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Is the People's Bank of China consistent in words and deeds?

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ABSTRACT

The People's Bank of China (PBC) now frequently uses communication as a policy tool. Whether its words are consistent with its deeds is important for the public to understand the PBC's complex behavior. In this paper, we employ a supervised learning model to construct monetary policy (MP) and economic outlook (EC) communication indices based on the outlook section of quarterly China Monetary Policy Reports (MPRs). We find that the PBC not only adjusts its interventions according to the corresponding economic situation, but also takes into account the information released in the previous outlook section, which indicates its consistency in words and deeds. Using a time-varying parameter model, we further find that the PBC's consistency of words and deeds has made progress over time. The PBC tends to be more consistent in words and deeds under higher uncertainty, and the improvement of such consistency can significantly decrease disagreement about inflation expectations. An additional analysis shows that the full text of MPRs can help predict future monetary policies on a longer time horizon.

> "To me, that is the hallmark of credibility: matching deeds to words. … Credibility means that your pronouncements are believed – even though you are bound by no rule and may even have a short-run incentive to renege. In the real world, such credibility is not normally created by incentive compatible compensation schemes nor by rigid precommitment. Rather, it is painstakingly built up by a history of matching deeds to words."
>
> Alan Blinder, Central Bank in Theory and Practice (1998, page 64)

1. Introduction

Over the last several decades, central bank practice has undergone an important transition from "silence is golden" to

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"interpretation is policy". Especially since the 2008 global financial crisis, due to the zero lower bound on the nominal interest rate, central bank communication has become an important policy tool (Bernanke, 2020). In this context, the People's Bank of China (PBC) is no exception. Monetary policy communication has gradually developed as an important policy tool in China.

The mechanism and effectiveness of central bank communication have attracted great attention among researchers and policymakers.[1] Consistency in words and deeds can ensure the credibility of the central bank's communication and thereby strengthen the policy effect. However, there are two empirical challenges in studying the PBC's behavior. The first concerns China's monetary policy framework. During the process of transforming from quantitative monetary policy to price-based policy, the PBC has a number of policy instruments, several intermediate targets, and multiple policy objectives. Therefore, it is necessary to comprehensively measure the PBC's interventions. Second, the PBC's communication is in Chinese, and there is no available scheme for measuring the sentiments in the PBC's communication text.

Therefore, we first apply the supervised learning procedure proposed by Picault and Renault (2017) to generate a field-specific dictionary for the PBC communication to convert the "words" in China Monetary Policy Reports (MPRs) into meaningful quantities, that is, monetary policy and economic outlook communication indices. Considering the complexity of China's monetary policy framework, we then construct a comprehensive policy indicator by combining several policy variables to measure the "deeds" of the PBC. With a forward-looking monetary policy rule including the two communication indices, we find that the PBC is indeed consistent in words and deeds. The results show that the PBC adjusts current policy intervention according to the information released in the MPR of the previous quarter. Meanwhile, we conduct a thorough study on the time-varying model, finding that consistency in the words and deeds of the PBC has made apparent progress over time. Specifically, the PBC's words and deeds are more likely to be consistent under higher uncertainty. We also find that the improvement of consistency in words and deeds is conducive to reduce the public's disagreement about inflation expectations, indicating the importance of consistency in public expectation management. With the help of a Latent Dirichlet allocation (LDA) model, we also show that the discussions on economic situations in the full text of MPRs can help predict monetary policies on a longer horizon.

Our study relates to four strands of the literature on central bank communication. First, the impacts of central bank communication on the macroeconomy and financial markets have been widely considered and demonstrated by scholars (Aoki, Ichiue, Okuda, et al., 2019; Bernanke, 2013; Lamla & Vinogradov, 2019; McKay, Nakamura, & Steinsson, 2016). Through effective communication, the central banks can adjust the public's expectations by making monetary policy, such as nominal interest rates, more predictable (Coenen et al., 2017; Eusepi & Preston, 2010). In this way, central banks can promote the stability of output and inflation. In addition, many empirical studies consider the impacts of central bank communication on financial markets. Not only forward guidance (Hansen & McMahon, 2016) and the tone of central bank communication (Picault & Renault, 2017; Schmeling & Wagner, 2019) but also other factors such as semantic similarity (Ehrmann & Talmi, 2020) have significant effects on stock returns and bond yields.

Second, it is necessary to study whether the words and deeds of the central bank are consistent, which is an important prerequisite for ensuring its own authority and credibility (Lehtimaki & Palmu, 2019). Accurate and credible information has a greater impact on public expectations (Dong & Young, 2019; Nakata & Sunakawa, 2019). Honkapohja & Mitra, 2020 verify the impact of central bank credibility on monetary policy effectiveness under an adaptive learning framework, and Cole and Mart'ınez-Garc'ıa (2019) contain similar results with game theory. Other empirical studies also explore the relationship between communication and intervention in different economies, including the European Union (Beaupain & Girard, 2020; Bibow, 2004; Picault & Renault, 2017; Sturm & De Haan, 2011) the U.S. (Blinder, Ehrmann, Fratzscher, De Haan, & Jansen, 2008; Hansen & McMahon, 2016) and other developing countries, such as Turkey (Demiralp, Kara, & Ozlu, 2011), Brazil (Garc'ıa-Herrero, Girardin, & Santos, 2017), and Chile (Pincheira, Calani, & Landerretche, 2010). For China, the diversity of monetary policy tools has increased the difficulty for the public to understand actual policy intentions, which has become a potential problem affecting the effectiveness of monetary policy. Therefore, consistency in the PBC's words and deeds is even more crucial for expectation management.

Third, our paper links to studies on how to measure central bank communication. Early research manually coded central bank communication with discrete values (Romer & Romer, 1989), but it neglected subtle and continuous changes in policy tendencies and suffered from a lack of replicability (Rosa & Verga, 2007). With the introduction of the bag-of-words method (Tetlock, 2007), keyword-counting methods based on existing dictionaries, such as the Harvard Social Psychology Dictionary or the LM financial dictionary (Loughran & McDonald, 2011), have been widely used. However, as Picault and Renault (2017) point out, the dictionary method fails to capture all the dimensions and subtlety of central bank communication because these general dictionaries do not include concepts specific to central bank behavior. The supervised learning procedure proposed by Picault and Renault (2017) substantially enhances the accuracy and comprehensiveness of the information extraction by taking n-grams phrases into consideration. Meanwhile, the LDA model, one of the most popular unsupervised learning models, has been applied to measure the Federal Open Market Committee's (FOMC's) attitude toward economic situations (Hansen & McMahon, 2016) and information transparency (Hansen, McMahon, & Prat, 2018). The supervised learning and unsupervised LDA model are applicable to different scenarios according to the text features. We discuss the choice of text analysis methodology later in the paper.

Fourth, the PBC's communication has attracted increasing attention due to the development of the Chinese economy. Similar to the

[1] Empirical studies show that expectation management through communication at the zero lower bound can anchor consumers' inflation beliefs, which can effectively promote economic recovery (Aoki et al., 2019; Bernanke, 2013; Campbell et al., 2012). Hansen and McMahon (2016) find that communication has a significant impact on fluctuations of financial markets and real economic variables. Focusing on the impacts on the financial market, Schmeling and Wagner (2019) argue that the tone of central bank communication can move asset prices, while Beaupain and Girard (2020) find that communication can reinforce the central bank's actions and ease tensions in the sovereign debt markets.

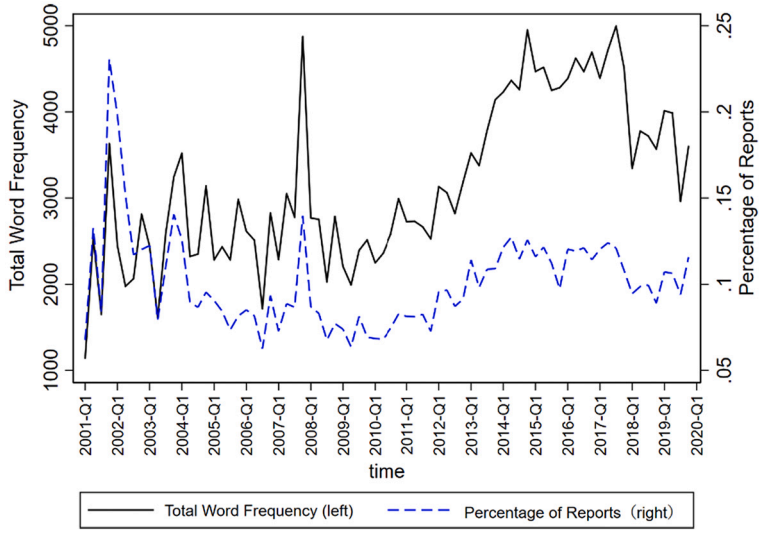


Fig. 1. Text Length of the Monetary Policy Outlook in the MPRs.
Note: This figure shows the total word frequency and percentage of the Monetary Policy Outlook section used in the quarterly China Monetary Policy Report. Quarterly reports are from 2001Q1 to 2019Q4 and are downloaded from the PBC's website.

central banks of developed countries, the PBC has increased its transparency and effectiveness through communication. As a result, the PBC's communication has a great impact on the financial market and real economic variables, such as market volatility, GDP and inflation. (Garcia-Herrero & Girardin, 2013; Sun, 2013; Sun, 2020). However, as McMahon, Schipke, and Li (2018) point out, although great progress has been made in China's monetary policy communication, it needs further improvement. China's monetary policy is difficult for the public to understand for two reasons. On the one hand, it includes the four policy objectives of maintaining price stability, boosting economic growth, promoting employment, and broadly maintaining balance of payments. On the other hand, as the framework changes from quantitative to price-based, monetary policy becomes more confusing, featuring the use of many types of policy tools (McMahon et al., 2018; Xiong, 2012). Therefore, to better manage the public's expectations, it is important for the PBC to release accurate information about the future policy path to the public, thereby improving monetary policy transparency.

In studying the consistency of the PBC's words and deeds, it is challenging to measure the "words" scientifically and objectively. First, it is important to ensure that words precede deeds. Hence, we retain only the last section in each MPR titled "Monetary Policy Outlook" (hereafter, the outlook section) as our dataset, see Subsection 2.1 for details. We adopt the supervised learning method of Picault and Renault (2017) to construct communication indices for its advantages, which determine the tone of each phrase by the term frequency summary statistics; see Section 3 for more details. This procedure takes the context of the phrases into consideration when determining their topics and tones. For example, the word "low" indicates a dovish stance in the sentences about interest rate, while it implies a hawkish stance when it comes to money supply. We determine the tone of "low" by the statistical method from Picault and Renault (2017) to avoid overly subjective determinations. Second, the supervised learning method allows us to construct communication indices of both monetary policy and economic outlook. Empirical studies have shown that while information about the monetary policy stance has significant effects, communication on the economic situation or other nonmonetary issues can have different effects (Cieslak & Schrimpf, 2019; Jarocin'ski & Karadi, 2020; Picault & Renault, 2017). In addition, we also show that we can predict the PBC's policy better by analyzing the full text of MPRs, for which the LDA model works well.

This paper contributes to the literature in three ways. First, with the help of the supervised learning method, we construct monetary policy (MP) and economic outlook (EC) communication indices. The measurements are significantly correlated to actual policy intervention and economic indicators, showing that our work is successful in extracting information from the PBC communication on the two essential topics.

Second, we systematically study the PBC's consistency of words and deeds with the communication indices measured. In sum, we find that the outlook section of the MPRs has significant explanatory power for policy intervention in the next quarter. The PBC tends to adjust its policy intervention based on the guidance released in the previous quarterly MPRs. However, the communication indices from supervised learning do not have strong predictive power for policy intervention over a longer time horizon. With the help of the LDA topic model, we can substantially enhance the predictive power when we take the full text of MPRs into account.

Third, we find evidence for the progress of monetary policy communication in China by a time-varying regression model, and the PBC has the incentive to be more consistent in words and deeds under higher uncertainty. Furthermore, we find that consistency in the words and deeds of the PBC indeed effectively decreases the public's disagreement about inflation expectations. These works provide a novel supplement to the literature regarding the influencing factors and macroeconomic effects of central bank communication in China.

This paper is organized as follows. Section 2 introduces the measurement in detail. Section 3 discusses the consistency of the words and deeds of the PBC via empirical studies. Section 4 presents further discussions, and Section 5 concludes.

Table 1
Examples of Sentence Classification.

Topic	Inclination	Sentence
Monetary Policy	Easing	2001Q3: Increase money supply at the right time to prevent further economic slowdown trend. 2010Q2: In the next stage, the People's Bank of China will continue to conscientiously implement the Scientific Outlook on Development, in accordance with the unified deployment of the State Council, and continue to implement moderately loose monetary policy.
	Tightening	2004Q1: The recent tendency of prudent monetary policy: moderately tight. 2008Q1: Putting more prominence on controlling inflation, insisting on implementing a tight monetary policy, enhancing the foresight and effectiveness of macro control, and making comprehensive use of various monetary policy tools to control the excessive growth of money and credit.
	Sound	2001Q1: For a period in the future, open market operations should be timely and appropriate "pre-adjustment" and "fine-tuning" to timely transmit the direction of monetary policy. 2019Q4: Implement a sound monetary policy, scientifically and steadily understand the strength of counter-cyclical adjustment, and maintain a reasonable abundance of liquidity.
Economic Outlook	Positive	2007Q2: At present, the international economic outlook is generally positive, the domestic economic growth momentum is strong, the economy is expected to continue to develop faster in the second half of 2007. 2016Q4: From an international perspective, the global economy shows a recovery trend in general, the growth of some developed economies may accelerate, the International Monetary Fund and other forecasts for 2017 global economic growth will exceed the previous year.
	Neutral	2004Q3: It is expected that in the fourth quarter, China's economic situation will continue to develop in the direction of expectations, the economic growth rate will fall back, price will tend to stabilize. 2018Q4: Downside risks to global economic growth have increased, but the overall recovery continues, with the IMF's forecast for economic growth in 2019 essentially unchanged from the average of previous years.
	Negative	2008Q4: Under the impact of the global financial crisis and other factors, the world economy may still tend to decline in the coming period, the recovery will take time, the economy will still face a tough external environment. 2019Q4: Domestic and foreign economies are in a period of adjustment, and the domestic economy is under downward pressure.
Others	None	2016Q3: We will strengthen the infrastructure construction and overall management of the financial market, and maintain the safe, efficient and overall stability of the market. 2019Q4: Continue to deepen the reform of large commercial banks and other large financial enterprises, and improve corporate governance.

Note: This table displays several examples of sentence classifications. The sentences related to the monetary policy content will classified into a tightening, sound or easing inclinations; those related to the economic outlook content will classified into a positive, neutral or negative inclinations.

2. Measurement of the PBC's communication

2.1. Text data source

The PBC uses the following four main channels to communicate with the public: (1) quarterly Monetary Policy Reports (MPRs); (2) press releases on Monetary Policy Committee meetings; (3) speeches and press conferences; (4) open market operation notices (McMahon et al., 2018). Among them, the quarterly MPRs issued by the People's Bank of China is the core medium of monetary policy information, which conveys timely, accurate and comprehensive information to the public (Sun, 2020; Xiong, 2012). The major sections of MPRs summarize the PBC's deeds by design, including money and credit analysis, monetary policy interventions, financial market conditions and macroeconomic overview. Moreover, the section titled "Monetary Policy Outlook" also includesfurther information on the Chinese economy and monetary policy in the next stage. For example, in early 2008, China saw a rapid rise in inflation, so it is made clear in the MPR that monetary policy in the next stage will focus on inflation control, and insist on a hawkish policy stance.

Studying consistency between words and deeds, we need to ensure that words proceed deeds. Hence, we retain only the "Monetary Policy Outlook" part of the MPRs, whose data sample is from 2001Q1 to 2019Q4.

2.2. The applicability of the supervised learning method

After selecting the text content, we apply the supervised dictionary method proposed by Picault and Renault (2017) to the last part of monetary policy reports, and extract key information about future policy stance and economic outlook. Our main consideration is based on the following two points:

First, the outlook section of MPRs tends not to convey information in a quite straightforward manner. Shen, Chen, and Huang (2019) believe that in view of the complexity of Chinese text and the carefully organized statements in the PBC communication, simple machine learning methods cannot easily identify the PBC's tone about the future monetary policy stance.

Second, the last part of the monetary policy reports is too short for the LDA model to take advantage of dimension reduction or clustering. As shown in Fig. 1, the share of the outlook section in the total quarterly report is only approximately 10%. Such short texts also make it possible to judge the direction sentence by sentence manually. Therefore, we refer to Picault and Renault (2017) to manually classify the sentences into different topics and tones, and construct indices about monetary policy and economic outlook through MPRs. Moreover, the supervised dictionary approach can preserve the professional wording of central bank communications, which is applicable to shorter texts. In addition, we also compare the results of supervised learning to those from the LDA model.

Table 2
Phrase frequency statistics (some examples).

Phrase	Phrase(in Chinese)	Frequency	Monetary Policy			Economic Outlook			Others	Inclination
			Easing	Sound	Tightening	Positive	Neutral	Negative		
Moderately loose monetary policy	适度宽松的货币政策	11	9	0	0	1	0	0	1	Easing
Maintain reasonable and sufficient liquidity	保持流动性合理充裕	7	4	2	1	0	0	0	0	Easing
Implement a prudent monetary policy	实施稳健的货币政策	23	3	11	7	0	0	0	0	Sound
Keeping the interest rate	保持利率	5	0	3	0	0	0	0	2	Sound
Moderately tight	适度从紧	6	0	0	6	0	0	0	0	Tightening
Controlling the growth of money and credit	控制货币信贷增长	6	0	1	4	0	0	0	1	Tightening
Maintain rapid growth	保持较快增长	21	0	0	0	13	4	2	2	Positive
High enthusiasm	热情较高	10	0	0	0	6	4	0	0	Positive
Relatively stable	相对稳定	24	0	1	2	2	14	1	4	Neutral
The overall economic operation is stable	经济运行总体平稳	11	0	0	1	0	9	0	1	Neutral
Existential uncertainty	存在不确定性	12	0	0	0	0	0	8	4	Negative
Economic downturn	经济下行	16	1	0	0	1	3	10	1	Negative

Note: This table shows, for a list of selected n-grams, the total frequency and the associated sub-frequency. For example, the phrase "moderately loose monetary policy" was pronounced 11 times in the outlook section from 2001Q1 to 2019Q4, and 9 occurrences among these 11 (82%) are in sentences about "dovish monetary policy". Consequently, it is classified as "easing".

2.3. Construction of the communication index

First, following Picault and Renault (2017), we classify all sentences into "monetary policy" (MP, hereafter), "economic outlook" (EC, hereafter) and "others" based on their main contents. Then, according to their tones, the sentences about monetary policy are further classified into three inclinations, namely: tightening, sound, and easing; while those about economic outlook have the three inclinations of positive, neutral, and negative.

The specific classification process is as follows. According to some common rules, two people with professional knowledge divide the sentence independently. If the two results are consistent, then the classification of the sentence will be determined directly; In the case of any inconsistency, an expert shall be added to discuss again to obtain the final division result, and confirm the previous consistent division result. It is also a common practice in the current literature (Hansen & McMahon, 2016; Picault & Renault, 2017). Summary statistics on the text dataset reveal that the outlook sections of all quarterly reports contain 4245 semantically complete sentences, of which 390 are related to MP (including 172 tightening, 94 sound, and 124 easing sentences), and 830 are related to EC (including 297 positive, 224 neutral, and 309 negative sentences). The remaining sentences are "others". Some examples are shown in Table 1.

Second, all sentences are divided into words using the Jieba package in Python software. Meanwhile, we consider the possible combination of words to form n-gram phrases. As Picault and Renault (2017) point out, considering only a single word rather than an n-gram phrase may lead to wrong inclination classification. For example, since the LM Financial Dictionary proposed by Loughran and McDonald (2011) assigns a negative sentiment to the word "unemployment", the phrase "low unemployment rate" will be mistaken for a negative sentiment. Gentzkow, Kelly, and Taddy (2019) also believed that the method of using n-gram phrases can avoid such errors. See Appendix A for specific n-gram phrase combination ideas and algorithms.

Third, we keep only the phrases that occur at least twice in the sample, and calculate the probability of phrases occurring in a sentence about monetary policy inclination (tightening, sound, and easing) or that about economic outlook inclination (positive, neutral, and negative). The probability of the phrase in the corresponding inclination is defined as:

$$p_n^{c,i} = \frac{f_n^{c,i}}{f_n} \tag{1}$$

where f_n is the total occurrence of the n-th phrase, $c = \{MP, EC\}$ means the topic, and $f_n^{MP,\,i}$ is the occurrence of the phrase in the MP topic with tendency i, where $i = \{tightening, sound, easing\}$ $f_n^{EC,\,i}$ is the number of occurrences of the phrase in the EC topic with tendency $i, i = \{positive, neutral, negative\}$. When $p_n^{c,\,i}$ is greater than 50%, it means that the n-th phrase has a clear inclination so that we include it in our lexicon specifically for China central bank communication. (Picault & Renault, 2017). This selection criterion produces a lexicon with 2838 phrases out of the 17,464 phrases in the whole corpus.

Table 2 lists some examples of n-gram phrases and reports the total number of occurrences, the number of occurrences in a certain topic, and the inclination. For example, "moderately loose monetary policy" appeared a total of 11 times in the sample, and for 9 of these times (82%), it appeared in the sentences classified as easing monetary policy, so its inclination is classified as easing.

Based on the lexicon generated above, the conditional probability that a report at time t belongs to a certain inclination of the MP topic or EC topic is calculated by

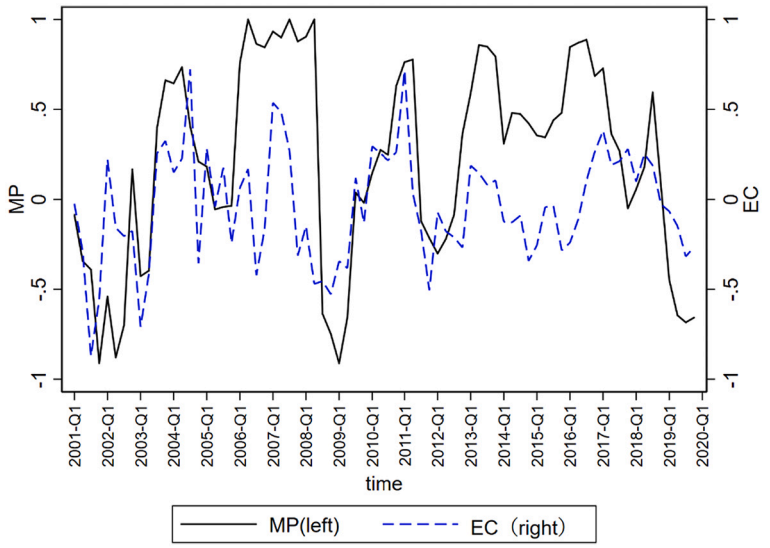


Fig. 2. Communication Indices: MP_t^{Sup} and EC_t^{Sup}.
Note: The communication indices are measured by the supervised learning method, based on the last part of monetary policy reports from 2001Q1 and 2019Q4. The Pearson correlation coefficient is 0.484, atsignificance level of 1%.

$$p_t^{MP,i} = \frac{\sum_{n=1}^{l} p_n^{MP,i} \times f_{n,t}}{\sum_{n=1}^{l} p_n^{MP} \times f_{n,t}}$$
$$p_t^{EC,i} = \frac{\sum_{n=1}^{l} p_n^{EC,i} \times f_{n,t}}{\sum_{n=1}^{l} p_n^{EC} \times f_{n,t}} \tag{2}$$

where $l = 2838$ (the number of n-grams in field-specific lexicon), $f_{n,\,t}$ is the number of the n-th phrase used at time t, and $p_n^{MP}$is the probability of the phrase in the MP topic $p_n^{MP} = \sum_{i=1}^{3} p_n^{MP,i}$, which is the same as $p_n^{EC} = \sum_{i=1}^{3} p_n^{EC,i}$.

Finally, the MP communication index MP_t^{Sup} is defined as the difference between the probability of tightening and the probability of easing, and the EC communication index EC_t^{Sup} is defined as the difference between the probability of a positive and the probability of a negative inclination:

$$MP_t^{Sup} = p_t^{MP,easing} - p_t^{MP,tightening}, MP_t^{Sup} \in [-1, 1]$$
$$EC_t^{Sup} = p_t^{EC,positive} - p_t^{EC,negative}, EC_t^{Sup} \in [-1, 1] \tag{3}$$

Fig. 2 shows our communication indices MP_t^{Sup} and EC_t^{Sup}. The Pearson correlation coefficient is 0.484, at significance level of 1%. A positive tone in economic outlook statements usually accompanies a hawkish tone in monetary policy reports. In general, the index can indicate the tendency of actual monetary policy intervention. For example, from the fourth quarter of 2001 to the third quarter of 2002, MP_t^{Sup} showed an easing trend, and the PBC increased the money supply at the same time. Since 2003, China has faced the pressure of high inflation, and the communication index has fallen. From the third quarter of 2008 to the fourth quarter of 2009, MP_t^{Sup} reached the highest value. Recently, the tone of communication is also relatively loose.

3. Consistency in words and deeds

3.1. Empirical model specification

In this section, we study the consistency in the PBC communication and its actual policy intervention. In particular, we examine whether the PBC implements monetary policy intervention in the current period according to the communication information released in the previous monetary policy reports. Following Lucca and Trebbi (2009), Hendry and Madeley (2010) and Picault and Renault (2017), we estimate the extended monetary policy reaction function for the period from Q1 2001 to Q4 2019:

$$PBC_t = \alpha + \rho PBC_{t-1} + \beta_1 MP_{t-1}^{Sup} + \beta_2 EC_{t-1}^{Sup} + \gamma_1 \Delta\left(\pi_t - \pi_t^*\right) + \gamma_2 \Delta\pi_t^e + \gamma_3 \Delta\widetilde{y}_t + \gamma_4 \Delta\widetilde{y}_t^e + \varepsilon_t \tag{4}$$

where PBC_t is the actual policy intervention at time t, with a positive value indicating a hawkish policy decision, MP_{t-1}^{Sup} and EC_{t-1}^{Sup} are lagged communication indices constructed by the supervised learning method. We expect significantly positive β_1 and β_2, which

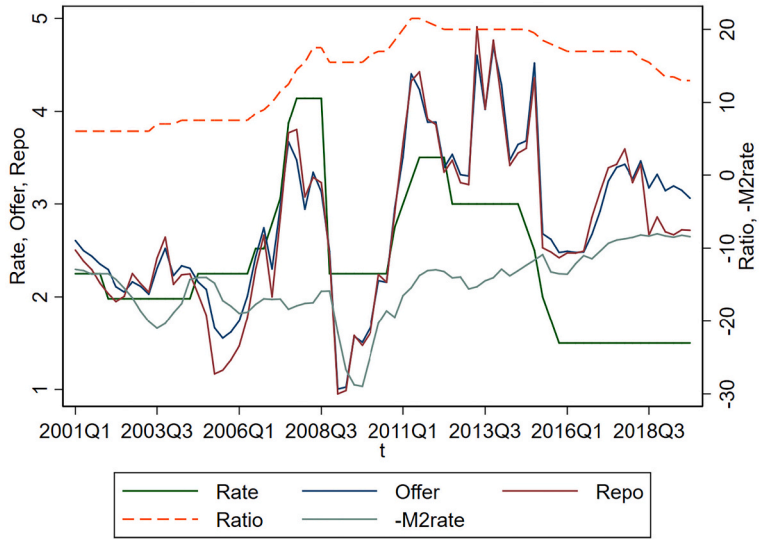


Fig. 3. Real Monetary Policy Intervention Indicators.
Note: A larger value of $M2Rate_t$ represents a dovish monetary policy stance, while the opposite is the case for the other variables. We use the opposite value of the $M2Rate_t$ to ensure consistent trends of all indicators.

implies that the PBC is consistent in words and deeds since both a hawkish tone and a positive economic outlook at time t-1 are expected to indicate a hawkish policy intervention at time t. We include the lagged intervention PBC_{t-1} to control for the smooth transition of monetary policy. $\Delta(\pi_t - \pi_t^*), \Delta\pi_t^e, \Delta\widetilde{y}_t, \Delta\widetilde{y}_t^e$ are the control variables, including the difference in inflation gap, inflation expectation, output gap and output gap expectation.

Specifically, we apply the HP filter to quarterly seasonally adjusted real GDP[2] and macroeconomic climate indicator (leading) to estimate the output gap $\widetilde{y}_t$ and expected output gap $\widetilde{y}_t^e$, respectively. For the inflation deviation $\pi_t - \pi_t^*$, we use the monthly year-on-year CPI growth rate as π_t and the inflation target announced by the National Development and Reform Commission as π_t^*. In addition, following the ideas of Picault and Renault (2017) and Andrade, Gaballo, Mengus, and Mojon (2019), the index of future price expectations published by the PBC is employed as a proxy variable for inflation expectation π_t^e.[3]

We use the first difference of macroeconomic variables for the sake of both stationarity and economic implications. The policy intervention PBC_t is constructed by the changes in five policy indicators, which is discussed in the next subsection. Note that the communication indices are expected to correlate with the change in policy indicators instead of their level. For example, a high value of MP_t^{Sup} implying a hawkish tone in communication does not necessarily indicate a higher interest rate, but rather an increase in the interest rate.

3.2. Measurement of the PBC's policy intervention

To measure policy intervention PBC_t, we need to consider the fact that China is moving from a quantitative policy to a more price-based policy framework (McMahon et al., 2018) and now employing a range of different instruments. No single indicator can adequately reflect the PBC's monetary policy interventions (Sun, 2013; Xiong, 2012). As Huang, Ge, and Wang (2019) point out, the transmission mechanism of China's monetary policy includes the following four main components: (1) operational instruments, including quantity-based instruments (such as required reserve ratios and open market operations) and price-based instruments (such as bank base deposits and lending rates); (2) operational targets, including reserves and the monetary base, among others; (3) intermediate targets, including money supply, bank credit and market interest rates; and (4) policy objectives related to growth, employment, inflation and external accounts, as mentioned above. Therefore, we measure China's monetary policy interventions from different perspectives.

To this end, we select the one-year deposit benchmark interest rates ($BMRate_t$) as a price-based instrument, and the required reserve ratio (RRR_t) as a typical quantitative instrument. For the intermediate targets, we choose the 7-day interbank offered rate ($IBOR_t$) and

[2] Raw macroeconomic data including real GDP, the inflation rate and a macroeconomic climate indicator (leading) are from the National Bureau of Statistics, CEInet Statistics Database and Wind.

[3] The PBC conducts a questionnaire survey of urban depositors every quarter, and one of the main questions is about the public's expectation of future price trends.

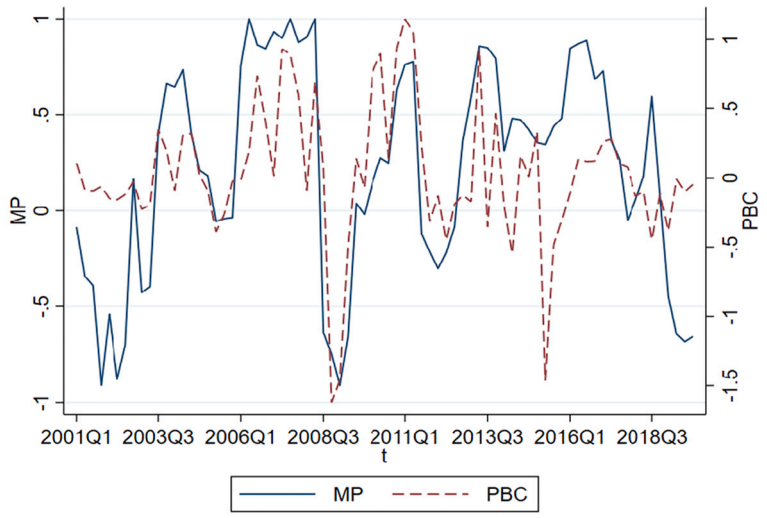


Fig. 4. MP Communication Index MP_t^{Sup} and Policy Intervention PBC_t.
Note: The communication -index MP_t^{Sup} is measured by the supervised learning method, based on the last part of monetary policy reports from 2001Q1 and 2019Q4. The policy intervention PBC_t is measured by five monetary policy tools comprehensively, including one-year deposit benchmark interest rates, the required reserve ratio, the 7-day interbank offered rate, the 7-day interbank pledged repo interest rate and the M2 growth rate.

Table 3
The Consistency in Words and Deeds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t
PBC_{t-1}	0.446***	0.284**	0.321***	0.235**	0.403***	0.262**	0.311***	0.228*
	(4.26)	(2.42)	(2.95)	(2.01)	(3.73)	(2.23)	(2.75)	(1.92)
MP_{t-1}^{Sup}		0.289***		0.205*		0.255**		0.204*
		(2.68)		(1.82)		(2.56)		(1.93)
EC_{t-1}^{Sup}			0.516***	0.398**			0.377**	0.257
			(2.93)	(2.15)			(2.17)	(1.42)
$\Delta(\pi_t - \pi^*)$					0.151**	0.147**	0.143**	0.143**
					(2.49)	(2.52)	(2.43)	(2.46)
$\Delta\pi_t^e$					0.011	0.010	0.005	0.006
					(1.00)	(0.98)	(0.49)	(0.62)
$\Delta\tilde{y}_t$					8.813	7.069	7.740	6.690
					(0.96)	(0.80)	(0.87)	(0.76)
$\Delta\tilde{y}_t^e$					0.016	0.020	0.021	0.023
					(0.33)	(0.44)	(0.43)	(0.49)
_cons	0.015	−0.05	0.037	−0.011	0.013	−0.041	0.030	−0.018
	(0.28)	(−0.84)	(0.74)	(−0.20)	(0.27)	(−0.80)	(0.63)	(−0.35)
N	75	75	75	75	75	75	75	75
R^2	0.199	0.272	0.284	0.316	0.364	0.420	0.405	0.437

Note: The regression results of Eq. (4), which examine whether the current action PBC_t is adjusted according to the communication in the previous quarter; MP_{t-1}^{Sup} and EC_{t-1}^{Sup} are measured by the supervised learning method, based on the last part of monetary policy reports from 2001Q1 and 2019Q4; t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7-day interbank pledged repo interest rate ($Repo_t$)[4] as price-based targets and the M2 growth rate[5] ($M2Rate_t$) as the quantitative target. Fig. 3 shows the five monetary policy variables in our sample period.[6]

Following Hansen and McMahon (2016) and Picault and Renault (2017), we measure the PBC's monetary policy stance based on the first difference of these five indicators as $PBC_{1t} = \Delta BMRate_t$,$PBC_{2t} = \Delta RRR_t$,$PBC_{1t} = \Delta IBOR_t$, $PBC_{1t} = \Delta Repo_t$and $PBC_{1t} = -\Delta M2Rate_t$. The comprehensive policy intervention indicator is given by

[4] Because only monthly data are available, we use transaction amount f and calculate the weighted average to obtain quarterly data: $\bar{i_t}(i_{t1}f_{t1} + i_{t2}f_{t2} + i_{t3}f_{t3})/(f_{t1} + f_{t2} + f_{t3})$.
[5] The quarterly M2 growth rate is represented by the three-month average.
[6] The raw Data are from the PBC's official website and CEInet Statistics Database.

Table 4
The Predicting Ability of Words for Future Deeds.

	(1)	(2)	(3)	(4)	(5)	(6)
	PBC_{t+2}	PBC_{t+2}	PBC_{t+2}	PBC_{t+3}	PBC_{t+3}	PBC_{t+3}
PBC_t	−0.009	−0.031	−0.028	0.004	−0.069	−0.005
	(−0.06)	(−0.24)	(−0.20)	(0.03)	(−0.50)	(−0.03)
MP_t^{Sup}	0.023		−0.009	−0.166		−0.179
	(0.18)		(−0.07)	(−1.19)		(−1.25)
EC_t^{Sup}		0.218	0.222		0.042	0.105
		(1.03)	(1.01)		(0.18)	(0.44)
$\Delta(\pi_t - \pi^*)$	0.143**	0.133*	0.134*	0.097	0.076	0.092
	(2.00)	(1.87)	(1.85)	(1.25)	(0.97)	(1.16)
$\Delta\pi_t^e$	0.007	0.008	0.008	0.014	0.015	0.014
	(0.64)	(0.70)	(0.69)	(1.11)	(1.17)	(1.12)
$\Delta\tilde{y}_t$	20.40*	16.54	16.62	18.458	14.226	16.592
	(1.96)	(1.51)	(1.50)	(1.62)	(1.17)	(1.35)
$\Delta\tilde{y}_t^e$	0.042	0.048	0.048	0.022	0.031	0.025
	(0.79)	(0.91)	(0.90)	(0.39)	(0.54)	(0.44)
_cons	0.031	0.044	0.046	0.083	0.042	0.089
	(0.50)	(0.79)	(0.71)	(1.20)	(0.69)	(1.25)
N	73	73	73	72	72	72
R^2	0.239	0.251	0.251	0.137	0.119	0.140

Note: The regression results of Eq. (6), which examine whether the current communication can predict future policy intervention; MP_t^{Sup} and EC_t^{Sup} are measured by the supervised learning method, based on the last part of monetary policy reports from 2001Q1 and 2019Q4; t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$$PBC_t = \sum_{i=1}^{5} \frac{PBC_{it}}{\max_t PBC_{it} - \min_t PBC_{it}} \tag{5}$$

Where maxPBC_{it}, min PBC_{it} represent the maximum and minimum change amplitudes, respectively.

Fig. 4 shows the monetary policy communication index MP_t^{Sup} and actual policy intervention indicator PBC_t. These two indicators are positively correlated, with a Pearson correlation coefficient of 0.510. Table C-1 presents descriptive statistics of all time series that we use in the whole empirical study; all series used in this subsection are stationary according to the Augmented Dickey-Fuller (ADF) test.

3.3. Baseline results

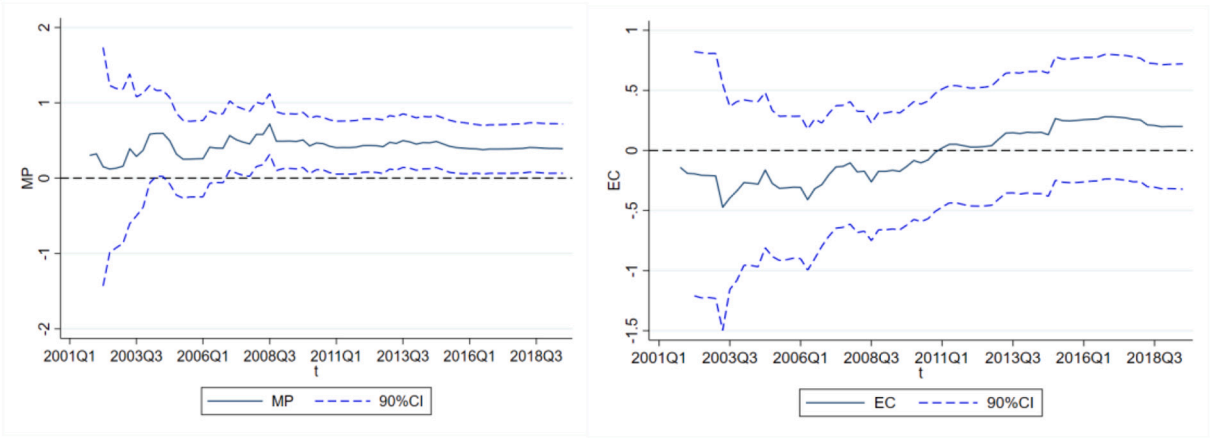
Table 3 reports the results for the baseline regression. In column (1), ρ is significantly positive, indicating that China's monetary policy has the characteristics of policy continuity and stability. In columns (2) and (3), the coefficients of MP_{t-1}^{Sup} and EC_{t-1}^{Sup} are significant at 1% level. When both MP_{t-1}^{Sup} and EC_{t-1}^{Sup} are included as in column (4), the coefficients of both indicators are still significant at the 10% and 5% levels respectively. With a hawkish tendency in monetary policy communication or positive economic outlook released in the MPR of the previous quarter, the actual intervention stance is tighter in the current stage. These results show that words and deeds of the PBC are consistent , that is, the PBC adjusts its intervention according to the guidance of communication.

Columns (5)–(8) show the results with the control variables. The coefficients of MP_{t-1}^{Sup} remain significant, indicating that the current monetary policy will not only adjust its interventions according to the economic situation in the corresponding period, but also take into account the policy tendency released by the last communication, so as to maintain the consistency between words and deeds and ensure the reputation of the central bank. Compared with columns (1)–(4), the R^2 is significantly improved after adding macroeconomic variables to the model, although only the inflation gap $\Delta(\pi_t - \pi_t^*)$ has a significant impact due to collinearity. In fact, when we control each macroeconomic variable separately, all variables have significant explanatory power except expected the output gap$\Delta\tilde{y}_t^e$.[7] Finally, the insignificance of the coefficients of EC_t^{Sup} implies that the economic outlook of the PBC does not convey extra information in addition to real macroeconomic data.

3.4. Predicting future policy stances

In addition to exploring whether the PBC adjusts the current intervention according to the previous communication information, we also want to investigate whether the current communication can predict the actual intervention changes in the future, and whether the central bank is consistent in its words and deeds from the perspective of prediction. To explore the predictability of the indices on future policies, we estimate the following regression model:

[7] This phenomenon also exists in the Table 4 and Table 8.



(a) Time-varying Coefficient of MP_{t-1}^{Sup} (b) Time-varying Coefficient of EC_{t-1}^{Sup}

Fig. 5. Time-Varying Coefficients of the Communication Indices.
Note: The time-varying regression results of Eq. (7), which examine whether the current action PBC_t is adjusted according to the communication in the previous quarter; MP_{t-1}^{Sup} and EC_{t-1}^{Sup} are measured by the supervised learning method, based on the last part of monetary policy reports from 2001Q1 and 2019Q4.

$$PBC_{t+h} = \alpha + \rho PBC_t + \beta_1 MP_t^{Sup} + \beta_2 EC_t^{Sup} + \gamma_1 \Delta(\pi_t - \pi^*) + \gamma_2 \Delta\pi_t^e + \gamma_3 \Delta\widetilde{y}_t + \gamma_4 \Delta\widetilde{y}_t^e + \varepsilon_{t+h} \tag{6}$$

Based on the benchmark regression results, the current communication can predict the actual intervention in the next period. Thus, we focus on $h = 2$ for the two-quarters ahead monetary policy intervention and $h = 3$ for the two-quarter-ahead intervention. Table 4 shows the regression results. The coefficients of MP_t^{Sup} and EC_t^{Sup} are not significant. The R^2 is much smaller than the results in Columns (5)–(8) in Table 1. It shows that the MPRs can only reflect the policy intervention in the next quarter and have no significant predictive power for the policy on a longer horizon.

To summarize, our results show that the PBC's communication truly leads to better understanding of its policy decisions. Monetary and non-monetary contents in central bank communication have different explanatory performance not only in Europe and the U.S. (Cieslak & Schrimpf, 2019; Hansen & McMahon, 2016; Picault & Renault, 2017) but also in China. Moreover, the results verify the necessity of considering information about monetary policy and the economic outlook since these information has different powers to explain the PBC's intervention. However, the PBC's communication only has no significant predictive power on the policy stance over a longer time horizon.

4. Further discussion

4.1. Time-varying effects and its influencing factors

China's monetary policy framework remains in transition, and communication is still evolving. It is necessary to examine the time-varying pattern of the relationship between central bank communication and actual interventions (Cogley & Sargent, 2005). Thus, following Kim and Nelson (2006), we introduce a time-varying parameter (TVP) regression model

$$PBC_t = \alpha_t + \rho_t PBC_{t-1} + \beta_{1t} MP_{t-1}^{Sup} + \beta_{2t} EC_{t-1}^{Sup} + \gamma_{1t} \Delta(\pi_t - \pi^*) + \gamma_{2t} \Delta\pi_t^e + \gamma_{3t} \Delta\widetilde{y}_t + \gamma_{4t} \Delta\widetilde{y}_t^e + \varepsilon_t \tag{7}$$

We estimate the time-varying coefficients by using the Kalman filter following Koop and Korobilis (2012). The estimation scheme is also recommended by Raftery, Ka'rny, and Ettler (2010), which can greatly reduce the computational burden without Monte Carlo procedures. Since the time-varying parameters of the first few periods are affected by the initial values,[8] we mainly focus on the time-varying coefficients after 2002. As Fig. 5 shows, words and deeds are not always consistent, but a changing process occurs. Specifically, the coefficient of EC_t^{Sup} is not significant all the time, which is consistent with the baseline result in Column (8) Table 3. However, MP_{t-1}^{Sup} shows significant explanatory power for monetary policy interventions after 2007.

For the time-varying pattern, we further explore the driving factors affecting the consistency in words and deeds of the PBC. The central bank's communication strategy might be affected by the business cycle (Siklos, 2013) and uncertainty. Chen, Ren, and Zha (2018) argue that the PBC responds asymmetrically in periods of good and bad economic conditions. Besides, Ehrmann, Gaballo,

[8] We use the OLS estimate results as the initial values here.

Table 5
Driving Factors of Consistency in the Words and Deeds of the PBC.

	(1)	(2)	(3)	(4)	(5)
	$\widehat{\beta}_{1t}$	$\widehat{\beta}_{1t}$	$\widehat{\beta}_{1t}$	$\widehat{\beta}_{1t}$	$\widehat{\beta}_{1t}$
t	0.022***	0.012***	0.027***	0.023***	0.021***
	(5.28)	(4.26)	(9.99)	(7.25)	(4.92)
ECI_t	0.018				0.039
	(0.38)				(1.38)
EPU_t		0.008***			0.006***
		(4.16)			(2.96)
MEU_t			6.297***		5.260***
			(5.68)		(4.05)
VIX_t				0.019**	−0.001
				(2.17)	(−0.08)
cons	−1.002	0.207	−1.435***	0.424*	−5.509*
	(−0.20)	(0.88)	(−3.33)	(1.96)	(−1.81)
N	72	72	70	72	70
R^2	0.480	0.598	0.584	0.530	0.661

Note: The regression results of Eq. (8), which explore the driving factors of consistency in words and deeds of the PBC; $\widehat{\beta}_{1t}$ is the estimated time varying coefficient of MP_{t-1}^{Sup} on PBC_t from 2001Q1 and 2019Q4; t statistics calculated by bootstrap in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Hoffmann, and Strasser (2019) find that monetary policy communication may become vague if the central bank does not have a clear picture of future economic situations to formulate policy plans. Thus, we regress $\widehat{\beta}_{1t}$ on a linear time trend term t and the proxy variables of economic outlook as well as domestic and global uncertainty:

$$\widehat{\beta}_{1t} = \alpha + \gamma_1 \cdot t + \gamma_2 ECI_t + \gamma_3 EPU_t + \gamma_4 MEU_t + \gamma_5 VIX_t + e_t \tag{8}$$

where ECI_t denotesthe economic climate indicator used as the proxy for the economic outlook. For China's economic uncertainty, we construct the macroeconomic uncertainty indicatorMEU_t using the stochastic volatility of the unpredictable components of more than 100 variables in China (Jurado, Ludvigson, & Ng, 2015). The China economic policy uncertainty indicator EPU_t is provided by Huang and Luk (2020).[9] To measure global uncertainty, we use volatility index VIX_t as a proxy.[10] The reason why we control the time trend term is to describe the trend that the PBC has strengthening policy interpretation and information disclosure.

As shown in Table 5, the coefficients of the time trend are always significantly positive, implying the gradual improvement of the consistency between words and deeds. The economic climate indicator ECI_t is not significantly correlated with the consistency in words and deeds. Siklos (2013) shows that the central bank tends to adjust the macroeconomy by managing public expectations through communication during recession periods. This phenomenon is not evident in China based on our empirical findings. Domestic economic uncertainty MEU_t and policy uncertainty EPU_t have significantly positive effects on the time-varying consistency. This indicates that the PBC has more incentive to adjust the current policy intervention according to the pre communication information to ensure reputation under high uncertainty. From the significantly positive coefficient of VIX_t in column (4), we can see that global economic uncertainty can also facilitate the consistency of the PBC's words and deeds. In column (5), the coefficient of VIX_t is no longer significant when all other variables are contained in the model, showing that domestic uncertainty plays a more important role than external uncertainty in PBC's consistency of words and deeds.

The literature has found that central bank communication may become vague under high uncertainty (Demertzis & Hallet, 2004). Distinct from the central banks in other developed economies, the PBC makes efforts to be more consistent in words and deeds, perhaps to guide market expectations to avoid the negative impact of high uncertainty.

4.2. Can consistency of words and deeds reduce disagreement about inflation expectation?

Disagreement in expectations will damage the effectiveness of monetary policy transmission (Falck, Hoffmann, & Hürtgen, 2021) and the implementation effect of fiscal policy (Ricco, Callegari, & Cimadomo, 2016). Since a monetary policy stance is a crucial factor of inflation expectation, accurate information from the PBC about policy can affect the public's view on future inflation. In this subsection, we examine whether consistency in the words and deeds of the PBC can effectively decrease disagreement about inflation expectations. We consider the following regression model:

$$DIS_t = \alpha + \gamma_1 \cdot t + \gamma_2 \widehat{\beta}_{1t} + \gamma_3 EPU_t + \gamma_4 MEU_t + \gamma_5 VIX_t + e_t \tag{9}$$

[9] Data source: https://economicpolicyuncertaintyinchina.weebly.com. The EPU_t is constructed by the number of articles about economic policy uncertainty in Chinese media news, following Baker, Bloom, and Davis (2016)
[10] The data source: Wind.

Table 6
Disagreement and Consistency in Words and Deeds.

	(1)	(2)	(3)	(4)	(5)
	DIS_t	DIS_t	DIS_t	DIS_t	DIS_t
t	0.002***	0.002**	0.002*	0.003***	0.002**
	(2.81)	(2.28)	(1.87)	(4.15)	(2.18)
$\widehat{\beta}_{1t}$	−0.071**	−0.091***	−0.054**	−0.089***	−0.069***
	(−2.51)	(−3.22)	(−2.05)	(−3.77)	(−2.76)
EPU_t		0.001**			0.000
		(2.22)			(0.35)
MEU_t			−0.219		−0.440
			(−0.58)		(−1.21)
VIX_t				0.003**	0.004*
				(2.22)	(1.81)
cons	0.935***	0.896***	0.992***	0.870***	0.995***
	(38.35)	(25.62)	(7.66)	(20.86)	(7.90)
N	72	72	70	72	70
R^2	0.167	0.206	0.159	0.258	0.270

Note: The regression results of Eq. (9), which explore whether consistency in the words and deeds of the PBC can reduce the disagreement about inflation expectations; $\widehat{\beta}_{1t}$ is the estimated time varying coefficient of MP_{t-1}^{Sup} on PBC_t from 2001Q1 and 2019Q4; t statistics calculated by bootstrap in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

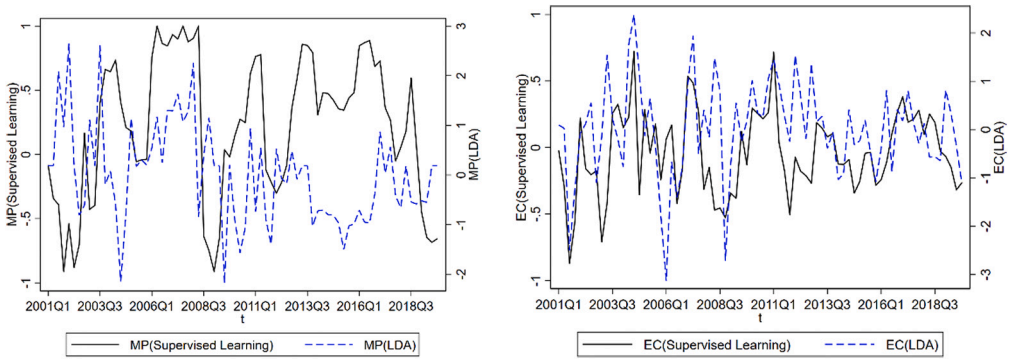


Fig. 6. Communication Indices Using LDA and Supervised Learning.
Note: MP_t^{LDA},MP_t^{Sup},$EC_t^{LDA}$and $EC_t^{Sup}$are measured by the supervised learning method or LDA model, based on the last part of monetary policy reports from 2001Q1 and 2019Q4. The correlation coefficient between $MP_t^{LDA}$and MP_t^{Sup} is −0.038 and insignificant, the correlation coefficent between$EC_t^{LDA}$and EC_t^{Sup} is 0.366, which is significant at the 1% level.

DIS_t is the disagreement about inflation expectations, which is measured with the quarterly survey data of urban depositors about inflation expectations. We include time trend t and the uncertainty as covariates to control the factors that may affect disagreements about inflation expectations. The PBC randomly selects 20,000 depositors in 50 cities across the country to conduct a questionnaire survey every quarter to ask the respondents about their expectations about future prices. The options include "rise", "fall" and "unchanged". Let *up*and *down* denote the proportions of the survey participants who choose "rise" and "fall" options, respectively. Following Meinusch and Tillmann (2017), we measure disagreement about inflation expectation as $DIS_t = 1 - (up - down)^2$.

Table 6 shows the regression results. From the significantly positive coefficients of the uncertainty indicators in Columns (2) and (4), we can see that higher uncertainty can cause more severe disagreement among the public. In all columns, the coefficients of the time-varying consistency are significantly negative at the 5% level. Consistency in words and deeds of the PBC indeed effectively decreases the public's disagreement about inflation expectations, indicating the importance of consistency in public expectation management.

4.3. Comparison to the LDA model based on the outlook section

To verify the reasonability of the choice of methodology, we also test the performance of the popular LDA topic model on the outlook section of the MPRs. Considering the length of the text, we set the number of topics as $K = 20$. Based on the phrase tones and outputs of the topic information from the LDA model, we construct another two communication indices namely, MP_t^{LDA} and EC_t^{LDA}. Detailed technical illustrations are available in Appendix B.

The measurement results are shown in Fig. 6. The results show that there are great differences between the MP indices constructed

Table 7
Comparison of Different Text Analysis Methods.

	Supervised learning method				The LDA model			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t	PBC_t
PBC_{t-1}	0.284**	0.321***	0.235**	0.228*	0.442***	0.405***	0.390***	0.328***
	(2.42)	(2.95)	(2.01)	(1.92)	(4.21)	(3.60)	(3.44)	(2.84)
MP_{t-1}	0.289***		0.205*	0.204*	0.049		0.063	0.047
	(2.68)		(1.82)	(1.93)	(0.93)		(1.17)	(0.94)
EC_{t-1}		0.516***	0.398**	0.257		0.057	0.071	0.088
		(2.93)	(2.15)	(1.42)		(0.99)	(1.22)	(1.64)
$\Delta(\pi_t - \pi^*)$				0.143**				0.164***
				(2.46)				(2.70)
$\Delta\pi_t^e$				0.006				0.008
				(0.62)				(0.74)
$\Delta\tilde{y}_t$				6.690				8.334
				(0.76)				(0.91)
$\Delta\tilde{y}_t^e$				0.023				0.019
				(0.49)				(0.41)
_cons	−0.05	0.037	−0.011	−0.018	0.015	0.015	0.016	0.014
	(−0.84)	(0.74)	(−0.20)	(−0.35)	(0.28)	(0.29)	(0.30)	(0.29)
N	75	75	75	75	75	75	75	75
R^2	0.272	0.284	0.316	0.437	0.209	0.210	0.225	0.392

Note: The regression results of Eq. (4), which examine whether the current action PBC_t is adjusted according to the communication in the previous period; MP_{t-1} and EC_{t-1} are measured by the supervised learning method or LDA model, based on the last part of monetary policy reports from 2001Q1 and 2019Q4; t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8
Predicting Future Policy Using different text.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PBC_{t+2}	PBC_{t+2}	PBC_{t+2}	PBC_{t+2}	PBC_{t+3}	PBC_{t+3}	PBC_{t+3}	PBC_{t+3}
PBC_t	−0.009	−0.031	−0.088	−0.074	0.004	−0.069	−0.157	−0.072
	(−0.06)	(−0.24)	(−0.68)	(−0.54)	(0.03)	(−0.50)	(−1.13)	(−0.50)
MP_t^{Sup}	0.023			−0.070	−0.166			−0.266*
	(0.18)			(−0.53)	(−1.19)			(−1.87)
EC_t^{Sup}		0.218		0.108		0.042		−0.059
		(1.03)		(0.48)		(0.18)		(−0.25)
$EC_t^{LDA,\ all}$			14.864**	14.929*			16.168**	21.464**
			(2.01)	(1.82)			(2.00)	(2.47)
$\Delta(\pi_t - \pi^*)$	0.143**	0.133*	0.112	0.113	0.097	0.076	0.040	0.061
	(2.00)	(1.87)	(1.59)	(1.57)	(1.25)	(0.97)	(0.53)	(0.79)
$\Delta\pi_t^e$	0.007	0.008	0.008	0.008	0.014	0.015	0.015	0.014
	(0.64)	(0.70)	(0.67)	(0.67)	(1.11)	(1.17)	(1.22)	(1.12)
$\Delta\tilde{y}_t$	20.403*	16.543	12.841	11.890	18.458	14.226	6.066	9.712
	(1.96)	(1.51)	(1.20)	(1.06)	(1.62)	(1.17)	(0.52)	(0.80)
$\Delta\tilde{y}_t^e$	0.042	0.048	0.033	0.034	0.022	0.031	0.022	0.006
	(0.79)	(0.91)	(0.65)	(0.64)	(0.39)	(0.54)	(0.40)	(0.10)
_cons	0.031	0.043	−0.117	−0.098	0.083	0.042	−0.128	−0.117
	(0.50)	(0.79)	(−1.25)	(−0.97)	(1.20)	(0.69)	(−1.25)	(−1.09)
N	73	73	73	73	72	72	72	72
R^2	0.239	0.251	0.283	0.288	0.137	0.119	0.170	0.216

Note: The regression results of Eq. (10), which examine whether the current communication can predict the future policy intervention; MP_t^{Sup} and EC_t^{Sup} are measured by the supervised learning method, based on the last part of monetary policy reports, $EC_t^{LDA,\ all}$ are measured by the LDA model based on the whole reports from 2001Q1 and 2019Q4; t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

by the two methods, while the EC indices share some correlation.

We further compare the empirical results with the indices by these two methods through the regression Eq. (4) again, with the communication indices replaced by those from the LDA model.

The indices constructed by the LDA model do not provide effective information to explain the policy stances, as shown in Table 7. Columns (1)–(4) show that MP_{t-1}^{Sup} andEC_{t-1}^{Sup} have a significant and positive impact on current intervention, while the two communication indices based on the LDA model in columns (4)–(8) have no significant explanatory power for the monetary policy intervention. In addition, supervised learning still dominates the LDA method from the perspective of goodness of fit. This comparative study clearly shows that compared to the LDA model, the supervised learning procedure is more suitable for the study of the PBC's consistency between words and deeds with the outlook section only.

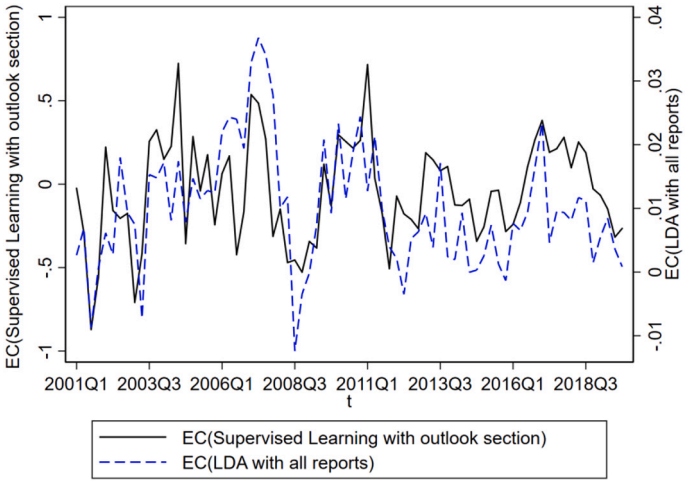


Fig. 7. Economic Communication Indices Using Different Text.
Note: EC_t^{Sup} is measured by the supervised learning method, based on the last part of monetary policy reports, $EC_t^{LDA,\ all}$ are measured by the LDA model based on the entire reports from 2001Q1 to 2019Q4. The correlation coefficient between the two indicies is 0.570, which is significantat the 1% level.

4.4. Can the full text of MPRs help predict policy on a longer horizon?

In the previous analysis, we find that the information in the outlook section has no prediction ability for further policy interventions. Then can the full text of MPRs help predict policy on a longer horizon? To answer this question, we use the LDA model to construct communication indices based on the full text of the MPRs. On the premise of consistency in words and deeds, the description of current monetary policy has been reflected by the actual intervention PBC_t.[11] Thus, we focus only on the economic outlook index here. We consider the LDA model with $K = 40$ topics and select 12 of them for the $EC_t^{LDA,\ all}$ index. The technical details again follow the illustrations in Appendix B. As shown in Fig. 7, $EC_t^{LDA,\ all}$ has a strongly positive correlation with EC_t^{Sup} based only on the outlook section. We then run the following regression model

$$\begin{aligned} PBC_{t+h} = {} & \alpha + \rho PBC_t + \beta_1 MP_t^{Sup} + \beta_2 EC_t^{Sup} + \beta_3 EC_t^{LDA,all} \\ & + \gamma_1 \Delta(\pi_t - \pi^*) + \gamma_2 \Delta\pi_t^e + \gamma_3 \Delta\widetilde{y}_t + \gamma_4 \Delta\widetilde{y}_t^e + \varepsilon_{t+h} \end{aligned} \tag{10}$$

The empirical results in Table 8 show that the economic situation communication index $EC_t^{LDA,\ all}$ measured based on the entire reports can effectively predict the actual policy intervention in the next two or three quarters, while such predictive power cannot be seen from $MP_t^{Sup}$and EC_t^{Sup} . $EC_t^{LDA,\ all}$ also substantially improves the goodness of fit. Therefore, using the LDA model to analyze the full text of MPRs can effectively improve the predictive power of the communication contents for future monetary policies. This result again emphasizes that we need to screen a suitable text dataset according to different research purposes, and adopt appropriate text analysis methods based on text features.

5. Conclusion

Communication has currently become an important tool for central banks, and its effectiveness depends on consistency in words and deeds. In this paper, we consider China's monetary policy practice, and focus on the PBC's communication. We first extract information from the PBC's Monetary Policy Reports through the supervised learning method, and construct two indices to measure the tone of the statements on monetary policy and the economic outlook. We show that the PBC adjusts its current policy intervention in line with the monetary policy and economic outlook communication indices in the last quarter's report. Meanwhile, the current communication can predict further policy intervention. In addition, we show a time-varying pattern for the consistency in the PBC's words and deeds and find that the PBC is more likely to improve consistency under high economic uncertainty. Subsequently, we find that the progress in the PBC's consistency in words and deeds can decrease disagreement about inflation expectations, which illustrates the importance of consistency in expectation management. With the help of the LDA model, we have a better prediction of future policy interventions by analyzing the full text of the MPRs.

Although this paper builds a comprehensive indicator to measure actual monetary policy interventions, our measure does not reflect the differences between the PBC's quantitative and price-based instruments. Nowadays the effectiveness of money supply continues to decline, and the continuous advancement of the interest rate marketization process provides the conditions for China's

[11] We thank the editor for this insightful comment.

transition to price-based regulation. In the future, we may further discuss the change in the PBC's communication and consistency in words and deeds under a price-based policy framework. In addition to the MPRs, oral communication, such as speeches and talks, is also a useful tool in China. Again, we believe that it is particularly important to choose appropriate text analysis methods according to the text features when studying the effects of oral communication by the PBC or differences among various communication tools.

Data availability

Data will be made available on request.

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Appendix A

A.1. Text Data Pretreatment

To extract information more precisely, contiguous terms are combined into a phrase if the combination is a common expression. N-gram phrase generation is performed through the following steps:

Step 1. Divide the entire text by punctuation and apply jiebaR to segment the short sentences. Numbers and stop words, such as "too" and "afterward", are deleted in this step.

Step 2. Combine single terms into phrases. A phrase includes no more than 5 terms. For example, there are six terms in a short sentence: A, B, C, D, E and F (a term can consist of multiple Chinese characters). Thus, we obtain 14 phrases in total, including "AB", "ABC", "ABCD", "ABCDE", "BC", "BCD", "BCDE", "BCDEF", "CD", "CDE", "CDEF", "DE", "DEF" and "EF".

Step 3. Summarize the total occurrence of each phrase. Drop the phrases that appear fewer than 5 times in the whole corpus. This step lowers the calculation complexity. Phrases with extremely low frequency usually share a low probability of appearing across all topics, making almost no difference to the LDA results.

Step 4. Keep the longest phrase. More precisely, if the frequency of phrase "ABCD" is not greater than that of phrase "ABCDE", then the former is dropped.

Then a phrase dictionary is generated, as shown in Table A-1 with some example phrases. This dictionary is used as a user dictionary for Jieba, allowing us to prevent some special phrases from being divided. More precisely, suppose that there is a sentence consisting of 9 terms "ABCDEFGHI", and phrases "ABCDE" and "HI" are in the user dictionary. Then the sentence will be divided into "ABCDE/F/G/HI" instead of "A/B/C/D/E/F/G/H".

Table A-1
Some n-gram Phrases Examples.

n-gram Phrases	Original word segmentation results
open market operations	open/market/operations
weighted average interest rate	weighted average/interest rate
RMB exchange rate formation mechanism	RMB/exchange rate/formation mechanism
emerging market economies	emerging market/economies
prices rose year on year	prices/rose/year on year

Appendix B. The LDA Model

B.1. Model Description and Choice of Tuning Parameters

The LDA model, a text mining method proposed by Blei, Ng, and Jordan (2003), can group words into different topics. Porteous et al. (2008) proposed a Gibbs sampling scheme to estimate an LDA model in the Bayesian framework. Here, we focus on how to use the LDA model to analyze and interpret central bank communication. Mathematical explanations can be found in Heinrich (2005) for more details. In the LDA model, both the occurrence of topics in each document and the occurrence of phrases in each topic follow multinomial distributions. In a Bayesian estimation, the parameters of a multinomial distribution are regarded as random variables, and Dirichlet distributions are very often used as their prior distributions.

The required inputs of the LDA model include (1) a corpus with Ddocuments, which are pretreated with standard procedures; (2) a vocabulary list including V phrases; (3) number of topics K; and (4) hyperparameters in the prior Dirichlet distributions.

The main outputs of the LDA model are two matrices, specifically, ϕ and θ. The $K \times V$ matrix ϕexhibits the probability of the appearance of every phrase in each topic. The matrix ϕ with elements $\phi_{k,\,v} = P\{Phrase_v | Topic_k\}$ is

$$\begin{array}{lcccc} & Phrase_1 & Phrase_2 & \cdots & Phrase_V \\ Topic1 & \phi_{1,1} & \phi_{1,2} & \cdots & \phi_{1,V} \\ Topic2 & \phi_{2,1} & \phi_{2,2} & \cdots & \phi_{1,V} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ TopicK & \phi_{K,1} & \phi_{K,2} & \cdots & \phi_{K,V} \end{array} \tag{B.1}$$

where $k = 1, 2, \ldots, K$ and $v = 1, 2, \ldots, V$. We can infer what topic k is mainly about based on key phrases with the highest values of $\phi_{k,v}$. For example, if the phrases "monetary supply" and "interest rate" appear in the same topic with high probability, then we can interpret this topic to be monetary policy (Hansen et al., 2018; Hansen & McMahon, 2016; Larsen & Thorsrud, 2019). Matrix θ with elements$\theta_{d,k} = P\{ Topic_k | Document_d\}$ captures the topic distributions in all documents, which is given by

$$\begin{array}{lcccc} & Topic_1 & Topic_2 & \cdots & Topic_K \\ Document_1 & \theta_{1,1} & \theta_{1,2} & \cdots & \theta_{1,K} \\ Document_2 & \theta_{2,1} & \theta_{2,2} & \cdots & \theta_{1,K} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Document_D & \theta_{D,1} & \theta_{D,2} & \cdots & \theta_{D,K} \end{array} \tag{B.2}$$

where $d = 1, 2, \ldots, D$are tokens of documents. We use θ to construct the communication indices.

In our study, we have only 76 Monetary Policy Reports, and all the reports have similar structures and topics, which may cause poor performance of the LDA model. Several studies that process text data on central bank communication provide a two-step solution. For example, Hansen et al. (2018) treat each statement in an FOMC meeting as a document to estimate the topic-word distribution, and then treat all statements from each speaker as an aggregate document to estimate the topic distribution of each speaker's statements. Hansen, McMahon, and Tong (2019) estimate the topic-word distribution of the Bank of England's Inflation Report at the paragraph level, and then estimate the topic distribution in every whole report. Following this two-step method, we first treat each paragraph as a document (D documents, denoted by $Document_d$, $d = 1, 2, \ldots, D$) to estimate the topic-phrase matrix $\widehat{\phi}_{K\times V}$and the document-topic matrix $\widehat{\theta}_{D\times K}$ and then treat each report as a document ($T = 76$quarterly reports, denoted by $Report_t$, $t = 1, 2, \ldots, T$) to update the document-topic matrix into $.\widetilde{\theta_{T\times K.}}$

For the first step, the selection of the hyperparameters of the LDA model is important. In this paper, we set $\alpha = 50/K$ and $\eta = 0.025$ (Hansen et al., 2018). A low value of η allows the topics to feature a limited number of prominent words, making the topics easy to interpret (Griffiths & Steyvers, 2004). Meanwhile, the ability of LDA to generate easy-to-interpret topics depends on the number of topics, K. Considering the length of the last part of reports, we set the number of topics to 20,$K = 20$. For all long reports, we set $K = 40$.

B.2. Topic Selection

Following Hansen et al. (2018), we select topics containing useful information about monetary policy or the economic outlook. However, the effect of topic extraction is far from that based on all reports. In addition, most of these keywords are nouns and have no tendency, which is not conducive to inferring whether the overall policy direction is loose or tight. We select 3 topics related to monetary policy (MP) and 3 topics related to economic outlook (EC). Fig. B-1 shows word clouds for three monetary policy topics. In each cloud, a larger size of a character or set of characters implies a higher probability in the topic. For example, within Topic 9, the phrases "next stage" and "maintain continuity and stability in policies" account for a large proportion of the phrases, while the phrase "monetary policy tools" occupy the main positions in Topic 15. Fig. B-2 shows three topics related to the economic outlook. We can easily observe that Topic 6 is about inflation, Topic 8 is about the overall economic situation and Topic 10 is about economic restructuring.

(a) Topic 2 (b) Topic 9 (c) Topic 15

Fig. B-1. Topics for MP in the Outlook Section.

Note: The top 10 meaningful phrases with the highest probability in (a) Topic 2: increase, Eurozone, capital flows, continue to optimize, expectation, strengthen liquidity management, deposit reserve ratio, interest rate, open market operation; (b) Topic 9: next stage, timely, main policy ideas, maintain continuity and stability in polices, improve finance condition, The People's Bank of China, continue to implement a sound monetary

policy, sustainable development, further improve the regulation effect, structure; (c) Topic 15: changes, monetary policy tools, as the whole, monitor, portfolio of monetary policy tools, balance, economic restructuring, reasonable growth of financing scale, macro prudential management.

(a) Topic 6 (b) Topic 8 (c) Topic 10

Fig. B-2. Topics for EC in the Outlook Section.
Note: The top 10 meaningful phrases with the highest probability in (a) Topic 6: influence, international, price, inflation expectations, resources, the near future, pressure, rise in price, preventing financial risks, commodity price; (b) Topic8: economy, global economy, price, China's macroeconomic outlook, structural adjustment, challenge, relatively stable, long-term, uncertainty, outlook; (c) Topic 10: economic growth, investment, consumption, enhance, structural adjustment, export, continue, price, promote, downward pressure.

The topics extracted this time have a clearer economic meaning based on the entire reports as shown in Fig. B-3.

(a) Topic 16: Consumption (b) Topic 27: Economic Growth (c) Topic 35: Economic Restructuring

Fig. B-3. Topics for EC in the Entire Reports.
Note: The top 10 phrases with the highest probability in (a) Topic 16: consumption, resident, investment, enhance, inflation-adjusted effective growth, drive, consumption demand, improve, GDP, deposit; (b) Topic 27: overall, economy, economic growth, external, stability, money and credit, situation, larger, beneficial to, period; (c) Topic 35: economy, Chinese economy, China, restructuring, leverage, strengthen, structure, face, future, service industry.

B.3. Phrase Tone Determination

Although the LDA model is effective for topic mining, it does not provide clear tones for either the topics or phrases. For this reason, Hansen and McMahon (2016) construct a word list with the dictionary from Tetlock (2007) and Loughran and McDonald (2014) to measure the tone of FOMC statements after estimating the LDA model. To date, there is no word list that can be fully applicable to the PBC communication. Therefore, we need to determine the tone of every phrase in all topics of interest through the following steps:

First, we check every phrase with a high probability in selected topics. Phrases with low probability are treated as irrelevant. For example, in Topic 1 (fixed-asset investment), all the phrases other than the top 687 phrases share the lowest probability of 3.14×10^{-6}. Therefore, we keep only the top 687 phrases in Topic 1.

Next, we focus only on phrases concerning changes in monetary policy interventions (such as "increase" and "decrease") and the state of the economic situation (such as "developing steadily and rapidly" and "not optimistic").

Third, tones of the same phrase might be different in different contexts. For example, "increasing rapidly" means contraction in the "interest rate" topic, while it indicates expansion in the "money supply" topic.

The tone of $Phrase_v$ in $Topic_k$, denoted as $tone_{k,\,v}$, has three possible assignments, namely, −1, 0, or 1. In regard to the economic outlook, −1 means depression or a poor situation. In terms of monetary policy, −1 represents monetary expansion.

B.4. Communication Index Construction

In this subsection, we directly use the frequency of specific indicative phrases to construct indicative indices (Hansen & McMahon, 2016; Loughran & McDonald, 2014; Tetlock, 2007). In addition, the topics have different weights among the documents; therefore, we assign a greater weight to the phrases that are important within topics. The weight is given by $P(Topic_k | Report_t, Phrase_v)$, denoting the probability that $Phrase_v$ relates to $Topic_k$ if the phrase occurs in $Report_i$. Specifically, the communication index for each quarter t (corresponding to an entire report) for $Topic_k$ is given by

$$I_{t,k} = \frac{\sum_v n_{t,v} P(Topic_k|Report_t, Phrase_v) tone_{k,v}}{\sum_v n_{t,v} P(Topic_k|Report_t, Phrase_v)} \tag{B.3}$$

The numerator of $I_{t,\,k}$ represents the "score" of $Topic_k$, $n_{t,\,v}$ is the occurrence of $Phrase_v$ in $Report_t$. $P(Topic_k|\,Report_t, Phrase_v)$ denotes the weight of $Topic_k$ within the whole $Report_t$, is given as

$$\begin{aligned} &P(Topic_k|Report_t, Phrase_v) \\ &= \frac{P(Phrase_v|Topic_k, Report_t) P(Topic_k|Report_t)}{P(Phrase_v|Report_t)} \\ &= \frac{P(Phrase_v|Topic_k) P(Topic_k|Report_t)}{\sum_{j=1}^{K} P\left(Phrase_v|Topic_j, Report_t\right) P\left(Topic_j|Report_t\right)} \\ &= \frac{\widehat{\phi}_{k,v} \widetilde{\theta}_{t,k}}{\sum_{j=1}^{K} \widehat{\phi}_{j,v} \widetilde{\theta}_{t,j}} \end{aligned} \tag{B.4}$$

Let $\mathscr{K}^{MP}$ denote the set of topics concerning monetary policy and $\mathscr{K}^{EC}$ denote the topics for the economic outlook. Then, we construct the monetary policy communication index and economic situation communication index by

$$\begin{aligned} MP_t^{LDA} &= \sum_{k \in \mathscr{K}^{MP}} P(Topic_k|Report_t) I_{t,k} \\ EC_t^{LDA} &= \sum_{k \in \mathscr{K}^{EC}} P(Topic_k|Report_t) I_{t,k} \end{aligned}, \tag{B.5}$$

where $P(Topic_k|\,Report_t)$ denotes the weight of $Topic_k$ within the entire report, reflecting different importance of the same topic in different quarterly reports. Finally, we use the standardized indicators denoted by the same notations.

Appendix C. Summary Statistics

Table C-1
Summary Statistics.

Variables	Obs	Mean	Std Dev	Min	Max	ADF *P*-Value
PBC_t	76	0.029	0.502	−1.622	1.149	0.000
MP_t^{Sup}	76	0.217	0.555	−0.911	1.000	0.071
EC_t^{Sup}	76	0.016	0.246	−0.871	0.723	0.000
$\Delta(\pi_t - \pi^*)$	75	0.048	0.986	−3.133	2.500	0.000
$\Delta\pi_t^e$	75	0.1280	5.138	−13.900	14.550	0.000
$\Delta\widetilde{y}_t$	75	−0.000	0.006	−0.017	0.017	0.000
$\Delta\widetilde{y}_t^e$	75	−0.014	1.082	−2.686	3.368	0.000
π_t	76	102.332	1.949	98.467	108.033	0.204
π_t^e	76	64.391	6.718	51.550	81.70	0.004
$\widetilde{y}_t$	76	0.000	0.009	−0.023	0.022	0.005
ECI_t	76	101.092	1.799	97.05	105.533	0.142
EPU_t	76	119.262	35.483	61.145	194.907	0.069
MEU_t	70	0.330	0.044	0.257	0.474	0.088
VIX_t	76	19.284	7.989	10.308	58.596	0.009
DIS_t	76	0.893	0.084	0.598	0.999	0.002

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