveyance" terms for transferring the mortgage pool from the underwriter to the CMBS trust and allows the reader to easily compare the text. Exhibits 1–5 in Appendix B reproduce these sections for the following CMBS deals: (1) Morgan Stanley Bank of America Merrill Lynch Trust 2012-C6; (2) LB-UBS Commercial Mortgage Trust 2007-C6; (3) Citigroup Commercial Mortgage Trust 2006-C5; (4) Banc of America Commercial Mortgage Inc. Commercial Mortgage Pass-Through Certificates, Series 2004-1; and (5) Banc of America Commercial Mortgage Inc., Commercial Mortgage Pass-Through Certificates, Series 2008-1.

The pairwise uniqueness score comparing Exhibits 1 and 2 ($U(d_1, d_2)$) is 0.55, indicating that these documents are relatively dissimilar. Likewise, the pairwise score comparing Exhibits 2 and 3 ($U(d_2, d_3)$) is 0.2, suggesting that these documents share a higher degree similarity versus the pair in Exhibits 1 and 2. For instance, Exhibits 2 and 3 contain the same final paragraph prohibiting the trust from issuing additional securities. In addition, both list the conveyance between different parties and indicate the same month end of the fiscal year for the trust. Finally, Exhibits 4 and 5 report Section 2.1(a) for two Banc of America deals. Not surprisingly, given that these deals are from the same underwriter, the pairwise uniqueness score ($U(d_4, d_5)$) is very low (0.015), revealing a high degree of overlap. In fact, the only difference between these paragraphs is the security names.

B. Falsification Test

Based on the previous example, one may be concerned that the algorithm assigns a nonzero uniqueness score even if documents differ on trivial elements, or elements that are already being captured by hard data (e.g., origination year, number

of loans, the geographic distribution of properties, etc.). To alleviate this concern, we perform the following exercise. We artificially constructed a comparison pseudo-PSA by altering the deal name, series numbers, and origination year for the PSA document associated with Banc of America Commercial Mortgage Inc. Commercial Mortgage Pass-Through Certificates, Series 2004-1. In other words, we simply replaced the deal name, series identification numbers, and origination year in the pseudo-PSA to something completely different, leaving the rest of the document identical to the original. We then use the algorithm to calculate a unique-ness score for these documents. The uniqueness score between the original PSA and the corresponding pseudo-PSA is approximately 0, thus verifying that our algo-rithm correctly identifies these documents as being identical.[10]

IV.   Documenting Heterogeneity in PSAs

Our analysis starts with documenting the variation in the pairwise uniqueness scores defined in equation (1). In particular, we document that variation across PSAs does exist, and we explore the heterogeneity within and across issuers and deal origination years.

The object of analysis is U, the $N \times N$ matrix of uniqueness scores. Each row of the matrix compares a given deal (d_i) to all other deals (d_j). In other words, each row of the matrix represents a distribution of uniqueness scores. Let $U_{i,j} \equiv U(d_{i,.,.}, d_{j,.,.})$ be the pairwise uniqueness score comparing d_i and d_j vector scores as defined in equation (1) such that $U_{i,j} \in U$. Figure 2 presents a visual depiction of the matrix U. Since $U_{ij} = U_{ji}$ we retain only that portion of the matrix which lies above the diagonal.

Since each uniqueness score represents the comparison of a pair of deals, the unit of analysis is a deal-pair. To better organize our analysis, we partition the set of

FIGURE 2

Distance Score Visualization of CMBS Deals

Figure 2 presents a visualization of the $N \times N$ matrix of uniqueness scores. Each row of the matrix compares a given deal (d_i) to all other deals (d_j). The distance score for d_i, d_i will always result in a 0 value and similar documents are usually from the same underwriter. Therefore, the lighter colors are often found close to the diagonal axis.


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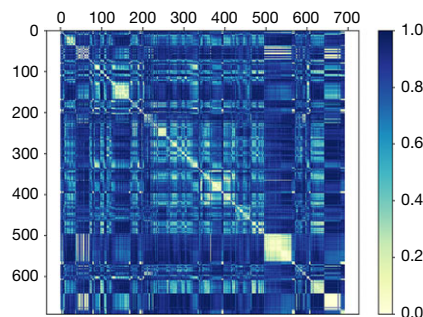
[10]We provide the PSA and pseudo-PSA comparison in Appendix E of the Supplementary Material.

deal pairs into different groups. Let D represent the set of all deal pairs in the sample ($|D| = N$, where $N = 239{,}086$) with $(d_{i,u,t}, d_{j,w,s}) \in D$ representing a pair of deals indexed by i and j. u and w index the deals' underwriters, while t and s indicate the deals' closing years.[11] To begin, we partition D into deal pairs where the underwriter is the same for both deals ($D_u \subset D$ such that for any $d_{i,u,.}, d_{j,w,.} \in D_u$, $u = w$). Next, we define the set of deal pairs where the underwriter is different for both deals ($D_{-u} \subset D$ such that for any $d_{i,u,.}, d_{j,w,.} \in D_{-u}$, $u \neq w$). We can also partition sets of deal pairs depending on the closing year of each deal. For example, define $D_t \subset D$ such that for any $d_{i,u,t}, d_{j,w,s} \in D_t$, $t = s$, and $D_{-t} \subset D$ such that for any $d_{i,u,t}, d_{j,w,s} \in D_{-t}$, $t \neq s$.

We first document that deals originated by the same underwriter (D_u) have PSAs with a higher degree of similarity to each other (i.e., have lower average uniqueness scores) than when comparing PSAs from deals across underwriters (D_{-u}). Graph A of Figure 3 describes the distributions of the deal-pair

FIGURE 3

Distribution of Deal-Pair Uniqueness Measures

Figure 3 documents the distribution of pairwise uniqueness scores for various partitions of the set of deal pairs. Graph A focuses on deal pairs by the same or different underwriter. Graph B focuses on deal pairs from the same underwriter. Graph C focuses on deal pairs from the same year cohort.
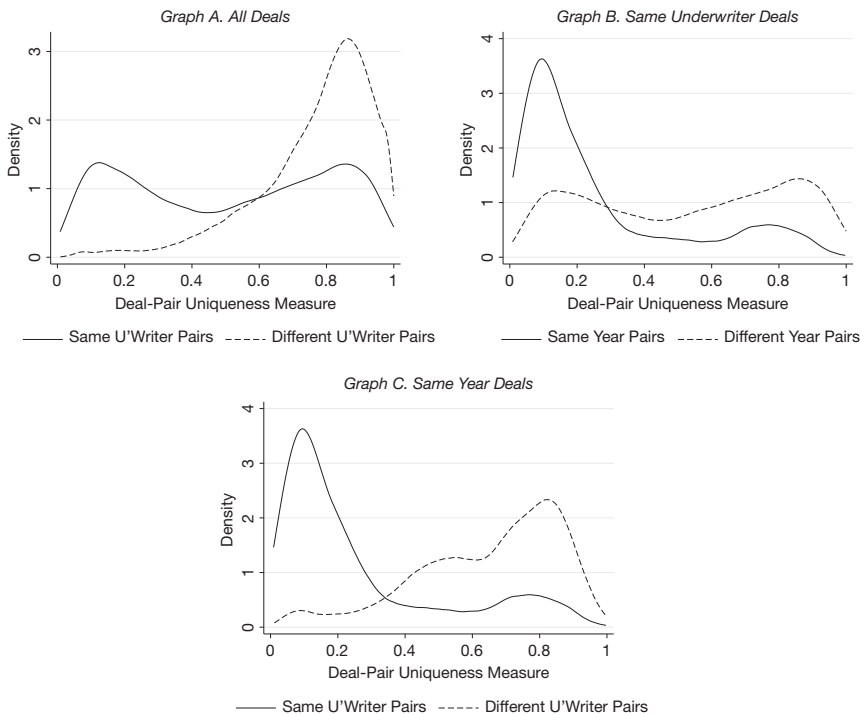
uniqueness scores based on whether each pair contains deals by the same under-writer (solid line) or different underwriter (dashed line). The solid line is con-structed by using pairwise combinations of deals that had the same underwriter, and vice versa for the dashed line. We note that both distributions indicate a high degree of PSA document uniqueness. Overall, the distributions confirm the intuition of the uniqueness score.

We show that the PSAs tend to mimic each other when deals are originated in the same year, under similar economic conditions. To document this, Graph B of Figure 3 restricts attention to deal pairs with the same underwriter across both deals. However, we now partition the set of deal pairs based on when the deals were originated. The solid line describes the distribution of the score for pairs originated in the same year ($D_{u,t}$). The dashed line describes the distribution for deal pairs originated in different years ($D_{u,-t}$). As expected, deal pairs have similar PSAs on average (low uniqueness scores) when both deals were originated in the same year ($D_{u,t}$). When comparing across years ($D_{u,-t}$), we see higher uniqueness scores on average, indicating less similarity in PSAs. However, we also note that significant heterogeneity in PSA uniqueness exists even when considering deal pairs within the same underwriter and year of closing.

Graph C of Figure 3 completes the analysis by showing that even when deals were originated during similar macro-economic conditions (i.e., in the same year), their PSAs may yet be very different when comparing across underwriters. It does so by restricting analysis to deal pairs where both deals closed in the same year. It then partitions these pairs based on whether they involve deals with the same, or different underwriters. Confirming the finding in Graph A, deal pairs involving distinct underwriters have markedly higher uniqueness scores. The patterns documented here might arise for several reasons. For example, under-writers could systematically differ in the type of collateral they include in the loan pool. Alternatively, underwriters may differ in the extent to which their docu-ments reflect their expectations of loan pool outcomes. While we cannot perfectly distinguish between the various channels, we later examine the extent to which variation in observable characteristics of the loan pools drive the uniqueness scores, and whether uniqueness scores are correlated with pairwise differences in deal performance.

Finally, in Figure 4, we document variation across underwriters in the degree of standardization of their own deals' PSA contracts. The box–whisker plots document significant heterogeneity in the distribution of uniqueness scores across the top 17 underwriters. For example, we note significantly higher unique-ness scores for deals underwritten by Banc of America and Barclays versus those underwritten by Chase or Wachovia. Furthermore, Figure 4 shows the extent of variations within underwriters. For example, the box–whisker plots reveal that Chase and Wachovia have relatively small distributions of their respective unique-ness scores whereas Bear Stearns and RBS Securities, in contrast, have very wide distributions in their respective uniqueness scores. This may be suggestive of Chase and Wachovia specializing in particular collateral or deal structure versus a more diverse offering of Bear Stearns.

FIGURE 4

Average Deal-Level Uniqueness Measure Across Issuers

Figure 4 shows the distribution of uniqueness scores for the top 17 underwriters by volume. The dark bars show the distribution of uniqueness scores for pairs from the same underwriter.

Excludes Outside Values
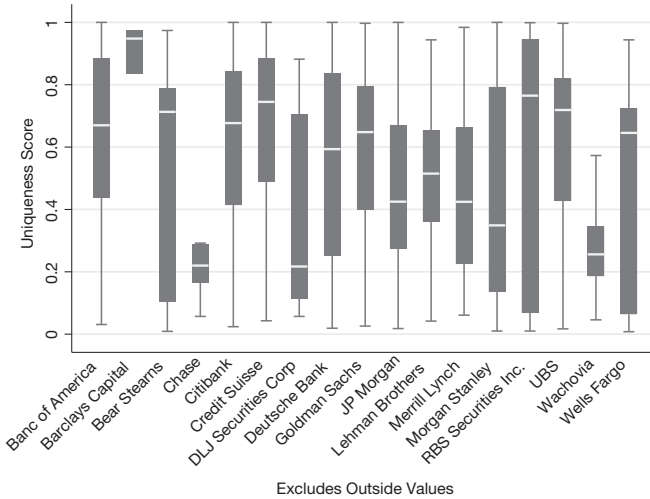
V.   What Drives Variation in PSAs?

Having established that there does exist meaningful heterogeneity in the PSAs across deals, we now explore what drives this variation. We examine whether variation across deals in underlying mortgage characteristics, securitization structure, and deal governance are correlated with differences in the PSAs. In other words, we ask whether differences in the mortgage pools and securitization structure of CMBS deals i and j are reflected in $U_{i,j}$.

To measure the observable differences in every deal-pair (d_i, d_j), we compute the "distance" between the deal-level characteristics ($|\Delta X_{ij}|$), defined as

$$(2) \qquad |\Delta X_{ij}| = \frac{|X_i - X_j|}{\frac{1}{2}(X_i + X_j)},$$

where X_i is a set of deal i observable characteristics. Therefore, $|\Delta X_{ij}|$ is a vector of measures that compare the collateral underlying deals i and j. We formally examine how heterogeneity in observable characteristics affect deal uniqueness by estimating the following regression:

$$(3) \qquad U_{i,j} = \alpha + \beta|\Delta X_{ij}| + \Gamma + \varepsilon,$$

where Γ represents the set of fixed effects (defined below) and ε is the error term. Since the measure $|\Delta X_{ij}|$ has the support $[0,2]$ for all values of X_i and X_j, $2 \times \beta_k$ predicts how $U_{i,j}$ changes as two deals move from being perfectly identical ($\Delta X_{ij} = 0$) to drastically different ($\Delta X_{ij} = 2$), in terms of their underlying collateral.

Since the PSA is drafted to reflect the underlying risk of the collateral and it describes the relationships between agents involved in the operation of the trust, we define X_i to reflect measures of observable collateral risk, deal structure, and agent affiliation. Following the empirical literature on mortgage pricing and performance, we consider the following observable characteristics of the underlying mortgages: loan balance, the difference between the amortization term and the term to maturity (measured in months) that serves as a proxy for mortgage duration, contract interest rate, and the LTV ratio.[12] To examine differences in collateral type, we consider deal-level measures of the fraction of loans collateralized by office, multifamily units, and retail properties. We also construct a HHI-based measure of property mix across all the property-type categories in the data. Additionally, we construct a HHI measure of property location (MSA-level) concentration to capture geographic dispersion of the underlying loan pool. To further focus on the geographic exposure associated with each deal, we determine whether the deal contains a high concentration of collateral loans in each census region.[13] We classify a deal as having high exposure to a census region if the deal has more than 5% of the collateral loans located in a state associated with that region.[14] To capture dispersion in the underlying collateral, we include the standard deviations of ln(ORIGINAL LOAN_ BALANCE), ln(DURATION_PROXY), LTV_RATIO, and INTEREST_RATE. To capture differences in the deal size, we consider the deal loan count.

At the deal level, we consider factors associated with variation in subordination levels required to support the AAA tranche. We also consider variations in affiliation between the master servicer, special servicer, and lead underwriter to capture securitization governance. Ambrose et al. (2016) document how relationships between master and special servicers can impact the cash flows received by investors, while An, Deng, and Sanders (2008) provide evidence concerning the interaction of the collateral assets and level of deal subordination. Thus, if the master and special servicer are the same firm, then we denote the deal as having an affiliated servicing status. Similarly, if the deal lead underwriter and master servicer are the same entity, then we denote the deal as having an affiliated underwriter status.[15]

A.   Summary Statistics

Table 1 summarizes the various characteristics. We construct summary statistics by first aggregating loan-level data to the deal level, and then present the distribution of deal-level moments in Table 1. Panel A shows the summary statistics

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[12]The literature indicates that these characteristics are related to mortgage and securitization deal performance (e.g., Ambrose and Sanders (2003), An et al. (2008), Yildirim (2008), Seslen and Wheaton (2010), Titman and Tsyplakov (2010), An et al. (2011), and among others).

[13]The Census Bureau groups states into four census regions: North East, South, Midwest, and West (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

[14]For example, if more than 5% of the collateral loans in a deal are located in New York, then that deal is coded as having exposure to the North East (NE) census region, which comprises Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont.

[15]Note that the regional exposure indicators, the AAA subordination indicator, and the affiliation indicators that are part of X_i are not normalized when forming $|\Delta X_{ij}|$. This is because these variables can often be equal to 0.

TABLE 1

Summary Statistics of the Deal Outcome and Control Variables

Table 1 reports summary statistics on the variables employed in the analysis. Panel A summarizes control variables derived from loan-level data, Panel B summarizes deal-level variables, and Panel C summarizes the key outcome variables.

	N	Mean	Std. Dev.	p5	p50	p95
	1	2	3	4	5	6
Panel A. Control Variables						
NO. OF LOANS_IN_DEAL	692	131.3	82.83	44	109.5	300
AVERAGE_LOAN-LEVEL_BALANCE ($ mil)	692	13.68	6.387	4.260	13.36	24.62
AVERAGE_LOAN-LEVEL_INTEREST_RATE (p.p.)	692	5.802	1.115	4.413	5.652	8.181
AVERAGE_LOAN-LEVEL_LTV (p.p.)	692	66.76	5.754	55.62	68.26	72.83
AVERAGE_LOAN-LEVEL_DURATION_PROXY	692	205.8	34.07	146.1	213.7	242.2
HHI_INDEX_GEOGRAPHIC_(MSA)_CONCENTRATION	692	0.0790	0.0528	0.0373	0.0686	0.147
HHI_INDEX_PROPERTY_TYPE_CONCENTRATION	692	0.281	0.149	0.174	0.247	0.435
% RETAIL_PROPERTIES (p.p.)	692	31.24	11.01	13.33	31.36	48.19
% MULTIFAMILY_PROPERTIES (p.p.)	692	24.21	18.93	5	19.38	62.65
% OFFICE_PROPERTIES (p.p.)	692	16.59	7.544	3.401	16.67	29.66
Panel B. Deal Characteristics						
AAA_SUBORDINATION	669	11.98	9.755	0	12.38	24.75
MASTER_SPECIAL_SERVICER_AFFILIATED (p.p.)	692	13.87	34.59	0	0	100
MASTER_SERVICER_UNDERWRITER_AFFILIATED (p.p.)	692	8.382	27.73	0	0	100
NORTHEAST_EXPOSURE_INDICATOR	692	83.24	37.38	0	100	100
SOUTH_EXPOSURE_INDICATOR	692	95.81	20.05	100	100	100
MIDWEST_EXPOSURE_INDICATOR	692	44.36	49.72	0	0	100
WEST_EXPOSURE_INDICATOR	692	93.21	25.18	0	100	100
Panel C. Outcome Variables						
5 YEAR_CUMULATIVE_DELINQUENCY_RATE (p.p.)	582	6.324	6.554	0	3.960	19.62
10 YEAR_CUMULATIVE_DELINQUENCY_RATE (p.p.)	430	18.30	9.696	4.803	16.88	34.93
5 YEAR_CUMULATIVE_DEFAULT_RATE (p.p.)	582	8.286	7.889	0	5.634	24.56
10 YEAR_CUMULATIVE_DEFAULT_RATE (p.p.)	430	20.03	10.18	5.240	19.12	38.11
5 YEAR_CUMULATIVE_LOSS (p.p.)	534	0.722	1.853	0	0	3.865
10 YEAR_CUMULATIVE_LOSS (p.p.)	409	3.767	3.914	0	2.600	11.11
WGTAVG._COUPON_(10 YR_TREASURY_SPRD) (p.p.)	645	−1.033	1.335	−2.735	−1.471	0.881
IRR_HIGH-RATED_BONDS (p.p.)	176	−19.99	20.89	−49.88	−24.98	5.237
IRR_MEDIUM-RATED_BONDS (p.p.)	165	−2.511	15.39	−34.16	3.832	5.203
IRR_LOW-RATED_BONDS (p.p.)	165	−22.43	29.04	−87.23	−13.56	4.250

for the observable control variables. For example, the typical conduit CMBS deal comprises 131 mortgages with an average loan balance of $13.7 million at origination. On average, the mortgages in the typical deal have a 66.7% LTV ratio. Furthermore, reflecting the rating agencies favorable view of pool-level diversification, we see that the typical deal comprises 31% retail, 24% multifamily, and 16.6% office properties, respectively.

Panel B of Table 1 summarizes the observable deal-level risk characteristics. The average AAA tranche was protected from default risk on the underlying mortgages by subordination levels of almost 12%. In looking at the entities involved with governing and managing the deal, we see that the master and special servicer were affiliated in 13.9% of the deals, while the master servicer and deal underwriter were affiliated in 8.4% of the deals. Since the rating agencies view pool-level geographic diversification as a mitigating risk metric, we note that 83% of deals contained loans in the Northeast region, 95% were exposed to the South region, 93% had loans in the West region, and 44% were exposed to the Midwest region.

B.   Estimation Results

Figure 5 displays the estimated coefficients and associated 95% confidence intervals for equation (3). Since most independent variable represents a relative scaled difference between deals for that characteristic over the interval [0,2],

FIGURE 5

Multivariate Analysis; Deal-Pair Regression Coefficients

Figure 5 reports the estimated coefficients for the regression equation

$$U_{i,j} = \alpha + \beta |\Delta X_{ij}| + \Gamma + \varepsilon,$$

where $U_{i,j}$ is the deal-pair uniqueness score, ΔX_{ij} is the differences in observable deal-pair characteristics, and Γ is the set of fixed effects used. Graphs A and B show results from estimating this regression on the full sample of deal pairs. In Graphs C and D, we restrict attention to deal pairs with the same underwriter (D_u) while in Graphs E and F, we consider deal pairs with different underwriters (D_{-u}). Graphs A, C, and E control for the differences in origination time between the two deals in a pair (year-difference fixed effect) and the earlier of the two origination years in the deal-pair. Graphs B, D, and F control directly for each possible combination of deal-pair origination years. We use either underwriter fixed effects (Graphs A, C, and E) or underwriter-pair fixed effects (Graphs B, D, and F) to control for uniqueness scores driven by an underwriter's idiosyncratic tastes for particular contract types. Lines around the point estimates represent the 95% confidence interval based on robust standard errors in Graphs C and D and clustered standard errors (at the underwriter pair) in Graphs A, B, E, and F.
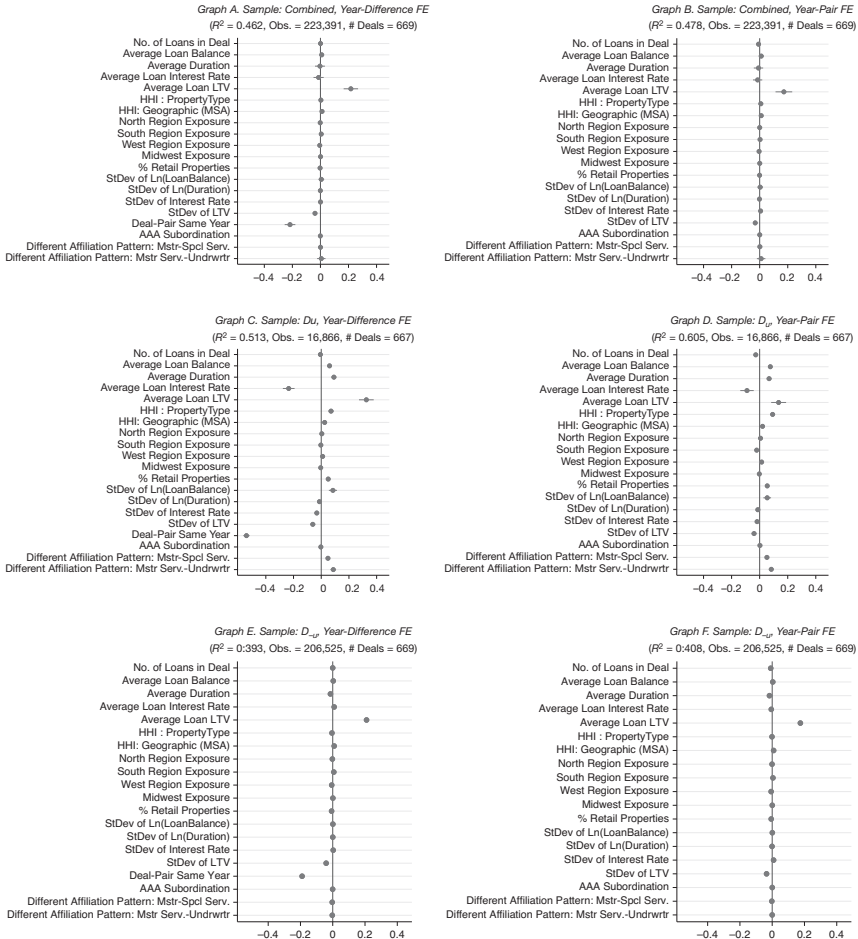
Figure 5 provides a quick visual reference showing the relative importance of the characteristics in explaining the variation in deal-pair uniqueness scores. Each graph reports estimation results using different specifications of fixed effects or choice of deal-pair samples (D_u or D_{-u}). Graphs A and B report results for the full sample of deal pairs. Graphs C and D display the estimated coefficients from using only deal pairs involving the same underwriter (D_u) while Graphs E and F show estimations using deal pairs involving different underwriters (D_{-u}). Table C.1 in the Supplementary Material reports the results in tabular form.[16] Each regression includes underwriter and either origination year-difference or origination year-pair fixed effects. Since the various coefficient estimates and their corresponding significance levels remain similar across the fixed effects specifications, we focus the discussion on the year-difference specifications in Graphs A, C, and E.[17]

Focusing first on the regression coefficients estimated using the combined sample (Graphs A and B of Figure 5), we clearly see that the difference in average collateral LTV ratios and the indicator for deal pairs originated in the same year cohort are the dominate characteristics driving variation in PSA uniqueness scores. Both variables have coefficients that are of similar magnitude- and significance-level, but operate in the opposite direction. The positive coefficient for LTV indicates that deal uniqueness increases with the dispersion in the underlying collateral pool average LTV ratio. The estimated coefficients imply an approximate 43 basis point increase in the deal-pair uniqueness score if two deals move from having exactly identical ($\Delta X_{ij} = 0$) average LTV ratios to substantially different ($\Delta X_{ij} = 2$) ratios. As a common observable measure of collateral risk used in underwriting, it stands to reason that deals with significantly divergent average pool LTV ratios would also have different PSA documents. In contrast, the negative coefficient for the variable indicating that the deals in a pair were originated in the same year implies that the deal-pair PSA uniqueness score is about 22 basis points smaller when deals belong to the same year-cohort. It stands to reason that deals originated during the same time period should be underwritten to reflect the same underlying economic conditions and thus their respective PSAs should be more similar to each other than deal pairs containing mortgages originated under different economic environments. The other variables having statistically significant coefficients (geographic HHI, standard deviation of the LTV ratio, and AAA subordination-level) are an order of magnitude less important in accounting for variation in deal-pair PSAs. For example, if a deal-pair has highly different geographic concentrations ($\Delta HHI_{ij} = 2$), then the deal-pair uniqueness measure would increase by about 2 basis points.

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[16]In Table C.1 in Supplementary Material, we report clustered standard errors (at the underwriter pair) in columns 1, 2, 5, and 6 and report robust standard errors in columns 3 and 4.

[17]Note that only Graphs A, C, and E include an indicator variable for whether two deals in a pair were issued in the same year. In Graphs B, D, and F, we include a full set of fixed effects for every possible combination of years in a deal-pair. Thus, the same year indicator variable is collinear to these fixed effects in this specification. Similarly, Graphs A, B, E, and F do not include an indicator variable for whether two deals in a pair have the same underwriter, because these specifications include a full set of underwriter pair fixed effects.

C.   Comparing Underwriter Samples

Figure 5 also provides a quick visual check on whether differences in observable characteristics can account for variation in PSAs across deal pairs depending on whether the deals were originated by the same underwriter (D_u) or different underwriters (D_{-u}). Looking at Graphs C and E, two interesting observations are immediately apparent. First, observable variation in collateral and deal characteristics have a much stronger influence over deal-pair uniqueness scores in the D_u sample versus the D_{-u} sample. Second, with the exception of the difference in average LTV ratios, the majority of collateral and deal characteristics appear to have little impact on the observed differences in deal-pair PSAs when comparing deals across different underwriters (D_{-u}).[18] This suggests that comparisons of PSAs across underwriters may convey additional information to investors over and above the deal and collateral characteristics.

D.   Observable Collateral Characteristics

Focusing on the regression with same underwriter specification, Graph C of Figure 5 reveals several interesting insights into the differences in PSAs. First, as discussed above, we note that the differences in average loan interest rates and average LTV have the greatest impact on determining deal-pair uniqueness scores. The negative coefficient for average loan interest rate indicates that deal uniqueness decreases as the average loan interest rate differences increase. Since average collateral loan interest rate is an observable measure that largely reflects the economic conditions at the time of deal formation, the negative coefficient implies less need to differentiate deals by PSA when the difference in contract loan rates is large. In contrast, when average loan interest rates are similar, then differences in the governing contract becomes more important and deal PSAs tend to be more unique. Other variables describing the underlying pool collateral have a positive, albeit smaller, impact on deal uniqueness. For example, we note that as the absolute difference increases in the average loan balance, and loan duration, the more different (unique) are the PSAs.

The estimation results also indicate that the dispersion of deals' underlying collateral correlates with PSA uniqueness. We capture heterogeneity in the underlying collateral by focusing on the standard deviations of the LTV ratios, log loan balances, and interest rates of a deal's underlying mortgages. For example, we compare a deal whose mortgages have very similar loan balances (i.e., a low standard deviation) to another deal that has a wide distribution of loan balances. The positive and statistically significant coefficient indicates that PSA uniqueness increases with the difference in underlying collateral dispersion across deal pairs.

E.   Observable Deal Characteristics

The estimated coefficients in Graph C of Figure 5 that capture differences in the securitization structure and agent relationships also reveal a strong connection

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[18]As in the combined sample regression, we note that the difference in the average LTV ratio has a sizeable positive impact on deal-pair uniqueness scores in both underwriter samples.

to differences in PSAs. For example, the positive and statistically significant coefficient for AAA subordination indicates that deal-pair PSAs have greater variation as the difference in the level of subordination required to support the AAA tranche increases. Since the AAA subordination level is set at deal origination and reflects the underlying riskiness of the collateral pool, it stands to reason that deals with different amounts of subordination required to support the AAA tranche would have greater differences in the PSA contracts. Following the analysis of Ambrose et al. (2016), we also explore how differences in affiliations between deal agents impact the comparisons of PSAs. For example, Ambrose et al. (2016) demonstrate when the master and special servicing rights are concentrated in one firm, the likelihood that a defaulted loan terminates in foreclosure is reduced. Thus, we create a dummy variable that denotes whether both deals in the deal-pair have a different affiliation pattern (e.g., the dummy equals to 1 if one deal has the master and special servicer functions concentrated in one firm and the other does not) to capture variation in deals with respect to the servicing structure.[19] To study the relationship between deal underwriter and the servicing function, we construct a similar variable that denotes whether the deal pairs have different underwriter-master servicer relationship. This allows us to see how differences in relationship patterns are correlated with the uniqueness score. Finally, we note that variation across deals in collateral geographic exposure (as measured by concentration of loans in census regions) have very little impact on differences in PSAs.

   We also explore the extent that PSAs provide additional information beyond observable collateral and deal structure information. To do so, we examine the adjusted R^2s from the regressions. Across the specifications, we note that observable variation between deals in collateral explain approximately 40% to 60% of the variation in PSA differences. Therefore, while observable collateral and deal characteristics explain some of the differences across PSAs, there is still a significant amount of variation in U_{ij} that is orthogonal to the typical observable variables. In other words, the estimation results suggest that comparisons of PSAs across underwriters reflect more than just a simple difference in pool or deal characteristics. Rather, the differences in uniqueness scores potentially also reflect fundamental differences in how each underwriter structures their CMBS deals.

F.   Robustness Checks

   One potential concern with the regression specification underlying the analysis in this section is that the dependent variable is a series of deal-pair observations, where individual deals are paired with many other deals. While each deal-pair only appears once, each individual deal will appear multiple times. As a result, this raises a concern about the consistency of the estimated coefficients given that the error terms may not be independent. To ensure the robustness of our results to this concern, we augment our specifications with deal fixed effects (Wooldridge (2015)). More specifically, we include in each regression a set of dummy variables corresponding to each deal in our sample. A dummy variable is

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[19]The alternative is for both deals to have the servicing functions concentrated or for both deals to have them separated.

equal to 1 if that particular deal appears in a deal-pair. Thus, every observation has two dummy variables that equal to 1. This approach directly addresses concerns about incorrect estimation of the coefficient due to the appearance of a single deal in multiple observations. We report the results from this exercise in Table C.2 in the Supplementary Material.[20] The results and conclusions based on this specification remain unchanged.

VI.   Does PSA Uniqueness Convey Information Beyond Hard Information?

Having established that observable differences in deal characteristics are related to the similarity or uniqueness of the deal's underlying governing document, we now focus on whether PSA uniqueness corresponds to differences in the performance ($|Y_{d,u,t} - Y_{i,j,k}|$) of the underlying collateral, ex ante deal pricing, and realized investor returns beyond those reflected in observable hard information about the collateral assets or security structure. We do this while controlling for differences across CMBS deals in collateral and securitization characteristics, X_i. To perform these tests, we estimate the following regression:

$$(4) \qquad |Y_{d,u,t} - Y_{i,j,k}| = \alpha + \beta U_{i,j} + \gamma |\Delta X_{ij}| + \Gamma + \varepsilon.$$

The configuration of the set of fixed effects (Γ) depends upon the sample of deal pairs analyzed. When analyzing deal pairs involving the same underwriter (D_u), the fixed effects mirror those used in Graphs C and D of Figure 5. When considering deal pairs with different underwriters (D_{-u}) the fixed effects mirror those in Graphs E and F. The fixed effects controlling for the timing of deal origination provide flexible controls for general credit market trends.

A.   Differences in Ex Post Deal Performance

Equation (4) allows us to examine whether variation in PSA contracts translate into differences in deal performance after controlling for differences in the underlying pools. This research design implies that, like our uniqueness score, the dependent variable also is a measure of "distance." Therefore, we relate differences in the PSA to differences in performance. We do not conclude on whether performance improves or deteriorates as PSAs look different. Our prior is that the coefficient of interest, β, will be positive implying that PSAs that are more observably different from each other will have greater differences in loan performance. The dependent variable ($|Y_{d,u,t} - Y_{i,j,k}|$) measures deal-pair performance differences for measures that reflect the underlying credit risk experienced by CMBS investors within 5 and 10 years of origination. The performance measures include the deal-level loan delinquency rate (60-days past due), the percentage of loans transferred to special servicing (a default measure), and the deal-level cumulative loss.[21] We measure each performance metric at 5 and 10 years

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[20]Due to the large number of fixed effects, we estimate this specification only on the full (combined) sample of deal pairs.

[21]To be precise, we measure the percentage of loans that were ever 60+ days delinquent within 5 and 10 years of their origination.

following deal origination to capture both early termination risk and credit risk at deal maturity. Panel B of Table 1 shows the summary statistics for the various deal outcome variables. The average 5-year cumulative delinquency and default rates are 6.3% and 8.3%, respectively. The delinquency and default rates rise to 18.3% and 20.0%, respectively, by the 10-year mark, which reflects the increased risk surrounding the typical 10-year maturity date on commercial real estate mortgages. Although the average default rate experienced by the typical CMBS deal is about 20%, the actual cumulative loss rate is 3.7%.

Table 2 presents the estimated coefficients with columns 1 and 2 showing the results with the comparison group defined as deals originated by the same underwriter in the same year. Columns 3 and 4 report the estimated coefficients when the comparison group consists of deals originated by other underwriters. Columns 1 and 3 show the estimation results for the specification that uses year-difference fixed effects (number of years between deal origination dates) and columns 2 and 4 report the results for the specification that includes year-pair fixed effects.[22]

We focus on three outcome variables that capture various aspects of ex post credit risk that may be reflected in a CMBS's PSA document. Panels A–C in Table 2 present the estimated coefficients (β) for the uniqueness score where the outcome variable is the deal-pair difference in deal-level averages for the loan delinquency rate, the cumulative default rate, and the cumulative loss rate. Each of these variables reflects the choices of different participants in any given securitization.[23]

1.   Serious Delinquency and Default

In Panel A of Table 2, we study a loan's entry into serious delinquency, which results from the action of the mortgage borrower.[24] In Panel B, following industry practice, we use the transfer of a loan from the collateral pool to the special servicer as an indicator of a loan being in default. Provisions within the PSA define the events that determine when the master servicer is required to transfer a loan from the collateral pool to the special servicer. Therefore, default is a combination of borrower actions–becoming delinquent–and the master servicer's decision to place loans with the special servicer. The special servicer is then responsible for pursuing a foreclosure or loan modification in order to minimize losses to the security holders. Thus, in Panel C, we examine the difference in the cumulative loss rate on the pool of securitized mortgages, which reflects both the borrower credit quality and the servicers' actions.

We highlight two insights from this analysis. First, as anticipated, the β coefficients in Panel A of Table 2 are positive and statistically significant at the

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[22]To address concerns about a single deal appearing in multiple deal pairs, Table C.3 in the Supplementary Material documents these results on the full sample of deal pairs while including a fixed effect for every deal in the sample.

[23]To provide a sense for the distribution of these deal-pair outcome difference variables across the distribution of uniqueness score levels, we report in Table C.5 in the Supplementary Material, the mean values of the various outcome variables across uniqueness score deciles. Panel A shows the mean values for the same underwriter deal pairs (D_u) and Panel B shows the different underwriter deal pairs (D_{-u}). In general, we find that deals that are more similar (first decile) have smaller outcome differences than those in the highest decile.

[24]As such, it is often interpreted as a measure of unobserved loan-pool quality.

TABLE 2

CMBS Outcomes

Table 2 reports the regression coefficient estimate for the deal-pair uniqueness score (U_{ij}) from the equation:

$$|Y_{d,u,t} - Y_{i,j,k}| = \alpha + \beta U_{i,j} + \gamma |\Delta X_{ij}| + \Gamma + \varepsilon,$$

where $U_{i,j}$ is the deal-pair uniqueness score, ΔX_{ij} is the differences in observable deal-pair characteristics, and Γ is the set of fixed effects used. The configuration of the set of fixed effects (Γ) depends upon the sample of deal pairs analyzed. When analyzing deal pairs involving the same underwriter (D_u), the fixed effects mirror those used in Graphs C and D of Figure 5. When considering deal pairs with different underwriters (D_{-u}) the fixed effects mirror those in Graphs E or F. The control variables (ΔX_{ij}) are listed in Table C.1 in the Supplementary Material. The dependent variables are in percentage, and all specifications include underwriter fixed effects, and year-pair fixed effects. Standard errors appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Compared to Same Underwriter		Compared to Different Underwriter		Mean Difference F-Stat.	
	1	2	3	4	1 vs. 3	2 vs. 4
Panel A. Serious Delinquency						
5-YEAR_CUMULATIVE_DELINQUENCY_RATE	0.677***	1.116***	0.214	0.619**	−1.13	−1.50
	(0.197)	(0.180)	(0.359)	(0.278)		
10-YEAR_CUMULATIVE_DELINQUENCY_RATE	0.908***	0.824**	1.648***	1.593***	1.39	1.42
	(0.338)	(0.329)	(0.409)	(0.431)		
Panel B. Default (Transfer to Special Servicer)						
5-YEAR_CUMULATIVE_DEFAULT_RATE	1.055***	1.494***	0.254	0.645*	−1.57	−1.95
	(0.226)	(0.211)	(0.457)	(0.382)		
10-YEAR_CUMULATIVE_DEFAULT_RATE	0.796**	0.943***	1.384**	1.458**	0.89	0.78
	(0.354)	(0.340)	(0.557)	(0.566)		
Panel C. Cumulative Loss Rate						
5-YEAR	0.401***	0.599***	−0.0994	−0.0391	−2.53	−3.10
	(0.0743)	(0.0689)	(0.183)	(0.194)		
10-YEAR	0.581***	0.704***	1.403***	1.396***	2.61	2.30
	(0.165)	(0.165)	(0.268)	(0.251)		
Panel D. Deal Pricing at Origination						
COUPON	−0.00149	0.154***	0.0571	0.0558	0.88	−1.66
	(0.0316)	(0.0350)	(0.0586)	(0.0479)		
Panel E. Weighted-Average Bond IRR						
HIGH-RATED_BONDS	−3.911*	−2.708	−0.469	−0.140	1.48	0.98
	(2.141)	(2.419)	(0.915)	(1.001)		
MEDIUM-RATED_BONDS	5.989***	7.146***	−4.058	−3.336	−3.34	−3.83
	(1.440)	(1.417)	(2.636)	(2.340)		
LOW-RATED_BONDS	8.924***	10.02***	0.472	2.683	−1.89	−1.86
	(2.781)	(2.607)	(3.505)	(2.965)		
Deal characteristic controls	Yes	Yes	Yes	Yes		
Year-difference fixed effects	Yes		Yes			
Year-pair fixed effects		Yes		Yes		
Underwriter fixed effects	Yes	Yes				
Underwriter-pair fixed effects			Yes	Yes		

1% level. This suggests that differences in PSAs are correlated with differences in the rate of serious delinquency between two deals. For example, the estimated coefficients in column 1 of Panel A show that if we examine two PSAs originated by the same underwriter that are unique (i.e., $U_{ij} = 1$), the deal-pair level differences in 5- and 10-year delinquency rates are about 10% higher relative to the average difference in delinquency rates across all deal pairs in the regression sample (i.e., the set D_u), respectively.[25] Similarly, column 3 indicates that if we compare

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[25]We obtain this figure by dividing the coefficients in column 1 by the deal-pair-level average.

two deals originated by different underwriters that are unique, the difference in delinquency rates is higher by 3% to 15% relative to the average difference in delinquency rates. In other words, increasing the difference in the underlying contract ($U_{ij} = 0$ to $U_{ij} = 1$) is reflected in the difference in the two deals' delinquency rates. We find that the specification using the year-difference fixed effects has no meaningful effect on the estimated coefficient or the relative impact of uniqueness (columns 1 vs. 2 and 3 vs. 4). This is suggestive evidence that underwriters may use the PSA as a signaling mechanism to distinguish their deals from those of other underwriters. We find similar patterns in Panel B for the loan default measure.

2. Cumulative Losses

The second insight arises in Panel C of Table 2, which examines the cumulative ex post loss rate. Here, we find that differences in the PSA are reflected in differences in the cumulative loss-rate of the deal over the 10-year horizon. This holds true whether we examine deal pairs originated by the same, or by different underwriters. When comparing deals by different underwriters, the difference in loss-rates for unique deals ($U_{ij} = 1$) is 36% higher relative to the average deal-pair in the regression sample. The corresponding effect for the sample of same-underwriter deal pairs is between 15% and 18%. At a shorter, 5-year horizon, we only find sizeable and significant effects on loss-rate differences for the within-underwriter PSA comparisons (32% to 50% relative to average difference).

B.   Is Uniqueness Reflected in Security Coupon?

In Panel D of Table 2, we focus on the interaction of deal pricing at origination and PSA uniqueness. We proxy for a deal's pricing by calculating the dollar weighted average of the tranche coupons making up each deal. The deal pricing at origination reflects the overall ex ante investor risk expectations. Again, a positive estimated coefficient for the deal uniqueness measure would indicate that investors demand a different coupon, on average, for deals that are more unique.

The estimated coefficients reported in Panel D of Table 2 provide only weak evidence that investors perceive two deals to be differentially riskier if they have different, more unique, PSAs. Of our four specifications, only one has a positive, statistically significant coefficient. The coefficient in column 2, which examines deal pairs involving the same underwriter, shows that coupons for unique deal pairs differ by about 10% relative to the average difference in coupons across deal pairs.

C.   Does Uniqueness Reflect Ex Post Investor Returns?

In Panel E of Table 2, we turn to an analysis of the ex post weighted average bond internal rate of return (IRR). By measuring bond IRRs across tranche seniorities, we test whether and how differences in deal cash flows are related to our measure of PSA uniqueness. We calculate the tranche level IRR using the actual monthly periodic cash flow payments, with the tranche origination balance representing the amount invested (Cordell, Roberts, and Schwert (2020)). Under this construct, if the deal performs exactly as planned at origination, then the bond IRR should be equal to the deal coupon. We aggregate the deal tranches into three

categories based on their ratings at origination (high, medium, and low) and calculate a weighted-average bond IRR for each group.

We find no relationship between the differences in senior bond IRRs and their PSA uniqueness scores. The high-rated bond category represents the senior tranches in the deal structure. As these bonds are at the top of the cash flow waterfall and typically have subordination levels in excess of 10%, it is not surprising that we observe that differences in their IRRs are not correlated with the deal-pair uniqueness score. This is consistent with the idea that senior level bonds in the typical CMBS structure are created so that their cash flows are largely predictable under almost all credit events.

In contrast, we find a statistically significant association between deal-pair differences in the low- and medium-rated bond IRRs and our uniqueness score. This finding is consistent with our uniqueness score capturing unobserved variation in the loan pool quality that would affect the ex post bond IRRs. The positive and significant coefficient indicates that more unique deals, when comparing within the set D_u, have larger differences in the ex post IRRs of medium- and lower-rated bonds. The differences in IRRs are 29% to 61% higher, relative to the average difference in IRRs. Interestingly, we do not observe the same effect when comparing deals across underwriters, as the coefficients in columns 3 and 4 of Table 2 are not statistically significant. Thus, for non-investment grade rated tranches, deals that are more unique appear to have significantly greater differences in ex post IRRs.[26]

D.   How Does PSA Uniqueness Impact CMBS Outcomes?

We also explore the extent to which differences in PSAs interact with securitization structure to alter how underlying collateral assets are managed following deal origination. For this exercise, we focus on the 10-year deal delinquency rate and the 10-year special servicing rate. Our analysis takes the following form:

$$(5) \quad |Y_{d,u,t} - Y_{i,j,k}| = \alpha + \beta_1 U_{i,j} + \beta_2 |\Delta AAA_{i,j}| + \beta_3 MS_{i,j} + \beta_4 MU_{i,j}$$
$$+ \beta_5 (U_{i,j} \times |\Delta AAA_{i,j}|) + \beta_6 (U_{i,j} \times MS_{i,j}) + \beta_7 (U_{i,j} \times MU_{i,j}) + \Gamma + \varepsilon,$$

where $|\Delta AAA_{i,j}|$ represents the difference in AAA subordination level between deals i and j; $MS_{i,j}$ is a dummy variable equal to 1 if the master servicer-special servicer affiliation status is different between deals i and j and is 0 if both deals have the same servicer affiliation status (either affiliated or not affiliated); $MU_{i,j}$ is a dummy variable equal to 0 if the master servicer-underwriter affiliation status is different between deals i and j and is 1 if both deals have the same servicer affiliation status (either affiliated or not affiliated); and Γ represents a set of underwriter and year-pair fixed effects.

Columns 1 and 2 of Table 3 report the estimation results for the difference in deal-pair 10-year delinquency rate while columns 3 and 4 report the results for the differences in the 10-year special servicing transfer rate. Focusing first on the specification without interaction terms (columns 1 and 3), we see the anticipated

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[26]Our results on performance should be interpreted alongside our results on risk (Panels A–C) as the differences in performance will be at least partially explained by the differences in risk. However, we are unable to say whether the performance differences are fully accounted for by these differences in risk.

TABLE 3

CMBS Outcomes

Table 3 reports the regression coefficient estimate for the deal-pair uniqueness score (U_{ij}) from the equation:

$$|Y_{d,u,t} - Y_{i,j,k}| = \alpha + \beta U_{i,j} + \gamma |\Delta X_{ij}| + \Gamma + \varepsilon,$$

where $U_{i,j}$ is the deal-pair uniqueness score, ΔX_{ij} is the differences in observable deal-pair characteristics, and Γ is the set of fixed effects used. The specifications are identical to those in column 2 from Table 2; that is, they restrict deal pairs to those with the same underwriter, and use underwriter fixed effects and deal-pair fixed effects. Columns 1 and 2 consider differences in 10-year serious delinquency rates. Columns 3 and 4 consider differences in rates of transfers to special servicing. In columns 1 and 3, we examine the relationship between pairwise differences in default rates, AAA subordination, and affiliation patterns. In columns 2 and 4, we augment our specification with the interaction of these variables with $U_{i,j}$. Standard errors appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	10-Year Default		10-Year Special Transfer	
	1	2	3	4
AAA_SUBORDINATION	0.0227	0.0639***	0.0960***	0.128***
	(0.0160)	(0.0238)	(0.0169)	(0.0256)
UNIQUENESS × AAA_SUBORDINATION		−0.0914**		−0.0698
		(0.0421)		(0.0438)
MSTR-SPCL_DIFF_AFFIL	−0.177	−0.992***	−0.365*	−0.922**
	(0.184)	(0.360)	(0.191)	(0.372)
UNIQ × MSTR-SPCL_DIFF_AFFIL		1.590**		1.091
		(0.653)		(0.678)
MSTR-UNDRWRTR_DIFF_AFFIL	0.379	−5.432***	0.881*	−0.601
	(0.462)	(1.532)	(0.518)	(1.916)
UNIQ × MSTR-UWRTR_DIFF_AFFIL		9.337***		2.399
		(2.521)		(3.002)
UNIQUENESS	1.089***	1.289***	1.289***	1.480***
	(0.332)	(0.419)	(0.346)	(0.429)
No. of obs.	6,618	6,618	6,618	6,618
R^2	0.389	0.391	0.426	0.427
Sample	Same U'writer	Same U'writer	Same U'writer	Same U'writer
UWFE	Yes	Yes	Yes	Yes
Year-diff FE	No	No	No	No
Year-pair FE	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust

results, and note that the coefficient on U_{ij} remains significant. Setting the dependent variable to the difference in the 10-year delinquency rate, we see in column 1 that the difference in the securitization structure variables are not statistically significant. In contrast, when the dependent variable is the difference in the transfer to special servicing rate (column 3), we see that greater difference in AAA subordination between deals results in a greater variation in default outcome. The negative coefficient for MS suggests that when deals in a pair have different master-special servicer affiliation statuses, then the deals have greater similarity in transfers to special servicing. In contrast, the positive coefficient on MU indicates that when the servicer-underwriter affiliation statuses are different across two deals, the differences in default and special servicing rates are greater.

While the variation in deal-pair agent affiliations and AAA subordination may suggest differences in performance, it is possible that the PSA could be drafted to minimize those differences. Thus, the key test we want to perform is to examine whether the PSA contents interact with these deal characteristics or not. Hence, in columns 2 and 4, we interact our uniqueness measure with differences in AAA subordination, and compare the signs of the coefficients on the main effect and the interaction term. For example, looking at the delinquency rate (column 2) the

negative and statistically significant coefficient on the interaction of the unique-ness score and the AAA subordination difference suggests that as differences in PSAs become greater, the variation in AAA subordination levels becomes less important in explaining the differences between the deals' 10-year delinquency rates. For example, when two deals are identical ($U_{i,j} = 0$), a greater difference in the AAA subordination level corresponds to a greater difference in underlying asset quality. In other words, as the variation in PSAs increases from one deal to another, these differences attenuate the impact of observable variation in deal AAA subordination levels.

We next compare the signs of the coefficients on U_{ij}, MS, MU and their interactions. Note that when affiliation patterns are the same across a deal-pair (i.e., MU $= 0$ or MS $= 0$) then differences in PSAs are positively correlated with differences in performance (positive coefficient on U_{ij}). However, when affilia-tion patterns are different (i.e., MU $= 1$ or MS $= 1$), then the difference in PSAs attenuate the effect of observable differences in affiliation. The positive coeffi-cient for the interaction indicates that differences in PSAs mitigates the impact of variation in affiliation status.

## VII.   Which Part of the PSA Drives Uniqueness?

As noted above, the PSA governing document consists of several sections (or articles) that cover various aspects of the deal. The major articles in each PSA follow a set template determined by the SEC, while the individual sections within each article may vary across deal. For example, Article 2 contains the provisions covering the conveyance of the mortgage loans and security issuance, while Article 3 concerns the administration and servicing of the loans. Thus, a natural question is whether examining the full PSA document yields additional information beyond analyzing specific articles, such as the representation and warranties section, com-monly thought to govern the securitization.

To tackle this question, we repeat the textual analysis described in Section III, restricting the text to only Articles 2 and 3. We obtain the vector representations for Article 2 and Article 3 for each of the 692 conduit deals in our sample. We then calculate the Article 2 and Article 3 pairwise uniqueness scores ($U(d_1, d_2)$) using equation (1) and compare them to the full document PSA uniqueness scores.

Figure 6 displays the cosine distance matrices for Articles 2 and 3, which correspond to the full PSA document distance matrix shown in Figure 2. As before, darker shades represent pairs that have greater differences, while lighter shading indicates deal pairs that are more similar. The lighter color variations evident in the Article 2 and 3 matrices versus the darker colors shown in the full PSA matrix visually confirms our intuition that deal-pair uniqueness increases as the totality of the governing document is considered, as opposed to only individual articles. For example, in examining the differences between the individual deal-pair uniqueness scores for Article 3 compared to the full PSA, we find that 62.5% of the deal pairs have Article 3 uniqueness scores that are smaller than their corresponding full PSA uniqueness scores. Furthermore, when examining the similarities between deals based on Article 2 compared to their corresponding PSA, we find that fully 89%

FIGURE 6

Distance Score Visualization for Articles 2 and 3 of the
Pooling and Servicing Agreement

Figure 6 shows the cosine distance matrices for Articles 2 (Graph A) and 3 (Graph B).
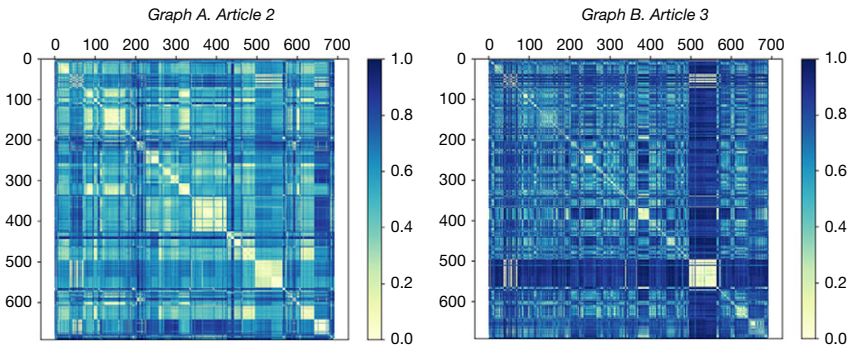
of the deal-pair Article 2 uniqueness scores are smaller than their full PSA score. Again, since smaller uniqueness scores indicate documents that are more alike, it is clear that expanding the comparison to include all PSA sections is important in order to establish the extent to which individual security governing documents convey unique information.[27]

Having confirmed that analyzing the full PSA leads to higher uniqueness scores across CMBS deal pairs, we now examine the variation in the information content of the Articles 2 and 3 uniqueness scores compared to the full document results. To do so, we replicate the multivariate regression analysis using the Article 2 and Article 3 uniqueness scores. For this analysis, we focus on deal pairs within the same underwriter (D_u) in order to hold as many factors constant as possible. Again, statistically significant estimated coefficients indicate that documents that are more unique have greater differences in loan performance. Figure 7 plots the estimated coefficients and 90% confidence intervals from these regressions along with the corresponding uniqueness score coefficients for the full PSA document reported in Table 2. Panels A–C report the results for serious delinquency, default, and cumulative loss rate, respectively.[28] The plots confirm our prior that individual components of the PSA contain less information than the full document. For example, the estimated coefficients for the full PSA uniqueness score are statistically significant when looking at loan performance (serious delinquency, default, or cumulative loss) whereas the coefficients for the uniqueness scores based only on Articles 2 or 3 are not statistically significant.[29] Our finding is consistent with the well-practiced legal principle that a contract should be read as an entirety and the

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[27]We provide additional analysis comparing differences in uniqueness scores between Articles 2 and 3 and the full PSA in Appendix D of the Supplementary Material.

[28]The regressions include year-difference fixed effects.

[29]Table C.4 in the Supplementary Material repeats this analysis on the sample of deal pairs with different underwriters.

FIGURE 7

Comparison of Estimated Coefficients

Each graph of Figure 7 presents the estimated coefficients (and 95% confidence interval) for the performance regressions (equation (4)) with year-difference fixed effects. D_U indicates that the comparison group is the same underwriter.

Graph A. Serious Delinquency – D_U

Graph B. Default – D_U

Graph C. Cumulative Loss Rate – D_U
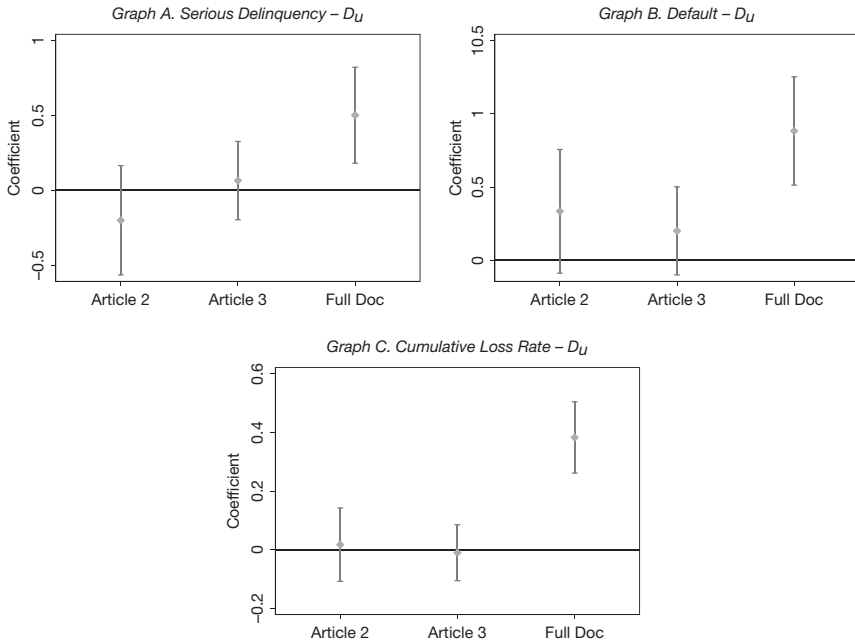
language of contract components should be interpreted within the contracts in which they appear (Epstein (1984), DiMatteo and Morant (2010)).

VIII.   Conclusion

In this study, we use the advantages of NLP to process large quantities of textual data. The advantage of this tool is that it allows the researcher to calculate the uniqueness of contracts relative to other deals.

We find that heterogeneity in PSA documents both within and across time and underwriters suggests that these contracts are not simply boiler-plate but reflect differences across CMBS deals. Differences in PSAs are correlated with variation in the underlying loan pool. They are also correlated with differences in ex post outcomes driven by borrower credit-quality, special servicer actions, and their combined effect, which is reflected in cumulative losses. Underwriters appear to use PSAs to distinguish their deals from those of other underwriters. Finally, we find that bond IRRs, particularly for medium and lower rated tranches, reflect the uniqueness of the deals' governing PSA. Thus, our study shows the importance of the considering the totality of the document that governs an asset-back securitization's operations and cash flows to its investors.

Appendix A. Machine Learning and Textual Analysis

In Appendix A, we briefly describe the document vectorization (DV) algorithm introduced and implemented in Le and Mikolov (2014), Shen and Ross (2021), and Shen and Springer (2022) that we use to convert each PSA into a high-dimensional numerical vector. The vectors produced by the DV algorithm preserve the meaning of the document, unlike supervised learning algorithms that attempt to make predictions based on training samples. The vector for a given document has analytical content when compared to the vector for another document. Thus, PSAs with similar content are closer to each other in the vector space.

The DV algorithm follows a fundamental linguistic principle: the meaning of words and sentences are defined by their contexts because the contextual elements often share syntactic and semantic relations with each other. Therefore, the first step of implementing this algorithm is to process the entire set of PSAs and create a list of all unique words in the document. Given the algorithm's key principle, it is imperative to preserve the information about each word's location. We denote the target word at the ith location in document j as w_{ij}^{out}.

An effective way to identify a word is to use the words that appear near it. Thus, for each word w_{ij}^{out}, the algorithm uses words that fall within a window of size L surrounding w_{ij}^{out}.[30] In addition, each word at location l within the window, denoted as w_{ij}^{in}, has a numerical weight (denoted as z_{ijl}) associated with it. Correspondingly, we denote the vector representation for the collection of the weights of these "input" words w_{ij}^{in} to be Z_{ij}.[31] In addition to the information contained in each window L, other words in the document may also provide information. Thus, we use a vector v_j to characterize the contents of document j. One can view this as a "pseudo-word vector" that stores the meaning of the words outside of the window L.

With these two sources of information, the second step is to define an index x_{ijk} that describes the likelihood of a target word in location i in document j being the kth word in the choice set given the set of L input words surrounding location i in document j:

$$(6) \qquad x_{ijk} = \beta_k' v_j + \sum_{l=1}^{L} \gamma_k' z_{ijl}.$$

Here, β_k and γ_k are parameter vectors to be estimated by the algorithm. The γ's are word specific and the z's are location specific, and thus they can be separately identified. Similarly, β_k and v_j are separately identified. The algorithm simultaneously estimates the standard parameter vectors γ_k and β_k as well as the document vector v_j and the weight vectors z_{ijl}.

In a third step, the DV algorithm will choose these parameters to maximize the probability of correctly choosing the target word w_{ij}^{out} using the words surrounding it. The conditional probability of a target word being chosen is

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[30]The window size or bandwidth is selected by cross validation. However, we verify that the results are very robust to bandwidth choice, and we find nearly identical estimates for bandwidths between 10 and 50 words.

[31]The dimension of each of the weighting vectors is the same for every word and every PSA. This setup helps further analysis when we want to find the numerical representation of the PSA document.

$$(7) \qquad Pr\left[w_{ij}^{out}|i,j\right] = \frac{e^{x_{ijw_{ij}^{out}}}}{\displaystyle\sum_{k=1}^{K} e^{x_{ijk}}},$$

where $x_{ijw_{ij}^{out}}$ is defined as

$$(8) \qquad x_{ijw_{ij}^{out}} = \beta_{w_{ij}^{out}}' v_j + \sum_{l=1}^{L} \gamma_{w_{ij}^{out}}' z_{ijl}.$$

By definition, the sum of the probabilities calculated from equation (7) is guaranteed to equal one for all candidate words. The algorithm chooses the β's, γ's, and numerical weights (Z_{ij} for surrounding words w_{ij}^{in} and v_j for document j) to maximize equation (7). In other words, the algorithm seeks to maximize the probability of choosing the correct target word.

Assuming that there are I words from J documents, the log likelihood problem can be written as

$$(9) \qquad \underset{\beta_k, \gamma_k, v_j, z_{ijl}}{Min} \sum_{j=1}^{J} \sum_{i=1}^{I} -\log\left(PR\left[w_{ij}^{out}|w_{ij}^{in}\right]\right),$$

where

$$(10) \qquad \begin{aligned} \log\left(PR\left[w_{ij}^{out}|w_{ij}^{in}\right]\right) &= x_{ijw_{ij}^{out}} - \log\sum_k \exp\left(x_{ijk}\right) \\ &= \left(\beta_{w_{ij}^{out}}' v_j + \sum_{l=1}^{L} \gamma_{w_{ij}^{out}}' z_{ijl}\right) \\ &\quad - \log\sum_k \exp\left(\beta_k' v_j + \sum_{l=1}^{L} \gamma_k' z_{ijl}\right). \end{aligned}$$

This setup is often described as a neural network in machine-learning applications. The neural network outputs document-specific vectors v_j. We use these vectors to quantify the relationship between the PSA documents.[32]

Appendix B. Scoring Examples

Appendix B provides an illustration of the ML-based document comparison method applied to a brief section from the CMBS PSA. In the interest of brevity, we selected subsection (a) from Section 2.1 for five representative CMBS deals. The PSA Section 2.1 subsection (a) identifies the "Conveyance" terms for transferring the mortgage pool from the underwriter to the CMBS trust.

Exhibits 1–5 report the text used in this scoring example and correspond to the following CMBS deals: (1) Morgan Stanley Bank of America Merrill Lynch Trust 2012-C6; (2) LB-UBS Commercial Mortgage Trust 2007-C6; and (3) Citigroup Commercial Mortgage Trust 2006-C5.

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[32]We follow Le and Mikolov (2014) and minimize the log-likelihood function using the stochastic gradient descent with back-propagation optimization technique, following the machine-learning literature.

The pairwise uniqueness score for Exhibits 1 and 2 is 0.55, indicating that these documents are relatively dissimilar. Likewise, the pairwise score for Exhibits 2 and 3 is 0.2, suggesting that these documents share a relatively high degree of common elements. For instance, both the two documents discuss bullet points from (i) to (iv) with the same subjects and order. They both list the conveyance between different parties and indicate the end of the fiscal year of the Trust is at the same time.

Finally, Exhibits 4 and 5 report Section 2.1(a) for two Banc of America deals. Not surprising, given that these deals are from the same underwriter, the pairwise uniqueness score is 0.015 revealing a high degree of overlap, which is one order of magnitude lower than the other sample comparisons. This comparison can also serve as a sanity check for the proposed algorithm, which demonstrates that the model can pickfig out very fine details between documents and quantify them at a basis that can be shared across the entire document pool.

Note that the pairwise uniqueness scores reported above measure the similarities of Section 2.1 of these PSAs. When comparing full PSAs, our algorithm focuses on the overall contract contents and minimizes any immaterial differences such as origination years and deal names. To show this, we artificially constructed pseudo-PSAs by altering the deal names/series numbers/origination years in the PSA to something completely different, leaving the rest of the PSAs identical. The uniqueness scores between an original PSA and its corresponding pseudo-PSA is approximately 0. We show a comparison between two PSAs (main text body of a PSA for a CMBS deal and its modification) in Appendix E of the Supplementary Material.

Exhibit 1: Morgan Stanley Bank of America Merrill Lynch Trust 2012-C6
ARTICLE II
DECLARATION OF TRUST;
ISSUANCES OF CERTIFICATES
Section 2.1 Conveyance of Mortgage Loans (Pages 107–108)

(a) Effective as of the Closing Date, the Depositor does hereby establish a trust designated as "Morgan Stanley Bank of America Merrill Lynch Trust 2012-C6" and assign in trust to the Trustee, without recourse, for the benefit of the Certificateholders all the right, title and interest of the Depositor, in, to and under (i) the Mortgage Loans identified on the Mortgage Loan Schedule including the related Mortgage Notes, Mortgages, security agreements and title, hazard and other insurance policies, including all Qualifying Substitute Mortgage Loans, all distributions with respect thereto payable after the Cut-Off Date, the Mortgage File and all rights, if any, of the Depositor in the Distribution Account, all REO Accounts, the Collection Account and the Reserve Accounts, (ii) the Depositor's rights under each Mortgage Loan Purchase Agreement that are permitted to be assigned to the Trustee pursuant to Section 14 thereof, (iii) the Initial Deposit, (iv) the Depositor's rights under any Intercreditor Agreement, Non-Serviced Mortgage Loan Intercreditor Agreement and the related Non-Serviced Mortgage Loan Pooling and Servicing Agreement with respect to any Non-Serviced Mortgage Loan, (v) with respect to the EC Trust Certificates, each of the EC Trust REMIC III Regular Interests, and (vi) all other assets included or to be included in REMIC I or the Class J Grantor Trust. Such assignment includes all interest

and principal received or receivable on or with respect to the Mortgage Loans and due after their respective Due Dates in October 2012. The transfer of the Mortgage Loans and the related rights and property accomplished hereby is absolute and is intended by the parties to constitute a sale. In connection with the initial sale of the Certificates by the Depositor, the purchase price to be paid includes a portion attributable to interest accruing on the Certificates from and after October 1, 2012. The transfer and assignment of any Non-Serviced Mortgage Loans to the Trustee and the right to service such Mortgage Loans are subject to the terms and conditions of the related Non-Serviced Mortgage Loan Pooling and Servicing Agreement and the related Non-Serviced Mortgage Loan Intercreditor Agreement, and the Trustee, by the execution and delivery of this Agreement, hereby agrees that such Mortgage Loans remain subject to the terms of the related Non-Serviced Mortgage Loan Intercreditor Agreement and, with respect to each Serviced Pari Passu Mortgage Loan and Serviced Companion Loan, the related Intercreditor Agreement. The transfer and assignment of any A Notes and Serviced Pari Passu Mortgage Loans to the Trustee and the right to service such Mortgage Loans are subject to the terms of the related Intercreditor Agreements, and the Trustee, by the execution and delivery of this Agreement, hereby agrees, that such Mortgage Loans remain subject to the terms of the related Intercreditor Agreements (or with respect to a Joint Mortgage Loan treated as a Loan Pair in accordance with Section 8.30 hereof, the applicable Mortgage Loan documents and Section 8.30 hereof).

Exhibit 2: LB-UBS Commercial Mortgage Trust 2007-C6

ARTICLE II

CONVEYANCE OF TRUST MORTGAGE LOANS; REPRESENTATIONS AND WARRANTIES;

ORIGINAL ISSUANCE OF CERTIFICATES

SECTION 2.01. Creation of Trust; Conveyance of Trust Mortgage Loans (Page 122)

(a) It is the intention of the parties hereto that multiple common law trusts be established pursuant to this Agreement and the laws of the State of New York and that such trusts be designated as: "LB-UBS Commercial Mortgage Trust 2007-C6," in the case of the Mortgage Trust individually or all the subject trusts collectively, as the context may require; "Class A-2FL Grantor Trust," in the case of Grantor Trust A-2FL; and "Class A-MFL Grantor Trust," in the case of Grantor Trust A-MFL. LaSalle is hereby appointed, and does hereby agree, to act as Trustee hereunder and, in such capacity, to hold the Trust Fund in trust for the exclusive use and benefit of all present and future Certificateholders.

The Depositor, concurrently with the execution and delivery hereof, does hereby assign, sell, transfer, set over and otherwise convey to the Trustee in trust, without recourse, for the benefit of the Certificateholders, all the right, title and interest of the Depositor in, to and under (i) the Trust Mortgage Loans, (ii) the UMLS/Depositor Mortgage Loan Purchase Agreement(s), (iii) any Co-Lender Agreement(s), and (iv) all other assets included or to be included in the Trust Fund. Such assignment includes all interest and principal received or

receivable on or with respect to the Trust Mortgage Loans and due after the Cut-off Date and, in the case of each Trust Mortgage Loan that is part of a Loan Combination, is subject to the provisions of the related Co-Lender Agreement. With respect to each Trust Mortgage Loan that is part of a Loan Combination, the Trustee, on behalf of the Trust, assumes the obligations of the holder of such Trust Mortgage Loan and the related Mortgage Note under, and agrees to be bound by, the related Co-Lender Agreement.

The parties hereto acknowledge and agree that, notwithstanding Section 11.07, the transfer of the Trust Mortgage Loans and the related rights and property accomplished hereby is absolute and is intended by them to constitute a sale.

The Trust Fund shall constitute the sole assets of the Trust. Except as expressly provided herein, the Trust may not issue or invest in additional securities, borrow money or make loans to other Persons. The fiscal year end of the Trust shall be December 31.

Exhibit 3: Citigroup Commercial Mortgage Trust 2006-C5

ARTICLE II

CONVEYANCE OF MORTGAGE LOANS; REPRESENTATIONS AND WARRANTIES; ORIGINAL ISSUANCE OF CERTIFICATES

SECTION 2.01 Conveyance of Trust Mortgage Loans (Page 92)

(a) The Depositor, concurrently with the execution and delivery hereof, does hereby establish a common law trust under the laws of the State of New York, designated as "Citigroup Commercial Mortgage Trust 2006-C5," and does hereby assign, sell, transfer, set over and otherwise convey to the Trustee, in trust, without recourse, for the benefit of the Certificateholders (and for the benefit of the other parties to this Agreement as their respective interests may appear) all the right, title and interest of the Depositor, in, to and under (i) the Trust Mortgage Loans and all documents included in the related Mortgage Files and Servicing Files, (ii) the rights of the Depositor under Sections 1, 2, 3, and 5 (and to the extent related to the foregoing, Sections 8 through 17 and 19) of each of the Mortgage Loan Purchase Agreements, (iii) the rights of the Depositor under each Co-Lender Agreement, and (iv) all other assets included or to be included in the Trust Fund. Such assignment includes all interest and principal received or receivable on or with respect to the Trust Mortgage Loans and due after the Cut-off Date and, in the case of each Trust Mortgage Loan that is part of a Loan Combination, is subject to the provisions of the corresponding Co-Lender Agreement. The Trustee, on behalf of the Trust, assumes the rights and obligations of the holder of the Mortgage Note for each Combination Mortgage Loan under the related Co-Lender Agreement; provided that Master Servicer No. 2 and the Special Servicer shall, as further set forth in Article III, perform the servicing obligations of the holder of the Mortgage Note for each A-Note Trust Mortgage Loan under the related Co-Lender Agreement. The transfer of the Trust Mortgage Loans and the related rights and property accomplished hereby is absolute and, notwithstanding Section 11.07, is intended by the parties to constitute a sale.

The Trust Fund shall constitute the sole assets of the Trust. Except as expressly provided herein, the Trust may not issue or invest in additional securities, borrow money or make loans to other Persons. The fiscal year end of the Trust shall be December 31.

Exhibit 4: Banc of America Commercial Mortgage Inc. Commercial Mortgage Pass-Through Certificates, Series 2004-1

It is the intention of the parties hereto that a common law trust be established pursuant to this Agreement and further such trust be designated as "Banc of America Commercial Mortgage Inc. Commercial Mortgage Pass-Through Certificates, Series 2004-1." Wells Fargo Bank, N.A. is hereby appointed, and does hereby agree to act, as Trustee hereunder and, in such capacity, to hold the Trust Fund in trust for the exclusive use and benefit of all present and future Certificateholders. It is not intended that this Agreement create a partnership or a joint stock association.

Exhibit 5: Banc of America Commercial Mortgage Inc., Commercial Mortgage Pass-Through Certificates, Series 2008-1

It is the intention of the parties hereto that a common law trust be established pursuant to this Agreement and further such trust be designated as "Banc of America Commercial Mortgage Inc., Commercial Mortgage Pass-Through Certificates, Series 2008-1." Wells Fargo Bank, N.A. is hereby appointed, and does hereby agree to act, as Trustee hereunder and, in such capacity, to hold the Trust Fund in trust for the exclusive use and benefit of all present and future Certificateholders. It is not intended that this Agreement create a partnership or a joint stock association.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000509.

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