Do U.S. Financial Regulators Listen to the Public? Testing the Regulatory Process with the RegRank Algorithm

Shawn Mankad, UMD Smith School of Business
Joint work with:
Andrei Kirilenko, MIT Sloan
George Michailidis, Univ. Michigan
Do U.S. Financial Regulators Listen to the Public?

The notice-and-comment process is the basis for the public voice in federal regulatory activity.

Following a financial crisis and with new congressional authority (Dodd-Frank), did the financial regulators listen to the public?

• New big data technology needs to be developed due to the increasing volume of comments.

• Example: Proposed net neutrality rule received over 1 MILLION public comments!

Our paper provides a data mining framework that can be used to test whether regulators listen and summarize an enormous number of regulatory documents in a fully automated or computer-driven way.
Administrative Procedures Act and Rulemaking

• Typically laws give congressional authority to agencies to regulate certain activities.
• Agencies must stay within the scope of the law and constitution, but does the public have a voice in the new regulations?
• Administrative Procedures Act (APA) was enacted in 1946 to provide this due process.
Congress passes a bill and the President signs it into law. Federal agency must propose a rule to enforce the law. Agency lawyers write the final rule. Public comment submission begins. Submission ends.

The APA Rulemaking Process

Does the democracy of rulemaking work?

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Literature Review


This issue has been addressed, but not in a data-mining framework. Thus, previous works utilize
I. Subsets of comments;
II. Only portions of the rule, not full text.

This leads to potential for selection bias, which we overcome using new big data technology.
Data and Methodology

Data – The universe of CFTC rule-making documents
• 104 CFTC proposed rules enforcing Dodd-Frank Act.
• 60,000 public comments.
• 64 final rules.

Analysis Framework
1. Use RegRank to score each document between -1 (anti-regulation) and 1 (pro-regulation).
2. Feed RegRank scores into a regression to test whether the final rule changes according to comments received.

Framework easily scales to tens of millions of documents, multiple agencies, etc.
RegRank Algorithm
And a brief introduction into Text Mining
Text Preprocessing: Filtering the Noise

1. A term should not be too common.
A term occurring in every document is not useful – it does not distinguish anything!
2. Each “term” should really be “unique”.
Ex: “valuing”, “valued”, “values” → “valu”.

Standard Preprocessing:
- Very common words called stopwords are removed from the documents (e.g., “and”, “the”, “of”, etc.).
- Lower limits are placed on the number (or fraction) of documents in which a word may occur.
- Stemming all words to their base form.
Creating Structure from Unstructured Data

A major idea in text analysis is to treat every document as a collection of individual words or phrases.

Text documents (e.g., reviews)

D1: This rule would be a disaster ....
D2: This rule would be fantastic ....

Transform documents into structured data, i.e., a table of word counts.

| Doc# | rule | disaster | fantastic | ...
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>...</td>
</tr>
</tbody>
</table>
Motivation: Regression with Text Documents

<table>
<thead>
<tr>
<th>Doc#</th>
<th>rule</th>
<th>disaster</th>
<th>fantastic</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>...</td>
</tr>
</tbody>
</table>

Why not plug the entire term-document matrix into a statistical model?

→ Usually not identifiable, since there are too many words and phrases.

We utilize \textit{dimension reduction} to solve this technical issue, i.e., represent each document using a handful of numbers that capture the themes in every document.
Creating Structure from Unstructured Data

Text documents (e.g., reviews)
D1: My stay was a disaster 
D2: My stay was fantastic 

Transform documents into structured data, i.e., a table of word counts.

<table>
<thead>
<tr>
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<th>rule</th>
<th>disaster</th>
<th>fantastic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
</tbody>
</table>
Dimension Reduction in Text Mining

Let $X$ be the term-document matrix.

<table>
<thead>
<tr>
<th>Doc#</th>
<th>rule</th>
<th>disaster</th>
<th>fantastic</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>...</td>
</tr>
</tbody>
</table>

Notice that

- $\sum_{j=1}^{p} X_{ij}$ is the word count for document $i$.
- $\sum_{j=1}^{p} w_j X_{ij}$ is the sentiment for document $i$.

These are the most common forms of dimension reduction in the text mining / econometric literature.
Creating Structure from Unstructured Data

Text documents (e.g., reviews)
D1: My stay was a disaster ....
D2: My stay was fantastic ....

Weakness of most measures: Does not capture the underlying meaning or semantics behind a document.

<table>
<thead>
<tr>
<th>Doc#</th>
<th>rule</th>
<th>disaster</th>
<th>fantastic</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>...</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>...</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Doc#</th>
<th>Doc Length</th>
<th>Sentiment</th>
<th>Grade Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>52</td>
<td>-0.77</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>101</td>
<td>0.91</td>
<td>7</td>
</tr>
</tbody>
</table>
Motivation: Regression with Text Documents

**Big Idea**: Combine words that have common meaning, e.g., “rule”, “requirement”, “stipulation”, “directive”, “law” $\rightarrow$ “regulation”

- Just like Principal Component Analysis, where variables are combined together.
Probabilistic Topic Models

Bayesian hierarchical model of how documents are generated.

• Developed by David Blei in 2007

• Main idea:
  
  I. Documents are mixtures of topics, and topics are distributions over words.

  II. Using the documents as the observed data, reverse engineer both the underlying topics and their mixtures for each document.

  III. Topic Models estimate in 2 key quantities: \( P(topic|doc) \) and \( P(word|topic) \).

• Introduction paper by Blei 2012 in Communications of the ACM
Text documents (e.g., reviews)

D1: This rule would be a disaster ....
D2: This rule would be fantastic ....

Transform documents into structured data, i.e., a table of word counts.

| Doc# | rule | disaster | fantastic | ...
|------|------|----------|-----------|
| 1    | 1    | 1        | 0         | ...
| 2    | 1    | 0        | 2         | ...

Keywords: speculation, position limits, exacerbate volatility

Keywords: implementation, costs, reporting

Summarize the table of word counts.

<table>
<thead>
<tr>
<th>Doc #</th>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.92</td>
<td>0.07</td>
<td>0.00</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>0.43</td>
<td>0.10</td>
<td>0.47</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Suffering severe casualties within the first two months, the defenders were pushed back to a small area in the south of the Korean Peninsula, known as the Pusan perimeter. A rapid U.N. counter-offensive then drove the North Koreans past the 38th Parallel and almost to the Yalu River, when the People’s Republic of China (PRC) entered the war on the side of North Korea.
LSA versus Topic Modeling

Topic modeling usually features more interpretable results due to the probabilistic framework.

Figure from Xu et al. 2003
RegRank Algorithm

1. Use topic models to
   • Estimate 'topics' $P(\text{word}|\text{topic})$
   • Decompose each document into a mixture of topics $P(\text{topic}|\text{doc})$

2. Calculate topic sentiment score:
   $$\delta(\text{topic}) = \sum_{\text{word}} P(\text{word}|\text{topic}) \times \pm \text{Tone}$$
   • Tone comes from a labeled dictionary

3. Calculate RegRank for each document:
   $$\text{RegRank} = \sum_{\text{topic}} P(\text{topic}|\text{doc}) \times \delta(\text{topic})$$

RegRank is always between -1 and 1
Summary of Approach

- Primary challenge – “unstructured” nature of textual data
- Approach – transform “unstructured” data to “structured” data

**Pre-processing:**
- Remove common words
- Combine similar words

**Transformation:**
- Represent text as structured matrix

**RegRank Algo:**
- Measure regulatory sentiment

**RegRank Sentiment Score**
Summary of Approach

1. RegRank is applied to:
   • All final rules
   • All proposed rules
   • All public comments

2. RegRank scores are used for the following regression

\[ RegRank_{Final} = F(RegRank_{Proposed}, RegRank_{Comments}, Controls) \]
Results and Implications
Regression:
\[ R^2 = 0.180 \]

\[ f(t) = 1.207 - 0.125 R + 1.661*A + 0.116 S - 0.013 N \]

* denotes significance

Does the government listen? Yes!

Evolution of all finalized rules.
RegRank Evolution of a Selected Rule

FR 85 81519
### But Who Did the CFTC Listen to?

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>RegRank Score from Proposed Rule</td>
<td>-0.052</td>
<td>0.202</td>
<td>-0.257</td>
<td>0.799</td>
</tr>
<tr>
<td>Avg RegRank Score from Finance</td>
<td>1.263</td>
<td>0.170</td>
<td>2.458</td>
<td>0.019</td>
</tr>
<tr>
<td>Avg RegRank from Lawyers</td>
<td>0.163</td>
<td>0.170</td>
<td>0.959</td>
<td>0.344</td>
</tr>
<tr>
<td>Avg RegRank from Professional</td>
<td>0.349</td>
<td>0.260</td>
<td>1.345</td>
<td>0.187</td>
</tr>
<tr>
<td>Avg RegRank from Other</td>
<td>0.316</td>
<td>0.351</td>
<td>0.902</td>
<td>0.373</td>
</tr>
<tr>
<td>Avg RegRank from Unknown</td>
<td>-0.105</td>
<td>0.195</td>
<td>-0.538</td>
<td>0.594</td>
</tr>
<tr>
<td>Range RegRank Scores</td>
<td>-0.127</td>
<td>0.080</td>
<td>-1.598</td>
<td>0.121</td>
</tr>
<tr>
<td>Number of Comments Received</td>
<td>-0.000</td>
<td>0.000</td>
<td>-1.446</td>
<td>0.157</td>
</tr>
</tbody>
</table>

Comments from the financial industry were predictive of the final regulatory sentiment.
Can we predict whether a rule is finalized?

Yes, there is predictive signal from the RegRank index.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>RegRank Score from Proposed Rule</td>
<td>-1.308</td>
</tr>
<tr>
<td>Range RegRank Scores</td>
<td>-13.216</td>
</tr>
<tr>
<td>Number of Comments</td>
<td>0.348</td>
</tr>
<tr>
<td>RegRank from Asset</td>
<td>-92.671</td>
</tr>
<tr>
<td>RegRank from Association</td>
<td>-101.932</td>
</tr>
<tr>
<td>RegRank from Bank</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Broker</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Clearing</td>
<td>3.786</td>
</tr>
<tr>
<td>RegRank from Commercial</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Consulting</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Exchange</td>
<td>-118.813</td>
</tr>
<tr>
<td>RegRank from Forex</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Hedge Fund</td>
<td>94.174</td>
</tr>
<tr>
<td>RegRank from Law Firm</td>
<td>-41.337</td>
</tr>
<tr>
<td>RegRank from News Agency</td>
<td>-</td>
</tr>
<tr>
<td>RegRank from Unknown</td>
<td>12.074</td>
</tr>
<tr>
<td>RegRank from Public Advocacy</td>
<td>17.019</td>
</tr>
<tr>
<td>RegRank from Technology</td>
<td>57.411</td>
</tr>
</tbody>
</table>
Insights from the *RegRank* Framework

- The **CFTC did respond to comments**, especially from insiders, like the **financial industry**.

- The **more aggressive** the initial proposal, the **less likely** the rule becomes finalized.

- **Greater consensus among public comments** increases the chance of a proposed rule getting finalized. **Greater spread of public tone** decreases the chance of a final rule.

- Comments from **public advocacy groups, hedge funds and technology** increase the likelihood of a rule becoming finalized.

- Comments from **asset management, associations, exchanges, and law firms** tend to **lower** the likelihood of a rule becoming final.
Insights from the *RegRank* Framework

We arrived at similar conclusions as from the leading political science literature through a fundamentally different methodology based in data mining and text analytics.


Frameworks like *RegRank* are necessary for the public to truly have a voice, as the cost of submitting comments is decreasing with electronic submission.

*Consider the sum of all the rules and regulations, testimony, budgets, planning, etc.*

*1 million public comments on net neutrality is just the beginning.*