Received: 16 November 2021 | Revised: 20 May 2022 | Accepted: 27 July 2022

DOI: 10.1002/jae.2946

RESEARCH ARTICLE

WILEY Journal of APPLIED ECONOMETRICS

Real-time macroeconomic projection using narrative central bank communication

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Funding information
This work was supported by the National Natural Science Foundation of China [grant numbers: 72073148; 71773147; 71991474].

Summary
Unlike the central banks of most developed economies, the People's Bank of China (PBC) does not release its macroeconomic forecasts to the public but instead carries out narrative communication. We apply a hurdle distributed multinomial regression to PBC communication texts in real time, addressing the ultrahigh dimensionality, sparsity, and look-ahead biases. In addition, we embed text-based indices into mixed-data sampling (MIDAS)-type models and conduct forecast combinations for prediction. Our results argue that the predictive information from communication texts improves the real-time out-of-sample prediction performance. We connect textual analysis and real-time macroeconomic projection, providing new insights into the value of central bank communication.

KEYWORDS
central bank communication, nowcasting and forecasting, real-time data, text analysis

1 | INTRODUCTION

Real-time macroeconomic projection is not only a challenge for policy implementation but also important information for agents when making their investment and consumption decisions. However, while most studies concentrate on the predictive ability of traditional and structural economic indicators, recent literature has paid attention to new and alternative data sources, such as textual data, which serve as a good and appealing supplement to macroeconomic indicators (Baker et al., 2016; Gentzkow et al., 2019; Larsen & Thorsrud, 2019). Moreover, Shiller (2017, 2019) argues that narrative information can affect people's decision-making and even change the trend of the whole economy. Therefore, textual data can be used to predict financial crises, depressions and other economic events.

In particular, the texts of central bank communication contain rich predictive information since central banks have strong research capabilities and unique information access (Bybee et al., 2020; Heij et al., 2011). For instance, the Federal Reserve (FED) and European Central Bank (ECB) publish their quantitative forecasts via the *Summary of Economic Projections* and *Economic Bulletin*, respectively. Central bank communication has been recognized as an independent monetary policy tool, influencing the market and household expectations, as well as financial stability (Binder, 2017; Born et al., 2014; Kawamura et al., 2019). Similar to other monetary authorities in major economies, the People's Bank of China (PBC) has continuously strengthened its communication to convey monetary policy stances and economic outlooks. However, unlike the Fed or ECB, the PBC usually communicates its projections or judgments through narrative descriptions rather than quantitative forecasts. Thus, narrative central bank communication contains the official assessment of current and future economic situations (Beaupain & Girard, 2020; Bernanke, 2013) and indeed provides a kind of unique information for the public to make macroeconomic projections.

Nevertheless, the raw central bank communication texts are unstructured, high-dimensional and sparse, as well as time-varying.[1]

In this paper, we provide a unified framework for real-time macroeconomic projection with central bank communication, combining mixed-frequency forecasting models and the latest text analysis techniques. First, we construct a unique textual database of the PBC's written and oral communications and form a special user-defined dictionary to identify and retain all meaningful expressions of PBC communication. Second, we use the hurdle distributed multinomial regression (HDMR) proposed by Kelly et al. (2021) to address the high dimensionality and sparsity of PBC communication texts. In addition, to meet the time-varying characteristics of texts and avoid look-ahead biases, we modify HDMR to a real-time model and sufficiently transform the textual data of PBC communication into quantitative time series predictors. Third, we use the mixed-data sampling (MIDAS) regression and model combination method to nowcast and forecast six macroeconomic indicators of interest, including the quarterly gross domestic product (GDP) growth rate and monthly consumer price index. Adding our text-based predictors into forecasting models, we investigate the unique value of central bank communication from the perspective of out-of-sample (OOS) performance in real time.

We find that adding text-based PBC communication indices improves the OOS prediction performance, indicating the information gains of PBC communication in nowcasting and forecasting China's economy. First, PBC communication indices measured using full-sample and real-time data are relatively similar, and our main empirical results are similar for both pseudo and real-time OOS forecasting, which is also robust for numerous empirical setups. Second, both PBC communication indices for word repetition and inclusion have successfully contributed to improving the forecasting performance of macroeconomic variables, whereas the former performs better in most cases. Third, predicting with all PBC communication indices is, in most cases, better than using just the one that is based on the prediction target. The optimal text-augmented model varies for different target variables and forecast horizons, whereas at least one of them outperforms the benchmark. Fourth, the text appearing in the PBC communication is more informative about longer horizons, indicating the role of central bank communication in shaping long-run market expectations. Finally, compared with professional forecasts, the model with PBC communication texts also seems to be attractive, especially for nowcasting the GDP growth rate.

We contribute to the literature along several dimensions. First, we perform a real-time OOS forecasting analysis with central bank communication texts and a rich macroeconomic dataset. More concretely, we apply HDMR to construct the text-based predictors from the PBC communication texts and then embed them into a MIDAS-type model that can learn from mixed-frequency macro and textual data, as well as produce the forecast to the target of interest. Accordingly, our results are related to the recent forecasting literature that uses text as data, for example, Kelly et al. (2021) and Ellingsen et al. (2021). In contrast, our work extends these applications by studying an entirely different corpus, central bank communication texts.

Our second contribution is emphasizing the importance of real-time textual analysis in economic applications to avoid look-ahead biases, especially in macroeconomic projections. For our real-time forecasting application, a key issue is to avoid look-ahead biases (Larsen et al., 2021; Lima et al., 2020; Thorsrud, 2020), which is also important for textual analysis but often ignored in the literature (Kelly et al., 2021; Lin et al., 2021).[2] Our work refines HDMR to construct the PBC communication index in real time and documents that the OOS performances are to some extent different (especially for nowcasting), even though the full-sample and real-time estimates for text-based indices are analogous.

Finally, our work speaks to recent studies about central bank communications and their macroeconomic implications. Central bank communications can affect economic agents via the information channel, uncertainty channel, and investor demand channel (Blinder et al., 2008; Hanson & Stein, 2015).[3] While these studies discuss the value of central bank communication on the macroeconomy and financial market (Hansen et al., 2019; Lehtimäki & Palmu, 2019), this

[1]The time-varying characteristics of textual data indicate that there are significant differences between the meanings of the same phrase when it is used in different periods. For example, the term "sound monetary policy" might have conveyed a kind of hawkish bias in 2004 when inflation occurred in China; however, as China's economy has tended to decline in the last decade, the same term, which appears frequently in the contemporaneous China Monetary Policy Executive Report, may now imply a mildly dovish tone.

[2]For example, the emergence of new phrases or expressions makes it more difficult for the public to understand central bank communications, and the same phrase may have different meanings in different periods.

[3]The information channel argues that communication shapes market expectations by "creating news" and becomes an important driver of economic fluctuations (Larsen & Thorsrud, 2019). The uncertainty channel emphasizes the predictability of policy, which anchors the expectations of agents and ultimately reduces market volatility (Coenen et al., 2017; Lehtimäki & Palmu, 2019; Winkelmann, 2016). The investor demand channel focuses on yield-oriented investors who adjust their investment strategies in response to a policy inclination shift (Hanson & Stein, 2015).

paper provides a new perspective to understand the role of narrative central bank communication in expectation guidance (Boguth et al., 2019; Nakamura & Steinsson, 2018). We show that central bank communication has additional information gains in macroeconomic projection, especially for a central bank that does not publish quantitative forecasts.

The remainder of the paper is organized as follows. Section 2 introduces the HDMR model and PBC communication texts, whereas Section 3 describes the forecasting model and empirical setup. Section 4 presents the results. Section 5 concludes the paper.

2 | TEXT-AS-DATA

In Section 2.1, we introduce HDMR for modeling textual data. Next, Section 2.2 refines HDMR to avoid look-ahead biases for nowcasting in real time. Section 2.3 describes the PBC communication and textual data, whereas Section 2.4 provides the target variables and macroeconomic dataset. Finally, we illustrate our real-time PBC communication index in Section 2.5.

2.1 | Hurdle distributed multiple regression

Unlike conventional economic data, textual data such as central bank communications contain ultrahigh dimensional phrases and sparse phrase counts, which require modeling techniques used in machine learning (Gentzkow et al., 2019). However, the existing methods, including dictionary-based approaches and the Latent Dirichlet Allocation (LDA) topic model, fail to address these issues efficiently.[4] Therefore, we turn to the Hurdle Distributed Multiple Regression (HDMR) proposed by Kelly et al. (2021), a supervised textual analysis technique that addresses the high dimensionality and sparsity of texts, as well as computational savings, for real-time estimation.

To establish our notation, we consider a textual database containing T periods and let $\mathbf{c}_t$ be a phrase vector in d categories for period $t=1,2,...T$. Therefore, c_{tj} are counts of words (n-grams) j in observation t, where $j=1,...,d$. The total word counts in observation t sum to $m_t=\sum_{j=1}^{d} c_{tj}$ with $d_t=\sum_{j=1}^{d}\mathbf{1}(c_{tj}>0)$ categories. As in the double-hurdle model, HDMR first decides whether to use a phrase and then determines its corresponding counts as follows:

$$h_{tj}^{*}=\gamma_t+\kappa_j+\mathbf{w}_t'\boldsymbol{\delta}_j+\nu_{tj}, \tag{1}$$

$$h_{tj}=\mathbf{1}\left(h_{tj}^{*}>0\right), \tag{2}$$

$$c_{tj}^{*}=\lambda\left(\mu_t+\alpha_j+\mathbf{v}_t'\boldsymbol{\varphi}_j\right)+\varepsilon_{tj}, \tag{3}$$

$$c_{tj}=\left(1+c_{tj}^{*}\right)h_{tj}. \tag{4}$$

Equations (1) and (2) describe the word inclusion process, where phrase j is included $\left(h_{tj}=1\right)$ or excluded $\left(h_{tj}=0\right)$ in period t based on the binary choice model. Equations (3) and (4) represent the word repetition process, in which only positive counts of the included phrase $\left(h_{tj}=1\right)$ are modeled. Notably, the observable covariates $\mathbf{w}_t$ and $\mathbf{v}_t$, which determine phrase inclusion and repetition, can be identical or different, whereas ν_{tj} and ε_{tj} are both unobservable errors. Maximum likelihood estimation (MLE) provides efficient estimators of parameters $\mu_t,\alpha_j,\boldsymbol{\varphi}_j,\gamma_t,\kappa_j,\boldsymbol{\delta}_j$. Following the augmentation of Kelly et al. (2021), HDMR provides two univariate sufficient reduction projections, which can be low-dimension and serve as predictors constructed from text to predict covariates $\mathbf{w}_t$ and $\mathbf{v}_t$. Specifically, suppose that $v_{ty}=w_{ty}$ as the target variable is an element of both $\mathbf{w}_t$ and $\mathbf{v}_t$. Conditional on the parameters, we obtain two sufficient

[4]A dictionary-based approach cannot make full use of the raw information in texts, nor can it accommodate the high dimensionality and sparsity of textual data. However, although LDA can address the high dimensionality of texts, it is computationally heavy for real-time estimation (Ellingsen et al., 2021; Thorsrud, 2020).

text-based predictors, $z_{ty}^0 = \widehat{\boldsymbol{\delta}}_y \mathbf{h}_t / d_t$ and $z_{ty}^+ = \widehat{\boldsymbol{\varphi}}_y(\mathbf{c}_t - \mathbf{h}_t)/(m_t - d_t)$,[5] containing the word inclusion and repetition information separately.

In our empirical application, we refer to z_{ty}^0 and z_{ty}^+ as our PBC communication indices (PCIs). The former emphasizes the value of rare words that appear suddenly in the text or the emergence of new phrases, whereas the latter may emphasize the importance of some frequently occurring phrases. Thus, HDMR links the inclusion and repetition of phrases in central bank communication texts with macroeconomic variables, which suggests that the manner of a central bank's communication changes according to economic conditions (Kawamura et al., 2019). Intuitively, if v_{ty} represents the interest rate, then z_{ty}^0 and z_{ty}^+ contain the relevant information from communication texts, which might refer to a signal of easing or tightening.

2.2 | HDMR for real-time textual analysis

To meet the time-varying characteristics of texts (Lima et al., 2020), we conduct a recursive window to estimate and update our text-based PBC communication indices, which makes it more efficient to use all data when the parameters do not change substantially over time. It is also widely used in a number of forecasting studies (Andreou et al., 2013; Ellingsen et al., 2021; Stock & Watson, 2006).

In addition, we adjust HDMR to produce communication indices when nowcasting macroeconomic aggregates in real time to avoid potential look-ahead biases. Specifically, covariates $\mathbf{w}_t, \mathbf{v}_t$ in Equations (1) and (3) must be available as supervised signals to extract predictive information from texts. However, in reality, the publication of statistics and macroeconomic variables often arrives with a lag, whereas the central bank's communication is timely and spreads faster. Therefore, macroeconomic targets are not available; only textual data are available for real-time nowcasting procedures. Thus, we estimate the parameters of HDMR based on the available information up to current period and maintain the contemporaneous link between covariates and phrase vectors for the next period to produce the predicted value of two sufficient statistics. For instance, to nowcast the target in period $t+1$ using timely communication texts, we construct estimates of PCIs by computing $z_{t+1y}^+ = \widehat{\boldsymbol{\varphi}}_y^{(t)}(\mathbf{c}_{t+1} - \mathbf{h}_{t+1})/(m_{t+1} - d_{t+1})$ and $z_{t+1y}^0 = \widehat{\boldsymbol{\delta}}_y^{(t)} \mathbf{h}_{t+1}/d_{t+1}$, where $\widehat{\boldsymbol{\varphi}}_j^{(t)}, \widehat{\boldsymbol{\delta}}_j^{(t)}$ are estimates of parameters $\boldsymbol{\varphi}_j^{(t)}, \boldsymbol{\delta}_j^{(t)}$ based on the information up to period t. Moreover, we can obtain a longer-term estimate of PCIs based on the same logic in practice.

For forecasting issues, both texts and covariates (including the target) are available in period t; thus, we use all covariates and phrase vectors to estimate the parameters and obtain the in-sample fit of reduction projections to predict the target for the next period. Figure 1 summarizes the different calculation processes of PCIs for real-time nowcasting and forecasting. Intuitively, this adjustment reflects a learning process in interpreting central bank communication; that is, the agents understand and analyze existing texts based on the current economic situation and predict the future accordingly.

2.3 | PBC communication and textual database

To better understand the central bank in China, we first provide the institutional context of the People's Bank of China and its communication. First, the PBC is not independent of other central government units; it formulates and implements monetary policy under the leadership of the State Council according to Chinese law (Chen et al., 2018).[6] Second, the PBC has numerous monetary policy objectives, including growth, employment, inflation, reform, financial stability and so on (Huang et al., 2020; Zhou, 2016). Third, the broad money supply (M2) growth rate has been the intermediate target for China's quantity-based monetary policy since 2000. In terms of the features of PBC communication, the first is that the PBC rarely communicates explicitly about short-term economic judgments but is clearer and slightly more optimistic for long-term trends. Second, the PBC mainly conveys explanatory messages but rarely uses forward guidance or credibly commits on monetary policy operations (Ma & He, 2020). Finally, the PBC's statements are usually

[5]In line with Kelly et al. (2021), note that both projections are adjusted for a document-scale effect by normalizing them by the document size, $m_t - d_t$ and d_t.

[6]Although the PBC lacks independence, it is hard to say that PBC's communication is specifically designed to align with the releases of macroeconomic numbers (e.g., GDP), since the National Bureau of Statistics (NBS) of China rather than the PBC is responsible for the statistics and surveys of the GDP.

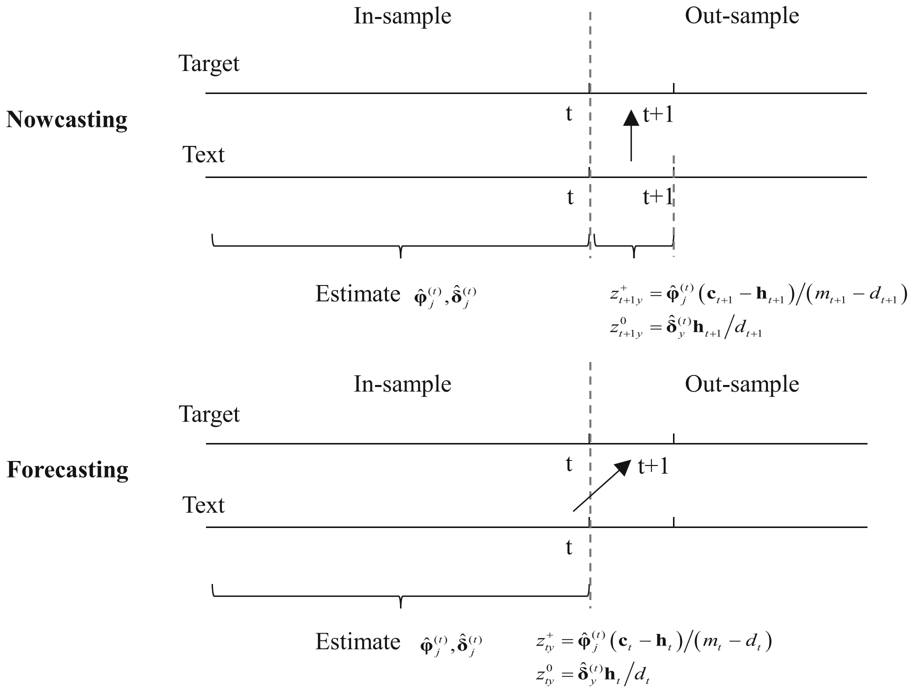

FIGURE 1 Different calculation processes for nowcasting and forecasting. Note: This graph shows the difference in calculation processes to obtain People's Bank of China (PBC) communication indices in nowcasting and forecasting. The main difference is whether one uses covariates and textual data in the same period for parameter estimation. Note that we use the estimated parameters based on the information up to period t to compute the PBC communication indices in period $t+1$ for nowcasting.

ambiguous regarding its monetary policy stance. Such phrases as "appropriate," "reasonable," and "sound" are frequently used in the communication texts, and they have multiple meanings in monetary policy practice. Despite this, the PBC's narratives indeed contain information about economic conditions and monetary policy stance (refer to Appendix S1 for some examples).

As documented by Bernanke (2020), central bank communication occurs in many venues, such as speeches, monetary policy reports, congressional testimonies and press conferences. Currently, there are two main PBC communication channels, namely, written and oral communications. For written communication, we download all the quarterly *Monetary Policy Executive Reports* (MPERs) from the PBC's official website, which regularly covers the most recent monetary policy decisions and the assessment of prospects for China's macroeconomic development. Between official reports, the PBC is committed to providing more timely information through irregular oral communication, for example, speeches and press conferences (McMahon et al., 2018; PBC, 2021). Since this communication is irregular and usually unpublished officially, our oral communication textual database for the PBC is constructed by keyword searching in Baidu News,[7] following the method of Lucca and Trebbi (2009). We recheck news from the central bank information publicity column and China's official publication "Ziguangge." MPERs have been published since 2001, and the oral communication texts have been on record since former Governor Zhou Xiaochuan, whose term started in 2003, took office. Therefore, we collect all MPERs and available oral communication texts starting in 2003:M1, aggregate them at a monthly frequency and obtain a total of $T=198$ documents.[8] In addition to the oral communications by Governors Zhou Xiaochuan (2003–2017) and Yi Gang (2018 to the present), we also collect other officials' oral communications, such as those from the PBC's Vice Governors.[9]

[7]"Zhou Xiaochuan," "Zhou Xiaochuan & currency," "Zhou Xiaochuan & economic situation," "Yi Gang," "Yi Gang & currency," "Yi Gang & economic situation," and so on. All names are listed as the PBC Governors or other officials.

[8]As the MPER is published at a quarterly frequency and with a significant lag (e.g., the report for 2019:2 was actually published in 2019:M8), the latest updated and available quarterly report for each month is used in order to avoid potential look-ahead biases.

[9]We obtain a total of 345 oral communication events from the PBC Governors, and 72 from other officials.

TABLE 1 Summary of the PBC communication texts

	Written communication	Oral communication			
	MPER	**Speech**	**Press**	**Article**	**Interview**
Frequency	66	311	21	11	74
Proportion (%)	13.66%	64.39%	4.35%	2.28%	15.32%

Note: This table summarizes the People's Bank of China (PBC) communication texts that we collected. The written communication contains the quarterly Monetary Policy Executive Report (MPER), and the oral communication consists of speeches by the Governor and other officials, press conferences, articles by the Governor and interviews of the officials. The MPER is downloaded from the PBC's website, and the oral communication is collected by keyword searching in Baidu News. The sample period is 2003:M1–2019:M6.

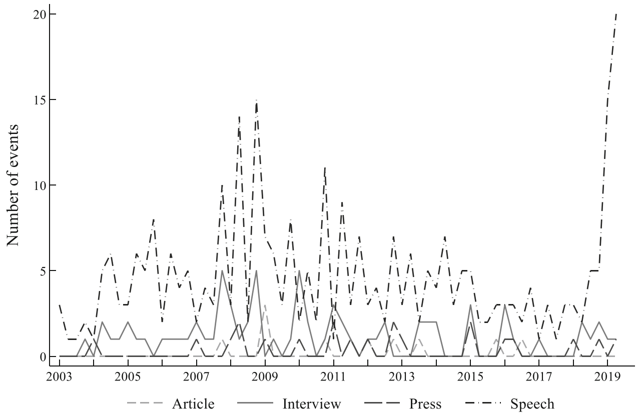

FIGURE 2 Frequency of People's Bank of China (PBC) oral communication events. *Note*: This graph shows the quarterly frequency chart for oral communication events of the PBC with four types of communication channels: articles, interviews, press releases and speeches. The sample period is 2003:M1 to 2019:M6.

Table 1 summarizes the collected PBC communication texts. Across the sample period, MPERs are regularly issued at a quarterly frequency. "Speech" is the most frequently used form of oral communication, including speeches by the Governor at financial forums, New Year's speeches, and speeches made at a wide range of other communication occasions. Figure 2 illustrates the quarterly frequency of PBC oral communication events. Due to baby-stepping issues at the early stage (McMahon et al., 2018), few oral communication events took place at the beginning; however, they increased dramatically after 2007, when PBC communications began to attract more attention because of the overheating of the economy and the hawkish monetary policy at that time. Recently, the use of oral communication has become more frequent, as the PBC delivers its policy intentions in a timely way and reasonably guides market expectations.

After collecting the raw communication texts, we engage in standardized preprocessing prior to estimation, such as removing meaningless expressions and stop words and applying term frequency–inverse document frequency (TF-IDF) calculations to trim the data. Finally, $d = 13{,}507$ phrases with the highest TF-IDF score are kept to form the final corpus. After these feature selection steps on the PBC communication texts, we obtain the document-phrase matrix as the input into HDMR, where each element is the phrase count for a specific phrase in the document. A more detailed explanation of the preprocessing is given in Appendix S1.

2.4 | Target variables and macroeconomic dataset

China has "the characteristics of a large transition economy and an emerging market economy" (Zhou, 2016); thus, the PBC lays out "multiple objectives" of its monetary policy, including economic growth and price stability. Accordingly, the target variables focused on in this paper are matched as much as possible and comprise two broad categories: output-related and price-related. We use the year-on-year growth rate of each target variable, which is not only essential but also common in Chinese practice (Chang et al., 2016; Fernald et al., 2014; Jiang et al., 2017).

TABLE 2 Categories of the macroeconomic dataset

Category	Number of series
Real output	12
Real investment	4
Real estate	9
Consumption	4
Import and export	9
Futures market	9
Stock market	2
Exchange rate	6
Public finance	3
Money and credit	9
Price index	28
Interest rate	23
Treasury bond yield	20
US economy	7
Commodity	6
Total	151

Note: This table summarizes the categories of our macroeconomic dataset, containing 151 monthly macroeconomic series. The raw data are obtained from the National Bureau of Statistics of China and the China Economic Information Network (*CEInet*) statistical database. The sample period is 2003:M1–2019:M6.

For the perspective of promoting economic growth, we form the group of output-related variables. First, we select quarterly year-on-year real GDP growth rate as one of our main target variables,[10] which is the macroeconomic variable of greatest importance and widest interest for government departments, researchers and the public (Aastveit et al., 2014; Bok et al., 2018; Jokubaitis et al., 2021; Richardson et al., 2021; Thorsrud, 2020). Second, following the literature (Ellingsen et al., 2021; Kelly & Pruitt, 2015), the growth rates of industrial value added (IVA) and fixed asset investment (FAI) are also considered in our analysis. The former is an important indicator of the real economy and is even often used as a "proxy" for monthly GDP growth rate in China; the latter is a comprehensive indicator reflecting the scale and speed of the fixed asset investment in society that is closely related to economic growth.

To meet the goal of price stability, we forecast the consumer price index (CPI) and producer price index (PPI) to focus attention on inflation in China (Di Filippo, 2015; Kelly & Pruitt, 2015; Lin et al., 2021).[11] To monitor the PBC's monetary policy stance, the year-on-year growth rate of the broad money supply (M2) is also considered. The first two indicators reflect the overall price level in consumption and production, and the last indicator is the intermediary target of China's monetary policy. We refer them into our group of price-related variables.

It is important to emphasize that the last five macro indicators are published at a monthly frequency, and all of them (including GDP) are obtained from the same source, the China Economic Information Network (*CEInet*) statistical database.

To obtain the hard-based predictors in the era of big data, we construct a high-dimensional macroeconomic dataset containing 151 monthly macroeconomic and financial indicators for China. Specifically, we use the "final data" rather than "vintage data" for these series so that our macroeconomic dataset is not truly real-time.[12] As presented in Table 2,

[10]There is an unsettled debate about the quality of China's economic data, especially the GDP figures. However, our view is that one should not abandon the official series of GDP (growth rate) in favor of other less comprehensive indicators, such as industrial value added (IVA). After all, the official series of GDP is what policymakers, financial markets, researchers, and agents have paid most attention to when assessing China's aggregate activity (Higgins et al., 2016).

[11]We use the raw price indices (CPI and PPI), since they are computed based on the same period last year and can also be viewed as year-on-year data.

[12]First, to the best of our knowledge, there is no official, recognized or standard macroeconomic database in China that contains a large set of real-time vintages. Second, the real-time data collected by other Chinese scholars has several limits, such as being collected manually, small in size and length, not publicly available and no longer updated.

we select 138 macro series to represent broad categories of macroeconomic time series in China: real output and income, consumption, trade sales, money and credit, interest rates, price indices, future and stock market indices, bond yields, and foreign exchange measures (Bernanke et al., 2005; Hansen & McMahon, 2016; Ludvigson & Ng, 2010; McCracken & Ng, 2016). Considering that China is an open economy, we add seven US economic indicators and six international commodity indicators to reflect China's linkages with the world. See Appendix S2 for more descriptions of our macroeconomic dataset.

With such a data-rich macroeconomic dataset, we apply a common factor model for dimension reduction (Stock & Watson, 2012) as follows:

$$X_t = \Lambda F_t + e_t, \tag{5}$$

$$F_t = \Phi_1 F_{t-1} + \cdots + \Phi_p F_{t-p} + \eta_t, \tag{6}$$

where X_t represents 151 monthly macroeconomic indicators in our dataset in observation t and $F_t = \left(f_{1,t}, \cdots, f_{q,t}\right)'$ is the latent factor vector of size q with loading matrix Λ. To embed the dynamic structure in factors, we specify a p-order autoregressive process with the autoregressive coefficient matrix $\Phi_j (j = 1, \cdots, p)$, and both e_t and η_t are error terms. Consistent with the existing findings, we set $q = 5$ as the number of monthly macro factors (Forni et al., 2000; Stock & Watson, 2012). According to the Bayesian information criterion (BIC), we determine the lag order of factors p to be 2 and estimate latent factors using a Bayesian approach (Koopman & Mesters, 2017; Stock & Watson, 2016).

2.5 | Real-time PBC communication indices

To measure PBC communication for predicting a specific target variable, we consider the corresponding target as the supervised variable in HDMR and include the five macroeconomic factors as additional covariates. HDMR requires that all covariates and communication texts have the same frequency, as must the computed sufficient reductions. For monthly target variables, we estimate the time series of two PCIs (for both word repetition and inclusion) by matching the monthly texts to the contemporaneous target variables and factors. For quarterly GDP growth rate, we assign the corresponding quarterly value to each monthly text and construct two monthly text-based sufficient reduction projections to reflect the timeliness of central bank communication.[13] Overall, we construct 12 monthly PBC communication indices, that is, two for each target variable. To produce the real-time estimate of PCIs, the HDMR model is initially estimated using texts from 2003Q1 to 2009Q4 (or 2003:M1 to 2009:M12), and the remaining data, 2010Q1 to 2019Q2 (or 2010:M1 to 2019:M6), are used to recursively update and construct PBC communication indices based on real-time information.[14] The process for re-estimation is rapid and easy since HDMR provides computational savings.

To build intuition, we first use the complete macroeconomic dataset and PBC communication texts to construct the full-sample estimations of 12 PCIs, and we illustrate the relationship between PCIs and the target variables via simple descriptive statistics prior to the following empirical analysis. As presented in Figure 3, Panel A displays the time series of the word repetition and inclusion indices (denoted as z^+_{GDP} and z^0_{GDP}, respectively). Generally, the z^+_{GDP} can track the movements of GDP. For example, both the GDP growth rate and z^+_{GDP} tended to decrease at the introduction of hawkish monetary policy in China in 2004 and at the beginning of the 2008 financial crisis. The other index, z^0_{GDP}, is fairly flat in most periods but closely followed the fluctuations in GDP growth rate at the beginning of the 2008 financial crisis. Although these two indices are different over the sample period, they indeed show an analogous pattern with the movement of GDP growth rate. We find similar results in Panel B, which illustrates the PCIs with the CPI as the target variable. A variety of basic descriptive statistics for PBC communication indices can be found in Appendix S3.

[13]Similar results are found when we construct two quarterly PCIs for GDP by replacing the monthly macro factors with their 3-month average value at the corresponding quarter to align the frequency to the GDP growth rate.

[14]As we add five macroeconomic factors as additional covariates in HDMR, we apply the same recursive estimation to the common factor model. The initial training window is consistent in the real-time text analysis and in the forecasting experiment and is shown to be robust against different selections.

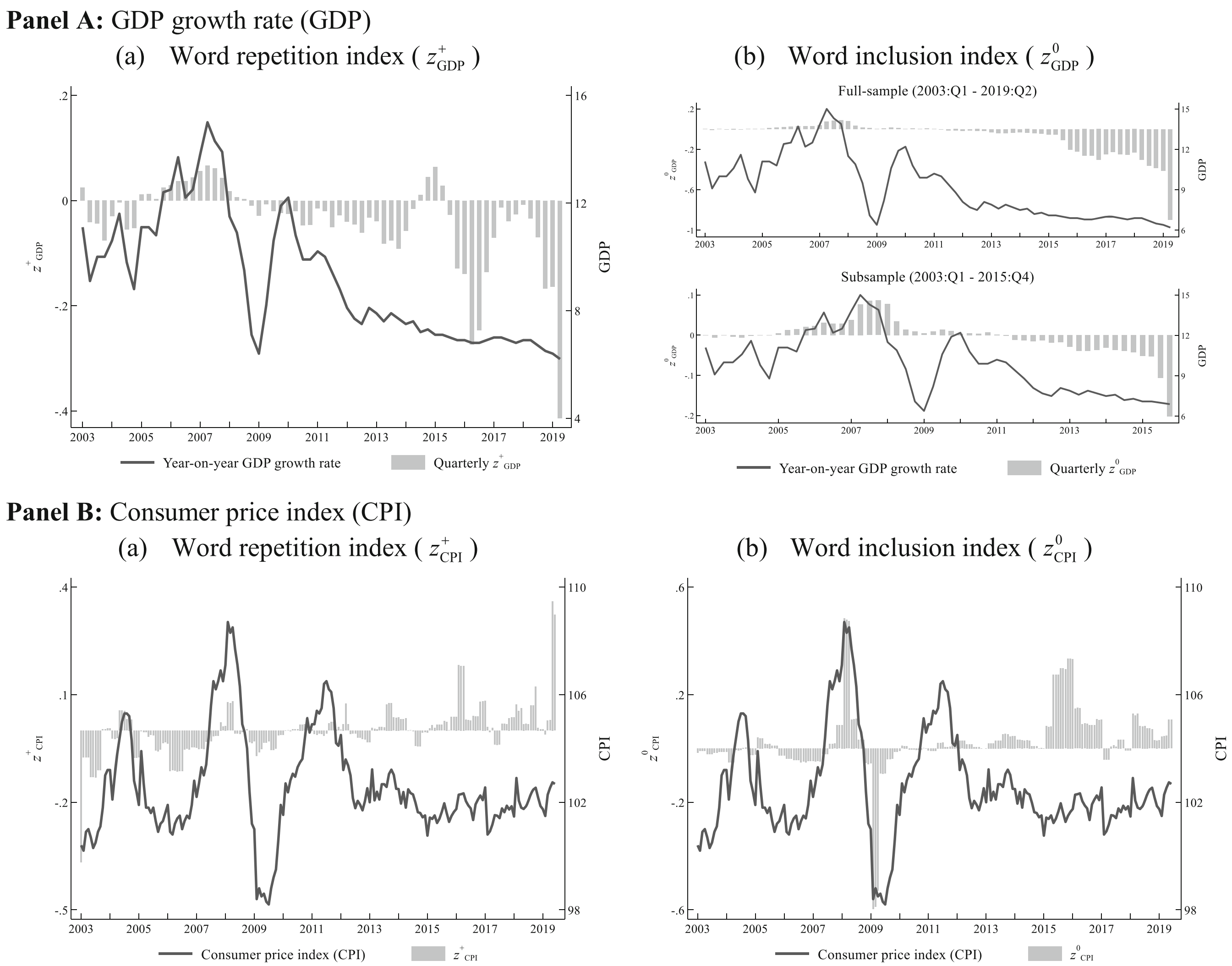

FIGURE 3 Full-sample estimation of the People's Bank of China (PBC) communication indices for predicting gross domestic product (GDP) and consumer price index (CPI) from the repetition and inclusion of words. Note: This graph shows the full-sample estimation of the PBC communication indices with the GDP growth rate as the target variable in Panel A and the CPI in Panel B. Plot (a) shows the word repetition index, and Plot (b) shows the word inclusion index. The black solid line represents the actual time series of the target variable. The gray bar shows the PBC communication index (PCI), which contains the predictive information in word repetition (or inclusion) for the target. In Panel A, the raw PCI is monthly frequency and is estimated using full-sample data, while aggregated to a quarterly frequency using the mean of monthly indices, denoted as "quarterly z^{+}_{GDP}" or "quarterly z^{0}_{GDP}. " The top figure in Panel B uses a sample of texts from 2003Q1 to 2019Q2, but the bottom figure is truncated at 2015Q4. The sample period is 2003Q1 to 2019Q2 (or 2003:M1 to 2019:M6, equally).

Figure 4 provides us with the appealing correlation relationships between the target variables and PCIs. In line with expectations, almost all PBC communication indices are positively correlated with their corresponding target variables. Therefore, HDMR seems to learn about macroeconomic fundamentals from PBC communication texts and further illustrates the feasibility of our text-based measures. Moreover, one PBC communication index also has potential predictive value for other target variables. For instance, the word repetition and inclusion indices (z^{+}_{IVA} and z^{0}_{IVA}) with the IVA growth rate as a supervised signal show a strong positive relationship with the GDP growth rate, which is not even inferior to z^{+}_{GDP} and z^{0}_{GDP}. Therefore, all PCIs can serve as potential text-based predictors for one specific target.

To compare the PBC communication measures based on full-sample and real-time estimation, Figure 5 illustrates the 6-month moving average time series of PCIs with the GDP growth rate or CPI as the target variables. Indeed, there is a fairly close pattern between full-sample estimation and real-time estimation. Plot (a) in Panel A shows that the full-sample and real-time PCIs for word repetition generate a positive correlation of 0.76. Both show a simultaneous tendency to rise and fall, especially in the pre-2014 sample. However, the real-time estimated PCI recovered more

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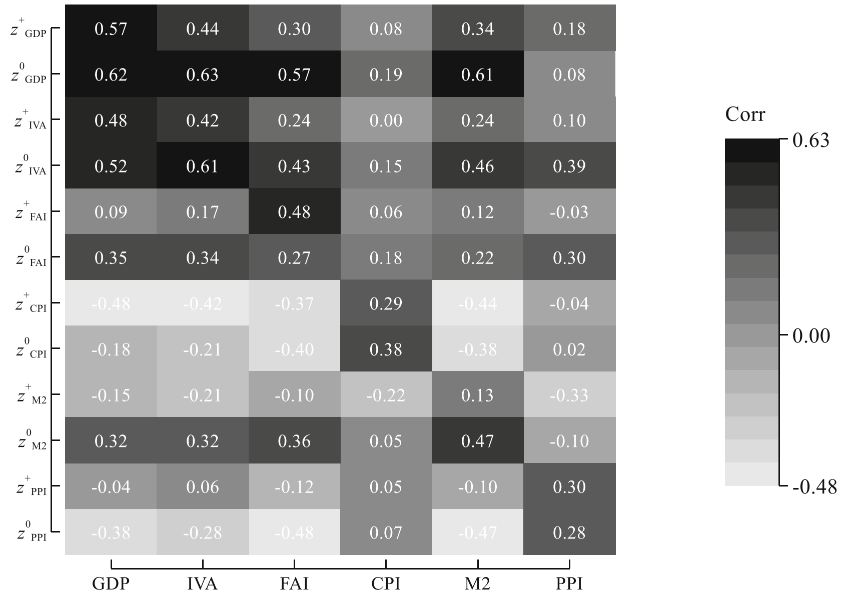

FIGURE 4 Correlation between target variables and People's Bank of China (PBC) communication indices. *Note*: This graph shows the Pearson correlation coefficients between six target variables and 12 full-sample estimated PBC communication indices. The coefficients are computed at the frequency of each target variable. Black represents a positive correlation, gray represents a negative correlation, and coefficients are displayed as white numbers. The sample period is 2003Q1 to 2019Q2 (or 2003:M1 to 2019:M6, equally).

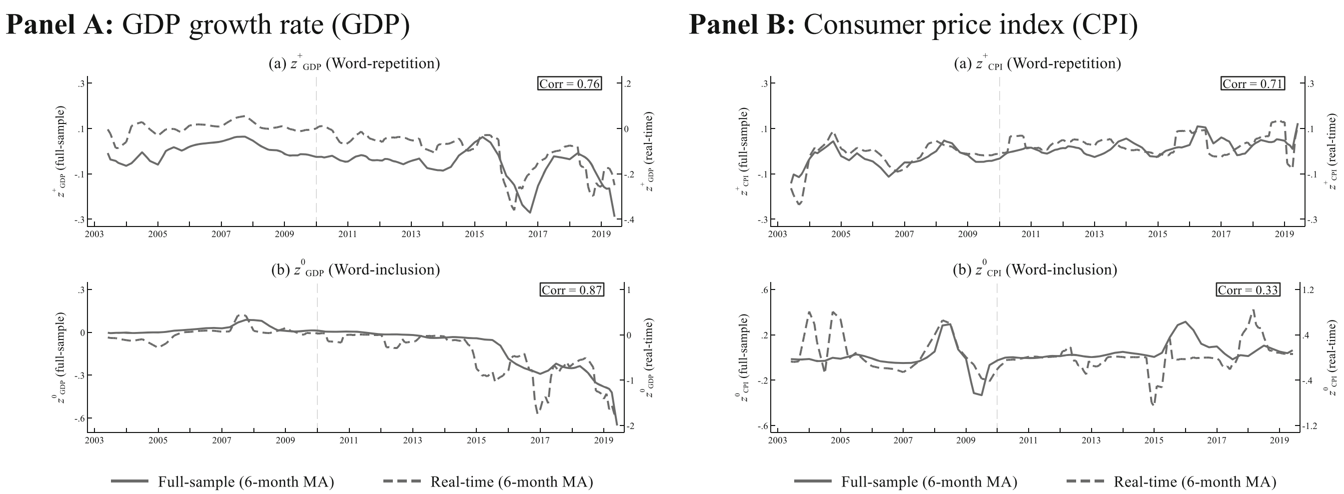

FIGURE 5 Full-sample and real-time estimations of People's Bank of China (PBC) communication indices for predicting gross domestic product (GDP) and consumer price index (CPI). *Note*: The target variables are the year-on-year GDP growth rate (GDP) in Panel A and the CPI in Panel B. The black solid line represents the 6-month moving average of the full-sample PBC communication index (PCI) based on the complete communication texts from 2003:M1 to 2019:M6. The black dashed line represents the 6-month moving average of real-time PCI, which is initially estimated from 2003:M1 to 2009:M12 and recursively re-estimated for the next month. The gray dashed line indicates the starting point of the real-time estimation outside the initial window, and the Pearson correlation coefficients are calculated based on the moving average sequences.

quickly after the trough of 2014. Similarly, Plot (b) in Panel B shows the two PCIs for word inclusion with CPI as a supervised signal; they are highly correlated and show an almost consistent trend of movement. In short, the full-sample and real-time estimations are relevant, whereas real-time estimation without look-ahead biases is more feasible in practice. More real-time PCIs can be found in Figure S3.

3 | FORECASTING MODELS

In this section, we introduce the forecasting models. Section 3.1 presents the MIDAS-type model and the forecast combination, whereas Section 3.2 shows the details of the empirical setup and model evaluation.

3.1 | MIDAS and forecast combination

As mentioned above, the most important macroeconomic indicator, namely, the GDP growth rate, is released quarterly, whereas the other macroeconomic indicators are recorded monthly. To exploit the high-frequency information captured by monthly predictors, we apply the MIDAS technology proposed by Ghysels et al. (2004), which is simple, popular, and has been shown to perform well in a wide range of applications (Andreou et al., 2013; Clements & Galvão, 2008; Ghysels et al., 2006).

Formally, let $Y_{t+\tau}$ denote the low-frequency target variable in a τ-step ahead forecast at period t, and let $X_t^{(m)}$ represent the high-frequency predictor, sampled m times at low-frequency units from period $t-1$ to t. The MIDAS model with a single high-frequency regressor $X_t^{(m)}$ and lag term of Y_t is given by the following:

$$Y_{t+\tau} = \alpha + \sum_{j=0}^{p_Y-1} \gamma_j Y_{t-j} + \beta \sum_{k=0}^{p_X-1} w_X(k;\boldsymbol{\theta}) X_{t-k/m}^{(m)} + \varepsilon_{t+\tau}, \tag{7}$$

where p_Y is the maximum lag order of the target and $w_X(k;\boldsymbol{\theta})$ is the polynomial weight with a maximum lag order of p_X for the predictor. We provide several settings of the lag polynomial operator, as shown in Appendix S4. For the monthly target variables, we use the unrestricted MIDAS (U-MIDAS) suggested by Foroni et al. (2015), which is shown to work for small values of m.

In our empirical analysis, five macroeconomic factors and 12 text-based PBC communication indices are viewed as predictors. Instead of putting all predictors into a multivariate MIDAS (M-MIDAS) regression, we first form an individual regression with a single predictor and then conduct a model combination to produce the final forecast.[15] Following the suggestion of Stock and Watson (2006) and Andreou et al. (2013), the baseline forecast (*MF*) is the time-varying weighted average of five individual MIDAS regressions with one macro factor as the predictor[16]:

$$\widehat{y}_{t+\tau|t}^{MF} = \sum_{s=1}^{q} \widehat{w}_{s,t} \widehat{y}_{s,t+\tau|t}, \tag{8}$$

where $\widehat{y}_{s,t+\tau|t}$ is the τ-step ahead forecast computed at period t of the sth individual MIDAS regression with combination weight $\widehat{w}_{s,t}$, and $\widehat{y}_{t+\tau|t}^{MF}$ is the forecast of the benchmark using q macroeconomic factors. Unless otherwise stated, we use the mean squared forecast error (MSFE) weight to produce the forecast, which dominates the others in most cases (Appendix S4 provides the details about the combination weight).

Obtaining the forecasts from MIDAS regressions with PBC communication indices as predictors via Equation (7), we embed texts in the forecast combination to produce the text-augmented forecast (denoted as *MF+TEXT*):

$$\widehat{y}_{t+\tau|t}^{MF+TEXT} = \sum_{s=1}^{q+\ell} \widehat{w}_{s,t} \widehat{y}_{s,t+\tau|t}, \tag{9}$$

where ℓ represents the number of models using text-based PCIs, $\widehat{y}_{s,t+\tau|t}$ is the sth individual forecast with time-varying weight $\widehat{w}_{s,t}$, and $\widehat{y}_{t+\tau|t}^{MF+TEXT}$ is the final combination forecast combining the macro factors and PBC communication texts.

[15]Timmermann (2006) notes that multiple forecasts of the same target variable are often available to decision makers, as they reflect the differences in forecasters' subjective judgments due to the heterogeneity in information sets or modeling approaches.
[16]Appendix S5 provides further discussion on the specification of the benchmark.

TABLE 3 Specification of forecasting models

		Benchmark	Text-augmented model			
		MF	MF + PCI (z^+)	MF + PCI (z^0)	MF + PCIs (z^+ and z^0)	MF + PCIs (all)
Macroeconomic factor		Y	Y	Y	Y	Y
PBC communication index (PCI)	z^+		Y		Y	
	z^0			Y	Y	
	all					Y
# Predictors		5	6	6	8	17

Note: This table reports the specification of forecasting models. Specifically, we combine five macroeconomic factors and perform the benchmark model, denoted as "benchmark (MF)." To forecast using People's Bank of China (PBC) communication texts, we add the PBC communication index (PCI) for word repetition of the target variable as an additional predictor and perform "MF + PCI (z^+)," PCI for word inclusion of the target variable and perform "MF + PCI (z^0)," two PCIs for both word repetition and inclusion of the target variable and perform "MF + PCIs (z^+ & z^0)," and we add all 12 PCIs of six target variables and perform "MF + PCIs (all)." The number of predictors, excluding the autoregressive term unless otherwise stated, is reported in the last row.

Table 3 summarizes our specification of the forecasting models. Unless otherwise stated, we use the combination model with $q=5$ macroeconomic factors to form our benchmark for comparison and conduct the text-augmented models by adding $\ell=1$ PCI for word repetition (or inclusion) of a specific target, $\ell=2$ PCIs for the target, and all $\ell=12$ text-based PCIs.

3.2 | Empirical setup and evaluation

In our analysis for real-time macroeconomic projection, the OOS forecasting experiment is conducted as follows. We use the data from 2003Q1–2009Q4 (or 2003:M1–2009:M12) as the initial window to estimate the predictors and train the forecasting models, and we recursively update and expand them for the OOS evaluation. Following the general settings (Lima et al., 2020; Lin et al., 2021), we consider both short- and long-term forecasting horizons. More concretely, we set $\tau=1,2,3,4$ for quarterly targets (e.g., GDP growth rate) and $\tau=1,3,6,12$ for monthly targets. For nowcasting, we use $\tau=0$ for notation simplicity. Appendix S4 provides more details about our empirical setups.

To evaluate the average performance over the whole OOS period for a specific model s, we focus on point prediction and use the root-mean-square error (RMSE):

$$RMSE_s=\sqrt{\frac{1}{T-T_0+1}\sum_{t=T_0-\tau}^{T-\tau}\left(y_{t+\tau}-\widehat{y}_{s,t+\tau|t}\right)^2}, \tag{10}$$

where $y_{t+\tau}$ is the actual value of the target variable in period $t+\tau$, $\widehat{y}_{s,t+\tau|t}$ is the prediction of model s at time t, and T_0 is the point at which the first τ-step ahead OOS forecast is computed (i.e., $T_0=2010:\mathrm{Q1}$ or $2010:\mathrm{M1}$ in our practice). Moreover, we use the two-sided Diebold–Mariano (DM) test (Diebold & Mariano, 1995) to judge whether the differences in forecasting performance are significant.

4 | EMPIRICAL RESULTS

To investigate whether central bank communication provides informational gains beyond a large number of macroeconomic indicators, Section 4.1 evaluates the OOS performance in real time. Section 4.2 illustrates the pivotal phrases that drive the OOS prediction, whereas Section 4.3 demonstrates how good the predictions actually are by comparing predictive performance with the professional forecast.

TABLE 4 Real-time estimation and OOS predictive performance

Panel A: Output-related								Panel B: Price-related							
	Type	Horizon	RMSE of Benchmark	Relative RMSE					Type	Horizon	RMSE of Benchmark	Relative RMSE			
Target	Info.		MF	MF + PCI (z^+)	MF + PCI (z^0)	MF + PCIs (z^+ & z^0)	MF + PCIs (all)	Target	Info.		MF	MF + PCI (z^+)	MF + PCI (z^0)	MF + PCIs (z^+ & z^0)	MF + PCIs (all)
GDP	Nowcast	0	0.19	0.91**	0.96***	0.93***	1.03	CPI	Nowcast	0	0.42	0.92***	0.96***	0.90***	0.84***
	Forecast	1	0.43	1.01	0.98*	0.99	0.81***		Forecast	1	0.42	0.92***	0.97***	0.90***	0.82***
		2	0.81	0.71***	0.75***	0.64***	0.68***			3	0.68	0.80***	0.86*	0.78***	0.67***
		3	1.18	0.61***	0.88**	0.58***	0.59***			6	0.67	0.96*	0.83**	0.79***	0.59***
		4	1.45	0.57**	0.54***	0.45***	0.53***			12	0.86	0.98***	0.91***	0.91***	0.79***
	Average	-	0.81	0.76	0.82	0.72	0.73		Average	-	0.61	0.92	0.91	0.86	0.74
IVA	Nowcast	0	1.50	0.96***	0.94***	0.92***	0.84***	M2	Nowcast	0	0.77	0.95***	0.99	0.95***	0.92***
	Forecast	1	1.50	0.98***	0.95***	0.95***	0.86***		Forecast	1	0.77	0.98***	0.99	0.98***	0.91***
		3	1.40	0.98	0.97**	0.98	0.96**			3	1.33	0.94***	0.95***	0.92***	0.84***
		6	1.79	0.98*	0.95***	0.95***	0.82***			6	2.08	0.90***	0.92***	0.89***	0.62***
		12	2.29	1.01	0.99	1.00	0.85***			12	2.79	0.93	0.94	0.91	0.69***
	Average	-	1.70	0.98	0.96	0.96	0.87		Average	-	1.55	0.94	0.96	0.93	0.79
FAI	Nowcast	0	5.02	0.96***	0.98***	0.95***	0.89***	PPI	Nowcast	0	0.47	0.95***	0.95***	0.92***	0.86***
	Forecast	1	5.02	0.97***	0.97***	0.95***	0.89***		Forecast	1	0.47	0.95***	0.95***	0.92***	0.87***
		3	6.25	0.97***	0.92***	0.91***	0.83***			3	1.50	0.92**	0.94***	0.91**	0.86*
		6	5.56	0.91**	0.96**	0.91**	0.87***			6	2.78	0.85*	0.88**	0.81*	0.66*
		12	6.31	0.99	0.99	0.99	0.87***			12	3.93	0.76**	0.86**	0.74**	0.63*
	Average	-	5.63	0.96	0.96	0.94	0.87		Average	-	1.83	0.88	0.92	0.86	0.78

Note: This table reports the real-time out-of-sample (OOS) predictive performances (measured by root-mean-square error, RMSE) using the models summarized in Table 3, where the target variables are output-related variables (GDP, IVA, and FAI) in Panel A and price-related variables (CPI, M2, and PPI) in Panel B. A value less than 1 in the column "Relative RMSE" indicates additional predictive value for People's Bank of China (PBC) communication indices for lowering the benchmark's RMSE. All predictors and forecasting models are initially estimated using data from 2003Q1 to 2009Q4 (or 2003:M1 to 2009:M12), as well as recursively re-estimated and evaluated using the remaining data. Significant differences in predictive performance (marked in gray) are calculated using the Diebold–Mariano test statistic (Diebold & Mariano, 1995).
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

4.1 | Information gains based on real-time exercise

In this subsection, we recursively estimate the predictors, hard-based macroeconomic factors and text-based PCIs and perform OOS prediction in real time to avoid the look-ahead biases.[17] Table 4 summarizes the results and provides the following stylized facts.

First, the forecasting performances of the benchmark deteriorate as the forecasting horizon increases, which means that macro factors capture information on current economic status but are less informative in the long run. Second, regarding the predictive value of central bank communication, we find that PBC communication popularly contributes to improving the real-time predictive performances for all target variables and forecasting horizons. For instance, according to the first row in Panel A when nowcasting GDP growth rate, the text-augmented model with word repetition index (z^{+}_{GDP}) obtains a lower RMSE, 0.91, than the baseline forecast. In terms of one-quarter-ahead forecasting ($\tau = 1$), we find that the inclusion of PBC communication texts is also necessary and powerful, for example, adding all PCIs significantly improves the short-term accuracy by 19%. We also find additional value for our communication texts for the other two output-related variables (IVA and FAI). As shown in Panel B, PBC communication texts strongly and significantly improve the OOS real-time predictive performances of price-related variables. For example, for nowcasting CPI and PPI, including all PCIs yields relative RMSEs of 0.84 and 0.86 compared to the benchmark, corresponding to 16% and 14% improvements in prediction accuracy, respectively.

Furthermore, central bank communication seems to be more valuable for long-term forecasting. For example, the inclusion of PBC communication texts generates an approximately 10% improvement in nowcasting GDP but nearly 40% in forecasting the four-quarters-ahead GDP. We attribute this finding to two reasons. First, although the RMSE increases with an increasing forecast horizon for all models, the benchmark with macro factors becomes worse at predicting the longer term. The significant reduction in baseline forecasting performance has resulted in a higher improvement from using PBC communication texts. Second, as one tool for expectation management, central bank communication transmits information about economic fundamentals that shape the long-run market expectations of economic conditions (Boguth et al., 2019; Nakamura & Steinsson, 2018). For instance, the "Monetary Policy Outlook" section in MPERs provides PBC's judgments on future economic conditions; thus, this narrative communication helps the market form its expectations and contributes to long-term forecasting (see Appendix S1 for some narrative examples).

Finally, combing other text-based indices that are not generated directly from the target also improves the prediction accuracy. For example, the relative RMSE score of including one PCI (z^{+}_{GDP} or z^{0}_{GDP}) for forecasting four-quarters-ahead GDP growth rate is 0.57 or 0.54. However, adding both z^{+}_{GDP} and z^{0}_{GDP} is preferable, with a lower relative RMSE of 0.45. We also find analogous results to other target variables. In addition, including all text-based indices mostly obtains the lowest RMSE, especially for IVA, FAI, and price-related variables. Hence, we argue that predicting with more PBC communication indices is, in most cases, better than using just the one that is based on the prediction target.

Overall, PBC communication texts have predictive information in real-time macroeconomic projections, which strongly and significantly reduces the benchmark's RMSE. As forecast error increases with the forecast horizon, PBC communication tends to perform better in long-term forecasting. Although there is no dominant model for different target variables and forecast horizons, adding all PCIs can mostly obtain a better prediction accuracy.

To check the sensitivity of our main conclusions to the empirical settings, we conduct several robustness analyses, including using a rolling window procedure, changing the initial training sample, and additional tests for nested model comparison. Our results are still valid. See Appendix S7 for more detailed discussions.

4.2 | Pivotal phrases and narrative realism

To better understand which phrase drives the improvement in OOS fit, Table 5 reports the important phrases on each target variable based on real-time exercise.[18]

For simplicity and esthetics, we report six pivotal phrases for each index, three for positive loadings and three for negative loadings, and list them in reverse order of total counts. Taking the word repetition index for GDP growth rate

[17]Table S6 reports the pseudo real-time estimation results, where the predictors are estimated based on the full-sample data. The pseudo OOS prediction suggests that the potential predictive value of central bank communication is also sizeable regardless the look-ahead biases.

[18]The method we use to measure the phrase importance and the full-sample result are available in Appendix S6.

TABLE 5 Pivotal phrases for out-of-sample fit based on real-time estimation

Panel A: Output-related	Word repetition index (z_y^+)				Word inclusion index (z_y^0)			
	Phrase (English)	Phrase (Chinese)	Count	Inclusion	Phrase (English)	Phrase (Chinese)	Count	Inclusion
GDP	GDP deflator	GDP 平减指数	51	22%	Window guidance	窗口指导	238	48%
	Prudential management	审慎管理	48	23%	Advance interest liberalization	稳步推进利率市场化改革	174	48%
	Year-on-year industry value added growth	工业增加值同比增长	47	23%	Promote financial enterprise reform	稳步推进金融企业改革	139	42%
	Raise policy rate	上调政策利率	36	14%	Consumer price index	居民消费者价格指数	129	40%
	Credit growth	信贷增长	34	17%	Total retail sales of consumer goods	社会消费品零售总额	108	52%
	Money supply	货币供应	13	6%	Improve the macroprudential policy framework	完善宏观审慎政策框架	105	21%
IVA	Note financing	票据融资	113	33%	GDP	GDP	908	96%
	Monetary loan growth	货币信贷增长	47	18%	Crisis	危机	168	39%
	Labor costs	劳动力成本	37	10%	Asset purchases	资产购买规模	98	38%
	Term structure and operational intensity	期限结构和操作力度	35	17%	Optimize the credit structure	着力优化信贷结构	80	24%
	Supporting the expansion of domestic demand	支持扩大内需	26	11%	Steady increase in the growth rate of industrial production	工业生产增速稳步提升	6	2%
	Price increases	物价涨幅	22	8%	Consumer demand grows	消费需求不断扩大	6	2%
FAI	Fixed asset investment (FAI)	全社会固定资产投资	56	28%	Deposit reserve ratio	存款准备金率	277	60%
	Term structure and operational intensity	期限结构和操作力度	35	17%	Window guidance	窗口指导	238	48%
	Credit growth	信贷增长	34	17%	Price	物价	203	54%
	Loan financing	贷款融资	30	14%	Advance interest liberalization	稳步推进利率市场化改革	174	48%
	Consumer credit	消费信贷	21	9%	Control risk	控制风险	9	3%
	Short-term financing bills and medium-term notes	短期融资券和中期票据	16	8%	Lending remains balanced	贷款保持均衡	7	2%

TABLE 5 (Continued)

Panel B: Price-related	Word repetition index (z_y^+)				Word inclusion index (z_y^0)			
	Phrase (English)	**Phrase (Chinese)**	**Count**	**Inclusion**	**Phrase (English)**	**Phrase (Chinese)**	**Count**	**Inclusion**
CPI	Liquidity	流动性	580	90%	Stable and rapid economic development	经济平稳较快发展	190	31%
	Inflation expectation	通货膨胀预期	62	10%	Optimize the credit structure	优化信贷结构	185	54%
	GDP deflator	GDP平减指数	51	22%	Inflation	通胀	183	46%
	Macroprudential policy framework	宏观审慎政策框架	51	16%	Liquidity management	流动性管理	181	41%
	New price-rising factors	新涨价因素	48	20%	Nonfood price increases	非食品价格上涨	64	31%
	Market supply and demand	市场供求关系	8	4%	Raise lending and deposit rates	上调存贷款基准利率	32	10%
M2	Short-term financing bills	短期融资券	177	57%	Inflation	通胀	183	46%
	Credit growth	信贷增长	34	17%	Further deepening the market-based interest rate reform	稳步推进利率市场化改革	174	48%
	Loan financing	贷款融资	30	14%	Deepen the reform of financial institutions	深化金融机构改革	102	44%
	Loan support	贷款支持力度	26	12%	Bond index fluctuates slightly	债券指数小幅波动	18	3%
	Interest rate policy	利率政策	19	9%	Economic stabilization and rebound	经济企稳回升	16	6%
	Financial policy	金融政策	12	6%	Increase in proportion of loans	贷款占比增加	9	5%
PPI	Money market interest rate	货币市场利率	209	61%	Unemployment rate	失业率	315	77%
	Year-on-year industry value added (IVA) growth	工业增加值同比增长	47	23%	Inflation	通货膨胀	190	46%
	Term structure and operational intensity	期限结构和操作力度	35	17%	Loan rate	贷款利率	148	43%
	Credit growth	信贷增长	34	17%	Price increases faster	价格上涨较快	45	17%
	Manage inflation expectations well	管理好通胀预期	21	7%	Economic stabilization and rebound	经济企稳回升	16	6%
	Commodity prices continue to rise	商品价格持续上涨	15	6%	Lending remains balanced	贷款保持均衡	7	2%

Note: This table reports the pivotal phrases on each target variable for the real-time estimations of the word repetition index (z_y^+) and word inclusion index (z_y^0). The target variables are output-related variables (GDP, IVA, and FAI) in Panel A and price-related variables (CPI, M2, and PPI) in Panel B. The People's Bank of China (PBC) communication indices are estimated in real time and are initially estimated using data from 2003Q1 to 2009Q4 (or 2003:M1 to 2009:M12), as well as recursively re-estimated and evaluated using the remaining data. The phrase importance is calculated using the method described in the text. This table presents the six selected (three for positive loading and three for negative loading) pivotal phrases both in English and Chinese, as well as their total phrase counts and inclusions across the full sample. Phrases are listed in descending order by their counts.

TABLE 6 Relative RMSE scores of text-augmented forecasts and professional forecasts

	GDP	IVA	CPI	M2	PPI
MF + PCI (z^+)	0.37*	1.20	1.42**	0.99**	1.25
MF + PCI (z^0)	0.39*	1.17	1.48***	1.04	1.26
MF + PCIs (z^+ & z^0)	0.38*	1.15	1.39**	0.99**	1.22
MF + PCIs (all)	0.42*	1.04	1.29	0.96***	1.15

Note: This table reports the real-time out-of-sample (OOS) nowcasting performances (measured by root-mean-square error, RMSE) using text-augmented models and professional forecasts (PF), where the target variables are output-related variables (GDP and IVA) and price-related variables (CPI, M2, and PPI). The mean forecast released by the Wind is used as the PF. A value less than 1 indicates that the text-augmented model has a lower RMSE relative to PF. All predictors and forecasting models are initially estimated using data from 2003Q1 to 2009Q4 (or 2003:M1 to 2009:M12), as well as recursively re-estimated and evaluated using the remaining data. Significant differences in predictive performance are calculated using the Diebold–Mariano test statistic (Diebold & Mariano, 1995).

*Significance at the 10% level.

**Significance at the 5% level.

***Significance at the 1% level.

(z^+_{GDP}) as an example, we find that words about “year-on-year industry value added (IVA) growth”, “GDP deflator” and “money supply” are useful to construct the word repetition index of GDP, whereas words about policies in China, such as “improve the macroprudential policy framework” are important to the inclusion index. For other output-related target variables (IVA and FAI), we find that some price-related words are helpful, “term structure and operational intensity” and “loan financing,” for instance. The phrase “fixed asset investment (FAI)” contributes to the construction of FAI-based repetition indices. For price-related target variables, interest rate-related phrases such as “raise lending and deposit rates” and “money market interest rate” are pivotal. Inflation-related phrases such as “inflation” and “inflation expectation” are also important. Overall, we find that HDMR could select some important and meaningful words related to macro variables and macro polices.

4.3 | Comparison with the professional forecast

Since the forecasting performance that incorporates the PBC communication texts is quite appealing, a practical question is how good the predictions actually are. To answer that question, we compare the nowcasting results based on our statistical models with the professional forecast (PF) from Wind Information Co., Ltd. (Wind), the largest and most prominent data provider in China. All target variables except fixed asset investment (FAI) growth rate are available in the Wind forecasts. The mean forecast from Wind is used with the OOS evaluation starting from 2010:M1.

Table 6 presents these comparisons. A value less than 1 in the relative RMSE score indicates that the text-augmented forecast has a lower RMSE relative to the mean of the PF. Unlike the findings based on US data (Bianchi et al., 2022; Ellingsen et al., 2021), all four text-augmented predictions for GDP growth rate outperform the PF in our exercise. The differences in predictive performance are also statistically significant according to the DM test. Similar results could be found in nowcasting M2 except for the case of using macro factors and the word inclusion index of M2 (z^0_{M2}). In contrast, the PF predictions have a lower RMSE than our statistical model for other target variables, especially CPI. The PF predictions are better than our forecasts, and the differences are economically large and highly significant. However, those differences in nowcasting performance for IVA and PPI are not significant. Although the Wind forecasts outperform our text-augmented forecast combination in most cases, our text-augmented model works well in real-time nowcasting GDP and M2, indicating that the PBC communication texts seem to contain supplementary information beyond the professional forecasters' data.

5 | CONCLUSION

Central bank communication not only represents public textual data conveying monetary policy intentions but also describes current and future macroeconomic statuses. There are few applications for evaluating the value of these communication texts in real-time macroeconomic projections. Our work empirically provides a unified text analysis and real-time forecasting procedure with several conclusions as follows.

First, adding text-based PBC communication indices improves the real-time OOS prediction performance, particularly in long-term forecasting. Second, PBC communication indices measured by using full-sample and real-time data are relatively similar, and our main empirical results are robust for both pseudo and real-time OOS forecasting under numerous experimental setups. Third, the optimal model including communication texts varies with different target variables and forecast horizons, whereas at least one of them outperforms the benchmark. Finally, compared with professional forecasters, the model with PBC communication texts also seems to be attractive.

In short, this article focuses on modeling PBC communication and confirming its informational gains in macroeconomic projection based on a mixed-frequency framework and real-time information flow. Our empirical results provide strong evidence of the connection between central bank communication and macroeconomic projection, which leads to some new applications for textual data.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at http://qed.econ.queensu.ca/jae/datasets/lin004/.

DATA AVAILABILITY STATEMENT

Data is available at http://qed.econ.queensu.ca/jae/forthcoming/lin-et-al/.

REFERENCES

Aastveit, K. A., Gerdrup, K. R., Jore, A. S., & Thorsrud, L. A. (2014). Nowcasting GDP in real time: A density combination approach. *Journal of Business & Economic Statistics*, *32*(1), 48–68. https://doi.org/10.1080/07350015.2013.844155

Andreou, E., Ghysels, E., & Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business & Economic Statistics*, *31*(2), 240–251. https://doi.org/10.1080/07350015.2013.767199

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Beaupain, R., & Girard, A. (2020). The value of understanding central bank communication. *Economic Modelling*, *85*, 154–165. https://doi.org/10.1016/j.econmod.2019.05.013

Bernanke, B. S. (2013). *The Federal Reserve and the financial crisis*. Princeton University Press. https://doi.org/10.1515/9781400847167

Bernanke, B. S. (2020). The new tools of monetary policy. *American Economic Review*, *110*(4), 943–983. https://doi.org/10.1257/aer.110.4.943

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics*, *120*(1), 387–422.

Bianchi, F., Ludvigson, S. C., & Ma, S. (2022). Belief distortions and macroeconomic fluctuations. *American Economic Review*, *112*(7), 2269–2315. https://doi.org/10.1257/aer.20201713

Binder, C. (2017). Fed speak on main street: Central bank communication and household expectations. *Journal of Macroeconomics*, *52*, 238–251. https://doi.org/10.1016/j.jmacro.2017.05.003

Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D.-J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. *Journal of Economic Literature*, *46*(4), 910–945. https://doi.org/10.1257/jel.46.4.910

Boguth, O., Grégoire, V., & Martineau, C. (2019). Shaping expectations and coordinating attention: The unintended consequences of FOMC press conferences. *Journal of Financial and Quantitative Analysis*, *54*(6), 2327–2353. https://doi.org/10.1017/S0022109018001357

Bok, B., Caratelli, D., Giannone, D., Sbordone, A. M., & Tambalotti, A. (2018). Macroeconomic nowcasting and forecasting with big data. *Annual Review of Economics*, *10*(1), 615–643. https://doi.org/10.1146/annurev-economics-080217-053214

Born, B., Ehrmann, M., & Fratzscher, M. (2014). Central bank communication on financial stability. *The Economic Journal*, *124*(577), 701–734. https://doi.org/10.1111/ecoj.12039

Bybee, L., Kelly, B. T., Manela, A., & Xiu, D. (2020). The structure of economic news. National Bureau of Economic Research Working Paper Series, No. 26648.

Chang, C., Chen, K., Waggoner, D. F., & Zha, T. (2016). Trends and cycles in China's macroeconomy. *NBER Macroeconomics Annual*, *30*, 1–84. https://doi.org/10.1086/685949

Chen, K., Ren, J., & Zha, T. (2018). The nexus of monetary policy and shadow banking in China. *American Economic Review*, *108*(12), 3891–3936. https://doi.org/10.1257/aer.20170133

Clements, M. P., & Galvão, A. B. (2008). Macroeconomic forecasting with mixed-frequency data. *Journal of Business & Economic Statistics*, *26*(4), 546–554. https://doi.org/10.1198/073500108000000015

Coenen, G., Ehrmann, M., Gaballo, G., Hoffmann, P., Nakov, A. A., Nardelli, S., Persson, E., & Strasser, G. H. (2017). Communication of monetary policy in unconventional times. ECB Working Paper, No. 2080.

Di Filippo, G. (2015). Dynamic model averaging and CPI inflation forecasts: A comparison between the Euro area and the United States. *Journal of Forecasting*, *34*(8), 619–648. https://doi.org/10.1002/for.2350

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, *13*(3), 253–263.

Ellingsen, J., Larsen, V. H., & Thorsrud, L. A. (2021). News media versus FRED-MD for macroeconomic forecasting. *Journal of Applied Economics*, *37*(1), 63–81.

Fernald, J. G., Spiegel, M. M., & Swanson, E. T. (2014). Monetary policy effectiveness in China: Evidence from a FAVAR model. *Journal of International Money and Finance*, *49*, 83–103. https://doi.org/10.1016/j.jimonfin.2014.05.007

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). The generalized dynamic-factor model: Identification and estimation. *The Review of Economics and Statistics*, *82*(4), 540–554. https://doi.org/10.1162/003465300559037

Foroni, C., Marcellino, M., & Schumacher, C. (2015). Unrestricted mixed data sampling (MIDAS): MIDAS regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society: Series a (Statistics in Society)*, *178*(1), 57–82. https://doi.org/10.1111/rssa.12043

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as data. *Journal of Economic Literature*, *57*(3), 535–574. https://doi.org/10.1257/jel.20181020

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). *The MIDAS touch: Mixed data sampling regression models*. CIRANO Working Papers.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2006). Predicting volatility: Getting the most out of return data sampled at different frequencies. *Journal of Econometrics*, *131*(1–2), 59–95. https://doi.org/10.1016/j.jeconom.2005.01.004

Hansen, S., & McMahon, M. (2016). Shocking language: Understanding the macroeconomic effects of central bank communication. *Journal of International Economics*, *99*, 114–133. https://doi.org/10.1016/j.jinteco.2015.12.008

Hansen, S., McMahon, M., & Tong, M. (2019). The long-run information effect of central bank communication. *Journal of Monetary Economics*, *108*, 185–202. https://doi.org/10.1016/j.jmoneco.2019.09.002

Hanson, S. G., & Stein, J. C. (2015). Monetary policy and long-term real rates. *Journal of Financial Economics*, *115*(3), 429–448. https://doi.org/10.1016/j.jfineco.2014.11.001

Heij, C., van Dijk, D., & Groenen, P. J. F. (2011). Real-time macroeconomic forecasting with leading indicators: An empirical comparison. *International Journal of Forecasting*, *27*(2), 466–481. https://doi.org/10.1016/j.ijforecast.2010.04.008

Higgins, P., Zha, T., & Zhong, W. (2016). Forecasting China's economic growth and inflation. *China Economic Review*, *41*, 46–61. https://doi.org/10.1016/j.chieco.2016.07.011

Huang, Y., Ge, T., & Wang, C. (2020). Monetary policy framework and transmission mechanism. In M. Amstad, G. Sun, & W. Xiong (Eds.). *Handbook of China's financial system*. Princeton University Press.

Jiang, Y., Guo, Y., & Zhang, Y. (2017). Forecasting China's GDP growth using dynamic factors and mixed-frequency data. *Economic Modelling*, *66*, 132–138. https://doi.org/10.1016/j.econmod.2017.06.005

Jokubaitis, S., Celov, D., & Leipus, R. (2021). Sparse structures with LASSO through principal components: Forecasting GDP components in the short-run. *International Journal of Forecasting*, *37*(2), 759–776. https://doi.org/10.1016/j.ijforecast.2020.09.005

Kawamura, K., Kobashi, Y., Shizume, M., & Ueda, K. (2019). Strategic central bank communication: Discourse analysis of the Bank of Japan's Monthly Report. *Journal of Economic Dynamics and Control*, *100*, 230–250. https://doi.org/10.1016/j.jedc.2018.11.007

Kelly, B., Manela, A., & Moreira, A. (2021). Text selection. *Journal of Business & Economic Statistics*, *39*(4), 1–21. https://doi.org/10.1080/07350015.2021.1947843

Kelly, B., & Pruitt, S. (2015). The three-pass regression filter: A new approach to forecasting using many predictors. *Journal of Econometrics*, *186*(2), 294–316. https://doi.org/10.1016/j.jeconom.2015.02.011

Koopman, S. J., & Mesters, G. (2017). Empirical bayes methods for dynamic factor models. *The Review of Economics and Statistics*, *99*(3), 486–498. https://doi.org/10.1162/REST_a_00614

Larsen, V. H., & Thorsrud, L. A. (2019). The value of news for economic developments. *Journal of Econometrics*, *210*(1), 203–218. https://doi.org/10.1016/j.jeconom.2018.11.013

Larsen, V. H., Thorsrud, L. A., & Zhulanova, J. (2021). News-driven inflation expectations and information rigidities. *Journal of Monetary Economics*, *117*, 507–520. https://doi.org/10.1016/j.jmoneco.2020.03.004

Lehtimäki, J. O., & Palmu, M. (2019). Central bank communication and monetary policy predictability under uncertain economic conditions. *Journal of Central Banking Theory and Practice*, *8*, 5–32. https://doi.org/10.2478/jcbtp-2019-0011

Lima, L. R., Godeiro, L. L., & Mohsin, M. (2020). Time-varying dictionary and the predictive power of Fed minutes. *Computational Economics*, *57*(1), 149–181. https://doi.org/10.1007/s10614-020-10039-9

Lin, J., Chen, L., Luo, Z., & Zhang, Y. (2021). Does central bank communication improve macroeconomic forecasting?—High-dimensional sparse modeling based on text data. *Economic Research Journal*, *56*(3), 48–64.

Lucca, D. O., & Trebbi, F. (2009). Measuring central bank communication: An automated approach with application to fomc statements. Chicago Booth Research Paper, No. 09–34.

Ludvigson, S. C., & Ng, S. (2010). A factor analysis of bond risk premia. In A. Ullah & D. E. A. Giles (Eds.). *Handbook of empirical economics and finance* (Vol. 1, pp. 313–372). Chapman and Hall.

Ma, J., & He, X. (2020). China's interest rate liberalization. In M. Amstad, G. Sun, & W. Xiong (Eds.). *Handbook of China's financial system*. Princeton University Press.

McCracken, M. W., & Ng, S. (2016). FRED-MD: A monthly database for macroeconomic research. *Journal of Business & Economic Statistics*, *34*(4), 574–589. https://doi.org/10.1080/07350015.2015.1086655

McMahon, M., Schipke, A., & Li, X. (2018). China's monetary policy communication: Frameworks, impact, and recommendations. International Monetary Fund, WP/18/244, 1. doi:zhttps://doi.org/10.5089/9781484385647.001

Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, *133*(3), 1283–1330. https://doi.org/10.1093/qje/qjy004

PBC. (2021). China Monetary Policy Executive Report (in English). Retrieved from Beijing.

Richardson, A., van Florenstein Mulder, T., & Vehbi, T. (2021). Nowcasting GDP using machine-learning algorithms: A real-time assessment. *International Journal of Forecasting*, *37*(2), 941–948. https://doi.org/10.1016/j.ijforecast.2020.10.005

Shiller, R. J. (2017). Narrative economics. *American Economic Review*, *107*(4), 967–1004. https://doi.org/10.1257/aer.107.4.967

Shiller, R. J. (2019). *Narrative economics: How stories go viral and drive major economic events*. Princeton University Press.

Stock, J. H., & Watson, M. W. (2006). Forecasting with many predictors. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.). *Handbook of economic forecasting* (Vol. 1, pp. 515–554). North Holland.

Stock, J. H., & Watson, M. W. (2012). Generalized shrinkage methods for forecasting using many predictors. *Journal of Business & Economic Statistics*, *30*(4), 481–493. https://doi.org/10.1080/07350015.2012.715956

Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. *Handbook of Macroeconomics*, *2*, 415–525. https://doi.org/10.1016/bs.hesmac.2016.04.002

Thorsrud, L. A. (2020). Words are the new numbers: A newsy coincident index of the business cycle. *Journal of Business & Economic Statistics*, *38*(2), 393–409. https://doi.org/10.1080/07350015.2018.1506344

Timmermann, A. (2006). Forecast combinations. In G. Elliott, C. W. J. Granger, & A. Timmermann (Eds.). *Handbook of economic forecasting* (Vol. 1, pp. 135–196). North Holland.

Winkelmann, L. (2016). Forward guidance and the predictability of monetary policy: A wavelet-based jump detection approach. *Journal of the Royal Statistical Society: Series C: Applied Statistics*, *65*(2), 299–314.

Zhou, X. (2016). Managing multi-objective monetary policy: From the perspective of transitioning Chinese economy. The 2016 Michel Camdessus Central Banking Lecture, June 24, 2016, International Monetary Fund, Washington, DC.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Lin, J., Fan, J., Zhang, Y., & Chen, L. (2023). Real-time macroeconomic projection using narrative central bank communication. *Journal of Applied Econometrics*, *38*(2), 202–221. https://doi.org/10.1002/jae.2946