Choosing Models to Explore Financial Supply Chain Relationships (Extended Abstract)

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1 INTRODUCTION

A residential mortgage-backed security **resMBS**, is a complex financial product that is constructed by pooling cash flows from a collection of mortgage loans. Figure 1 shows a simplified view of the complex product structure, composed of tranches (slices) of securities, on the right, with a prioritized *waterfall* payment structure. The cash flows from the pool of mortgages, on the left, both the principal and interest payments, are allocated to the securities based on the waterfall payment priority. The tranches served first are referred to as senior debt, or Class *A_* or *B_* securities, followed by mezzanine and then unsecured or equity debt. The securities are rated for their credit worthiness and are packaged within a prospectus that is issued, with the securities sold to investors. These products can be issued by government sponsored enterprises (GSEs such as Fannie Mae) or they may be issued as private label securities.

In the early 2000s, there was a boom in the issuance of private label **resMBS** products, which reached its peak around 2006, followed by a sharp decline in late 2007 and 2008. Following a housing bubble of 2007, housing prices began to decline sharply, leading to mortgage defaults, foreclosures and housing short-sales. This change in housing prices and mortgage status, coupled with a high rate of subprime lending prior to 2007, and an increase in speculative purchases, led to large losses for multiple financial institutions and investors holding these **resMBS** products.

Following the 2008 financial crisis, there has been much research around private label **resMBS** products. Researchers have investigated their performance from different angles,

Figure 1: Simplified overview of **resMBSs**.

including focusing on the variation in their credit rating over time [1], the effect of issuers size on both initial prices [8] and ratings [7], and the role of accounting rules on **resMBS** sales[9]. In contrast, our research has a focus on financial institutions and their role(s) in the supply chain. There has been limited prior research on the supply chain. A single study [5] 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. In our research, we use advanced text extraction and mining approaches to construct a unique and rich dataset of the supply chain. We then use probabilistic topic models to analyze the actions of financial institutions, how they build communities, and the impact of upstream communities on their downstream performance, in particular, the failure of securities to make payments.

2 DATASETS AND FEATURES

The **resMBS** dataset includes approximately five thousand prospectuses that were issued by private labels and filed with the Securities and Exchange Commission (SEC) between 2001 and 2008.

Financial entities (FEs) take on multiple roles within the upstream supply chain, including the following: issuer, originator, seller, trustee, servicer, depositor, sponsor, swap counterparty, insurer and underwriter. Each prospectus will be associated with a supply chain composed of a set of (Role, FE) pairs, e.g., (Issuer, Wachovia) and (Originator, National City). We used the IBM SystemT text analytics platform to extract the mentions of financial entities, and the role(s) that they play in the supply chain for each prospectus. The most common role extracted was servicer, followed by depositor,

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trustee and issuer. Originator and sponsor are also commonly found roles.

The next step in creating the data set was to match each prospectus with the set of associated securities. Each security has a unique identifier [4] but these CUSIP values are not included in the prospectus. We performed a search using the name of the issuing entity for each **resMBS** prospectus against the names of mortgage backed securities in Bloomberg [3]; when the match retrieved multiple entries, we had a human select the correct matching entry.

The features for each security include the class or tranche type, the initial principal, the maturity date for the loan, initial ratings by Moody, and additional characteristics such as the interest rate, and whether the underlying security is interest only. Each security is also associated with downstream historical payment information, including the original mortgage amount, the current balance, the sum of principal paid, as well as shortfall information. We developed simple heuristics based on the past payment histories to label the financial performance of each security. The labels range from **Meets expectation (ME)** to **Fails expectation (FE)**. The highest performing securities, **ME**, made all payments on time, with no payment shortfall, and have either paid off their entire principal, or are currently making payments. The lowest performing securities, **FE**, had stopped making payments, prior to at least 95% of the principal being paid off. In addition Interest Only securities were labelled as **FE** if they had a history of shortfall.

We consider a subset of 189 prospectuses issued in 2002, containing 2770 securities, and 268 prospectuses issued in 2006, containing 4021 securities. Figure 2 shows the distribution of labels, by year, for the class A and B securities. From Figure 2, we note that while none of the 2002 class A securities fail expectations, close to 10% of the 2006 class A securities fail expectations. As a result, if one would use the year as the only predictor in a prediction model, one can achieve a 100% accuracy on the 2002 sample. We further note that the senior secured A class of securities were the most credit worthy and were not expected to fail expectations. We also note that 14% of the 2002 class B securities fail expectations, while over 90% of 2006 class B fail expectations.

3 MODELS AND SUMMARY OF RESULTS

In this extended abstract, we summarize our model results. We start with regularized logistic regression with the objective of predicting the label of **FE** for the classes of A and B securities. This model will use a combination of features from the securities and the supply chain; we report on the benefits of including supply chain features. We then summarize results from applying a topic model to identify communities and model each prospectus as a mix over these hidden communities. We then use k-means clustering over the communities to determine if the upstream communities are correlated with downstream performance.

Figure 2: A histogram of the labels reflecting the performance of securities, by year. ME: Meeting expectations; NME: Not meeting expectations; FE: Fails expectations.

3.1 Logistic Regression

We run regularized Logistic Regression models, LASSO [6], with a binary indicator variable for whether or not a security fails expectations as the dependent variable. We train the model using information about all securities, but report the classification performance on the A and B securities. We train three different models. First, we use information about whether or not specific financial entities are associated with the prospectus. Next, we use the securities properties known at issuance to predict whether or not a security will fail expectations. Finally, we use a combined model, with both information about the presence of financial entities, as well as properties associated with each security.

Table 1 summarizes the performance of the three models by year and type, for the 2002 B securities and the 2006 A and B securities. The cut-off is held at the default value of 0.5. Each of the models classifies 2002 A securities with almost 100% accuracy. The results for the other securities is mixed. We note that for the 2006 A securities, using the securities' properties alone achieves higher accuracy, compared to using information on the presence of financial entities alone. However, for the 2006 B securities the story is not as simple, and we note that using information on financial entities alone outperforms using information on the securities' properties alone. This is in large part driven by financial entities that are only associated with securities in 2006. When we combine information on financial entities with a model built on securities' properties alone, there is a (small) jump in accuracy and other performance measures. Thus, additional information about the presence of financial entities associated with a prospectus can improve a model, compared to only using the properties of the securities themselves.

Beyond accuracy and the F1-score, we specifically analyze which financial entities are associated with securities being significantly more or less likely to be labelled as failing expectations. We note, that simply looking at the regression coefficients of the financial entities may be misleading. For example, we know that the failure rate of 2002 securities is

Accuracy (%)			
Model	2002 B	2006 A	2006 B
FinE	83.3	52.6	73.3
Properties	82.0	93.7	69.6
FinE & Properties	85.3	95.1	94.6
Sensitivity (%)			
Model	2002 B	2006 A	2006 B
FinE	0	63.5	75.8
Properties	13.5	54.7	72.2
FinE & Properties	17.4	68.2	98.5
F1 score			
Model	2002 B	2006 A	2006 B
FinE	-	0.200	0.839
Properties	0.177	0.618	0.814
FinE & Properties	0.254	0.721	0.971

Table 1: Performance Summary of the Logistic Regression Models. The LR models using information on financial entities only do not label any 2002 securities as FE, and therefore the sensitivity is 0 and the F1 score not defined.

zero, while it is close to 10% in 2006. Therefore, if a financial entity is primarily associated with prospectuses in 2002, any model that has information on the presence of financial entities could exploit this knowledge.

Most financial institutions which are associated with large increases in the risk of failing expectations are almost or only associated with prospectuses from 2006. These include for example **AMNET**, **Novastar**, **Litton Loan Servicing LP**, **Carrington**, **Agreement General** and **Weyerhaeuser Mortgage Company**. An example of a company that is associated with an increased risk of failing expectations, and is linked with prospectuses in both 2002 and 2006 (26 and 74% respectively) is **EMC Mortgage**.

We further analyzed the results of the models using the securities' properties. Some of the factors that contribute to increased odds of FE are not surprisingly indicators of a security whose principal and/or interest distributions are subordinate to a senior structure (either subordinate or mezzanine), of the security being a stepped rate bond as well as an indicator of the the initial Moody rating being NR or "not rated".

3.2 LDA Topic Modeling

To gain further insights into the roles and the behavior of financial entities in the supply chain we adopt topic modeling [2, 10]. Traditionally, documents are considered to be collections of keywords. Each topic is a distribution over these keywords, and then each document is a mix over these topics. In our model, prospectuses are collections of pairs of (Role, Financial entity) and a topic is a distribution over the (Role, Financial entity) pairs. One of the advantages of this model is that a financial entity (in a specific role) can occur in multiple communities, or in a single community, as appropriate.

Prior to running the analysis, we eliminated financial entities that appear in less than 20 prospectuses, and we eliminated prospectuses that contain less than three financial entities or five (Role, Financial entity) pairs.

We used prospectuses from 2002 through 2005 to generate the communities, and evaluated the generated topics using prospectuses from 2006 through 2008. The resulting topic models were evaluated using a perplexity metric as well as a coherence metric. The perplexity scores reflect that the models produce topics that can generate the contents of the unseen prospectuses with reasonable accuracy. The coherence scores reflect that the topics are a good agreement with the prospectuses. Interestingly over 25% of the prospectuses fall within a single topic (defined as having a topic weight $\geq .95$) and close to 70% of the prospectuses have a dominant topic (defined as having a topic weight $\geq .5$).

Examples of communities include the **Bank of America**, **Banc of America Securities LLC**, **Wells Fargo**, **Cendant Mortgage and Asset Backed Funding**. Another example of a community is the set of **Countrywide Home Loans**, **Countrywide Securities Corporation**, **Bank of New York Mellon Corp**, **Wilmington Trust** and **J.P. Morgan Chase**. An example of a community of financial entities playing specific roles is the following: **Countrywide Securities Corporation** as a depositor, **Countrywide Home Loans** as a master servicer and a seller, **Wells Fargo** as a seller and the **Bank of New York Mellon Corp** as the trustee.

Beyond statistical validation we also analyzed whether topic models could be applied to identify toxic communities, i.e., communities associated with many failed financial entities. We focus on models of (Role, Financial entity) pairs. We have observed from anecdotal evidence that communities with toxic entities in certain roles are more likely to impact the performance of securities. We first created a smaller dataset with higher quality, and then applied many additional tuning steps to achieve satisfactory results.

Examples of toxic communities include one with **Indymac** playing multiple roles (servicer, seller, depositor and issuer) with **Deutsche Bank** as the trustee. A second community has **National City** as the originator and servicer, **First Franklin Financial Corp** as the issuer, and **Bank of America** and **HSBC** as originators. We refer the reader to <https://dsfin.umi.acs.umd.edu/topicmodels/resMBS/> for visualizations of the topic models.

3.3 K-means Clustering

In order to investigate the potential of topic models as a foundation for grouping of failing securities we ran K-means clustering on the same dataset as was used for the logistic regression models. We hypothesize that certain toxic financial communities are more strongly connected to toxic securities; thus, by grouping prospectuses together based on their affiliations with various communities, we may be able to identify clusters of varying toxicity as reflected by their failure rate of securities.

The clustering analysis was run using the topic weights of each prospectus as the independent variables; we experiments with various values for k , but report on the results when $k = 20$. When analyzing the resulting clusters, we note a wide range of cluster behavior. For example, we note multiple clusters where no securities fail expectations. We provide two examples of clusters with high failure rates. The cluster with the highest failure rate, 68% is a cluster containing 200 securities, out of which 136 securities failed expectations. This cluster contains prospectuses associated with two financial communities (topics). First a partially toxic community of **Bear Stearns & Co. Inc.** as the issuer and depositor, **Encore Credit Corporation** as the originator and **EMC Mortgage** as the servicer and seller. Second a toxic financial community that consists of **INDYMAC**, **Olympus Servicing L.P.**, and **Weyerhaeuser Mortgage Company** as originators, and **Ameriquest Mortgage Co.** as a seller and servicer. The second example is a cluster of 48 securities with an elevated failure rate of almost 40%. This is also a toxic community with **Weyerhaeuser Mortgage Corp** as originator, **American Home Mortgage** as issuer, servicer and depositor, and **Wells Fargo** as trustee.

Our initial exploration has thus identified that upstream toxic financial communities may indeed impact downstream financial performance, and failure, of the associated securities.

4 CONCLUSION AND FUTURE WORK

This preliminary research has shown the importance of the financial entities, their roles, and the supply chain, on the performance of resMBS securities, in the years leading up to the US financial crisis in 2008. We have shown that information about financial entities involved in the issuance and sales of resMBS offers information about the probability of failure, and that toxic securities, defined as securities failing to meet expectations, are prominent in toxic financial communities. In this work we have specifically focused on prospectuses issued in 2002 and 2006, and significant work lies ahead in extending the analysis to cover the years from the time private label resMBSs became popular until the financial crash in 2008. The models and results presented above provide a first step in fully understanding the role of financial entities and their self organization in the resMBS supply chain and the results indicate that financial entities and their roles behind resMBSs are worth a detailed examination.

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