Predicting China’s CPI by Scanner Big Data

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ABSTRACT

Scanner big data has potential to construct Consumer Price Index (CPI). This work utilizes the scanner data of supermarket retail sales, which are provided by China Ant Business Alliance (CAA), to construct the Scanner-data Food Consumer Price Index (S-FCPI) in China, and the index reliability is verified by other macro indicators, especially by China’s CPI. And not only that, we build multiple machine learning models based on S-FCPI to quantitatively predict the CPI growth rate in months, and qualitatively predict those directions and levels. The prediction models achieve much better performance than the traditional time series models in existing research. This work paves the way to construct and predict price indexes through using scanner big data in China. S-FCPI can not only reflect the changes of goods prices in higher frequency and wider geographic dimension than CPI, but also provide a new perspective for monitoring macroeconomic operation, predicting inflation and understanding other economic issues, which is beneficial supplement to China’s CPI.

1. Introduction

Big data provides us an unprecedented opportunity to construct the real-time and high-frequency macroeconomic indicators, which can not only play an unique role in forewarning and monitoring in macroeconomic operation, but also provide a new perspective for the research in the field of economics. However, most of China’s important economic indicators, like the Consumer Price Index (CPI), which are used to measure the level of inflation, can only be monthly or quarterly released, and also there is a large time lag between the surveys and releases. In the big data era, the scanner big data provides a new data source to construct the CPI, which improves the effectiveness of CPI and releases the CPI at higher time frequency. Until now, some developed countries, such as Netherlands, Norway, Switzerland, Sweden and New Zealand, have officially applied scanner data to create their country-level CPI.

To our best knowledge, there is no research that directly applies scanner data to construct CPI in China. Therefore, we utilize the scanner data of supermarket retail sales provided by China Ant Business Alliance (CAA) to create the Scanner data Food Consumer Price Index, namely S-FCPI. It makes up for the gap in such studies, and due to its unique advantages, such as timeliness, diversified time frequency and wide geographical coverage, it provides a new perspective for real-time monitoring of changes in the price level of various goods, reflecting macroeconomic operation, measuring inflation inertia and inflation prediction, which is a beneficial supplement to China’s CPI research.

Scanner data refers to the highly structured data containing goods prices, sales volume, sales location and other information formed by scanning the barcode of the goods when the goods is sold, which not only provides a new source of data for the compilation of price indexes by national statistical agencies and related research, but also makes it possible to compile superlative price indexes at detailed aggregation levels since prices and quantities are available (see Haan and Van (2011)). Among the countries that currently use scanner data to compile CPI, the Dutch first tried to apply scanner data to the compilation of CPI in 1997 and constructed the price index of coffee at first (see Haan and Opperdoes (1997)). After a series of tests on the index effect, the scanner data was formally applied to the compilation of Dutch CPI in 2002. At present, the goods categories of the Dutch using scanner data to compile CPI have been expanded from the original food category to six categories in COICOP.

In Norway, the scanner data is officially used to compile the CPI in 2005, and the Törnqvist price index is applied to compile the basic classification price index. Now, 20% of the data used to compile the Norway CPI is already scanner data, covering seven categories in COICOP (see Nygaard (2010); Johansen and Nygaard (2011); Rodriguez and Haraldsen (2006); Johansen and Nygaard (2012)). In Switzerland, the scanner data is officially used to compile the CPI in 2008 which is provided by the two largest retail chains in Switzerland, and it covers six categories in COICOP.
New Zealand began to compile the CPI of electronics in September 2013 based on the scanner data provided by GfK and considering the rapid turnover of old and new products in electronics and the existence of seasonal products, as well as the price and sales volume information provided by scanner data. New Zealand uses Törnqvist price index as its index calculation formula. In addition to the practical application of the scanner data in the compilation of CPI in some countries, many scholars have also conducted a lot of research on how to overcome the impact of the potential problems when using scanner data, such as high loss rate of goods, large fluctuation of prices and sales volume affected by promotion. For example, Ivancic, Diewert, and Fox (2011) put forward the RYGEKS (Rolling Year GEKS) price index in their research, then Haan and Van (2011) introduced the Törnqvist price index into the RYGEKS price index, which can be free from the impact of chain drift, and New Zealand uses this method to compile the CPI now. And Diewert and Fox (2018) suggested that CCDI index and mean splice method should be used to update the price index in order to control the degree of chain drift.

Nonetheless, due to information protection and other unavoidable reasons, retail enterprises are often reluctant to provide their own scanner data, and the cost of purchasing access to scanner data also makes the higher cost of conducting the relevant research. Therefore, considering the correlation between online and offline goods prices, some research have turned their perspectives to online price data. Currently, the relatively mature research results are the Billion Price Project (BPP) carried out by MIT, and the iCPI issued by researchers from Tsinghua University. Cavallo and Rigobon (2016), the founders of MIT Billion Price Program, introduced the data source, data processing and application value of BPP in detail in their research. Considering that large multi-channel retailers (i.e. retailers selling online and offline at the same time, such as Wal Mart) participate in most retail sales in most countries, BPP takes the price data of such retailers as the main data source, but BPP of China only includes fresh food and supermarket food. Harchaoui and Janssen (2018) showed in their research that since online goods prices can reflect changes in offline goods prices to a certain extent, BPP can be used as one of the indicators to enhance the timeliness of national CPI. In addition, their research also realized mixed frequency prediction of U.S. CPI based on the U.S. BPP index and MIDAS model. The iCPI released by the iCPI project team of Tsinghua University is a relatively mature online price index in China at present. Taoxiong, Ke, Tingfeng, and Li (2019) discussed in detail the data source, compilation method and application value of iCPI in their research. iCPI takes China’s online shopping platforms (such as Taobao, JD, Suning, etc.) and goods prices information platforms (such as Price Quotations, Soufun, etc.) as the main data sources, and the classification of goods categories is basically consistent with China’s CPI. In addition, iCPI can achieve the compilation of daily and weekly high-frequency price indexes, but the main disadvantage of iCPI is that it cannot reflect the change of regional price level.

The remainder of the paper is organized as follows. Section 2 features the data source of S-FCPI and introduces the compilation method of S-FCPI. Section 3 analyzes the correlation between S-FCPI and CPI and other macro indicators, thus proving the reliability of S-FCPI. Section 4 uses S-FCPI to realize the quantitative and qualitative prediction of CPI growth rate. Section 5 is conclusion which summarizes the results.

2. Data source and S-FCPI

The retail scanner data of Chinese supermarkets integrated by CAA not only provide massive goods prices data, but also provide location, volume, amount, and detailed information, which provide the potential for constructing a consumer price index. This paper employed the supermarket retail scanner big data from CAA to construct China’s Food Consumer Price Index, named S-FCPI (Scanner-data Food Consumer Price Index). In this section, we elaborate data collection, data processing and S-FCPI construction.

2.1. Data collecting

The data source for compiling S-FCPI is the retail scanner data of Chinese supermarkets provided by China Ant Business Alliance (CAA), which is a retail resource alliance organization, since its establishment in 2017 by 12 chain retail enterprises in 6 provinces of China, CAA has experienced rapid development for five years. In 2020, it has more than 100 member enterprises in 32 provinces, cities, and autonomous regions of China, with a total annual turnover of nearly 100 billion Yuan. By utilizing the Alibaba Cloud and the MaxComputing platform Alibaba (2022), CAA collected and pre-processed the scanner big data generated by its member enterprises in real time.

The traditional survey-based method in most countries to collect retail data has remained the same, in which the process is expensive, complex and often slow. Scanner big data provided by CAA has three main advantages:
Low cost. The scanner data collection has been automatically adopted once an item is sold. And constructing and summarizing can be automatically implemented. S-FCPI significantly reduces the cost compared with market survey, especially labor cost.

High frequency. The scanner data is being uploaded to the database in real time, and the sales time record is extremely precise in seconds. It spends only a few minutes that S-FCPI can be calculated and summarized after the necessary data is stored. Therefore, S-FCPI has achieved a high- and multi-frequency release, including daily, weekly, and monthly frequency.

Rich dimensions. The scanner database stores the sales data of 12 million goods which covering 32 administrative regions in China. Based on it, we build an S-FCPI index system at the city (county), provincial (district) and national levels in the geographical dimension, which covers 75 basic categories, 14 sub-categories and general food category in the goods category dimension.

2.2. Data processing

Despite of the significant advantages of scanner big data, it takes effort to process the data, which also puts forward higher requirements for the optimization of data processing, which the most critical is the choice of data aggregation route. Specifically, goods sales summary table (daily), goods barcode information table and goods category table are the basic dataset when compiling S-FCPI. Among them, the goods sales summary table (daily) is the most important dataset, and it takes the date as a partition, which corresponds to independent folders on the distributed system in essence, and each folder stores scanner data of all stores on the same day. Its significance is to avoid unnecessary scanning of the whole dataset to optimize the query and improve the efficiency of data processing. However, when compiling S-FCPI, it needs to use the above datasets to vertically aggregate scanner data at the daily, weekly and monthly level according to the time dimension, and horizontally aggregate scanner data at the city (county), provincial (district) and national level according to the geographical dimension. Therefore, two possible data aggregation routes are as follows: vertical aggregation according to time dimension and then horizontal aggregation according to geographical dimension; horizontal aggregation according to geographical dimension and then vertical aggregation according time dimension.

Since the above two data aggregation routes cannot avoid full dataset scans, the aggregation route with the least number of full dataset scans is the most efficient one on the premise of the same aggregation results. For the first aggregation route, it only needs to scan goods sales summary table (daily) once to obtain the daily aggregated data at the city (county) level, then aggregate it into weekly, monthly aggregated data at the city (county) level, and finally aggregate the daily, weekly, monthly aggregated data at the city (county) level respectively into provincial (district) and national level. For the second aggregation route, it needs to scan goods sales summary table (daily) three times to obtain the daily aggregated data at the city (county), provincial (district) and national level, then aggregate them respectively into weekly and monthly level. Therefore, the first aggregation route can effectively reduce the number of full dataset scans and improve the efficiency of data aggregation, so we choose it as the final data aggregation route.

2.3. Index construction

To ensure the scientificity and rigor of the compilation of S-FCPI as well as the correctness and validity of the results, we mainly refer to the theories and methods of compiling CPI in China, and the “Circulation and Consumer Price Statistical Report System (2021)” published by the National Bureau of Statistics of China. In addition, other relevant materials such as “Consumer Price Index Manual: Concepts and Methods (2020)” published by the International Monetary Fund and the International Labour Organization are also referred. The detailed compilation process of S-FCPI is shown in Figure 1.

2.3.1. Categories of goods

In order to make the price changes reflected by S-FCPI reliable, we mainly refer to the “Classification of Personal Consumption by Purpose” published by the United Nations, and “Circulation and Consumer Price Statistical Reporting System (2021)” to reclassify the categories of goods in the CAA database. The S-FCPI’s categories of goods are generally consistent with China’s CPI, and the specific categories of goods are shown in Table 1.

2.3.2. Collection of goods prices

There is a significant difference between S-FCPI and CPI in the way of price collection. Specifically, the representative goods under each category of CPI are selected by local investigation teams based on the sales volume
Classification of goods
Collection of goods prices
Calculation of weights
Summarization into high-level S-FCPI
Compilation of basic category S-FCPI
Calculation of relative number of price
Calculation of unit price

Index calculation

**Figure 1**: The construction process of S-FCPI.

| Goods categories of S-FCPI. |
|--------------------------------|
| **Sub-category** | **Basic category** |
| Grain | Rice, noodles, other grains, and grain products |
| Tuber | Tuber, Tuber products |
| Bean | Dried beans, soy products |
| Edible oil | Rapeseed oil, soybean oil, peanut oil, sunflower oil, camellia oil, blend oil, linseed oil, corn oil, olive oil, butter, other edible oils |
| Vegetables and edible fungi | Onion, ginger, garlic and pepper, root vegetables, mushroom vegetables, nightshade vegetables, leafy vegetables, dried vegetables and dried bacteria and products |
| Neat of animal | Pork, beef, mutton, other livestock meat and by-products, livestock meat products |
| Meat of poultries | Chicken, duck, other poultry meat and products |
| Aquatic products | Fish, shrimp, crab, shellfish, algae, soft pod, other aquatic products |
| Eggs | Eggs, duck eggs, goose eggs, quail eggs, pigeon eggs, other egg products and products |
| Dairy | Pure milk, pure goat milk, yogurt, milk powder, milk beverage, other milk products |
| Dried fresh melons and fruits | Fresh fruit, nuts, candied dried fruit, other melon and fruit products |
| Candy and pastries | Sugar, sweets and chocolate, pastries, other confectionery pastries |
| Condiments | Edible salt, soy sauce, vinegar, cooking wine, chicken essence, monosodium glutamate, sesame oil, seasoning sauce, chili oil, spices, other condiments |
| Other food categories | Convenience food, starch, and products, puffed food, baby food |

Table 1

and supplemented by the opinions of the relevant local departments. It means that CPI constructs a fixed basket of goods and thus may have errors due to the incomplete selection of goods. The difference is that S-FCPI regards all goods with sales data as representative goods and uses the product ID to match the sales data of the different periods, that is, S-FCPI constructs a variable basket of goods to ensure that the goods in the basket meet the homogeneity and comparability.

On the frequency of goods prices collection, the data for compiling CPI is obtained through manual investigation by investigators, and different investigation frequencies are set according to the types of goods (1 to 5 times per month). But for the scanner data, each order can be regarded as a price collection of all goods in the bill, therefore, the scanner
data realize the real-time collection of goods prices, which also enables S-FCPI to be constructed not only into monthly with the same frequency as CPI, but also can be constructed into daily and weekly with higher frequency.

On the location of goods prices collection, the National Bureau of Statistics of China determines it by sampling cities (counties) and price survey points. S-FCPI regards all stores of CAA member enterprises as goods prices collection location instead of sampling, so it can not only be constructed into national provincial price index with the same geographical dimension as CPI, but it can also be constructed into a more detailed geographic dimension, such as county price index.

2.3.3. Weights setting of S-FCPI

Since different categories of goods account for different proportions in household consumption, it needs to set corresponding weights for compiling S-FCPI. The CPI weights are mainly derived from the household survey data in the base year, and it is adjusted slightly by using typical survey data and expert assessments. In addition, CPI has no weight data below the basic category, and only has weight data above the basic category. Different from the CPI weights, the S-FCPI weights are calculated based on the CAA database which enables timely adjustment of the weights according to the consumption structure of consumers during the reporting period. The main idea of S-FCPI weights is to select the corresponding aggregate data according to the time dimension and geographic dimension of S-FCPI, then the weights are obtained by calculating the share of goods sales.

On the composition of weights, the CPI weights include the city (county), province (state) and nation weights, the provincial (district) and national weights are further divided into the corresponding urban and rural weights. The composition of S-FCPI weights is roughly the same as CPI weights, which also includes the city (county), province (state) and nation weights, and all weights include the frequency of daily, weekly, and monthly.

On the update frequency of weights, the CPI weights are updated every five years since 2000, and slightly adjusted with relevant data during the period. However, the update frequency of CPI weights is still relatively low, which may lead to non-sampling error of CPI weights. S-FCPI improves the updating frequency of weights and realizes the updating frequency of weights with daily, weekly, monthly, or other frequencies to reflect the changes of residents’ consumption structure and pattern more accurately and timely.

2.3.4. Index calculation

The calculation of S-FCPI can be divided into four steps: calculating the unit price, calculating the relative number of price changes, compiling the basic categorical price index, and summarizing to the high-level price index. We use the monthly chain price index as the example to introduce the process of calculating S-FCPI.

Step one, calculating the unit price. Since the CAA database provides both the price and sales volume information of goods, S-FCPI uses the weighted average method to calculate the unit price instead of the simple arithmetic average used by CPI, thus more accurately reflecting the differences between different stores. The specific calculation method is to take the share of sales volume of goods as the weight, calculate the weighted average price of goods in one store firstly, then calculate the weighted average price of goods in multiple stores and take it as the unit price of goods. Taking goods \( k \) as an example, the calculation formula of unit price is as follows, where \( U_t^k \) is unit price, \( sales_t^k \) is total sale, \( q_t^k \) is total sale volume.

\[
U_t^k = \frac{sales_t^k}{q_t^k}
\]

(1)

Step two, calculating the relative number of price changes. Consistent with the compilation method of CPI, the relative number of price changes of each good in S-FCPI is calculated by comparing the unit prices of the two periods. Equation (2) is the calculation formula where \( R_t^k \) is relative number of price changes, \( U_t^k \) and \( U_{t-1}^k \) are the unit prices in period \( t \) and period \( t-1 \), respectively.

\[
R_t^k = \frac{U_t^k}{U_{t-1}^k}
\]

(2)

1The sampling of cities (counties) is stratified sampling. According to the size of cities, population, and income, and some small or medium-sized cities (counties) are appropriately added for investigation to enhance the representativeness of provincial price indexes. The sampling of the price survey points is to conduct equidistant sampling after sorting the transaction volume of each farmers market (fresh market), supermarket, etc. in descending order in the sampled cities (counties).
Step three, compiling the basic categorical price index. Different countries in the world have different theoretical bases for compiling their own basic categorical CPI. One is the Fixed basket index theory represented by China Qiang (2006), which core idea is to select a series of goods and services closely related to the daily life and consumption of residents and form an abstract goods basket, the change of the overall price level is reflected by investigating the change of the cost of purchasing the goods basket in different periods. The other is the cost-of-living index theory represented by the United States (see Konüs (1939); Abraham (2003); Diewert (2001); Triplett (2001)), which core idea is to reflect the change of the overall price level by comparing the minimum expenditure required by consumers in different periods to reach a certain utility level. Since there are two different theoretical bases for CPI, namely, the fixed basket index theory and the cost-of-living index theory, theoretically speaking, when CPI is constructed based on different theoretical bases, the index calculation method adopted should also have different emphasis.

Jevons price index is an index calculation method that does not consider consumer preference, which is used for the calculation of the basic categorical price index of China’s CPI, so we take it as one of the calculation methods of the basic categorical price index of S-FCPI. Taking the basic category $j$ under the sub-category $i$ of a city (county) as an example, the calculation formula of the Jevons price index is shown in Equation (3), where $M^i_{jk}$ is the number of goods in basic category $j$.

$$J^i_j = \prod_{k=1}^{M^i_{jk}} \left( \frac{R^i_{jk}}{R^i_{jk}} \right)^{\frac{1}{S^i_{jk}}}$$  (3)

In relevant research, the index calculation method that does not consider consumer preference (unweighted index form) is often used due to the limitation of the availability of weights data, while the development of scanner data makes it possible to compile basic categorical price index when considering consumer preference (weighted index form), and CPI Manual (2020) also points out that when detailed price and sales data are available, the weighted index form will be a better choice. Therefore, we also use Törnqvist (see Diewert (1976); Diewert (1979)) and GFT (see Basmann, Molina, and Slottje (1983); Basmann, Slottje, Hayes, Johnson, and Molina (2013); Swann (1999)) price indices to compile the basic categorical price index of S-FCPI. Taking the basic category $j$ under the sub-category $i$ of a city (county) as an example, the calculation formulas of Törnqvist and GFT price index are as follows, where $S^i_{jk}$ is the share of sales of goods $k$.

$$T^i_j = \prod_{k=1}^{M^i_{jk}} \left( \frac{R^i_{jk}}{R^i_{jk}} \right)^{\frac{S^i_{jk}-1+5^i_{jk}}{2}}$$  (4)

$$G^i_j = \prod_{k=1}^{M^i_{jk}} \left( \frac{R^i_{jk}}{R^i_{jk}} \right)^{S^i_{jk}}$$  (5)

$$S^i_{jk} = \frac{\text{sales}^i_{jk}}{\sum_{k=1}^{M^i_{jk}} \text{sales}^i_{jk}}$$  (6)

Step four, summarizing to the high-level price index. China’s CPI uses the Laspeyres price index for high-level summary, and its weights are the household consumption expenditure data obtained from the survey, but the weights update frequency is low, which may lead to non-sampling errors of weight. Therefore, S-FCPI takes the share of sales in the reporting period as the weight and uses the Paasche price index to conduct high-level summary, so that it can more accurately and timely reflect the changes in residents’ consumption structure and prices. The high-level summary process of S-FCPI is shown in Figure 2.

The first level of summary is city (county) level S-FCPI internal summarize. The basic category S-FCPI at the city (county) level is summarized into the sub-category S-FCPI at the city (county) level, and then summarized into the S-FCPI at the city (county) level. The second level of summary is to summarize the city (county) level S-FCPI
3. Relationship between CPI and S-FCPI

S-FCPI has significant advantages of diversified index frequency, release without lag, and wide geographical dimension, it provides a new perspective for real-time monitoring of goods prices changes, reflecting macroeconomic operating conditions, measuring inflation inertia, predicting inflation (CPI), and another related research. Based on this, this chapter will use the monthly S-FCPI data from February 2018 to May 2022 and other macro indicators such as CPI to analyze the reliability of S-FCPI from multiple perspectives.

3.1. Features selection

Table 2 shows the relevant indicators used in the following analysis and their specific meanings. The CPI, FCPI and FRPI published by the National Bureau of Statistics of China is selected to explore the correlation between S-FCPI and them. The online food price index published by the iCPI project is selected to analyze the correlation between S-FCPI and iCPI, as well as their ability to capture the change of CPI. The broad money supply M2 published by the National Bureau of Statistics of China and Shibor published on the official website of Shanghai Interbank Offered rate are selected to measure the impact of monetary shock, that is, the impact of demand shock on food prices. The consumer confidence index is selected to measure the correlation between consumers’ subjective feelings on the current economic situation and food price changes.

Among the above indicators, the data of CPI, FCPI, FRPI and M2 are obtained from the official website of the National Bureau of Statistics of China, the data of iCPI is obtained from the official website of the iCPI project of Tsinghua University, the data of Shibor is obtained from the official website of Shanghai Interbank Offered Rate, and the consumer confidence index is obtained from the China Economic Information NET.

3.2. Month-on-month volatility analysis

The chain index can be used to reflect the change degree of indicators in the report period compared with the previous period, therefore, to evaluate the ability of S-FCPI to reflect the fluctuation of price level, we draw the monthly chain price indexes of S-FCPI, CPI, FCPI and iCPI as the time series chart shown in Figure 3. Among them, the time
Table 2
Feature description. Here, we leave out the category \( i \) in the indexes, e.g., \( T \) is short for \( T_i \). \( i \) represents the category of foods in our study. 0: food; 1: grain; 2: tuber; 3: bean; 4: edible oil; 5: vegetables and edible fungi; 6: neat of animal; 7: meat of poultries; 8: aquatic products; 9: eggs; 10: dairy; 11: dried and fresh fruits; 12: candy and pastries; 13: condiment; 14: other food categories.

| Category | Index | Description |
|----------|-------|-------------|
| S-FCPI (Ours) | \( T \) | Monthly chain S-FCPI in Törnqvist form |
|          | \( G \) | Monthly chain S-FCPI in GFT form |
|          | \( J \) | Monthly chain S-FCPI in Jevons form |
| CPI      | CPI   | China monthly chain CPI |
|          | FCPI  | China monthly chain FCPI |
|          | FRPI  | China monthly chain RPI of food |
|          | iCPI  | Monthly chain iCPI of food |
| Other indexes | M2   | Broad money |
|          | Shibor | Shanghai Interbank Offered rate |
|          | CC    | Consumer confidence index |

range of S-FCPI, CPI, and FCPI is 52 months from February 2018 to May 2022, and the time range of iCPI is 41 months from January 2019 to May 2022.

Figure 3: Month-on-month CPI and S-FCPI.

In addition, to quantitatively measure the proportion of months with the same change directions of S-FCPI, CPI, FCPI and iCPI, we calculate the co-directional rate among different indicators and reports it in Table 3. Here, co-directional rate = \( \frac{m}{M} \times 100\% \), where \( m \) is total number of months with the same change directions, \( M \) is total number of months.

Figure 3 and Table 3 show that the variation directions and level of price reflected by S-FCPI and CPI are relatively close. Between January 2018 and May 2022, \( T \) and CPI changed in the same directions in 34 months, accounting for 65.38%; \( G \) and CPI changed in the same directions for 27 months, accounting for 51.92%; \( J \) and CPI changed in the same directions for 27 months, accounting for 51.9%.

The variation directions of price reflected by S-FCPI and FCPI is relatively close, but the variation level of FCPI is larger. Between January 2018 and May 2022, \( T \) and FCPI changed in the same directions in 37 months, accounting for 71.15%; \( G \) and FCPI changed in the same directions for 32 months, accounting for 61.54%; \( J \) and FCPI changed in the same directions for 32 months, accounting for 61.54%. However, Figure 3 also shows that FCPI has a larger range of variation, we think that the main reason for this difference lies in the different collection methods of price.
data. Specifically, the raw data of CPI are collected on a few days of the month, so it can only reflect changes of price on a few days and more volatile. But S-FCPI uses the price data of all goods on sale in a month, which reduces the fluctuation caused by randomness, and finally shows that S-FCPI has a smaller variation level.

The variation directions and level of price reflected by S-FCPI and iCPI are relatively close. In addition to comparing S-FCPI with CPI and FCPI, we also compare S-FCPI with food iCPI to verify the correlation between online and offline prices. Between January 2018 and May 2022, $T$ and iCPI changed in the same directions in 24 months, accounting for 58.54%; $G$ and iCPI changed in the same directions for 21 months, accounting for 51.22%; $J$ and iCPI changed in the same directions for 24 months, accounting for 58.54%, it means that the prices of online and offline goods are related.

### 3.3. Month-on-month correlation analysis

In relevant research, the chain index growth rate is usually used when analyzing the correlation between the two chain indexes, therefore, we firstly calculate the logarithmic growth rate of the chain index of each indicator, then calculates the correlation coefficient between the logarithmic growth rates of each indicator to analyze the correlation between them.

The calculation formula of logarithmic growth rate is shown in Equation (7), where $x_{rate,t}$ is logarithmic growth rate of the chain index of indicator $x$ from period $t-1$ to period $t$.

$$x_{rate,t} = \ln x_t - \ln x_{t-1}. \tag{7}$$

In the below, we leave out the subscript $rate$ in the indexes while discussing the growth rates.

Fig. 4 and Table 4 shows that there is significant positive relationship between the growth rate of S-FCPI and the growth rate of CPI, FCPI, and FRPI in the same period at the significance level of 1%. Specifically, the $J$ constructed by the Jevons price index, which is the same as the index formula used by the National Bureau of Statistics of China to compile CPI, and its growth rate $J$ has the strongest correlation with CPI, FCPI and FRPI, and the Pearson correlation coefficients are 0.770, 0.786, and 0.801, respectively. For $T$ constructed by Törnqvist price index, the correlation coefficients are 0.658, 0.491, and 0.561, respectively.
between its growth rate $T$ and CPI, FCPI, and FRPI is second, and the Pearson correlation coefficients are 0.742, 0.775, and 0.788, respectively. While $G$ constructed by GFT price index, its growth rate $G$ has lower correlation with CPI, FCPI, and FRPI, and the Pearson correlation coefficients are 0.718, 0.761, and 0.773, respectively.

Moreover, the growth rates of S-FCPI, CPI and FCPI are consistent with the growth rates of other macro indicators in the same period in terms of correlation and direction. Specifically, $T$, $G$, $J$, CPI and FCPI have significant positive correlation with iCPI at the significance level of 5% ($J$ is at the significance level of 1%). The Pearson correlation coefficient ranges from 0.375 to 0.510, which indicates a positive correlation between the variation of online and offline price. And they have a significant negative correlation with M2 at the significance level of 5% ($T$ at the significance level of 10%, $G$ at the significance level of 1%), and the Pearson correlation coefficient is between -0.580 and -0.380, it indicates that when the price level rises, that is, when the current inflationary pressure increases, the monetary authority will reduce the contemporaneous money supply. In addition, none of them has a significant correlation with Shibor and CC.

4. Predicting CPI by S-FCPI

Considering that CPI is an important indicator for measuring the degree of inflation in China, the prediction of CPI growth rate undoubtedly has certain practical significance. In this chapter, the quantitative and qualitative predictions of CPI will be realized from two perspectives: first, predicting growth rate of CPI; second, predicting the directions and levels of CPI growth rate.

4.1. Predicting the growth rate of CPI

When predicting the growth rate of CPI, six machine learning models are applied, including Linear Regression, Random Forest, K-Neighbors, Adaboost, GBDT, and Bagging. The target variable of the model is the current growth rate of CPI, and the features are the current growth rate of S-FCPI in Törnqvist form and its first-order and second-order lag terms. The prediction period is set to 12 months, so the last 12 months of the data are selected as the test data, it contains 12 months of data from June 2021 to May 2022, and the rest of the period is used as the training data, it contains 37 months of data from May 2018 to May 2021.

In addition to predicting the CPI growth rate, we also predict the FCPI growth rate, and except that the target variables are different, the rest are the same as the prediction of CPI growth rate. Table 5 reports the evaluation indicators of the prediction effects of six regression models, Figure 5 and Figure 6 report the prediction effect of CPI and FCPI growth rate respectively, where the left side of the dotted line is the in-sample prediction, and the right side of the dotted line is the out-of-sample prediction.

Table 5 and Figure 5 show that the GBDT model has the best prediction effect on CPI growth rate, its MAE (0.0026) and RMSE (0.0032) are the smallest among the six models, and meanwhile the $R^2$ (0.583) is the largest. The prediction effect of Bagging model is second to GBDT model, which MAE, RMSE and $R^2$ is 0.0030, 0.0035, and 0.514, while the prediction effects of the other models are relatively poor, which will not be described in detail.

Table 5 and Figure 6 show that the Bagging model has the best prediction effect on FCPI growth rate, its RMSE (0.0126) is the smallest among the six models and the $R^2$ (0.550) is the largest. The prediction effect of Random Forest model is second to Bagging model, which MAE, RMSE and $R^2$ is 0.0095, 0.0129, and 0.530, respectively, and using the logistic regression and the Adaboost models can also achieve a good prediction effect on the FCPI growth rate.
Table 5
Evaluation indicators of predicting CPI growth rate (regression).

| Model          | CPI MAE | CPI RMSE | CPI $R^2$ | FCPI MAE | FCPI RMSE | FCPI $R^2$ |
|----------------|---------|----------|-----------|----------|-----------|------------|
| Linear Regression | 0.0034  | 0.0039   | 0.398     | 0.0097   | 0.0134    | 0.489      |
| Random Forest   | 0.0031  | 0.0039   | 0.415     | 0.0095   | 0.0129    | 0.530      |
| K-Neighbors     | 0.0040  | 0.0050   | 0.013     | 0.0156   | 0.0186    | 0.015      |
| Adaboost        | 0.0036  | 0.0042   | 0.301     | 0.0117   | 0.0138    | 0.460      |
| GBDT            | 0.0026  | 0.0032   | 0.585     | 0.0112   | 0.0144    | 0.413      |
| Bagging         | 0.0030  | 0.0035   | 0.514     | 0.0103   | 0.0126    | 0.550      |

Figure 5: Prediction results of CPI growth rates by S-FCPI.

Figure 6: Prediction results of FCPI growth rates by S-FCPI.

4.2. Predicting the directions and levels of CPI growth rate
For the study of economic operation, while focusing on the Accuracy of quantitative prediction results, the relevant research often pays more attention to capture the characteristics of the changing trend in the process of economic
Table 6
Evaluation indicators of predicting the directions of CPI growth rate (two-category classification).

|               | CPI   | F1-score | Accuracy | FCPPI  | F1-score | Accuracy |
|---------------|-------|----------|----------|--------|----------|----------|
| Naive Bayes   | 0.667 | 0.583    | 0.824    | 0.750  | 0.750    |
| Logistic Regression | 0.588 | 0.417    | 0.737    | 0.583  |
| Random Forest | 0.615 | 0.583    | 0.800    | 0.750  |
| K-Neighbors   | 0.769 | 0.750    | 0.933    | 0.917  |
| Adaboost      | 0.800 | 0.833    | 0.800    | 0.750  |
| GBDT          | 0.727 | 0.750    | 0.800    | 0.750  |

operation, that is, the qualitative prediction of directions and levels of CPI growth rate. Therefore, we use the S-FCPI growth rate to qualitatively predict the CPI growth rate from the following two perspectives: first, predicting the directions of CPI growth rate; second, predicting the levels of CPI growth rate.

Predicting the directions of CPI growth rate is a binary classification task essentially, so we use Naive Bayes, Logistic Regression, Random Forest, K-Neighbors, Adaboost and GBDT for binary classification prediction. We take whether the CPI growth rate is greater than 0 as the target variable, the month with CPI growth rate not less than 0 (CPI) is labeled as 1, which is a positive sample, and the month with CPI growth rate less than 0 (CPI) is labeled as -1, which is a negative sample. The features are current growth rate of S-FCPI in Törnqvist form and its first-order lag term. The prediction period is also set to 12 months, and the division between the training data and the test data is as same as the prediction of CPI growth rate. The training data contains 38 months of data from April 2018 to May 2021, of which 23 months are labeled as 1 and 15 months are labeled as -1. The test data contains 12 months of data from June 2021 to May 2022, of which 5 months are labeled as 1 and 7 months are labeled as -1.

The binary classification often pays more attention to the prediction performance of the model for a certain type of samples, but when predicting the directions of CPI growth rate, the prediction performance of the model for the two types of samples is equally important. Therefore, we use F1 score as an index to evaluate the performance of the model in predicting positive samples, and we use Accuracy to evaluate the overall predicting performance of the model.

In addition to predicting the directions of CPI growth rate, we also predict the directions of FCPI growth rate, and except that the target variables are different, the rest are the same as the prediction of the directions of CPI growth rate. Table 6 reports the evaluation indicators of the prediction effects.

Table 6 shows that the Adaboost model has the best prediction effect on the directions of CPI growth rate, which Accuracy is 83.3% and accurately predicts the directions of CPI growth rate in 10 months of 12 months. The prediction effect of K-nearest and GBDT models are second to Adaboost model, which Accuracy is 75%. For the prediction of directions of FCPI growth rate, the K-nearest mode has the best prediction effect on the directions of FCPI growth rate, which Accuracy is 91.7% and accurately predicts the directions of FCPI growth rate in 11 months of 12 months. The prediction effect of Naive Bayes, Random Forest, and GBDT models are second to K-Neighbors model, which Accuracy is 75%. In conclusion, the prediction effect of K-nearest neighbor, Adaboost and GBDT models are generally excellent, and the directions of CPI and FCPI growth rate can be accurately predicted by using the S-FCPI growth rate and its first-order lag term.

Since the growth rate of CPI changes to a large extent in some periods, we further divide the growth rate of CPI into three categories and take them as the target variable of the prediction model to achieve the prediction of the levels of the CPI growth rate. Specifically, the month with CPI growth rate bigger than 0.003 \((\mu + \sigma/2)\) is labeled as 1 which means the CPI growth rate has risen sharply, the month with CPI growth rate smaller than -0.003 \((\mu - \sigma/2)\) is labeled as -1 which means the CPI growth rate has fallen sharply, and the other months are labeled as 0 which means the CPI growth rate fluctuates within a reasonable range. The features, the division of training data and test data, the prediction model and the model evaluation index are all the same as the prediction of the directions of CPI growth rate, which will not be described in detail. Finally, the training data contains 38 months of data from April 2018 to May 2021, of which 11 months are labeled as 1, 17 months are labeled as 0, and 10 months are labeled as -1. The test data contains 12 months of data from June 2021 to May 2022, of which 4 months are labeled as 1, 5 months are labeled as 0, and 3 months are labeled as -1s.
Table 7

|         | CPI F1-score | CPI Accuracy | FCPI F1-score | FCPI Accuracy |
|---------|--------------|--------------|---------------|---------------|
| Naive Bayes | 0.522        | 0.583        | 0.311         | 0.417         |
| Logistic Regression | 0.415        | 0.500        | 0.398         | 0.417         |
| Random Forest  | 0.815        | 0.833        | 0.667         | 0.667         |
| K-Neighbors   | 0.655        | 0.667        | 0.302         | 0.417         |
| Adaboost      | 0.815        | 0.833        | 0.311         | 0.417         |
| GBDT          | 0.739        | 0.750        | 0.667         | 0.667         |

In addition to predicting the levels of CPI growth rate, we also predict the levels of FCPI growth rate. Table 7 reports the evaluation indicators of the prediction effects.

Table 7 shows that the Random Forest and Adaboost models has the best prediction effect on the levels of CPI growth rate, which Accuracy is 83.3% and accurately predicts the levels of CPI growth rate in 10 months of 12 months. The prediction effect of GBDT model is second to them, which Accuracy is 75%. For the prediction of the levels of FCPI growth rate, the Random Forest and GBDT models has the best prediction effect on the levels of FCPI growth rate, which Accuracy is 66.7% and accurately predicts the levels of FCPI growth rate in 8 months of 12 months. While the prediction effect of the other models on the levels of FCPI growth rate is poor, which will not be described in detail.

In conclusion, this chapter mainly uses a variety of machine learning models to realize the quantitative prediction of CPI and FCPI growth rate, and also realizes the qualitative prediction of the directions and levels of CPI and FCPI growth rate, and obtains relatively accurate prediction effect. Therefore, the S-FCPI which with no lag can provide a new data source for the research of macro and micro economic problems such as inflation (CPI) prediction.

5. Conclusion

Given the development and abundance of scanner big data, it is of great significance to construct real-time and high-frequency macroeconomic indicators. Such indicators can not only play an unique role in warning and monitoring of macroeconomic operation, but also provide a new perspective for relevant economic research. Scanner big data provides a brand-new data source for construction of CPI. Moreover, CPI based on scanner big data make up for the defect that CPI has no weights data under the basic categories. To our best knowledge, there is no such research result in China at present. Therefore, we use the supermarket retail scanner data provided by CAA to create the Scanner-data Food Consumer Price Index (S-FCPI), and the main conclusions in our study are as follows:

First, we construct the S-FCPI based on scanner big data. S-FCPI has achieved a high- and multi-frequency release, including daily, weekly, and monthly frequency. Also we build an index system at the city (county), provincial (district) and national levels in the geographical dimension, which covers 75 basic categories, 14 sub-categories and general food category in the goods category dimension. S-FCPI demonstrates that scanner big data is applicable to construct price index in China.

Second, we examine the reliability of S-FCPI from three perspectives through month-on-month volatility analysis and correlation analysis. The conclusion of month-on-month volatility analysis shows that the changes of price reflected by S-FCPI and macro indicators (like CPI) are consistent. And month-on-month correlation analysis shows that there is a highly positive correlation between S-FCPI and the growth rate of macro indicators such as CPI. The experiment shows S-FCPI indicates scanner big data can reflect the real retail situation in China.

Third, we employ multiple machine learning models to achieve the quantitative and qualitative prediction of CPI growth rate. In quantitative prediction, we use the growth rate of S-FCPI and its first-order and second-order lag terms to predict the growth rate of CPI and FCPI, the GBDT regressor has the best prediction effect on the CPI growth rate which the $R^2$ is 0.585, the Random Forest regressor has the best prediction effect on the FCPI growth rate which the $R^2$ is 0.530. In qualitative prediction, we use the growth rate of S-FCPI and its first-order term to predict the directions and levels of CPI and FCPI growth rate, the Adaboost classifier has the best prediction effect on the directions of CPI growth rate which the F1-score is 0.800 and the Accuracy is 0.833, and the K-Neighbors classifier has the best prediction effect on the directions of FCPI growth rate which the F1-score is 0.933 and the Accuracy is 0.917.
Relying on the unique advantages of S-FCPI (low cost, high frequency and rich dimensions), it can not only reflect the changes in goods prices in a higher frequency and wider geographical dimension than CPI, but can also provide a new perspective for monitoring macroeconomic operation and forecasting inflation and economic issues, which is a beneficial supplement to China’s CPI. However, S-FCPI has some limitations. Researchers can carry out follow-up research from the promising directions: referring to index construction, S-FCPI can further expand goods categories besides food categories, and consider the online price data; in the research of index theory, we could conduct in-depth research on the application of chain drift and transcendental index in scanner big data. Referring to economic issues, we could study on the measurement of inflation inertia, the analysis of goods prices stickiness and the heterogeneity of goods prices fluctuation among regions.

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