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Read between the headlines: can news data predict inflation?[1]

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[1] This contribution was prepared for the workshop. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

Read between the headlines: can news data predict inflation?

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Abstract

Big data and machine learning applications are increasingly gaining traction in central bank operations. Among others, central banks have tapped big data and advanced techniques in their nowcasting exercises. In this study, we construct inflation news indices and examine if such indices can help predict inflation. The indices are developed using lexicon-based sentiment analysis refined using reinforcement learning and supervised machine learning method, particularly long short-term memory model. These indices are then used as additional feature variables in time series and machine learning models for nowcasting regional and nationwide inflation in the Philippines. We find empirical evidence that our constructed inflation news indices can improve the predictive capability of these forecasting models.

Keywords: inflation; news; nowcasting; text analytics; machine learning

JEL classification: C45, E31, E37

[1] All authors are from the Department of Economic Research, Bangko Sentral ng Pilipinas. The views expressed in this study are those of the authors and do not necessarily represent the official position of the Bangko Sentral ng Pilipinas.

1. Introduction

Big data and machine learning (ML) based applications are increasingly gaining traction in central bank operations. The 2020 survey conducted by the Irving Fisher Committee on Central Bank Statistics of the Bank for International Settlements indicates that 80 percent of the central banks surveyed utilize big data for their operations, up from just 30 percent in 2015. Among various types of applications, the survey showed that central banks have used big data in their nowcasting exercises. This study adds to this existing body of empirical studies by tapping novel data sources alongside advanced computational techniques for nowcasting regional and nationwide inflation in the Philippines. Inflation nowcasting and forecasting is important for central banks like the Bangko Sentral ng Pilipinas (BSP) that operates an inflation targeting framework for monetary policy formulation. The use of big data and ML models could further support inflation surveillance and forecasting tasks of a central bank.

While Beck et al (2023) and Macias and Stelmasiak (2019) used online price data to nowcast inflation, our research examines if textual data such as online news articles could be useful for inflation nowcasting. We opt to explore online news data as an indicator for inflation trends as major developments that are relevant for inflation are likely captured by news reports. This study also builds upon an earlier work by Gabriel et al (2020) for regional inflation nowcasting in the Philippines which employed machine learning techniques but did not incorporate big data.

To answer our research question, we employ a two-step approach. First, we build inflation news indices which provide information on whether there are more reports of increasing/higher inflation vis-à-vis decreasing/lower inflation in the news media. We take a comprehensive approach and explore two methods of text analytics: (a) lexicon-based sentiment analysis refined by reinforcement learning and (b) ML-based approach using long short-term memory model. Second, we employ these indices as additional feature variables in time series and machine learning (ML) models for inflation nowcasting.

Overall, we find empirical evidence that our indices are useful for nowcasting regional and nationwide inflation in the Philippines. The news-based indices have information content that help improve the forecasting accuracy of models that utilize the said indices as additional feature variables relative to models that did not.

2. Constructing the Inflation News Indices

Our proposed inflation news indices (INIs) harness the power of online news media to capture near real-time information on price trends of goods and services as well as other factors that could affect overall inflation. Essentially, the INIs are quantitative summaries of digital news coverage on inflation and the prices of goods and services. The INIs are not sentiment indices. They do not associate inflation with either positive or negative sentiment. Instead, these indices are meant to provide indication on the prevailing information on inflation trends as reported in online news data published by media outlets in the Philippines. This section outlines the steps in the construction of our own lexicon- and ML-based INIs.

2.1 Data sources and annotation

News articles for this study are sourced from media outlets in the Philippines that allowed us to web scrape the data from their websites' business, finance, or economy sections.[2] Our news database contains articles from different time periods but the common period when we have data from all media outlets is from January 2018 to present. We further filtered our data to news articles containing any of the words: "inflation", "price" and "prices". A total of 3,000 randomly selected sentences from our news database are annotated. These are manually labelled as 1, -1, or 0, indicating increase, decrease or no change in inflation, respectively. The annotation of sample sentences is a crucial first step to generate and to implement further enhancements of the lexicon- and ML-based INIs.

2.2 Lexicon with reinforcement learning method

The lexicon-based method involves creating a list of keywords associated with increasing or decreasing inflation based on our annotated dataset.[3] We also incorporated the negation rule but was tweaked to indicate *no change*.[4]

Following Church and Hanks (1990), pointwise mutual information (PMI) was leveraged to identify which words can be classified as *increase/decrease*. PMI is a measure of association which utilizes co-occurrence with each of the class. The overall score $Score_{PMI}$ for a given word w is the difference between PMI score of the word with respect to *increase* and *decrease*. Words having $Score_{PMI} > 0$ and $Score_{PMI} < 0$ are therefore assigned under *increase* and *decrease* wordlists, respectively.

The resulting wordlists is manually evaluated for suitability and reinforcement learning is used to further refine the wordlists. In particular, we use Q-learning (a type of reinforcement learning (Watkins and Dayan, 1992)) to retrieve the optimal set of words under *increase* and *decrease* that maximizes the Macro-F1 score of the test set within a reasonable amount of time.

2 These media outlets include Business Mirror, Business World, Manila Bulletin, Manila Standard and Philippine Daily Inquirer.

3 Standard pre-processing procedures were applied to the news dataset to reduce noise, remove unwanted parts of the data and subsequently improve the accuracy of the models used in this study. These include removal of extra spaces, numbers, punctuation marks and html tags as well as case normalization and tokenization. Furthermore, additional steps are applied such as the use of Part-of-Speech (POS) tagging and Named Entity Recognition (NER) to ensure that the dictionaries only include verbs, verb-nouns and adverbs.

4 Negation rule applies when a word is preceded by a negation word (e.g., "not" or "never").

2.3 ML-based method using neural networks and long short-term memory models

This method relies on supervised ML models trained using our manually annotated sentences.[5] The sentences are transformed using Word2Vec and are fed into artificial neural networks (ANNs) such as multilayer perceptron (MLP) and Bidirectional Long Short-Term Memory (BiLSTM) models. We test several model configurations and explore the use of Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al, 2002) to create synthetic entries and remedy data scarcity concerns.[6] For the purposes of this study, all ANNs are designed to classify three output classes: increase, decrease, and no change. We then compare the Macro-F1 scores of the different ANNs.

2.4 Index construction and evaluation

To construct the INIs, we evaluate the lexicon and trained neural networks based on their accuracy and Macro-F1 scores. Table 1 presents a summary of evaluation of different lexicons and ANNs. The results suggest that INIs derived using lexicon refined by reinforcement learning (hereafter referred to as INI-RL) and using BiLSTM (32) (hereafter referred to as INI-BiLSTM) have the best accuracy and Macro-F1 scores and are therefore preferred methods for index construction. These are then used to score the sentences in the news articles with scores aggregated per article and indexed for the month. Afterwards, the INIs are normalized to a mean of 100. Thus, any estimate above 100 suggests that relative to average, news about increasing inflation outnumber reports of declining inflation. Meanwhile, any estimate below 100 suggests otherwise.

INI methods: Evaluation metrics for test set

Table 1

	Accuracy (In percent)	Macro-F1 score (In percent)
Initial lexicon	64.3	41.8
Lexicon with reinforcement learning	89.3	69.3
MLP	68.9	45.7
BiLSTM (16)	78.4	56.2
BiLSTM (32)	79.8	57.9

Note: Number in parenthesis for ANNs refers to number of hidden units

Sources: Authors' estimates

[5] Similar to the lexicon approach, standard pre-processing procedures were applied.

[6] A common challenge with annotated datasets is having imbalanced datasets or having unequal number of entries per class. To remedy this, we explored the use of SMOTE. This technique synthesizes new samples of the minority class based on the nearest neighbors in the feature space. However, caution is advised in using this technique for text-based data as the synthetic samples may not be able to have a complete context.

Analyses of the resulting series indicate that the INI-RL and INI-BiLSTM tend to move together. This is reassuring as two different methodologies point to similar results. More importantly, we also find that both INIs tend to co-move with actual headline inflation. This hints of the ability of news data to mirror prevailing inflation trends.

3. Forecasting inflation using news data

Our main research objective is to determine the usefulness of news data in nowcasting both regional and nationwide inflation in the Philippines. Following Gabriel et al (2020), we first estimate time series and ML models without the INIs. These serve as our baseline models. We then augment these models with the INIs and perform forecast evaluation (using mean absolute error (MAE)) to determine if the inclusion of INIs leads to improved nowcasting capability. We use the Diebold-Mariano test to determine if there is indeed statistically significant improvement in forecast errors.

The target variable in these models is the year-on-year inflation rate.[7] We build individual models for each of the 16 regions and a separate model for nationwide inflation.

For the baseline time series model, we used auto ARIMA to help identify the optimal lag, integration, moving average and seasonal order that will yield the least error in nowcasting. We included additional feature variables such as the month-on-month difference in inflation and a dummy variable that takes a value of 1 if inflation is on an uptrend in the last two months and -1 if inflation is on a downtrend in the last two months to help improve nowcasting performance. The model was trained for the period January 2018 to December 2022. Out-of-sample nowcasts for regional and nationwide inflation were generated for the test period January to December 2023.

For the baseline ML models, we tried a number of models including Support Vector Regression (SVR), Gradient Boosted Machines (GBM) and Extremely Randomized Trees (EXT). We utilized similar feature variables as those in the baseline ARIMA models. We also employed the same training and test periods. We find that SVR produces the lowest nowcasting error among these ML models. We therefore only report the results for the SVRs.

For the INI-augmented models, we add another variable S^{INI} defined in Equation (1+:

$$S_t^{INI} = \begin{cases} 1, & if\ INI_t > INI_{t-1} \\ -1, & if\ INI_t < INI_{t-1} \\ 0, & otherwise \end{cases} \qquad (1)$$

where INI_t refers to either INI-RL or INI-BiLSTM. These augmented models were trained for the same period with regional and nationwide inflation nowcasts generated for the period January – December 2023.

[7] Data on regional and nationwide inflation for the Philippines are sourced from the Philippine Statistics Authority.

4. Analysis of Results

This section presents the results of our inflation nowcasting exercises. As we are concerned mainly with out-of-sample forecasting performance, we only present the MAE from the test set for the regional and nationwide models.

Table 2 shows the forecast evaluation of the baseline traditional time series and ML models vis-à-vis those that included INI-RL and INI-BiLSTM as additional regressor or feature variable. On average, forecast errors have declined in models augmented with INIs compared to baseline models. This holds true for either INI-RL or INI-BiLSTM. Particularly, for the SVR model, we find that the addition of INI-RL led to statistically lower MAEs based on the Diebold-Mariano test in 7 out of 17 regions and in the nationwide model. For the SVR model augmented with INI-BiLSTM, forecast errors were statistically lower for 8 regions and nationwide level.

Nowcast Evaluation

January – December 2023

Table 2

	Traditional Time Series Model (Auto-ARIMA)			Machine Learning Model (SVR)		
	Baseline	With INI-RL	With INI-BiLSTM	Baseline	With INI-RL	With INI-BiLSTM
NCR	0.24	0.24	0.27	0.29	0.28	0.02*
CAR	0.28	0.26	0.26	0.28	0.04*	0.24*
Region1	0.27	0.24	0.24*	0.46	0.33*	0.22*
Region 2	0.36	0.33	0.33*	0.47	0.32	0.39
Region 3	0.40	0.34*	0.32*	0.47	0.08*	0.03*
Region 4a	0.33	0.30	0.29	0.36	0.14*	0.02*
Region 4b	0.30	0.24*	0.23*	0.30	0.06*	0.02*
Region 5	0.31	0.28	0.27	0.38	0.22	0.12*
Region 6	0.41	0.37	0.37	0.41	0.40	0.45
Region 7	0.30	0.28	0.30	0.28	0.22	0.24
Region 8	0.22	0.21	0.21	0.27	0.30	0.29
Region 9	0.39	0.40	0.38	0.61	0.59	0.60
Region 10	0.26	0.29	0.27	0.30	0.21	0.23
Region 11	0.29	0.27	0.29	0.29	0.29	0.28
Region 12	0.38	0.38	0.37	0.33	0.35	0.33
BARMM	0.38	0.23*	0.25*	0.37	0.13*	0.25*
Region 13	0.16	0.15	0.16	0.20	0.14*	0.22
Philippines	0.30	0.31	0.29	0.37	0.03*	0.18*
Average	0.31	0.28	0.28	0.36	0.23	0.23

Note: * -passed Diebold-Mariano Test

NCR – National Capital Region; CAR – Cordillera Administrative Region; BARMM – Bangsamoro Autonomous Region in Muslim Mindanao

Sources: Authors' estimates

It is important to note a few caveats in the interpretation of the results. First, the evaluation period is relatively short owing to data limitations. This warrants further assessment when more data become available. Second, there is need to fine tune the news indices to the regional level. News data came from nationwide newspapers. There is need to acknowledge that certain news reports may not be relevant for all regions. For example, a typhoon in a particular region that led to agricultural crop damage in the area and consequently, higher regional food prices would likely be covered in nationwide newspapers and would therefore be part of our dataset. However, this may not be as relevant for regions not affected by the typhoon. Fine tuning the news reports to the regional level (i.e., by tapping regional newspapers and tagging reports based on regions) could further improve regional inflation surveillance and nowcasting. Third, 2023 is a relatively volatile year for inflation in the Philippines, leading to higher forecast errors. The results of the forecast evaluation of the workhorse models of the BSP, published in the May 2024 Monetary Policy Report, showed an increase in month-ahead MAE to 0.28 percentage point in 2023 from 0.17 percentage point in 2022 (BSP, 2024). For the same period, we estimated errors of the INI-augmented models at 0.23 – 0.28 percentage point, broadly similar to the nowcast errors of the BSP's workhorse models. This is encouraging as the INI-augmented models relied solely on textual data and time series properties of the inflation series. It did not incorporate any traditional economic data as regressor. Furthermore, the MAEs of the INI-augmented models are also lower compared to the 0.41 percentage point MAE of the month-ahead consensus forecasts from Bloomberg's monthly survey of private sector analysts (BSP, 2024). Thus, available evidence suggests that the INIs contain information that could be useful for nowcasting even as we acknowledge the need to fine tune the indices and undertake further evaluation in the future.

5. Conclusion and future directions

In this study, we develop news-based inflation indices. These indices rely on online news articles and are derived using two approaches: (1) lexicon refined by reinforcement learning and (2) machine learning model, particularly BiLSTM. The indices capture prevailing information on inflation trends as reported in digital news by Philippine media outlets. We find that augmenting ARIMA and SVR models for regional and nationwide inflation nowcasting with these indices help in lowering their nowcasting errors. Thus, these indices could be useful for inflation surveillance. Our findings contribute to the existing literature on the relevance of big data for nowcasting macroeconomic variables. Future plans to improve the indices include fine tuning the indices to the regional level, exploring additional keywords that could pave the way for the creation of sub-indices (i.e., food INI, energy INI) and further evaluation of nowcasting capability.

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* The usual institutional disclaimer applies.

Motivation

Leverage nontraditional data sources

Support inflation nowcasting

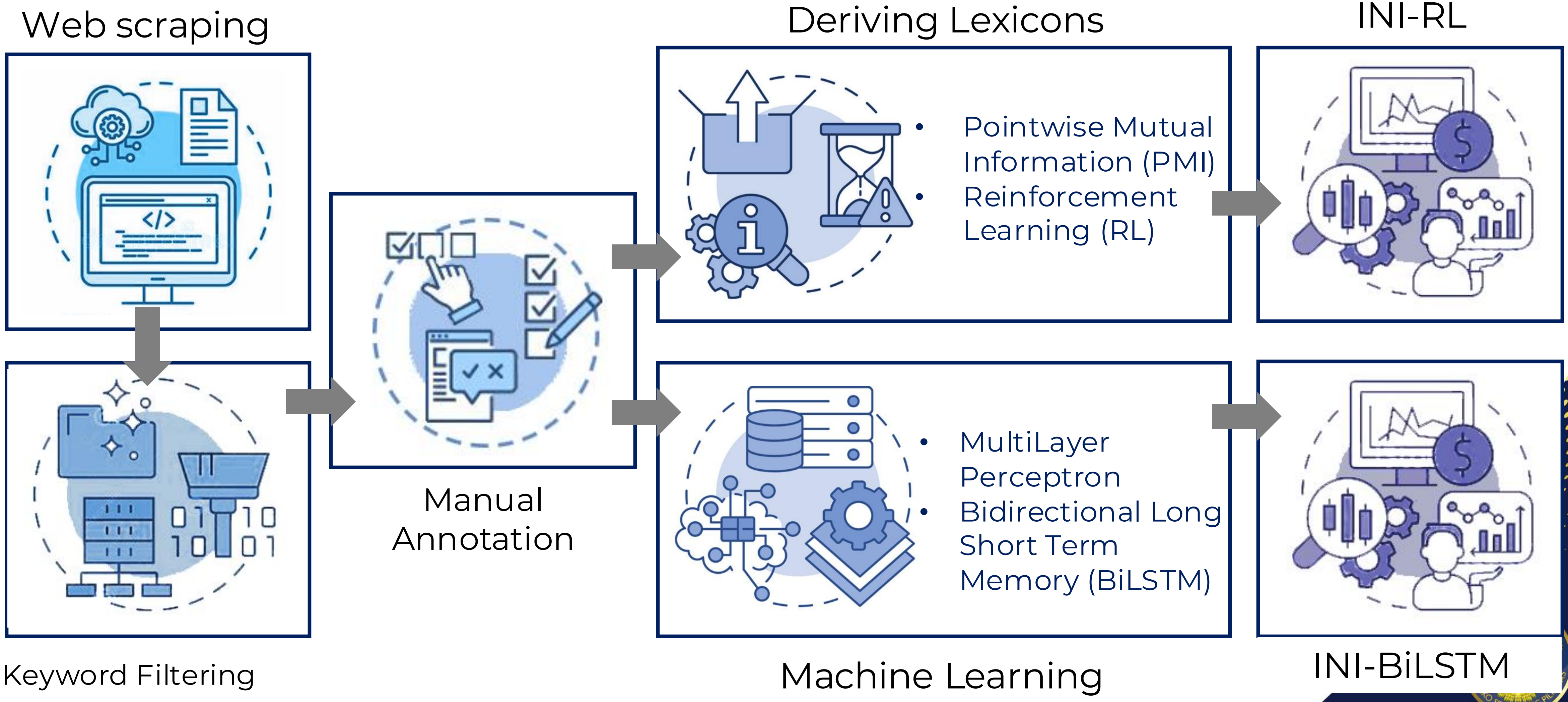
Inflation News Index (INI)

INI is

INI is **NOT**

The INI is a quantitative summary of digital news coverage on inflation and prices of goods and services

Constructing the INIs: An overview



Data sources and annotation

- ✓ Data were collected from multiple local news sources. [Sections of interest: economy, banking, finance].

- ✓ Articles are then filtered with the keywords: “inflation”, “price”, “prices”

- ✓ A random sample of 3,000 sentences were annotated

Sample annotated sentences and their classes/labels[

News Text	Label
Aside from flour, other ingredients also went up including LPG, and sugar which substantially increase prices.	1
This was a slight decline from last weeks price level of P37.83/kg.	-1
Some will not pass on the fuel price increases on passengers so they can keep their ticket prices low and haul in more customers.	0

Source: Various media websites, authors’ estimates

Data pre-processing

Pre-processing steps include:

- Removal of extra spaces in the text
- Case normalization
- Removal of punctuations marks
- Unicode conversion
- Tokenization
- Vectorization

Additional steps include:

- Part of speech tagging
- Named entity recognition

Methodology I: Lexicon refined with reinforcement learning

Dictionary based method involves a creating a list of keywords. Pointwise mutual information (PMI) was used to infer word associations with increasing and decreasing inflation

Overall PMI score for a word w:

$$Score(w) = PMI(w|increase) - PMI(w|decrease)$$

Initial lexicon: Words with Score > 0 are classified as increase and words with Score < 0 are classified as decrease

Reinforcement learning was used to improve the initial lexicon

Methodology II: Machine Learning models

Machine learning based method utilizes two artificial neural networks to predict association of text

- MultiLayer Perceptron (MLP)
  - A fully connected feedforward neural network, notable for finding nonlinear relationships.

- Bidirectional Long Short Term Memory (BiLSTM)
  - Contains two LSTM layers in opposite directions. LSTMs are used for finding long term dependencies in sequential data such as time series, text and audio.

Evaluation of methodologies

Both dictionaries and machine learning models were evaluated against test set of the manually-labelled sentences sampled from online news articles

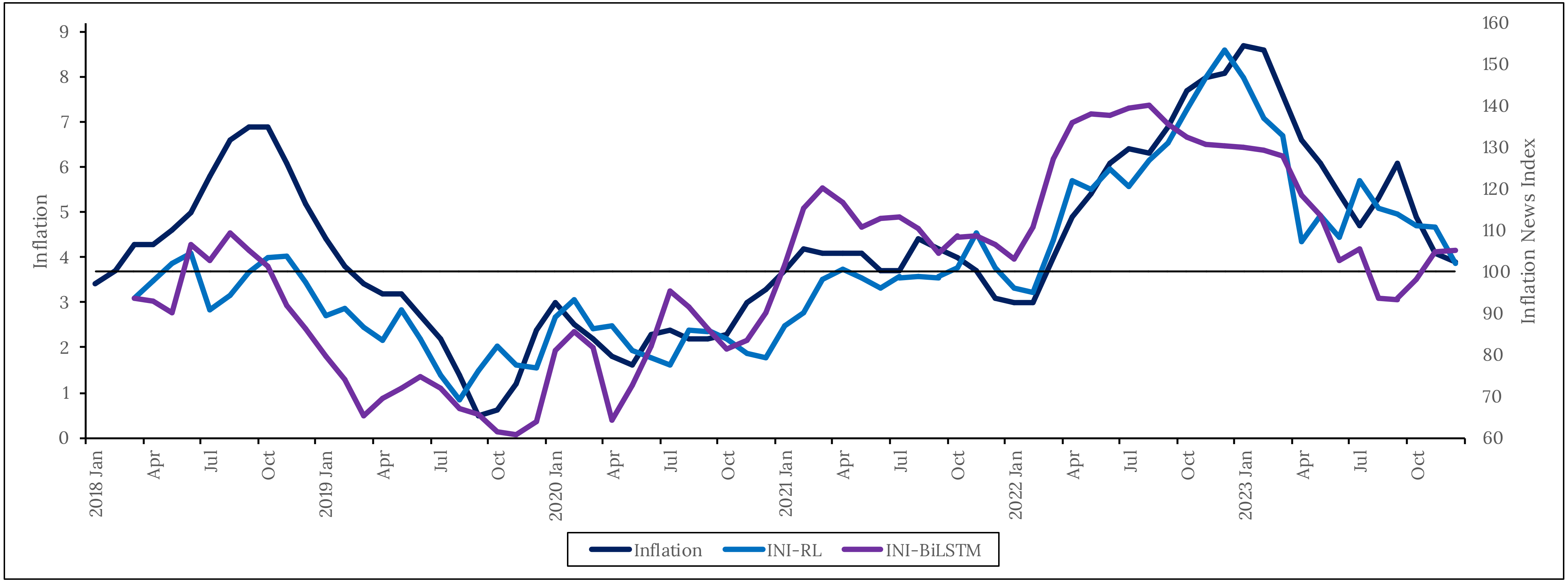
Lexicons	Accuracy (in percent)	Macro F1 (in percent)
Initial lexicon	64.3	41.8
Lexicon with RL	89.3	69.3
Machine Learning Models	**Accuracy (in percent)**	**Macro F1 (in percent)**
MLP	68.9	45.7
BiLSTM(16)	78.4	56.2
BiLSTM(32)	79.8	57.9

Note: Number in parenthesis for BiLSTM refers to number of hidden units.
Source: Authors' estimates

Results

Estimates of INIs strongly co-move with inflation.

INIs vis-à-vis inflation
Q1 2018 to Q4 2023



Source: Authors' estimates

Nowcast evaluation

On average, forecast errors have declined in models augmented with INI-RL compared to baseline models

Nowcast evaluation: Mean Absolute Error

January-December 2023

	Baseline AR	ARX+INI
NCR	0.24	0.24
CAR	0.28	0.26
R1	0.27	0.24
R2	0.36	0.33
R3	0.40	0.34*
R4A	0.33	0.30
R4B	0.30	0.24*
R5	0.31	0.28
R6	0.41	0.37
R7	0.30	0.28
R8	0.22	0.21
R9	0.39	0.40
R10	0.26	0.29
R11	0.29	0.27
R12	0.38	0.38
BARMM	0.38	0.23*
R13	0.16	0.15
Philippines	0.30	0.31
Average	**0.31**	**0.28**

	Baseline SVR	SVR+INI
NCR	0.29	0.28
CAR	0.28	0.04*
R1	0.46	0.33*
R2	0.47	0.32
R3	0.47	0.08*
R4A	0.36	0.14*
R4B	0.30	0.06*
R5	0.38	0.22
R6	0.41	0.40
R7	0.28	0.22
R8	0.27	0.30
R9	0.61	0.59
R10	0.30	0.21
R11	0.29	0.29
R12	0.33	0.35
BARMM	0.37	0.13*
R13	0.20	0.14*
Philippines	0.37	0.03*
Average	**0.36**	**0.23**

Source: Authors' estimates
*Passed Diebold-Mariano test

Nowcast evaluation

On average, forecast errors have declined in models augmented with INI-BiLSTM compared to baseline models

Nowcast evaluation: Mean Absolute Error
January-December 2023

	Baseline AR	ARX+INI
NCR	0.24	0.27
CAR	0.28	0.26
R1	0.27	0.24*
R2	0.36	0.33*
R3	0.40	0.32*
R4A	0.33	0.29
R4B	0.30	0.23*
R5	0.31	0.27
R6	0.41	0.37
R7	0.30	0.30
R8	0.22	0.21
R9	0.39	0.38
R10	0.26	0.27
R11	0.29	0.29
R12	0.38	0.37
BARMM	0.38	0.25*
R13	0.16	0.16
Philippines	0.30	0.29
Average	**0.31**	**0.28**

	Baseline SVR	SVR+INI
NCR	0.29	0.02*
CAR	0.28	0.24*
R1	0.46	0.22*
R2	0.47	0.39
R3	0.47	0.03*
R4A	0.36	0.02*
R4B	0.30	0.02*
R5	0.38	0.12*
R6	0.41	0.45
R7	0.28	0.24
R8	0.27	0.29
R9	0.61	0.60
R10	0.30	0.23
R11	0.29	0.28
R12	0.33	0.33
BARMM	0.37	0.25*
R13	0.20	0.22
Philippines	0.37	0.18*
Average	**0.36**	**0.23**

Source: Authors' estimates
*Passed Diebold-Mariano test

Key findings

- INIs are quantitative summary of digital news coverage on inflation and prices of goods and services
- INIs are found to co-move with actual inflation
- INIs exhibit strong correlation with survey-based inflation expectations of firms and professional forecasters
- INIs contain information that can help nowcast inflation

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Thank you!