Modeling Complex Financial Products*

Margrét V. Bjarnadóttir  
University of Maryland mbjarnad@umd.edu,

Louiqa Raschid  
University of Maryland, lraschid@umd.edu,

The objective of this paper is to explore how financial big data and machine learning methods can be applied to model and understand complex financial products. We focus on residential mortgage backed securities, resMBS, that were at the heart of the 2008 US financial crisis. The securities are contained within a prospectus and have a complex payoff structure. Multiple financial institutions form a supply chain to create the prospectuses. We provide insight into the performance of the resMBS securities through a series of increasingly complex models. First, models at the security level directly identify salient features of resMBS securities that impact their performance. Second, we extend the model to include prospectus level features. We are the first to demonstrate that the composition of the prospectus is associated with the performance of securities. Finally, to develop a deeper understanding of the role of the supply chain, we use unsupervised probabilistic methods, in particular, dynamic topics models (DTM), to understand community formation and temporal evolution along the chain. A comprehensive model provides insight into the impact of DTM communities on the issuance and evolution of prospectuses, and eventually the performance of resMBS securities.

Key words: Latent Dirichlet Allocation (LDA); topic models; probabilistic model; financial supply chain; mortgage backed securities; financial communities; subprime crisis; 2008 US financial crisis.

History:

1. Introduction

The 2008 US financial crisis highlighted several challenges and limitations in monitoring systemic risk. Informally, systemic risk corresponds to risks that impact multiple systemically important financial institutions, as was the case in 2008. It also considers situations where the risk may be contagious across multiple financial markets. The residential mortgage backed securities, resembles, at the heart of the crisis, were linked to massive defaults of subprime mortgages in the residential mortgage market. The risk was contagious due to the interconnectedness of resMBS

* Data Ethics Note: No data ethics considerations are foreseen related to this paper.
securities with other financial products. For example a resMBS security may have been one arm of a collateralized debt obligation (CDO), while the other arm of the CDO could have leveraged a security tied to a foreign currency exchange rate. The crisis also exposed a major shortcoming: the gaps in data collection around financial products, and the limited ability for synthesis across data sets. Multiple financial regulatory agencies are each responsible for monitoring individual lines of financial products, leading to silos of isolated data, and a lack of synthesis and analysis across products and markets. These silos and gaps severely restricted the ability of regulators to manage the crisis with data driven actions.

The primary villains of the 2008 crisis were generally believed to be the financial institutions that were closely related to the subprime residential mortgage market; subprime loans are those issued to borrowers with poor credit scores. Many of these institutions filed for bankruptcy protection either before or during the 2008 crisis, or they faced financial penalties. The rating agencies were also vilified for assigning the coveted Aaa ratings to many securities, including securities built on the subprime mortgages. However, an ex-post study conducted ten years after the crisis by Ospina and Uhleg (Ospina and Uhlig (2018)) painted a more nuanced picture. Their research concluded that the majority of the resMBS securities actually performed well. They found that, as expected, securities issued closer to the financial crisis, i.e., those issued from 2006 to 2007, suffered greater losses, compared to those issued before the crisis. Most notably, they found that only a small share of resMBS securities contributed the greatest losses.

Given this scenario, and the many challenges of monitoring these products, we believe that it would be invaluable for regulators and investors to have access to the relevant data and models, so as to gain insight into the systemic risk from these products. A valuable strategic outcome of our research would be the potential to isolate and quarantine the subset of securities that were found to pose the greatest risk (Ospina and Uhlig (2018)). In this research, we apply information extraction and integration approaches, and machine learning methods, to address this challenge. This research provides a proof of concept of how novel datasets, and models built on a rich set of features, can be synergistically exploited to understand complex financial products.

A key contribution of our research is understanding the impact of the supply chain. Many financial institutions came together to create communities during the product development of resMBS securities. Tasks performed by the institutions include originating residential mortgages, creating a real-estate trust or legal framework, issuing prospectuses that define the contractual obligations of these products, selling securities to institutional investors, and finally servicing the resMBS
securities, i.e., managing the payouts. Forming these communities incurs overhead, so a successful community may continue to repeatedly issue hundreds of prospectuses over time. Our research is the first to exploit this community structure. *Communities could enable us to potentially isolate the subset of prospectuses and securities that contributed the greatest losses.*

We study the performance of resMBS securities through a series of increasingly complex models. First, models at the level of individual securities identify salient features of resMBS securities that impact their financial performance. This includes the security class (from secured debt to unsecured debt), the year of issuance, and the initial Moody’s rating. Further, there are additional significant security level features reflecting the often complex waterfall payoff structure for these prospectuses (see details in Section 2). For example, the payoff to a security may be subordinated to the payoff to other securities, labeled *senior subordinated debt* (SSUP). The model reflects that the Moody’s ratings may only be able to capture some of the nuanced risk from the waterfall payoff structure.

The securities level model does not provide an approach to isolate the groups of securities that suffered the greatest losses. Thus, we extend the model to include prospectus level features. This includes composition features, e.g., the count, and the nominal principal (in US $), of the securities in the different security classes, bundled within a prospectus. Our model is the first to demonstrate that the composition of security classes within a prospectus can provide a quality signal. Further, the *act of inclusion* of securities labeled *senior subordinated debt* (SSUP) within the prospectus has an impact on performance, for the securities that carry the label, and more notably, for other securities within the prospectus that do not carry this label.

To provide even deeper insight, we draw upon unsupervised probabilistic topic models (Blei et al. (2003), Steyvers and Griffiths (2007)) that have been successfully used to identify topics from a collection of documents. In our context, topics represent communities of financial institutions that work together along the supply chain. We identify communities that capture complex relationships, e.g., Company X is the issuer of securities where Company Y originated the mortgages, and X issued prospectuses from 2002 through 2005. We use dynamic topic models (DTM) (Blei and Lafferty (2006)) that use time slices to understand the evolution of topics over time.

Our final and most comprehensive model includes the community (topic) associated with each prospectus, as well as the prior security and prospectus level features. This model highlights that even after accounting for the features of the securities and the prospectuses, the community that
issued the prospectus remains significant in predicting financial performance. Thus, our most notable research contribution is the identification of financial communities which can be used to identify and isolate subsets of prospectuses and securities. These communities can differentiate the securities based on their financial performance; this is notable since we do not include features of the securities, or features of financial performance, during the process of identifying the financial communities. Communities that included companies that were active in the subprime market, and failed or faced penalties during or after the crisis, were identified by our comprehensive model.

We note that we are not currently claiming a causal connection between the supply chain communities (topics) and the performance of resMBS securities. We well understand that the supply chain is only one factor among myriad that can influence the performance of these complex financial products. Nevertheless, our novel approach to modeling these products may prove to be groundbreaking, in showing the synergistic potential of utilizing financial big data and computational methods to understand complex financial products. Our research has the potential to identify and quarantine the most risky products in a complex product scenario such as resMBS.

2. Background and Related Work

2.1. Background

Mortgage backed securities have had a long and successful history as complex financial products and investment vehicles. They have been issued since 1990 by various government sponsored enterprises (GSEs) such as Fannie Mae, and by non-agency or private labels. Our focus is on the private label securities since they played a major role in the 2008 crisis. Figure 1 provides the nominal value associated with such issuance from 1990 through 2008 (Securities Industry and Financial Markets Association (SIFMA (2018)). As reflected in the figure, there was a boom in the early 2000s in the issuance of private label resMBS products. The issuance reached its peak around 2006, followed by a sharp decline in late 2007, in alignment with the financial crisis.

A residential mortgage-backed security is a complex financial product that is constructed by pooling cash flows from a collection of residential mortgage loans. The cash flows from the pool of mortgages, both the principal and interest payments, are allocated to a set of resMBS securities, based on a complex waterfall payoff priority. Figure 2 provides an illustration of the pool of mortgages and the waterfall payment structure (adapted from Commission (2011)). The securities served first, at the top of the waterfall, are referred to as investment grade senior secured debt, or Class A securities. This is followed by mezzanine (Class M) securities, and then discounted or unsecured securities (Class B securities). The securities are packaged within a prospectus -
a legal contract - and they are rated for their credit worthiness. The prospectus is issued and the securities are then sold to investors.

Figure 1  The nominal value of residential mortgage backed securities issued from 1990 to 2008 (Securities Industry and Financial Markets Association \(\text{SIFMA(2018)}.\))

Figure 2  The complex tranche and waterfall payoff structure of residential mortgage backed securities \(\text{resMBS}\), adapted and simplified from \(\text{Commission(2011)}.\)

2.2. The 2008 US Financial Crisis and Financial Monitoring

Following the 2008 financial crisis, there have been several papers describing \(\text{resMBS}\) and their role in the crisis. We refer the reader to research in \(\text{Ashcraft and Schuermann (2008), Ashcraft et al. (2010), Gerardi et al. (2010), Hunt et al. (2014)}\) that explicitly addresses how the residential
mortgage registration and transfer systems, and the subprime crisis, contributed to the 2008 US financial crisis.

Researchers have dived into the performance of the resMBS securities from different angles, including focusing on the variation in their credit rating over time (Ashcraft et al. (2010)), the effect of issuer size on initial prices (He et al. (2012)) and ratings (He et al. (2011)), and the role of accounting rules on resMBS sales (Merrill et al. (2012)). In contrast, our research focuses on financial institutions and their role(s) in the supply chain. A single study (Demiroglu and James (2012)) focuses on the effect when a particular financial institution is both an originator of mortgages, as well as either a sponsor or a servicer; in these cases, the default rates are found to be significantly lower. Our results suggest a more nuanced scenario where financial communities issue prospectuses and securities that have differentiated performance.

We briefly report on results on lower tranche securities issued between 2001 and 2007, presented in Ashcraft et al. (2010). They report that the fraction of highly rated securities in each prospectus decreases with increasing mortgage credit risk (measured either ex ante or ex post) This suggests that ratings indeed contain useful information for investors. However, there is also evidence of significant time variation in credit ratings, including a progressive decline in standards between 2005 and 2007. We note that this was the peak period for the issuance of low performing (toxic sub-prime) mortgages. They observe high mortgage defaults and losses, and large rating downgrades, for securities with observably higher risk mortgages based on a simple ex ante model. They also observe securities with a high fraction of opaque low documentation loans. These findings hold over the entire sample period.

An ex-post study conducted ten years after the crisis by Ospina and Uhleg (Ospina and Uhlig (2018)) provides a detailed picture of the payoff performance of these securities, and compares this to their ex-ante ratings. Their research concluded that the majority of the resMBS securities labeled Aaa actually performed well. They found that, as expected, securities issued closer to the financial crisis, i.e., those issued from 2006 to 2007, had greater losses, compared to those issued much before the crisis. They found that the mis-rating of Aaa debt was modest. Most notably, they found that only a small share of resMBS securities contributed the greatest losses. They further concluded that after controlling for the bust in home prices, the prior boom in the housing market was beneficial for the performance of the resMBS securities.

Since the 2008 US financial crisis, there has been research on monitoring for systemic risk, with a focus on systemic shocks, financial stability, capital reserves, etc. (Arnold et al. (2012),
Bisias et al. (2012), Liang (2013)). Billio et al. describe a seminal study on creating a novel dataset to study systemic risk (Billio et al. (2012)). They explore the interconnectedness of hedge funds, banks, brokers, and insurance companies using Granger causality. Our research is similar in spirit, but we apply topic modeling to study the interconnectedness among financial entities in the resMBS product supply chain. We believe that we are the first to apply topic modeling in this context.

2.3. Text Analytics in Finance

Our focus in this paper is to understand the drivers of the performance of complex financial products, including the impact of the financial communities that support the resMBS supply chain. This includes the participation of a financial institution in a community, and the role(s) played by the institution. To achieve this goal, we draw upon extensive research on document corpora, in the reference disciplines of information retrieval, computational linguistics and machine learning. We further utilize text analytics and topic modeling; below we review some of the related literature.

There is a long history of applying text analytics to understand firm behavior and financial product performance. Loughran and McDonald (2016) conducted an extensive survey of text analytics approaches in the accounting, finance, and economics literature. Their survey covered methods to determine topics in documents, to find hidden structures and to determine sentiment. As an example of text mining applications in finance, Hoberg and Philips (2018) study a collection of 10-K statements filed with the Securities and Exchange Commission (SEC) to determine how firms utilize product descriptions and product differentiation, in comparison to competitors. As a result of the study, they generated a new set of industries, competitor sets, and corresponding new measures of industry competition.

There is growing interest in exploiting financial big data and computational tools to better model and predict the behavior of financial ecosystems. The success of text extraction tools (Burdick et al., 2016, 2014, 2011, Hernández et al., 2010), and the availability of public financial documents that are typically filed with the SEC, has lowered the barriers to such research.

Latent Semantic Analysis (LSA) (Landauer and Dumais, 1997)) was one of the earliest approaches to claim that semantic information could be obtained from the word-document co-occurrence matrix of some (large) document collection. LSA used dimensionality reduction based on matrix factorization and represented words and documents as points in a Euclidean space. Our

---

1 10-K statements are comprehensive financial reports that publicly traded companies are required to produce.
research draws upon unsupervised probabilistic topic models (Blei et al. (2003), Steyvers and Griffiths (2007)) that have been successfully used to identify topics from a collection of documents. We use dynamic topic models (DTM) (Blei and Lafferty (2006)) that use time slices to understand the evolution of topics over time. Details are presented in Section 5.

3. Dataset and Estimating Financial Performance

The dataset for this paper originated from the approximately five thousand prospectuses for residential mortgage backed securities (resMBS) that were issued by private labels, and filed with the SEC between 2002 and 2007. Very few prospectuses (less than fifty) were issued in 2008 and we exclude them from our analysis. We use text extraction to construct the supply chain of financial institutions, and the roles that they play in each prospectus. We augment the securities within a prospectus with multiple features, including the performance history of each security, obtained from the Bloomberg repository (Bloomberg). We note that our dataset is unique; few financial product datasets are associated with a supply chain, and even the extensive Bloomberg repository, which contains the prospectuses and the payment history, does not provide the resMBS supply chain. This knowledge is not proprietary but it is not widely available, nor is it typically used for financial analysis; this contributes to the novelty of our research.

3.1. Data Extraction Protocol

We briefly discuss the protocol to extract the mentions of financial institutions, and the role that they played in the supply chain, from the prospectuses; details are available in (Burdick et al. (2016), Xu et al. (2016)). The extraction pipeline is developed using the rule-based algebraic information extraction system, IBM SystemT (Chiticariu et al. (2010)), and was executed within the IBM Discovery cloud infrastructure. We note that each prospectus could contain thousands of pages of semi-structured data, in varying formats including ASCII text, PDF files and tokenized HTML documents. Data was often contained within tables, itemized lists, and other document elements. This leads to a typical challenge of big data volume, variety and veracity, along our pipeline.

We developed a Named Entity Recognizer, Dict NER (Xu et al. (2016)) that is tuned to extract financial institution (FI) names from text. Financial institution names are typically composed of a root term, which is usually unique, and a suffix term, which is drawn from a small corpus of suffix terms. For example U.S. Bank National Association is composed of the root term, U.S. Bank and the suffix term, National Association. Dict NER utilizes both a root dictionary and a suffix dictionary to recognize such names. We also develop an entity resolution
tool, Rank ER (Xu et al. (2016)) to map the extracted name to a corpus of standardized financial institution names. For example, there are multiple variants of names in Figure 3 that will all be matched to the standard financial institution name Wachovia. The standardized corpus of names was curated from multiple resources including the ABSNet portal (ABSNet) and the National Information Center of the Federal Reserve System (NIC). A Role Extraction module uses keyword matching to extract roles such as issuer, depositor, originator, sponsor, etc. A Role to Financial Institution Matching module pairs a role with one, or more, financial institution names.

![Figure 3](image-url) Summary section of an example prospectus and the extracted 3-tuples.

Figure 3 illustrates the summary section of a sample resMBS prospectus. Example names in this summary include Wachovia Bank, National City, and HSBC Bank. We can also extract the Role played by the FIs, e.g., depositor, issuing entity, seller, sponsor, originator, servicer, trustee, etc. As can be seen, the tabular structure had to be correctly interpreted to align the originator or servicer role with the correct set of financial institution names.

Consider the three columns in the lower part of the figure; this includes the Role, the extracted name of the mentioned entity, and the matching standardized name (determined after entity resolution). For example, Wachovia plays the role of depositor, issuing entity, seller and sponsor, for this exemplar supply chain. Similarly, National City plays the role of originator and servicer.
The example prospectus in Figure 3 will finally be associated in the dataset with a set of pairs, e.g., (Issuing entity, Wachovia) and (Originator, National City).

Details about the quality of the Dict NER and Role to FI Matching are in (Burdick et al. (2016), Xu et al. (2016)). The extraction precision of the dataset is typically between 85 and 95 percent. There is a wide range in precision across the documents as is typical for text extraction methods. Several additional steps were taken to improve the data quality. For example, we used a second extraction pipeline, using a different Named Entity Recognizer, ORG NER (Chiticariu et al. (2010)), and only considered extracted pairs, associating roles with financial institution names, where the two pipelines showed agreement. This extension to the protocol increased the precision of the extracted data to 90 percent and higher.

The final step of the protocol was to obtain performance data for each of the securities that was identified in each prospectus. Each security has a unique identifier (CUSIP). However, these CUSIP values are typically not generated at the time of issuance. Thus, these values are not included in a prospectus. The name of the issuing entity for each resMBS prospectus was matched against the (issuer) names of securities available through the Bloomberg repository (Bloomberg). When this automated match retrieved multiple entries, a human selected the correct matching entry. Finally, based on anecdotal evidence and the literature, the roles of issuer and originator are important. Thus, we filtered the prospectuses to only include those where the issuer of the securities and the originator of the mortgages was successfully extracted.

We extract multiple descriptive properties from the Bloomberg repository including information on the structure of the security and tranche type, payment contingencies, and waterfall payoff details. For example, some securities are interest paying, or linked to floating interest rates, or their payment may be subordinated to the payment of other securities in the prospectus - senior subordinated debt (SSUP). We also obtain the initial Moody’s rating at issuance, as well as updated ratings.

Table 1 has the summary statistics of the prospectus and security counts obtained from the Bloomberg repository. Summary statistics for the frequencies of the different roles extracted are found in Table 3 in the Appendix. Details on the attributes available from the Bloomberg repository are in Table 4 in the Appendix.

3.2. Estimating Financial Performance

We utilize the historical payment information from the Bloomberg repository to estimate the financial performance of each security. This includes information on the original mortgage amount
(principal), the current principal balance, the sum of principal and interest payments, and shortfall and loss information. The history also indicates if payment was terminated before the principal payoff or maturity of the bond. In consultation with several investment experts, we define some (approximate) maximum shortfall and loss thresholds for each class, as follows:

- For investment grade (Class _A_) securities, to label a security as *meeting expectations*, neither shortfall in the principal that is repaid, nor the sum of other shortfalls and losses should exceed the maximum threshold of 100 Basis Points (a Basis Point is 0.01% of Principal). A threshold of 2,500 Basis Points was the cutoff to label an _A_ security as *failing expectations*. Securities whose performance lay between these two thresholds were labeled as *not meeting expectations*.

- For non-investment grade discounted securities (Class _M_ and _B_ securities), we used a threshold of 500 Basis Points as *meeting expectations*, and a threshold of 5,000 Basis Points as *failing expectations*.

Figure 4 highlights trends in the issuance of the three security classes over time. The issuance of securities grows rapidly from 2002 and peaks in 2006, with the issuance in 2007 falling below the 2005 levels. Of note is that the count of _M_ securities increases very rapidly over this period. The count of _M_ securities increased from less than 200 (less than 7% of all securities) in 2002, to a peak of over five thousand securities (approximately 34% of all securities) in 2006.

Figure 5 illustrates the performance trends over time for these securities. Figure 5(a) shows the trend over all securities, while (b), (c) and (d), correspond to the trends for _A_, _M_ and _B_ securities, respectively. The rate of failure or not meeting expectations (red curve) increases over time, for all securities. For _A_ securities, the rate is flat from 2002 to 2004, and then increases slowly after 2004. For _M_ securities, the rate starts increasing more sharply, starting in 2003. In contrast, for _B_ securities, the rate of failure starts increasing much earlier in 2002, and reaches a 95% rate of failing or not meeting expectations, by 2005.

|                | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|----------------|------|------|------|------|------|------|
| Count of prospectuses | 173  | 262  | 394  | 566  | 849  | 535  |
| Count of securities   | 2529 | 3694 | 5531 | 9069 | 14154| 9865 |
| Count of _A_ securities| 1519 | 2127 | 2835 | 4267 | 6653 | 5263 |
| Count of _M_ securities| 149  | 406  | 1016 | 2577 | 4849 | 2594 |
| Count of _B_ securities| 861  | 1161 | 1680 | 2225 | 2652 | 2008 |

Table 1 Summary statistics for Prospectuses and Securities in RESMBS with performance data in the Bloomberg repository.
4. Security and Prospectus Level Models to Predict Performance

We develop several models to predict financial performance. A first Security Level model captures the characteristics of individual securities. A second Prospectus Level model captures the composition and characteristics of the prospectus. We build our models for two binary outcomes: (i) securities that fail expectations (FE), and (ii) securities that either fail or do not meet expectations (FNE). We report on the results of a regularized logistic regression LASSO model (Tibshirani (1996)). LASSO compared favorably with other machine learning approaches ranging from simple classification trees to ensemble approaches for this dataset. The models were implemented using the glmnet package in R. Tuning was done using a 10-fold cross validation and a mean square error loss. We report on two metrics, accuracy and the F1 Score. The F1 Score is an unweighted average of precision (accuracy) and recall (sensitivity) for the positive labels.

The LASSO approach benefits from ease of regularization and the interpretability of the resulting models. Due to the strong impact of some features, the search range for the regularization parameter had to be significantly increased from the default values. Due to the shrinkage of the LASSO model, the model is not unbiased, and the regression coefficients cannot be directly interpreted as the log odds of the outcome. Almost all the features are binary, or have values between...
zero and one; the only exception is the original mortgage amount. Thus, despite the bias, the magnitude of the resulting regression coefficient can be an approximate indicator of the relative importance of that feature in predicting the outcome. We note that many features may be correlated, and this may contribute to the presence and magnitude of the regression coefficient.

In addition to the different models presented here, we developed more detailed regression models. For example, we built independent models for each security class and year of issuance, and incorporated time varying features. The detailed models were comparable in performance (accuracy and F1 Score) but they did not provide additional insights. Thus, we could not justify the additional modeling complexity.
4.1. Insights from the Security Level Model

Features for this model include the security class, the year of issuance, the Moody’s initial rating (MIR) and several characteristics of the waterfall payoff structure. There are over 60 values for the MIR. We aggregated these values to a higher level rating, where Aaa represents the securities that have the lowest credit risk. The Aaa rating is followed, in increasing order of risk, by Aa, A, Baa, Ba, B, Caa, Ca and C. There are also securities that were evaluated but did not give a rating; we label this value as MIR_NR. Finally, securities that were not evaluated for an MIR value is labeled MIR_null.

The waterfall payoff characteristics for the security class or tranche are captured using 73 binary variables. As an example, the following two features are key to identify the placement of the security in the waterfall payoff structure of Figure 2: Super Senior Bond (SSNR) indicates that the principal and/or interest distributions for this security have priority over other senior securities, while Senior Subordinated debt (SSUP) indicates that the principal and/or interest distributions are subordinated to other senior bonds, within the prospectus.

Figure 6 summarizes the results of the Security Level model for the two outcome variables, FE and FNE. The X axis has the values of the coefficients for FE and the Y axis has the values of the coefficients for FNE. The accuracy of the FE and FNE models are 91.3% and 84.7%, and the F1 Scores are 0.891 and 0.857, respectively.

A significant effect is that the annual controls for both 2007 and 2006 increase the predicted probability of FE and FNE. The annual controls for 2002 and 2003 and the _A_ security class decrease the probability of FE and FNE. This is consistent with the trends observed in Figure 5.

The MIR value of MIR_NR increases the probability of both FE and FNE. The MIR values of Baa, Ba, and C all increase the predicted probability of FE, while a value of Aa decreases the same probability. The MIR value Aa was primarily assigned to _M_ securities. Over 75% of _M_ securities have this rating and they were less risky, compared to the overall performance of _M_ securities.

After accounting for the security class and the year of issuance, many of the waterfall payoff features associated with a security class or tranche were retained. Notably, the presence of the label Senior Subordinated debt (SSUP) significantly increases the probability of both FE and FNE. The impact of SSUP on performance is consistent with the waterfall structure and we are the first to note this impact. Several other waterfall payoff features also increase the predicted probability of both FE and FNE. This includes CPT which is an indicator that each component of
the payback may vary, and sequential pay (SEQ), an indicator that the principal will be paid in sequence, after the principal of securities with an earlier priority have paid to zero.

Some features decrease the predicted probability of FE but they do not impact FNE. This includes Over Collateralization (OC) and Excess (EXE) – both indicators that these securities have the rights to certain excess interest and principal payments, and SC which indicates securities that are backed by structured collateral. These features reflect some middle ground since they decrease the probability of FE, but they also do not guard against the shortfalls and payoff losses of FNE. Finally, some features have no impact on FE, but they increase the probability of FNE. These features include Retail (RTL), an indicator that the security is designated for sale to retail investors, and Accrual (Z) which indicates that the accruing interest is added to the outstanding principal balance (for some period).

We note that the impact of the label Senior Subordinated debt (SSUP) is the largest of any individual feature, after accounting for the security class and the year of issuance. In addition, several waterfall payoff features also have a major impact. This may indicate that given the complexity of the resMBS waterfall payoff structure, the MIR values alone could not fully represent the nuanced risk.

To summarize, the Security Level model is consistent with the observed trends of Figure 5 and provides valuable insight into the waterfall payoff structure. The model is accurate for individual securities, yet it does not provide an approach to isolate groups of securities based on their losses. Isolating such groups may not improve prediction accuracy, but it is key to provide an explanation of the drivers of poor financial performance for resMBS securities.

4.2. Prospectus Level Model

Our hypothesis is that features at the level of the prospectus may provide additional insight into financial performance. We use thirteen variables to capture the composition of a prospectus. This includes the count and fraction of securities, and the nominal volume and fraction of the volume, (in US $), in each of the three security classes. In addition, given the significance of the feature Senior Subordinated debt (SSUP), we further hypothesized that the presence of SSUP securities within a prospectus may be significant; we use a binary indicator (HasSSUP) to signal when a prospectus contains at least one SSUP security.

The accuracy and F1 Score for the Prospectus Level model is similar to the Security Level model. Figure 7 provides the normalized coefficients. We note that many of the observations from the
Security Level models hold. The security class, the year of issuance, MIR values, some waterfall payoff features and SSUP continue to have a strong impact on both FE and NFE.

New to this model, the fraction of securities that are in classes _M_ and _B_ increase the probability of FE and NFE. The nominal volume (in US $) in _M_ securities decreases these probabilities. Most notably, the indicator HasSSUP increases the probability of both FE and NFE. To explain, the presence of even one security with the label SSUP, within a prospectus, can increase the probability of both FE and NFE, for all other securities in that prospectus, independent of whether these other securities are labeled SSUP.

In summary, the model reflects that the composition of the prospectus is significant. Prospectuses that include SSUP securities, and prospectuses with an excess of class _M_ and _B_ securities, increase the probability of FE and FNE, for all securities within the prospectus. This is a notable finding as one could have reasoned that the excess class _M_ and _B_ securities may have served as a buffer, to reduce the risk for the senior class _A_ securities. Our model shows that this is not the
case, and indeed, we observe the opposite effect; an excess of these classes is actually a negative signal for the performance of the class _A_ securities.

We further hypothesize that the prospectus may be a surrogate for the supply chain that produced the securities. This suggests that some supply chains may have produced prospectuses with varying composition across the security classes, and corresponding risk profiles. We therefore study the supply chain in the next model.

5. Dynamic Topic Models

Topic modeling ([Blei et al.](2003), [Steyvers and Griffiths](2007)) is a probabilistic model based on the idea that a collection of documents can be described using a set of topics. A document is modeled as a mixture over the set of topics, where a topic is represented as a probability distribution over a set of keywords in the vocabulary of that collection. More recently, time series extensions to topic models have been introduced to capture the time evolution of topics. This includes a continuous non-Markovian model of topics over time (ToT) ([Wang and McCallum](2006)) and
dynamic topic models (DTM) (Blei and Lafferty (2006)). We adopt DTM for our research. We briefly present a definition of latent Dirichlet allocation (LDA) based topic models (Blei et al. (2003)) and DTM.

LDA is a statistical model that aims to explain a set of documents using unobserved topics. LDA is based on a generative statistical model for collections of discrete data (documents); it allows us to extract topics based on assumptions about the probability distributions that were used to generate the documents. At a high level, it is assumed that to create a document, one first randomly chooses a distribution over a collection of (unobserved) topics. Then, for each word in a document, one independently and randomly chooses a topic from the previously sampled mix of topics assigned to the document, and then again independently and randomly draws a word from the (unobserved) word distribution for that topic. Based on these assumptions about the generative mechanism, and the associated underlying probability distributions, topic models aim to extract the underlying topic structure via maximum likelihood estimation.

More specifically, let $P(z)$ represent the distribution for a topic $z$ from $K$ topics in a particular document. Let $P(w|z)$ represent the probability distribution over words $w$ for the given topic $z$. Let $P(z_i = j)$ be the probability that the $j$-th topic was sampled for the $i$-th word token in the document. Let $P(w_i|z_i = j)$ be the probability of word $w_i$ for topic $j$. We then have the following probability distribution for words within a document:

$$P(w_i) = \sum_{j=1}^{K} P(w_i|z_i = j) \times P(z_i = j)$$ (1)

LDA represents each document as a random mix over latent topics. Each topic is characterized by a distribution over words. Associated with these two distributions are the hyper parameters $\alpha$ and $\beta$, corpus level parameters assumed to be sampled once in the process of generating a corpus. The variable $\theta$ is a document-level variable (a topic mixture over $K$ topics, sampled from a Dirichlet distribution parameterized by $\alpha$), sampled once per document. The variables $z_n$ and $w_n$ are word-level variables, sampled once for each word in each document. Specifically, for each word, a topic $z_n$ is sampled from a multinomial distribution conditioned on $\theta$, and, each word $w_n$ is sampled from a multinomial distribution conditioned on $z_n$ and parameterized by $\beta$.

One can re-write the probability of a document with $N$ words as follows:

$$p(w|\alpha, \beta) = \int p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta)p(w_n|z_n, \beta) d\theta$$ (2)
where \( w = \{ w_1, w_2, \ldots, w_N \} \) is a set of \( N \) words. Figure 8 is a graphical representation of the LDA process for a collection of \( M \) documents.

The LDA process just described assumes that the documents are drawn from a static set of topics. Extensions that relax this assumption include a continuous non-Markovian model of topics over time (ToT) \( \text{(Wang and McCallum (2006))} \) and dynamic topic models (DTM) \( \text{(Blei and Lafferty (2006))} \). ToT assumes that each topic is associated with a continuous distribution over the time slices. This allows a modeler to model how some topics may be more popular over certain time periods. In that case, for each document, the mix of topics (\( \theta \) in LDA) is influenced by both the word co-occurrence and the timestamps. In the Dynamic Topic Model (DTM) extension, which is the approach we adopted, the document collection is also divided by time, e.g., in our case a time slice for each year. As the Dirichlet distribution does not lend itself well to sequential modeling, the time dependent parameters evolve over time according to a Brownian motion. For example, \( \beta_{t,k} \) can be expressed as follows:

\[
\beta_{t,k} | \beta_{t-1,k} \sim \mathcal{N}(\beta_{t-1,k}, \sigma^2 I) \tag{3}
\]

The evolution of \( \alpha \) and \( \theta \) are expressed in a similar manner. We point the interested reader to \( \text{Blei and Lafferty (2006)} \) for additional technical details. Figure 9 is a graphical representation of the DTM process. Through the evolution described above, the topics can evolve over time. A tuning parameter controls how fast the topics can evolve. Setting the parameter at one extreme will convert DTM to a static topic model while the other extreme will result in the topics in each time slice becoming independent.
Figure 9  A graphical representation of a Dynamic Topic Model (DTM) for three time slices [Blei and Lafferty (2006)]. The parameters for each topic, $\beta_{t,k}$, as well as the parameter for the topic mix $\alpha_t$, evolve over time.

5.1. DTM Experimental Results

Configuration:

We used the Python *gensim* implementation of DTM (Rehurek and Sojka (2010)). Each document (prospectus) is represented as a bag of words over a vocabulary of (Role, Financial Institution) pairs. We filtered the data and eliminated financial institutions that appeared in less than 20 prospectuses, as well as prospectuses that had less than five pairs. This created a subset of 4472 prospectuses. Additional statistical information on the prospectuses is provided in Tables 5 and 7 in the Appendix. To set a baseline for topic evolution, we computed the static LDA topics, labeled as $LDA$.

Some roles such as *issuer* and *originator* are important in the supply chain. Others such as *servicer* may occur very frequently, but they do not play a central role in creating prospectuses, nor do they significantly impact financial performance. To address this varying importance, we doubled the token weight associated with pairs that involve the roles of *issuer* or *originator*.

We created annual time slices, from 2002 to 2007, using the date of the prospectus issuance. The data is insufficient to consider both month and year. We varied the hyperparameter $\alpha$ that affects sparsity of the topics in each time slice; however, this parameter did not have much impact. We varied the count of topics from twenty to fifty in increments of five. We did not observe much change in the community structure beyond thirty topics, and we report results for thirty topics.

The hyperparameter *top_chain_var* is significant since it controls the rate at which $\beta_{t,k}$ can evolve, and hence the rate at which the topic evolves with each new time slice. We used two
settings for this parameter, 0.005 and 0.75. A low value of 0.005 results in a slow evolution while a high value of 0.75 results in a fast evolution. We label the results with $\text{top\_chain\_var} = 0.005$ as $D_{TM_{\text{slow}}}$ and $\text{top\_chain\_var} = 0.75$ as $D_{TM_{\text{fast}}}$.  

**DTM Result Summary**

The $D_{TM_{\text{slow}}}$ model showed minimal temporal evolution, and the topics were very similar to LDA (by experiment design). We therefore compare the topics in the $D_{TM_{\text{fast}}}$ model with the (union of) topics in LDA and $D_{TM_{\text{slow}}}$. We observe the following three types of communities:

- **Stable**: Twelve topics that appear in $D_{TM_{\text{fast}}}$ are conserved and appear to be well aligned to topics in both LDA and $D_{TM_{\text{slow}}}$. There is very low evolution of topic composition across the time slices for these stable topics. In other words, these topics represent communities in the supply chain that do not evolve over the time period.

- **Evolving**: These are topics that appear in $D_{TM_{\text{fast}}}$ and show some overlap with topics in LDA and $D_{TM_{\text{slow}}}$; however, the topics are not fully aligned. In several Evolving $D_{TM_{\text{fast}}}$ topics, we observe an evolution of the issuer associated with the topic.

- **Dynamic**: Of most interest are eight topics that only emerge in $D_{TM_{\text{fast}}}$. In several cases, these topics may be associated with smaller financial institutions that issued a moderate volume of prospectuses. Consequently, these topics may have been merged with some other topics in the LDA or $D_{TM_{\text{slow}}}$ models. The additional modeling flexibility of DTM, explicitly modeling the community structure for each time slice, facilitates their appearance. Hence, the emergence of Dynamic topics clearly highlight the benefits of using DTM.

- Seven small topics (with less than twenty-five prospectuses each) were not studied further.

**Exemplar Topics**

We note that some evolving or dynamic communities may be focused on the issuer, while the originators of mortgages or service providers may join or leave a community over time. Alternatively, some communities may have a focus on the originators of the mortgages; as the community evolves, different issuers may engage with these originators and their loans may be pooled within prospectuses from these different issuers. In some cases, there may be a continuous evolution of financial institutions across the roles.

Figure 10 summarizes two topics with different time dynamics. The illustration is a Sankey diagram rendering of a bipartite graph. Each of the nodes on the left represent the community for that year. The nodes on the right are the pairs of (Role, Financial Institution). The thickness of the edge
represents the weight or significance of the financial institution and role, to the topic. The supply chain represented by Topic 8 in Figure 10(a) is Stable over the time slices. Wilmington Trust is the issuer and Countrywide participates in many roles including servicer, seller, depositor and sponsor, across all time slices.

The supply chain represented by Topic 26 in Figure 10(b) is Dynamic. Fremont served as the originator in the early time slices, but that role is then assumed by American Home Mortgage starting in 2005. There is also an evolution of issuers. Fremont and Fieldstone are issuers in the early time slices. Ace Securities and Deutsche Bank join as issuers in later time slices.

![Figure 10](image)

(a) Topic 8  
(b) Topic 26

Using Communities to Differentiate Performance

Recall that our strategic goal is to differentiate subsets of prospectuses and securities based on performance, and to isolate those that suffer the largest losses. To provide insight into how communities can be used for this objective, we highlight four communities. Topics 8 and 26 were
discussed previously. We also consider Topics 11 and 28. Topic 11 is a Stable topic where Bank of America is active in multiple roles through the different time slices. Topic 28 is Dynamic with Renaissance and Principal Residential as issuers. These four communities were each associated with 100 to 200 prospectuses and an average of approximately 1500 securities. The largest (Topic 8) is associated with approximately 200 prospectuses and more than 3000 securities.

These communities represent a range of behavior. Their activity level of issuing prospectuses varied across the time slices. The composition of the prospectuses, by security class, also varied across the topics. Figure 11(a) highlights the peak activity of each topic, based on the normalized fraction of prospectuses issued per year, versus the overall count of prospectuses for that topic. Of note is that Topic 11 peaks early in 2004, while the other three topics peak in 2006. More interesting is the varying composition of the prospectuses. Figure 11(b) summarizes the composition by security class, for each topic. The overall composition across all topics is shown at the far right of the figure. Topic 8 most resembles the overall composition across all topics. Topic 11 produces very few Class _M_ securities. Topic 26 produces an excess, close to 60%, of Class _M_ securities; the sample average is approximately 25%. Topic 28 produces approximately 50% of Class _B_ securities; the sample average is just over 20%.

![Figure 11](image_url)

(a) Activity per year

(b) Composition by class

**Figure 11** Heterogeneous characteristics of Topics 8, 11, 26 and 28. Normalized fraction of securities issued per year, versus the total count, for each topic (a). Normalized fraction of securities by class (b).

The overall performance of each of the topics is summarized in Figure 12. The X axis represents the percentage of securities that fail expectations (FE), and the Y axis is the percentage that are
labeled SSUP. The FE percentage ranges from the single digits to over 50%, and the percentage of securities that are SSUP ranges from 0% to 15%.

Topics 8 and 11 both issue a large fraction of SSUP securities. Topic 8 has a high FE failure percentage of 47% while Topic 11 has a moderately high percentage of 33%. In contrast, Topics 26 and 28 issue a smaller fraction of _A_ securities and SSUP securities; recall that SSUP is a label for _A_ securities so this is reasonable. The failure rate of Topic 26 is over 50%, the highest over all the topics, and it is a reflection of the high proportion of _M_ securities that are issued. The failure rate for Topic 28 is lower and is just over 40%. We further emphasize that the differing composition of the prospectuses, and the range of performance, across the four communities, is notable since we do not use any of this information in the DTM model.

Figure 12 The figure summarizes the performance for securities in each community. The X axis represents the percentage of securities that fail expectations (FE). The Y axis is the fraction of securities that are labeled SSUP.

5.2. Comprehensive Model

A final comprehensive model will include all features of the Security and Prospectus models. In addition, we use 30 indicator variables, one for each topic. The DTM model assigns a weight vector over the thirty topics to each prospectus. We select the largest topic weight that is also over a threshold of approximately 0.7, for each prospectus and its securities. The coefficients of this model are in Figure 13. The X axis has the values of the coefficients for FE and the Y axis has the values of the coefficients for FNE.
Of the 30 binary indicators for the communities, 23 were retained by the FE model, and 24 were retained by the FNE model. It is worth noting that the coefficients for the topics have similar weights, in comparison to features in the Security and Prospectus models. In other words, after accounting for the Security and Prospectus features, the supply chain has additional significant impact on the predicted performance. All four of the four previously discussed topics are retained by the LASSO model. Topics 8 and 26 both increase the predicted probability of FE and FNE. In contrast, Topics 11 and 28 both slightly decrease the predicted probability of FE and FNE. This further illustrates the synergy between the DTM, to identify communities, and the comprehensive prediction model that uses the communities as features.

![Figure 13](image.png)

**Figure 13** Key factors identified as predictive by the LASSO models, for the two outcomes, their impact on the predicted probability normalized such that the magnitude of the largest coefficient is 1 for each model. The full regression coefficients are found in Table 11 in the Appendix.

Table 2 provides a summary of six DTM topics that increase the predicted probability of FE and FNE. Their activity level ranges from 40 to almost 200 prospectuses per topic, issued across the time slices. Several topics peak in 2005 or 2006 as expected. The right column identifies the key
financial institutions and roles in the supply chains. This includes very large institutions such as Countrywide and Wilmington Trust that were very active within multiple communities in the supply chain. What is particularly notable is the significant role played by many institutions that were very active in the subprime market in four of the topics, e.g., Lehman, Aurora, IndyMac, Ameriquest, Weyerhauser, etc. Almost all filed for bankruptcy protection either before or during the 2008 crisis, or they faced penalties, or they were forced to merge with other companies.

| Topic | Description | Supply Chain |
|-------|-------------|--------------|
| Topic 3 | Dynamic DTM topic. 41 prospectuses. Active across all years. | Ameriquest and Weyerhauser and PHH are the issuers. **Ameriquest failed in 2007. Weyerhauser was prosecuted.** |
| Topic 7 | Stable DTM topic. 92 prospectuses. Very active in 2006, 2007. | IndyMac is the issuer and is also in many roles. **IndyMac Failed in 2008.** |
| Topic 8 | Stable DTM topic. 192 prospectuses. Peak in 2006. | Wilmington Trust is the issuer. Countrywide is in many roles. |
| Topic 18 | Stable DTM topic. 80 prospectuses. Peak in 2006. | Morgan Stanley is the issuer and is in many roles. |
| Topic 26 | Dynamic DTM topic. 85 prospectuses. Peak in 2006. | Fremont and American Home are the originators. Fremont and Fieldstone and Ace Securities. and Deutsche Bank are the issuers. **American Home and Fieldstone failed in 2007 and 2008, respectively.** |
| Topic 27 | Stable DTM topic. 144 prospectuses. Peak in 2005. | Structured Asset and Lehman are the issuers. Aurora is an originator. **Lehman failed in 2008 and Aurora failed in 2012.** |

**Table 2** Topics that are identified to increase the prediction probability of FE and FNE and the corresponding financial institutions and roles. The prospectuses and securities in these communities are candidates that suffered the greatest losses.

6. **Summary and Future Research**

This research is based on a novel dataset resMBS that extracted the financial institutions, and the roles that they played in the supply chain, from prospectuses. This paper is the first to study how financial institutions formed communities along the supply chain, and the impact of the communities on the financial performance of securities. We presented complementary models to gain insights into the drivers of performance. The models studied Security Level features, and then Prospectus Level features. Finally, a comprehensive model included Security, Prospectus and Community features.
The models reveal a number of insights. Notably, we find that different communities produced different products, in terms of the composition of prospectuses, the use of SSUP securities, and financial performance. This is especially notable since the DTM model did not use any of these features when identifying communities. Our study demonstrates the importance of a deeper understanding of the role of the supply chain, and the characteristics of their products.

The resMBS securities played a key role in the 2008 financial crisis. A contributor to the 2008 crisis was a lack of understanding of which securities would suffer the greatest losses, and our research addressed this problem. While private label residential mortgage backed securities issued in the US reduced significantly after 2007, these products have seen a recent resurgence. We further expect that an extension of our approach may apply to other products such as student loan backed securities.

There are multiple interesting research directions that can build on our the work. The first is prediction. We note that the models in this paper relied on post mortem labels. However, the payment history for these securities, including various shortfalls and delayed payments, are also gathered on a real time basis. The availability of such contemporaneous data could result in the development of prediction models, or time to failure models.

The next is the design of a monitoring framework for complex financial products. The resMBS dataset presents interesting temporal dynamics across multiple dimensions. There is constant change of financial institutions and roles across the supply chain. We observed an evolution in the composition of prospectuses. There is anecdotal research about diminishing quality control over the ratings of these products. Finally, the outcomes change over time. These dynamics need to be at the heart of any monitoring system.

We note that we are not currently claiming a causal connection between the supply chain communities (topics) and the performance of resMBS securities. We well understand that the supply chain is only one factor among myriad that can influence performance. However, our research was successful in identifying the most risky resMBS securities. This underscores the synergistic potential of utilizing financial big data and computational methods to understand complex financial products.

Acknowledgments
We thank the following individuals: Nancy Wallace and Paolo Issler (University of California Haas School of Business) and Joe Langsam for their help in identifying the resMBS prospectuses and labeling the performance of these securities; Doug Burdick and Rajasekar Krishnamurthy (IBM Research) for supporting the text extraction task using
the IBM SystemT platform; Soham De and Minchao Shao for implementing the resMBS extraction pipeline Zheng Xu, Elena Zotkina, Aaron Hunt, Chi-Hung Chen and Prabhath Kollimarla for technical support with data cleaning, data integration and topic model based analytics. This research was partially supported by NSF grants CNS1305368 and NIST award 70NANB15H194.
Appendix

A. Data Details and Summary Statistics

| Role                              | Frequency (total) | %    | Frequency (with Bloomberg data) | %    |
|-----------------------------------|-------------------|------|---------------------------------|------|
| Issuer                            | 3676              | 76   | 3183                            | 89   |
| Originator                        | 1757              | 36   | 1713                            | 48   |
| Seller                            | 3131              | 65   | 2588                            | 73   |
| Trustee                           | 3722              | 77   | 3284                            | 92   |
| Servicer (many variants)          | 4335              | 90   | 3502                            | 98   |
| Depositor                         | 4081              | 85   | 3314                            | 93   |
| Sponsor                           | 1731              | 36   | 1651                            | 46   |
| Securities administrator           | 873               | 18   | 842                             | 23   |
| Custodian                         | 733               | 15   | 706                             | 19   |
| Swap counterparty                 | 516               | 10   | 507                             | 14   |
| Cap counterparty                  | 424               | 8    | 392                             | 11   |
| Insurer                           | 355               | 7    | 330                             | 9    |
| Underwriter                       | 228               | 4    | 143                             | 4    |

Table 3 Distribution of Roles Across Prospectuses; 4787 Prospectuses (total) and 3537 Prospectuses (with Bloomberg data).

| Attribute                  | Description                                                                 |
|----------------------------|-----------------------------------------------------------------------------|
| CUSIP:                     | Unique identifier.                                                         |
| Name:                      | Unique name.                                                               |
| Tranche Description:       | Essential characteristics of multi-class mortgage and asset-backed securities (CMO, ABS, CMBS). |
| Original Principal:        | The principal balance at issuance of the security.                         |
| Maturity:                  | Date the principal of a security is due and payable.                       |
| Count of Loans:            | The current number of loans, created as collateral for the deal, which are still outstanding. |
| 60+ DQ:                    | (Percentage of loans which are 60 or more days delinquent, including loans in foreclosure, bankruptcy. |
| Cumulative shortfall:      | Cumulative supported shortfall that has yet to be repaid.                  |
| 2 shortfall:               | Cumulative shortfall that will not be repaid.                              |
| Cumulative Loss:           | Cumulative writedown on the principal.                                     |
| Historic Cashflow:         | A complete set of known historical cashflows starting from the bond issuance. The data includes the period number, date, coupon, interest, principal paid, and principal balance. |
| Ratings:                   | Multiple fields with the original and current ratings from Moody, Fitch, and SP, corresponding dates and a composite ratings from Bloomberg L.P. |

Table 4 Attributes for securities (Bloomberg).
Prospectus count (initial)

| Year | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | Total |
|------|------|------|------|------|------|------|------|-------|
| With Issuer or Originator and match in Bloomberg | 231 | 398 | 577 | 744 | 923 | 593 | 71 | 3537 |
| With >= 3 DISTINCT FE mentions | | | | | | | | 3146 |
| With >= 5 (Role, FE) mentions | | | | | | | | 4472 |

Table 5  Count of Prospectuses: With Issuer and/or Originator identified (4787); With match in Bloomberg (3537); Further filtered for specific models.

| Features                          | Level   | Number of Features | Description                                                                 |
|-----------------------------------|---------|--------------------|-----------------------------------------------------------------------------|
| Moody’s initial rating            | Security| 11                 | Over 60 initial rating values are grouped together into 9 higher level rating levels, in addition to a value for “not rated” and “no value”. |
| Payoff characteristics            | Security| 73                 | The pay-off structure of a security is captured with 73 binary indicators.    |
| Initial mortgage amount           | Security| 1                  | The initial mortgage amount of the pool of mortgages serving the security.   |
| Security class                    | Security| 3                  | The class of the security, _A_, _M_, or _B_.                               |
| Presence of SSUP                  | Prospectus| 1                  | A binary indicator for whether any security within a prospectus is a SSUP security. |
| Class distribution in a Prospectus| Prospectus| 6                  | Six variables that capture the fraction of the number securities within each class (_A_, _M_, or _B_) and the volume (in USD) within the same. |
| Financial Communities             | Prospectus| 30                 | Binary indicator variables for the topic that each prospectus is assigned to using the largest topic weight. |
| Annual controls                   | Security| 6                  | Binary indicators for the year of issuance.                                |

Table 6  Overview of the features used in the study

Table 7  Summary statistics for resMBS Topic Model Experiments.

| Count of documents | resMBS | 4472 |
|--------------------|--------|------|
| Count of distinct Financial Institutions | 85 |
| Count of distinct Roles | 27 |
| Distinct (Role_FI) pairs | 267 |
| Count of (Role_FI) occurrences | 41075 |
B. Detailed LASSO Model Results

| Model              | Accuracy | F1-Score |
|--------------------|----------|----------|
| Security Model     | 91.3%    | 0.891    |
| Prospectus Model   | 91.2%    | 0.889    |
| Supply Chain Model | 91.6%    | 0.894    |

Table 8 Performance Metrics for the LASSO Models.
Table 9  The regression coefficients for the security level model. Blank cells indicate that the variable was not retained by the LASSO model. Note that a number of variables not retrained by either model are not included in the table.
| Variable           | FE  | FNE  |
|--------------------|-----|------|
| Intercept          | -0.996 | 0.734 |
| Moody's Initial Rating |     |      |
| Class & Amount     |     |      |
| MTG.ORIG.AMT       | -0.003 |  |      |
| IsA                | -4.841 | -3.453 |
| IsB                | 0.023 | 0.069 |
| Tranche Type       |     |      |
| AD                 | -0.45 | -0.147 |
| AFC                | -0.303 | 0.349 |
| AS                 | 0.062 | 0.664 |
| CMPLX              | -0.174 | -0.056 |
| CPT                | 0.958 | 1.221 |
| CSTR               | 0.26 | 0.636 |
| DGT                | -0.311 |      |
| DLY                | 0.618 | -0.165 |
| EXCH               | -0.139 | 0.719 |
| EXE                | -1.287 |      |
| FLT                | -0.175 | -0.251 |
| FTV                | -0.482 | -0.144 |
| INV                | -0.16 |      |
| IRC                | -0.065 | -0.09 |
| MEZ                | 0.836 |      |
| MR                 | -0.604 |      |
| NAS                | 0.819 | 0.576 |
| NTL                | -0.595 | -0.85 |
| OC                 | -3.401 |      |
| PAC1               | -0.5 | -0.461 |
| PIP                | -0.032 |      |
| PT                 | 0.054 | -0.139 |
| RAKE               | -0.592 | -0.896 |
| RSTP               | -0.295 | -0.227 |
| RTL                | 2.208 |      |
| SC                 | -3.216 |      |
| SEQ                | -1.271 | -0.551 |
| SSNR               | -1.304 | 0.122 |
| SSUP               | 4.22 | 2.05 |
| STEP               | -0.021 |      |
| SUB                | 1.272 | 0.297 |
| SUP                | 0 | -0.339 |
| TAC.1.12.          | 0.283 |      |
| TAC.11.            | -0.066 |      |
| TAC.22.            | -0.072 |      |
| TAC.22.            | -0.408 |      |
| W                  | -0.271 |      |
| Z                  | 1.638 |      |

Table 10 The regression coefficients for the prospectus level model. Blank cells indicate that the variable was not retained by the LASSO model. Note that a number of variables not retrained by either model are not included in the table.
| Variable                  | FE  | FNE  |
|--------------------------|-----|------|
| Intercept                | -0.454 | 1.368 |
| Class & Amount           |     |      |
| MTG.ORIG.AMT             | -0.003 |      |
| IsA                      | -4.9 | -3.513 |
| IsB                      | 0.233 | 0.179 |
| Tranche Type             |     |      |
| AD                       | -0.32 | -0.031 |
| AFC                      | -0.17 | 0.388 |
| AS                       |      | 0.588 |
| CMPLX                    | -0.013 |      |
| CPT                      | 0.858 | 1.221 |
| CSTR                     | 0.407 | 0.698 |
| DGT                      |      | -0.004 |
| DLY                      | 0.547 | 0.239 |
| EXCH                     | -0.085 | 0.768 |
| EXE                      | -0.803 |      |
| FLT                      | -0.258 | -0.399 |
| FTV                      | -0.325 | -0.198 |
| INV                      | -0.166 | -0.042 |
| IRC                      | -0.009 | -0.055 |
| MEZ                      | 0.833 |      |
| NAS                      | 0.761 | 0.539 |
| NTL                      | -0.563 | -0.961 |
| OC                       | -3.326 |      |
| PAC1                     | -0.211 | -0.315 |
| PIP                      |      | -0.468 |
| PT                       | 0.146 |      |
| RAKE                     | -0.293 | -0.906 |
| RSTP                     | -0.125 |      |
| RTL                      | 2.243 |      |
| SC                       | -3.192 |      |
| SEQ                      | -0.929 | -0.408 |
| SSNR                     | -1.289 | 0.093 |
| SSUP                     | 4.317 | 2.093 |
| SUB                      | 1.096 | 0.373 |
| SUP                      | -0.258 |      |
| TAC.1.22.                | 0.032 |      |
| TAC.11.                  | -0.206 |      |
| TAC.22.                  | -0.186 |      |
| TAC.33.                  | -0.018 |      |
| Z                        | 1.694 |      |
| 2002                     | -4.206 | -3.192 |
| 2003                     | -3.064 | -2.164 |
| 2004                     | -1.611 | -1.327 |
| 2006                     | 1.995 | 1.351 |
| 2007                     | 2.094 | 1.484 |

Table 11 The regression coefficients for the community level model. Blank cells indicate that the variable was not retained by the LASSO model. Note that a number of variables not retrained by either model are not included in the table.
References

ABSNet (2018) Absnet. [http://www.absnet.net/ABSNet]

Arnold B, Borio C, Ellis L, Moshirian F (2012) Systemic risk, macroprudential policy frameworks, monitoring financial systems and the evolution of capital adequacy. volume 36, 3125–3132.

Ashcraft A, Goldsmith-Pinkham P, Vickery J (2010) Mbs ratings and the mortgage credit boom. Federal Reserve Bank of New York Staff Reports, number 449.

Ashcraft A, Schuermann T (2008) Understanding the securitization of subprime mortgage credit. Federal Reserve Bank of New York Staff Reports, number 318.

Billio M, Getmansky M, Lo A, Pelizzon L (2012) Econometric measures of connectedness and systemic risk in the finance and insurance sectors. volume 103, 535–559.

Bisias D, Flood M, Lo A, Valavanis S (2012) A survey of systemic risk analytics. volume 4, 255–296.

Blei D, Lafferty J (2006) Dynamic topic models. Proceedings of the International Conference on Machine Learning (ICML) 113–120.

Blei D, Ng A, Jordan M (2003) Latent dirichlet allocation. Journal of Machine Learning Research 3:993–2003.

Bloomberg (2018) Bloomberg l.p. [https://en.wikipedia.org/wiki/Bloomberg_Terminal]

Burdick D, De S, Raschid L, Shao M, Xu Z, Zotkina E (2016) resMBS: Constructing a financial supply chain graph from financial prospecti. SIGMOD DSMM (ACM).

Burdick D, Franklin M, Issler P, Krishnamurthy R, Popa L, Raschid L, Stanton R, Wallace N (2014) Data science challenges in real estate asset and capital markets. SIGMOD DSMM (ACM).

Burdick D, Hernández MA, Ho H, Koutrika G, Krishnamurthy R, Popa L, Stanoi I, Vaithyanathan S, Das SR (2011) Extracting, linking and integrating data from public sources: A financial case study. IEEE Data Eng. Bull. .

Chiticariu L, Krishnamurthy R, Li Y, Raghavan S, Reiss FR, Vaithyanathan S (2010) SystemT: an algebraic approach to declarative information extraction. ACL.

Commission TFCI (2011) Final report of the national commission on the causes of the financial and economic crisis in the united states. [https://www.govinfo.gov/content/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf]

CUSIP (2018) Cusip global services. [https://www.cusip.com/cusip/index.htm]

Demiroglu C, James C (2012) How important is having skin in the game? originator-sponsor affiliation and losses on mortgage-backed securities. The Review of Financial Studies 25:3217–3258.

Gerardi K, Lehner A, Sherald S, Willen P (2010) Making sense of the subprime crisis. Kolb R, ed., Lessons from the Financial Crisis: Causes, Consequences, and Our Economic Future (John Wiley & Sons, Inc.).

He J, Qian J, Strahan PE (2011) Credit ratings and the evolution of the mortgage-backed securities market. American Economic Review 101:131–35.

He J, Qian J, Strahan PE (2012) Are all ratings created equal? the impact of issuer size on the pricing of mortgage-backed securities. The Journal of Finance 67:2097–2137.
Hernández MA, Ho H, Koutrika G, Krishnamurthy R, Popa L, Stanoi IR, Vaithyanathan S, Das S (2010) Unleashing the power of public data for financial risk measurement, regulation, and governance. WWW.

Hoberg G, Phillips G (2018) Text-based network industries and endogenous product differentiation. Journal of Political Economy.

Hunt J, Stanton R, Wallace N (2014) U.S. residential mortgage transfer systems: A data management crisis. Brose M, Flood M, Krishna D, Nichols B, eds., Handbook of Financial Data and Risk Information II: Software and Data.

Landauer T, Dumais S (1997) A solution to plato’s problem: the latent semantic analysis theory of acquisition, induction and representation of knowledge. Psychological Review 104:211–240.

Liang N (2013) Systemic risk monitoring and financial stability. volume 45, 129–135.

Loughran T, McDonald B (2016) Textual analysis in accounting and finance: A survey. Journal of Accounting Research 54:1187–1230, URL http://dx.doi.org/http://dx.doi.org/10.2139/ssrn.2504147.

Merrill CB, Nadauld TD, Stulz RM, Sherlund S (2012) Did capital requirements and fair value accounting spark fire sales in distressed mortgage-backed securities? Working Paper No. 18270 (NBER).

NIC (2018) National information center. https://www.ffcie.gov/nicpubweb/nicweb/NicHome.aspx.

Ospina J, Uhlig H (2018) Mortgage-backed securities and the financial crisis of 2008: a post mortem. Working Paper 24509, URL http://dx.doi.org/10.3386/w24509.

Rehurek R, Sojka P (2010) Software framework for topic modelling with large corpora. Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, 45–50.

SIFMA (2018) Us mortgage-related issuance and outstanding. https://www.sifma.org/resources/research/us-mortgage-related-issuance-and-outstanding/.

Steyvers M, Griffiths T (2007) Probabilistic topic models. Landauer T, McNamara D, Dennis S, Kintsch W, eds., Handbook of Latent Semantic Analysis.

Tibshirani R (1996) Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B 58:267–288.

Wang X, McCallum A (2006) Topics over time: A non-markov continuous-time model of topical trends. Proceedings of the ACM Knowledge Discovery and Data Mining Conference.

Xu Z, Burdick D, Raschid L (2016) Exploiting lists of names for named entity identification of financial institutions from unstructured documents. University of Maryland Technical Report.