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Measuring macroprudential policy credibility using machine learning[1]

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[1] This presentation was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the event.

Measuring Macroprudential Policy Credibility Using Machine Learning

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Abstract

Macroprudential policies and their instruments can potentially be more effective when a central bank has credible track records. Credibility of Bank Indonesia's macroprudential policy is used to be measured by using surveys to selected stakeholder. However, machine learning and text mining are recently proven to be able to provide less biased and timelier indicator of credibility. In our previous research, we have developed machine learning-based methodology for measuring central bank monetary policy credibility index. In this paper, we extend such methodology using news data in application to the measurement of central bank macroprudential policy credibility index.

Keywords: central bank credibility, macroprudential policy, central bank communication, machine learning, text mining.

JEL classification: E58, C88

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Contents

1. Background

Bank Indonesia is the macroprudential authority as mandated by Act No. 21/2011 concerning Financial Services Authority. Since 2013, the effort to maintain financial system stability especially since the financial crisis 0f 1997/1998, has been focused on macroprudential policy. Global financial authorities also realizes the growing importance of Macroprudential policy in financial stability especially since the global financial crisis of 2007/2008. Bank Indonesia considers macroprudential policy as one of the three main policy framework in their mandate as central bank.

In upholding its macroprudential policy mandates, Bank Indonesia relies on a set of macroprudential policy instruments. Currently there are 5 macroprudential policy instruments:

1. Countercyclical Capital Buffer (CCB)

The Countercyclical Capital Buffer (CCB) functions as an additional buffer to anticipate losses caused by excessive credit growth with the potential to disrupt financial system stability. The risks are associated with procyclical lending in the banking industry, where banks tend to increase lending during an expansionary economic boom period and restrict lending during a contractionary economic bust period. Procyclicality in Indonesia necessitated CCB implementation, as evidenced by the direct correlation between credit growth and economic growth.

2. Loan-to-value / Financing-to-Value (LTV/FTV)

The Loan-to-Value or Financing-to-Value (LTV/FTV) Ratio is the ratio of the value of the loan/financing disbursed by a Conventional or Islamic Commercial Bank against the value of collateral in the form of property when the loan is originated based on the latest evaluation. One goal of LTV/FTV policy is to maintain financial system stability and mitigate systemic risk stemming from higher property prices.

3. Macroprudential Intermediation Ratio (MIR)

The Macroprudential Intermediation Ratio (MIR) and Sharia Macroprudential Intermediation Ratio (Sharia MIR) are macroprudential instruments to ensure the bank intermediation function is managed in line with economic capacity and target growth, while maintaining prudential principles.

4. Macroprudential Liquidity Buffer (MPLB)

The Macroprudential Liquidity Buffer (MPLB) and Sharia Macroprudential Liquidity Buffer (Sharia MPLB) are minimum liquidity reserves denominated in rupiah that must be maintained by conventional commercial banks and Islamic banks in the form of rupiah securities that can be used for monetary operations, the level of which is set by Bank Indonesia as a percentage of rupiah deposits.

5. Short-Term Liquidity Assistance (PLJP)

Short-term liquidity assistance (PLJP) is provided by Bank Indonesia to the banking industry in order to overcome short-term liquidity difficulties. Meanwhile, sharia short-term liquidity assistance (PLJPS) is sharia-compliant financing provided by Bank Indonesia to Islamic banks experiencing short-term liquidity difficulties.

These macroprudential policy instruments are the main tools that are constantly being monitored to ensure countercyclicality with Indonesia current economic conditions. Their application and effect into the economy and financial system will usually triggers responses from stakeholders. These responses are usually made public and captured by the press as news about responses of macroprudential policies. The press also publish news regarding stakeholder analysis about current financial system stability condition that can be provide insights to the public.

Central Bank credibility is defined as a commitment to follow well articulated and transparent rules and policy goals. Since the 2008 financial crisis, central bank macroprudential policy framework has been proven to help maintain macroeconomic and financial stability. The history of central bank credibility is tied up with the history of policy regimes (Bordo & Siklos, 2015).

Empirically, credibility is a qualitative concept, which is not easy to measure. There are several approaches have been used in measuring credibility, including using survey and constructing composite index from several indicators. For Indonesia's case Bank Indonesia regularly conducts survey to external stakeholders to measure the policy credibility. The policy credibility survey is prepared based on 6 (six) aspects of credibility, i.e. formulation, independence, communication, accountability, coordination, and effectiveness. But, in practice, the survey method has several weaknesses for measuring policy credibility (Zulen et al., 2020). Bank Indonesia has been using macroprudential policy instruments since 2011 to maintain overall financial stability in Indonesia. Therefore macroprudential credibility should also be taken into account for the overall Bank Indonesia credibility.

Central bank has been using machine learning for several of use cases. For example, they have used natural language processing to produce economic or policy uncertainty indices from textual data (Baker et al., 2016) or to gauge sentiment in response to monetary policy announcements, including those for unconventional policy measures (Hansen & McMahon, 2016). Combining natural language processing / text mining and financial stability part of Bank Indonesia mandates, this paper explores how the utilization of news data to measure its macroprudential credbility mandates.

Credibility survey that previously used are expensive, untimely and can contain biases from the stakeholders. News data that we have are highly available and can be collected in a daily basis. Using big data and machine learning we can utilize this data to capture unbiased public opinion regarding macroprudential policy much more timely. Previously we have developed methodology of Bank Indonesia monetary credibility using news data and text mining in (Zulen et al., 2020). In this paper, we use similar methodology to measure the macroprudential perspective of central bank credibility.

The paper is organized as follows. In section 2, we provide literature reviews on central bank usage of big data and machine learning, Bank Indonesia's policy credibility survey, macroprudential policy credibility and communication, and text mining of economic and financial news. In section 3, we discuss the data and methodology. In section 4, we provide a summary of the results. Lastly in section 5, we conclude the paper and offer some thoughts for future works.

2. Literature Review

2.1 Bank Indonesia's Policy Credibility Survey

From 2015 to 2018, Bank Indonesia conducted Semiannual survey to external stakeholders to measure macroprudential policy credibility. The survey is expected to provide a measure for policy credibility that is objective, accurate, reflecting broad view of stakeholders (including general public), and available timely in many aspects of policy credibility, which then can be used as feedback for formulating future policy and its communication strategies. The survey consists of a series of questions regarding macroprudential policy ranging from general aspects such as:

1. **Formulation**: Bank Indonesia's policy is formulated carefully according to its purpose;
2. **Independence**: Bank Indonesia formulates its policy independently, without intervention from any party;
3. **Communication**: Bank Indonesia's policy has been well communicated to the public;
4. **Accountability**: Bank Indonesia's policies are well accounted for;
5. **Coordination**: Bank Indonesia and the Government always coordinate well; and
6. **Effectiveness**: Bank Indonesia policies are effective in achieving its objectives.

And also specific questions such as:

1. The difference between the responsibility of Bank Indonesia and Financial Services Authority
2. The stakeholder understanding of Bank Indonesia macroprudential policy
3. If the stakeholders are confident that Bank Indonesia is able to maintain financial stability in Indonesia.

The macroprudential policy survey doesn't have consistent question during the 3 years it's being conducted since there are different aspects and specific questions that are set as the survey objectives every semester. Therefore we are unable use this survey as benchmark to compare the result. This paper methodology calculate credibility within 4 aspects of credibility from the survey that can be captured from the news sentiment, which are formulation, effectiveness, coordination, and communication.

2.2 Macroprudential Policy Credibility and Communication

Bank Indonesia is a central bank which have a policy mix consisting of 3 policies and its macroprudential policy should be part of its credibility. Warjiyo argues that there are three key reasons why central banks should assume macroprudential policy. First, the performance of their monetary policy functions provides central banks with macroeconomic focus and an understanding of financial markets, institutions and infrastructures needed for the exercise of macroprudential policy. Second, financial instability can be caused by and affect macroeconomic performances, with substantial consequences for economic activity, price stability and monetary policy transmission. And third, central banks are the ultimate source of liquidity for the economy, through its monetary policy and lender of the last resort functions, and appropriate liquidity provision is crucial for financial system stability (Warjiyo, 2016).

There are several reasons why central bank involvement in macroprudential policy is beneficial. Combining financial supervision with monetary policy tasks can lead to synergies, e.g. through information gains, thereby possibly leading to a more effective conduct of monetary policy and/or to more effective crisis prevention and management (Borio, 2011). Central banks should monitor and regulate systemic risk not only because a financial stability objective is related to the objectives of monetary policy, but also because it is likely to require a lender of last resort function Blinder (2010).

Macroprudential policy communication reflects the credibility of the central bank. A credible central bank policy should be able to affect the financial market and be properly reacted by the general public and stakeholders. In his paper, Born et al. (2010) states some example; if the central bank expresses a rather pessimistic view about the prospects for financial stability, and this view gets heard in financial markets, we would expect that stock prices for the financial sector decline. In that sense, these communications "create news". The other motive, to "reduce noise", should then be reflected in market volatility, in the sense that a communication by the central bank should contribute to reducing uncertainty in financial markets, thereby reducing volatility.

2.3 Text Mining of Economic News Data

Text mining is a methodology of automatically extracting high quality information from text data. Text data has proven to provide insightful information for many use cases, including for policy and analysis done by central bank.

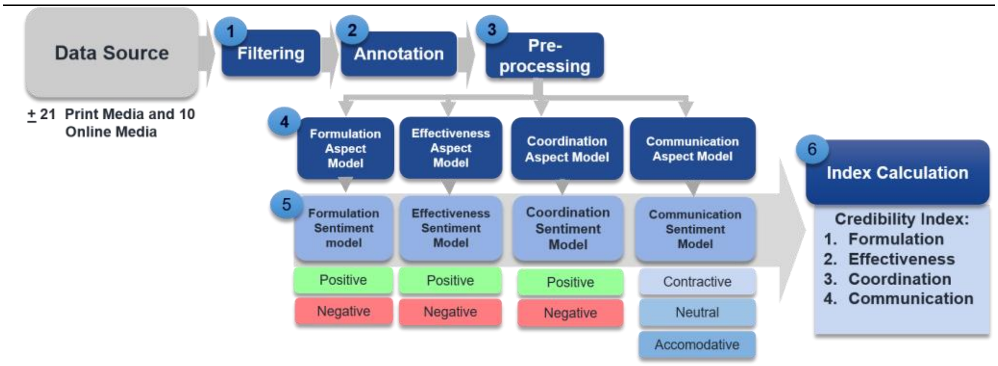
Bholat et al. (2015) states the methodologies of text mining that central bank has used. One of them is supervised machine learning. To quote Bholat, "perhaps the most fruitful application of supervised learning techniques in economics is when the researcher has well- motivated text classes". Supervised machine learning algorithms that start with a researcher manually classifying training data with predefined classes, as in dictionary-based methods. In order to avoid the issue of over-fitting, the algorithm is then validated on another set of documents termed test data before being applied to the rest of the corpus.

This paper develops further from Zulen et al. (2020) methodology in developing a measurement of policy credibility using news data and text mining. In the paper, the focus is monetary policy while in this paper the focus is macroprudential policy. The methodology differs in the keyword that specifically tailored toward macroprudential policy by using different set of keywords while having mostly the same text mining methodology and credibility aspects that are measured compared to the previous research.

3. Methodology

We utilize machine learning to develop sentiment prediction model of news sentences to measure the credibility of Bank Indonesia macroprudential policy in 4 aspects of credibility as stated in chapter 2.1. The workflow is as describe in figure 1

Macroprudential Policy Credibility Index Model Workflow — Figure 1



3.1. Data Collection

The news data is obtained from Bank Indonesia Institute's Cyber Library that collected economy and financial news from print and online press release. The news are filtered using macroprudential keywords that are acquired by consulting with Bank Indonesia Macroprudential policy department. The news data that we use are in Bahasa Indonesia. The keyword and its variants that we use to filters consists of word regarding policy mix, macroprudential policy, financial system stabliity, its instruments and also its effect in the financial system.

The news are filtered using the keywords above and then processed into sentences. From there we obtain 9060 sentences from January 2013 to June 2021.

3.2. Data Annotation

From the 9.060 sentence we randomly pick 5.030 sentences to be annotated with labels to provide each sentence the labels of relevancy and sentiment to each aspects of credibility. First phase annotation is done by 2 people and second phase is done by a 3rd person annotating if the result of annotation is not uniform for a sentence in the first phase. The annotation is done by the authors, and subject matter experts from the Macroprudential Policy Department of Bank Indonesia using an annotation guidebook that previously formulated by the annotators. The guidebook contains cases of news for each of the credibility aspect that can help the annotator to give the correct label to each news sentence that is relevant to macroprudential policy. Table 2 contains the possible labels for each credibility aspects:

Possible Label for Each Credibility Aspect

Table 1

Credibility Aspects	Possible Credibility Labels
Formulation	Positive: 1 Negative: -1 Not Relevant: -
Effectiveness	Positive: 1 Negative: -1 Not Relevant: -
Coordination	Positive: 1 Negative: -1 Not Relevant: 0
Communication/ Expectation	Contractive: 1 Accommodative: -1 Neutral: 0 Not Relevant: -

Table 3 provides the distribution of information labels annotated to the sentences:

Distribution of annotated sentences

Table 2

	Positive[1]	Negative[2]	Neutral	Irrelevant
Formulation	642 (12,8%)	70 (1,4%)	Not Applicable	4.318 (85,8%)
Effectiveness	387 (7,7%)	76 (1,5%)	Not Applicable	4.567 (90,8%)
Coordination	433 (8,6%)	30 (0,6%)	Not Applicable	4.567 (90,8%)
Communication/ Expectation	72 (1,4%)	585 (11,6%)	25 (0,5%)	4.348 (86,4%)

[1] Contractive for communication index. [2] Accommodative for communication index.

3.3. Data Pre-processing

There are 5 steps of pre-processing in order to ensure a high quality text data for the machine learning models.

1. **Sentence Cleansing**

   This step converts synonyms into one representative word, replace numbers, and replace common names into normative representative of each person.

2. **Tokenization**

   This step converts the news text dataset into tokens of words representation that will be vectorised into vector representation that is necessary for machine learning text model.

3. **N-gram and TF-IDF Feature Extraction**

   This step converts the tokens dataset into n-grams of the tokens and their weighted frequency in TF-IDF (term frequency-inverse document frequency) vector representation for each of the sentences in the dataset. This TF-IDF will be the main representation of the feature that is used in machine learning model.

4. **Removal of Rarely Occurring Terms**

   This step removes the rarely occurring terms from the feature.

5. **SMOTE**

   From the distribution of annotated sentences, we can see a potential problem of imbalanced data of minority negative sentiment sentences in the dataset. To deal with imbalanced dataset we use SMOTE (Synthetic Minority Oversampling Technique) to oversample and undersample the dataset. SMOTE uses synthetic data of the minority classes in the dataset to improve the accuracy of the model.

3.4. Model Construction

As mentioned before, there is a problem of imbalanced data from the distribution of the annotated sentences. To solve that issue, we model the sentences using 2 phases of modelling before we construct the credibility index of each aspects:

1. 1st phase: Aspect relevancy model that separates sentences relevant to each credibility aspect, and;
2. 2nd phase: Sentiment model that predict the sentiment of each sentences that considered relevant from the 1st phase model.

The aspect and sentiment model of each credibility aspects are trained using 7 machine learning algorithms:

1. Logistic Regression;
2. K-Nearest Neighbor;
3. Support Vector Machine;
4. Naive Bayes;
5. Decision Tree;
6. Random Forest; and
7. XGBoost.

The model of each aspect is then evaluated out-of-sample test data with k-folds cross validation with 80:20 training and test data split using F1 score to get the best aspect and sentiment model. The best models then used to predict periodical sentences relevant aspects and sentiments.

3.5. Index Calculation

After we have the best model for each aspects, we can predict the rest of sentences in the news dataset from January 2013 until June 2021. Using the predicted sentiment of each sentences we can calculate periodical index of each aspect of credibility. The index are calculated using these formulas:

1. Formulation, Effectiveness, and Coordination credibility aspects

   The indices are calculated using net balances of the number of positive and negative sentences for aspect a in a period t.

$$Index_{a,t} = \frac{\#positive_{a,t} - \#negative_{a,t}}{\#positive_{a,t} + \#negative_{a,t}}$$

2. Communication Credibility Aspect

   The communication index are calculated by calculating the difference between macroprudential policy forward guidance (Contractive, Neutral, or Accommodative) as stated in Bank Indonesia Board of Governor Meeting press release with the relative expectation of macroprudential policy in the news (expectation index). The forward guidance is available since January 2016 when Bank Indonesia communicate macroprudential policy communication is done more intensively to the general public. We calculate the expectation index using the number of contractive, accommodative and neutral predicted sentences from the period between previous month board of governors meeting to the current month board of governors meeting. The quarterly and semester index are calculated using average of monthly board of governors meeting index.

$$Index_{Communication,t} = 1 - |FwdGuidance - Index_{Expectation_t}|$$

$$Index_{expectation,t} = \frac{\#Contractive - \#Accommodative_t}{\#Contractive + \#Neutral_t + \#Accommodative_t}$$

3. Overall Credibility Index

   Lastly, the overall credibility index is calculated using simple average of each of credibility aspects.

$$Credibility\ Index_t = \frac{1}{4}(Index_{Communcation,t} + Index_{Effectiveness,t} + Index_{Coordination,t} + Index_{Communication,t})$$

The characteristics of the indices are as follows:

1. Range of index: [-100%,100%].
2. The index will be close to 100% if there are more news with positive sentiment on the policy credibility aspect. For communication index, the index will be close to 100% if public expectation of macroprudential policy is in line with Bank Indonesia macroprudential policy forward guidance.

   The index will be close to -100% if there are more news with negative sentiment on the policy credibility aspect. For communication index, the index will be close to -100% if public expectation of macroprudential policy is not in line with Bank Indonesia macroprudential policy forward guidance.
3. Positive index means more news with with positive sentiment on the policy credibility aspect compared to the negative ones. For communication index,

positive index means public expectation of macroprudential policy is in line with Bank Indonesia macroprudential policy forward guidance.

Zero index means equal number of news with positive sentiment and negative sentiment on the policy credibility aspect.

Negative index means more news with negative sentiment on the policy credibility aspect compared to the positive ones. For communication index, positivie index means public expectation of macroprudential policy is in line with Bank Indonesia macroprudential policy forward guidance.

4. If $indext1 > indext2$ then the proportion of news with positive sentiment on the policy credibility aspect is greater in $t1$ than in $t2$.

   For communication index if $indext1 > indext2$ then public expectation on macroprudential policy is more in line with Bank Indonesia's forward guidance in $t1$ than in $t2$.

   If $indext1 < indext2$ then the proportion of news with negative sentiment on the policy credibility aspect is greater in $t1$ than in $t2$.

   For communication index, if $indext1 < indext2$ then public expectation on monetary policy is more not in line with Bank Indonesia's forward guidance in $t1$ than in $t2$.

3.6. Model Validation

For a machine learning to be used in production, it has to be evaluated to make sure that it can predict the aspect and sentiment of the sentences well. We use F1 score for our evaluation metrics since we want a model with balanced model precision and recall. Using F1 score we can also pick the model with the best predictive power from the 7 machine learning algorithms that we use. As explained in section 3.3, we use k-fold shuffled cross validation with 5 k to get a more robust validation. Lastly we use 80:20 split for each of the cross validation split.

To calculate F1 score we need to have the number of true and false prediction against the test data. F1 score is calculated from calculating the harmonic mean of precision and recall. Precision is the percentage measure of accuracy for sentences identified as credibility and recall is the percentage measure of identified credibility sentences.

Macroprudential Policy Credibility Prediction Confusion Matrix Figure 2

Model Classification \ Annotation Label	Non-credibility	Credibility – Positive	Credibility – Negative
Non-credibility	TN	FN	FN
Credibility – Positive	FP	TP	FP
Credibility – Negative	FP	FP	TP

TP = True Positive; TN = True Negative
FP = False Positive; FN = False Negative

The formulas to calculate precision, recall and f1 score are as follows:

$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{(TP + FN)}$$

$$F1\ Score = \frac{2\ (Precision * Recall)}{(Precision + Recall)}$$

4. Result and Discussion

4.1 Machine Learning Model Evaluation

After performing a horse race of 7 machine learning algorithms, we obtained the best results for the macroprudential credibility news dataset for each credibility aspects. The model is evaluated using F1 score as explained before. The result is as follows:

Macroprudential Credibility Evaluation Index Table 3

	Best Model Combination	Aspect Model F1 Score	Sentiment Model F1 Score
Formulation	XGBoost & Decision Tree	66.15%	69.99%
Effectiveness	Logistics Regression & XGBoost	66.87%	75.81%
Coordination	Logistics Regression & SVM	70.64%	67.49%
Communication/ Expectation	Logistics Regression & Logistics Regression	77.13%	76.32%
Overall Average		70.19%	72.40%

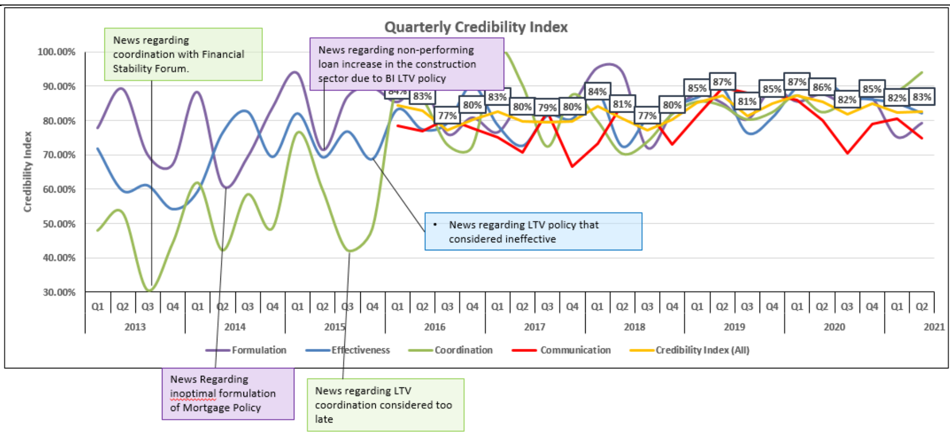
- Logistic regression algorithm is the most accurate in majority of cases (4 out of 8 models). This suggests that the relationship between sentence features and credibility labels is mostly linear, or that more (annotated) data is needed to be able to extract more accuracy from using nonlinear algorithms.

- The model individually is able to separate between the 4 aspects well and then predict positive and negative sentiment quite well. But due to the high number of non-aspects and non-sentiment news sentences in our dataset, the F1 score quite suffers from misclassifying non-relevant sentence as relevant.
- Since the model is a joint combination of 2 models the errors are also multiplied (50.81% average). The models need to have higher precision and F1 score for each of the classification task. The resulting error of the models is still an issue to be dealt with in the future development of the models.

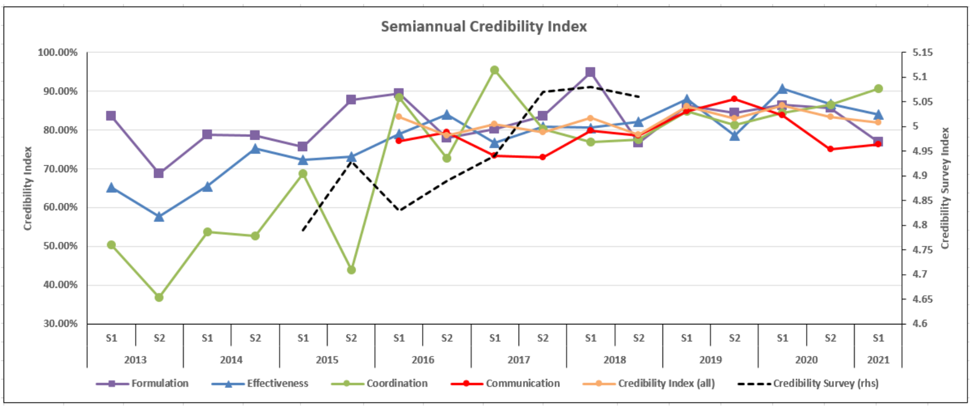
4.2 Index Results

Our previous paper for monetary policy credibility by Zulen et al. (2020) compared the credibility index result with the monetary policy credibility survey. Since the macroprudential policy survey doesn't have consistent and similar aspect compared with the big data credibility index, the two indexes do not have a good correlation. The semiannual index compared to the available credibility survey only have -23% correlation, while the monetary policy index compared to its survey counterpart have a high value of 79.7% correlation since its aspect is more similar and consistent.

Quarterly Macroprudential Credibility Index (2013 – 2021) Figure 3



Semiannual Macroprudential Credibility Index (2013 – 2021) Figure 4



We can also perform event analysis in the earlier 2013 to 2016 where the index result is more volatile and explain the drops of index results. Since we have granular news sentence prediction, we can also explain any spike or drop in the index with this methodology.

As seen from the figure 3 and 4, the red communication credibility index line is only available since 2016 where Bank Indonesia started to communicate macroprudential policy more intensively to the general public and leveraged macroprudential policy forward guidance in its board of governors meeting press release. Since then the overall index that has been calculated is more stable and relatively high with overall average of 82% during 2016 to the 1st quarter of 2021. We can say that communication of macroprudential policy to the general public affect the sentiment or tone of news regarding Bank Indonesia macroprudential policy positively, as captured in this macroprudential policy crediblity index.

5. Conclusion & Future Works

5.1. Conclusion

Based on our previous study of measuring monetary policy credibility, we develop a measurement of macroprudential policy credibility using text mining and machine learning. Using macroprudential policy keyword, we filter news data from our Bank Indonesia institute Cyber Library that collects economic and financial news data from online and printed press. Then we develop machine learning models to predict whether a news sentence is relevant to macroprudential policy and if it's relevant, what its sentiment is, is it positively or negatively describe Bank Indonesia policy and credibility. Using the aspect and sentiment model predictions we develop an index that can be used to measure Bank Indonesia macroprudential policy credibility from the news.

The model is evaluated using F1 score, while still leaving a room for improvement regarding its accuracy in predicting aspect relevancy and sentiment since the usage of 2 models combined its errors. The aspect relevancy models have an average F1 score of 70.19% while the sentiment models have an average F1 score of 72.40%.

The index result is compared to its survey counterpart but the resulting correlation is quite low since the survey mostly ask various specific questions regarding macroprudential policy while not consistently ask questions regarding the 4 aspects that are measured in the credibility index. The correlation between the credibility survey and the credibility index from machine learning is -23%. Bank Indonesia starts to communicate macroprudential policy forward guidance more intensively starting in 2016, and the result is captured in the index with the 4 aspects of the index become more stable and positive starting in 2016.

5.2. Future Works

Some possible improvement and possible further research include:

- **Data collection and annotation of more recent data**: As mentioned before, the accuracy of the model is not that robust (50.81% average F1 Score). In the future with more available data we can update the model with news from 2nd semester of 2021 and also 2022. Hopefully with using and annotating more data we can collect more relevant and recent news data so that the developed model can be more robust and produce better F1 score.

- **Expansion of macroprudential and policy mix:** There may be keywords that relevant to Bank Indonesia macroprudential policy or policy mix that contains positive and negative sentiment in the news during the covid-19 pandemic and recovery in the 2nd semester of 2021 and 2022. There are news regarding inclusive financing and SME definition expansion from 2022 that can be considered relevant to macroprudential policy. Updating the keyword list will help the model to be relevant to novel macroprudential policy formulated by Bank Indonesia in specific or unprecedented times
- **Econometric Analysis:** The index that developed here measures Bank Indonesia macroprudential policy credibliity using sentiment in the news. Following Wibisono et al. (2022) paper, we can perform econometric analysis to analyze whether the index can capture metrics of financial stability such as non-performing loan rate and credit growth and also whether the index capture the effect of any changes on macroprudential policy.

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Appendix A: Macroprudential Keyword

Macroprudential Policy Keywords — Table A.1

Policy mix	DP / Down Payment /Property credit down payment/ Vehicle Down Payment/ Mortgage	Prime Lending Rate
Macroprudential / Macroprudential + Microprudential	Green Financing	Financial Service Authority + Bank Indonesia
Financial System Stability	Macroprudential Intermediation Ratio	Indonesia Deposit Insurance Corporation + Bank Indonesia
Statutory Reserve Requirement / Statutory Reserve Requirement Incentive	Macroprudential Liquidity Buffer	Financial System Stability Forum
Countery Cyclical Buffer (CCB)	Short Term Liquidity Assistance	Bank Indonesia Integrated Reporting
Loan to Value (LTV)	Small and Micro Enterprise Credit Ratio	Primary Market Government Bond
Financing to Value (FTV)	Macroprudential Inclusive Financing Ratio	Government Bond Repo + Indonesia Deposit Insurance Corporation

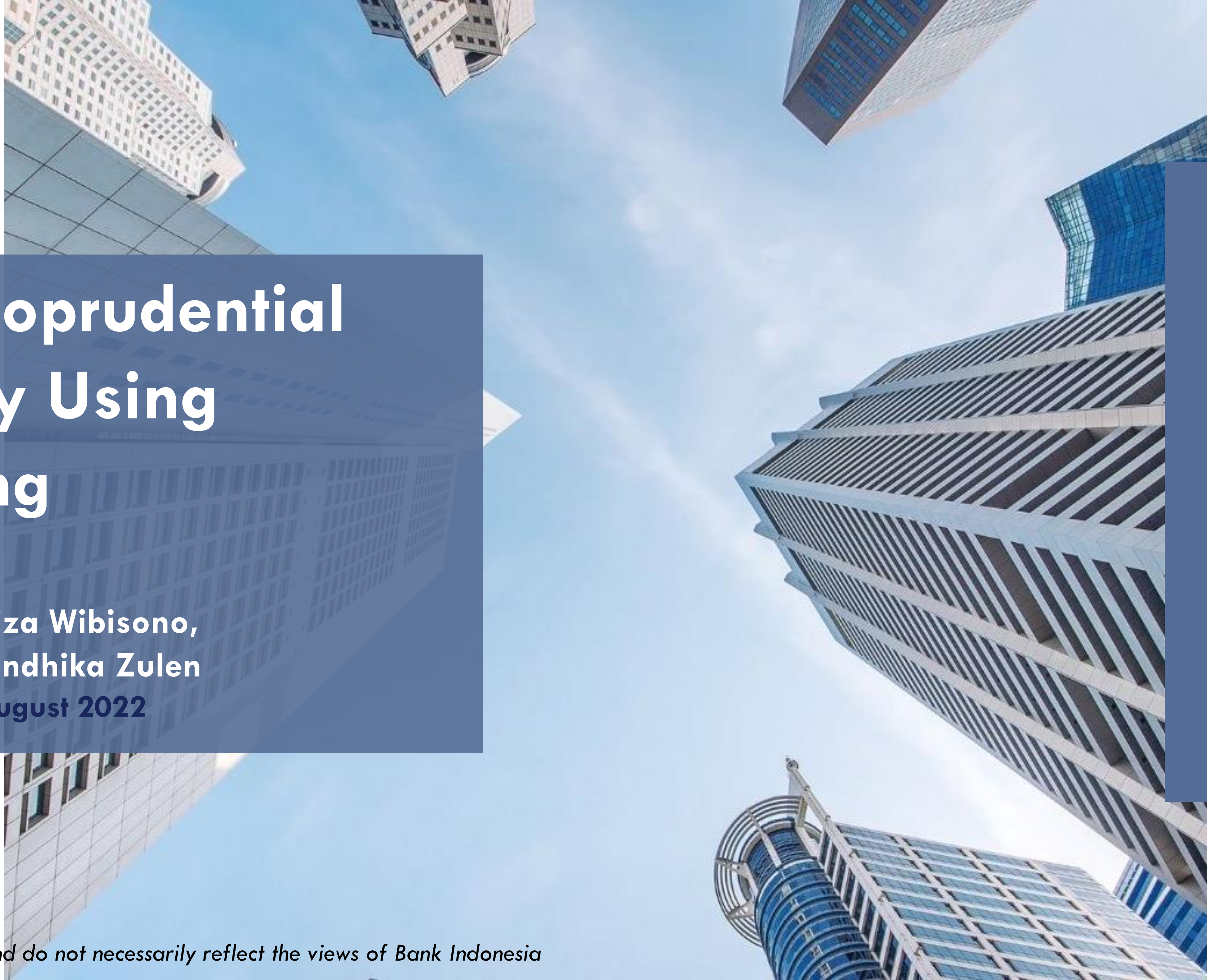
Appendix B: Sample of Annotated Sentences

Sample of annotated sentences — Table B.1

Sentences	**Credibility Aspect**	**Label**
Bank Indonesia has taken various anticipative measures to maintain macroeconomy and financial system stability and support sustainability of growth through monetary and macroprudential policy.	Formulation	**Positive**
Bank Indonesia policy to tighten rules of mortgage receive criticisim from property developer.	Formulation	**Negative**
With the rising consumption, relaxation of Loan-to-value ratio that will be applied on 1 August 2018, will help the growth of credit to its highest level to 12% this year.	Effectiveness	**Positive**
According to Paramadina University Rector, Prof Firmanzah Ph.D, Bank Indonesia macroprudential policy is not effective yet to support financial system stability.	Effectiveness	**Negative**
According to hendar, BI is preparing MOU with OJK. The purpose is to prevent data supply interference after the separation of macroprudential and microprudential function.	Coordination	**Positive**
Real Estate Company Union assess that there needs to be synchronization of loan-to-value ratio relaxation with the taxation system.	Coordination	**Negative**

Indonesia Credit Default Swap (CDS) can rise and Rupiah exchange rate will face turbulency and volatility that trigger vulnerability in the market. This will force BI to face it wih monetary and macroprudential tightening.	Communication/ Expectation	**Contractive**
Bank Indonesia will hold its loan to value policy on the property sector because it's considered an effective measures to reduce speculation and control credit risk.	Communication/ Expectation	**Neutral**
BI also predicted will loosen its macroprudential activity in the near future.	Communication/ Expectation	**Accommodative**
*The news samples above are translated by the authors from Bahasa Indonesia to English		

BANK INDONESIA
BANK SENTRAL REPUBLIK INDONESIA



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**The views expressed here are those of the authors and do not necessarily reflect the views of Bank Indonesia*

Outline

1. Background & Goals

Background:

1. Since the Global Financial Crisis in 2007/2008, **macroprudential policy has been proven to help maintain macroeconomic and financial stability.**
2. Central Bank credibility is defined as a commitment to follow well articulated and transparent rules and policy goals (Bordo & Siklos, 2015). **Macroprudential policy credibility should also be taken into account for the overall Bank Indonesia's credibility.**
3. Bank Indonesia used **semiannual survey to stakeholders** for measuring policy credibility,
4. Previous research has shown evidence that **news data and machine learning** can be used to measure Bank Indonesia's monetary policy credibility (Zulen et al., 2020).

Goals:

Utilizing **news data** and **machine learning** to **measure unbiased and timelier public perception on Bank Indonesia's macroprudential policy** in 4 aspects: Formulation, Effectiveness, Coordination, and Communication.

Literature Study:

1. Zulen, A. A., Wibisono, O., Widjanarti, A. (2020). Developing Machine Learning Technique for Measuring Central Bank Credibility. 2020 Data for Policy Conference.
2. Bordo, M. D., & Siklos, P. L. (2015). Central bank credibility: an historical and quantitative exploration (No. w20824). National Bureau of Economic Research.
3. Borio, C. (2011). Implementing the macroprudential approach to financial regulation and supervision. In The financial crisis and the regulation of finance. Edward Elgar Publishing.

2. Framework & Scope

Aspect Scope

Formulation: Perception regarding macroprudential policy formulation

Effectiveness: Perception regarding the effectiveness of macroprudential policy

Coordination: Perception regarding Bank Indonesia's coordination with other authorities

Communication: Perception regarding Bank Indonesia's communication on its' policy stance

Framework

Data Source

Source: Cyber Library (internal repository of curated economic and financial news)

~30 domestic news (in Bahasa Indonesia)
~850 articles daily

Whole corpus: since Jan 1999
Training data: Jan 2013 – Jun 2021

1 Filtering

2 Annotation

3 Pre-processing

4 Formulation Aspect Model | Effectiveness Aspect Model | Coordination Aspect Model | Communication Aspect Model

5 Formulation Sentiment Model | Effectiveness Sentiment Model | Coordination Sentiment Model | Communication Sentiment Model

Formulation Sentiment Model: Positive, Negative

Effectiveness Sentiment Model: Positive, Negative

Coordination Sentiment Model: Positive, Negative

Communication Sentiment Model: Ekspansive, Neutral, Contractive

6 Index Calculation

Credibility Index:
1. Formulation
2. Effectiveness
3. Coordination
4. Communication

Methodology: Data

Macroprudential keywords filter:

1. **Generic keywords** e.g: Policy mix, macroprudential, financial system stability
2. **Macroprudential policy instruments** e.g: Countercyclical Buffer / CCB, Loan to value (LTV), Financing to value (FTV), Macroprudential Intermediation Ratio (RIM), etc
3. **Credit and macroprudential indicators** e.g: Down payment, vehicle credit, property credit, green financing, prime lending rate, etc
4. **Other financial authorities:** Financial Services Authority (OJK), Indonesia Deposit Insurance Corporation (LPS), Financial System Stability Committee (KSSK).
5. **Others** e.g: Integrated Reporting, Government bond primary market.

9.060 News sentences (Jan 2013 – Jun 2021)

ID Berita	Tanggal Terbit	No. Kalimat	Kalimat	Formulasi			Efektivitas			Koordinasi			Ekspektasi		
cyberlib_2019-06-27_1898	27 Juni 2019	2	*Head of Macroprudential Policy Department BI, Juda Agung explains, in three to four years from 2022 to 2023, they will need to push banking intermediation function to the level of 15-16% annually (year on year/yoy).*	-	1	-	1	1	-	-	-	-	-	-	-
cyberlib_2019-06-27_1946	27 Juni 2019	1	*Bank Indonesia (BI) affirms accommodative macroprudential policy in the next three to four years.*	1	1	1	1	1	-	-	-	-	-	-1	-1
cyberlib_2019-06-28_1068	27 Juni 2019	11	*Based on Bank Indonesia data, during quarter 1/2019, the share of ownership through mortgage reaches 74.20%, higher than cash or gradual payment with 17,30% cash of 8,50%.*	-	1	-	-	1	-	-	-	-	-	-	1
cyberlib_2019-06-28_1352	27 Juni 2019	12	*He also shared his experience in the business world with hundreds of millennials in the Macroprudential Policy discussion held by Bank Indonesia.*	-1	1	-	-	1	1	-	-	-	-	-	1

Data Source

News with macroprudential keywords and Bank Indonesia in the text

Sentences with macroprudential keywords

3. Methodology: Annotation

- Sample of filtered sentences are annotated with positive (1), negative (-1), neutral (0), or not relevant (-) labels for each credibility aspect. One sentence can contain more than 1 aspect.
- Annotation are done by authors and domain experts within BI, using guidelines provided (incl. examples).
- Every sentence is annotated by 2/3 persons. The label are decided by the majority labels (or decided in annotator forum).

Sentences	Credibility Aspect	Label
Bank Indonesia has taken various anticipative measures to maintain macroeconomy and financial system stability and support sustainability of growth through monetary and macroprudential policy.	Formulation	**Positive**
Bank Indonesia policy to tighten rules of mortgage receive criticisim from property developer.	Formulation	**Negative**
With the rising consumption, relaxation of Loan-to-value ratio that will be applied on 1 August 2018, will help the growth of credit to its highest level to 12% this year.	Effectiveness	**Positive**
According to Paramadina University Rector, Prof Firmanzah Ph.D, Bank Indonesia macroprudential policy is not effective yet to support financial system stability.	Effectiveness	**Negative**
According to hendar, BI is preparing MOU with OJK. The purpose is to prevent data supply interference after the separation of macroprudential and microprudential function.	Coordination	**Positive**
Real Estate Company Union assess that there needs to be synchronization of loan-to-value ratio relaxation with the taxation system.	Coordination	**Negative**
Indonesia Credit Default Swap (CDS) can rise and Rupiah exchange rate will face turbulency and volatility that trigger vulnerability in the market. This will force BI to face it wih monetary and macroprudential tightening.	Communication/ Expectation	**Contractive**
Bank Indonesia will hold its loan to value policy on the property sector because it's considered an effective measures to reduce speculation and control credit risk.	Communication/ Expectation	**Neutral**
BI also predicted will loosen its macroprudential activity in the near future.	Communication/ Expectation	**Accommodative**

Total Annotated Sentences: 5,030

Aspect	Positive	Negative	Neutral	Irrelevant
Formulation	**642** (12,8%)	**70** (1,4%)	-	**4.318** (85,8%)
Effectiveness	**387** (7,7%)	**76** (1,5%)	-	**4.567** (90,8%)
Coordination	**433** (8,6%)	**30** (0,6%)	-	**4.567** (90,8%)
Communication	**72** (1,4%)	**585** (11,6%)	**25** (0,5%)	**4.348** (86,4%)

Methodology: Preprocessing & Feature Extraction

All the sentences are pre-processed to change the sentence from **text (*unstructured*)** form to ***structured TF-IDF Vector*** that can be further processed using machine learning.

Pre-processing

1 ***Sentence cleansing***

- *Replace synonyms*
- *Replace numbers*
- *Replace common names*

2 ***Tokenization***

3 ***n-gram vectorization***

4 ***Remove rarely occurring terms***

Machine Learning Flow

Annotated data

Preprocessing & Feature Extraction

- *TF/IDF Bag of Words vectorisation*

Machine Learning

K-Fold Cross Validation

80:20 Training and Testing Data Split

Machine Learning Algorithm:

- *Logistic Regression*
- *K-nearest Neighbor*
- *Support Vector Machine*
- *Naïve Bayes*
- *Decision Tree*
- *Random Forest*
- *XGBoost*

Tuning

Learning

Inference

Evaluation

Oversampling & Undersampling on learning process using SMOTE

3. Result: Model Evaluation & Index Calculation

After performing a horse race of 7 machine learning algorithms, we obtained the best model combination for each credibility aspects (using F1-score as evaluation metric)

Model Evaluation

Credibility Aspect	Best Model Combination	*F1 Score Details*	
		Phase 1 Aspect Relevancy	*Phase 2 Sentiment Prediction*
Formulation	XGBoost & Decision Tree	66,15%	69,99%
Effectiveness	Logistics Reg. & XGBoost	66,87%	75,81%
Coordination	Logistics Reg. & SVM	70,64%	67,49%
Communication	Logistics Reg. & Logistics Reg.	77,13%	76,32%

Average F1 Score:
Phase 1: 70.19%
Phase 2: 72.40%

Index Calculation

Formulation, Effectiveness, and **Coordination aspects formula:**

$$Index_{aspect\ k,t} = \frac{\#positive_{k,t} - \#negative_{k,t}}{\#positive_{k,t} + \#negative_{k,t}}$$

Communication aspect formula:

$$Index_{Communication,t} = 1 - |P_t - Tone_t|$$

Pt = Macroprudential policy stance in the press release

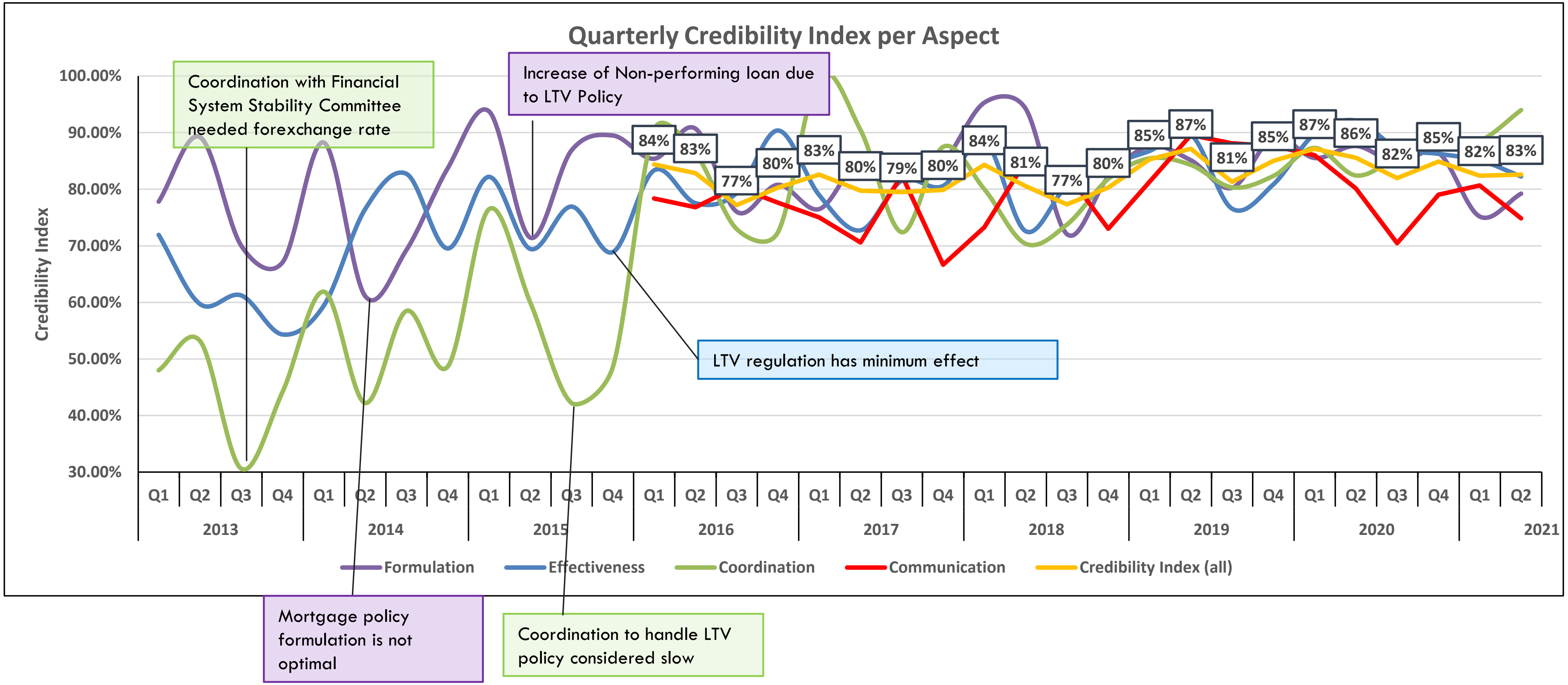
Tone = Index Expectation

$$Index_{Expectation,t} = \frac{\#Contractive_t - \#Expansive_t}{\#Contractive + \#Neutral_t + \#Expansive_t}$$

$$Credibility\ Index_t = \frac{1}{4}(Index_{formulation,t} + Index_{effectiveness,t} + Index_{coordination,t} + Index_{communcation,t})$$

3. Result: Analysis

- Earlier index from 2013 to 2016 has fewer news therefore the indexes are more volatile.
- Since 2016, Bank Indonesia started to communicate macroprudential policy more intensively in its Board of Governors meeting press release. Thus, the overall index is more stable and positive with overall average of 82% . Communication of macroprudential policy to the general public affect the sentiment or tone of news positively, as captured in this macroprudential policy crediblity index.



5. Conclusion & Future Works

Conclusion

1. Based on our previous study of measuring monetary policy credibility, we develop a measurement of macroprudential policy credibility using news data and machine learning.
2. The aspect relevancy models have an average F1 score of 70.19% while the sentiment models have an average F1 score of 72.40%.
3. Bank Indonesia starts to communicate macroprudential policy forward guidance more intensively starting in 2016, and the result is captured in the index with the 4 aspects of the index become more stable and positive starting in 2016.

Future Works

1. Data collection and annotation of more recent data.
2. Expansion of macroprudential and policy mix keywords.
3. Econometric analysis (econometric effect of the indexes on macro indicators).

THANK

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