Inflation Risk Forecasting ——Based on the Perspective of Systemic Risk

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Abstract

In the framework of quantile regression model, this paper explores the impact of systemic risk on future inflation risk. We use data from Chinese financial institutions to measure the overall risk of financial market in China, and study its effects, including direction, magnitude and predictability, in two types of inflation risk calculated by consumer price index (CPI) and producer price index (PPI). The results show that the systemic risk greatly improves the predictability of inflation risk, which implies that the ascent of systemic risk will lead to the significant increase of both deflation or inflation risk in the future. The impact lasts 6 to 12 months. Compared with the CPI, the PPI risk will increase more under the shock of systemic risk. In addition, we also find that there is difference in the persistence of the impact of systemic risk on the two types of inflation risk, that is, the PPI inflation responds to ascending systemic risk more quickly. Finally, we forecast the inflation risk in China from March 2020 to March 2021 and propose relevant policy recommendations.

Keywords: Systemic Risk, Inflation Risk, Quantile Regression Model

Introduction

Inflation refers that the currency supply far exceeds the actual demand for money. Moderate inflation can promote economic prosperity, while virulent inflation will result in severe currency devaluation, rising prices, and eventually destroy the healthy development of the economy, ending up with catastrophic crisis. Therefore, an accurate forecast of future inflation levels can help micro economic entities make investment and consumption decisions in advance to smooth their consumption. In addition, because there is a time lag between the formulation of economic policies and effectiveness, the forward-looking inflation forecast can be used as a basis to better solve this problem and ensure the stable development of prices and economy, which is the main goal of macro regulation.

The inflation forecast has been one of the most important issues in macroeconomics. Both domestics and foreign scholars have proposed many ways to achieve this goal. Stock and Watson (1999)[i] summarized the inflation forecasting model into six standard models, including three univariate models, two Phillips curve models, and an autoregressive-distributed lag model. They divided these models into four categories: (1) Prediction based on past inflation levels. This method mostly uses time series models; (2) Prediction based on Phillips curve. Zheng Tingguo et al. (2012)[ii] constructed the forecasting model based on the real-time data of Chinese output gap. The results showed that inflation-output Phillips curve model has a poor predictive ability; (3) Prediction based on others' inflation expectations, such as implicit expectations derived from asset prices; (4) Prediction based on other variables. For example, domestic scholar Sun Jianqiang et al. (2019)[iii] examined the impact of enterprises' aggregate earnings on people's inflation expectations.

Existing literature on the inflation forecast are more concentrated in predicting its levels, while there is little literature focusing on the risk of inflation. The inflation risk can be measured by its future distribution, that is, the

possibility that the inflation rate is lower than a certain value. By selecting different quantiles, the risk of inflation or deflation can be examined.

It is widely believed that compared to fully-expected inflation, inflation risk reflects the size of its uncertainty, and the uncertainty will cause volatility in the real economy, resulting in resource misallocation. In other words, the risk of inflation will bring about huge losses to social welfare and cause serious harm to the macro economy. Therefore, it is very important to accurately predict the risk of future inflation.

Based on the perspective of systemic risk, this paper studies the variation of future inflation risk levels. In recent years, with rapid innovation and development of financial markets, the relationship between financial markets and real economy has been closer and closer. After the US subprime mortgage crisis in 2008, people came to realize that the financial market not only has positive effect towards real economy, but also can retard economic growth. At the same time, the importance of systemic risk has been recognized once again, and people have begun to shift their focus to the measurement and prevention of systemic risk. The so-called systemic risk refers to the exposure of the financial system. Due to the business transactions between institutions and institutions in the system, as well as the complex relationship network and the extraordinarily high linkages, risks contaminate between financial institutions, which ultimately leads to the entire financial system exposed to risk. The global financial crisis in 2008 has proved that there is not only the effect of the real economy on the financial market, but also the impact of the financial market on the real economy, that is, once the financial system is in crisis, the real economy will also have devastating blow, so people started to pay attention to how systemic risk affects macroeconomics variables, such as inflation rate. Regarding the channels in which financial markets influences inflation, the current view generally focuses on the credit markets. In particular, the increase of systemic risk will cause shortages in credit supply, which will have negative effect on inflation rate. Cecchetti and Lee (2008)[iv] studied the changes in output and price distribution with the exuberance of real estate and stock market, in the framework of quantile regression and vector autoregression model. Their results showed that when there is real estate and stock price bubbles, the 90th percentile of the inflation distribution will significantly shift to the right.

In the framework of quantile regression model, this paper explores the impact of systemic risk on future inflation risk, and uses out-of-sample quantile R^2 to evaluate the predictive accuracy of the model with different lags. Firstly, we use data of Chinese financial institutions to measure the risk of financial market in China, and study its impact on future inflation risk, calculated by consumer price index (CPI) and producer price index (PPI), including direction, intensity and predictability. We find that the systemic risk indicators can significantly increase the predictability of the model, and that these indicators have different influence direction and intensity to future inflation rates at different quantiles, which is significantly different from OLS regression model. The results based on quantile regression model show that when the overall risk of the financial market increases, the inflation rate at lower quantile decreases, while inflation rate at upper quantile increases, that is, the future deflation or inflation risk rises, and this effect is mainly reflected in the lag of 6 to 12 months. In addition, compared with the CPI inflation rate, the PPI inflation rate will suffer more severely under the shock of systemic risk. Finally, based on the above model, we forecast Chinese inflation risk from March 2020 to March 2021 and propose relevant policy recommendations.

The remainder of this paper proceeds as follows. Section 2 constructs the quantile model and describes the data. Section 3 conducts empirical analysis, including testing the power of systemic risk indicators for forecasting inflation risk, analyzing regression result and robustness test. Section 4 predicts future inflation risk. Section 5 concludes and proposes policy recommendations.

Model Building and Data Description

2.1　Model Construction

2.1.1 Model Setting and Estimators

By constructing a quantile regression model of Chinese inflation rate based on systemic risk indicators, we obtain the conditional distribution function of inflation in China. Based on the traditional Phillips curve model, we introduce indicators that measure the overall risk of the financial market, and define the following linear regression form:

$$\pi_{t+h} = \delta_0 + \delta_1 \pi_t + \delta_2 SYS_t + v_{t+h} \qquad (1)$$

We indicate time-varying inflation π_{t+h} and π_t with a subscript t. The h-months lag of the systemic risk indicator is denoted by SYS_t. v_{t+h} represents the error term. Thus, the coefficient δ_2 examines the impact of the h-months lag of systemic risk on inflation rate π_{t+h}. In order to study the overall risk level of the current financial market and its effect on the future inflation rate distribution, we construct the following quantile regression model:

$$Q_{\pi_{t+h}}(\tau) = \delta_0(\tau) + \delta_1(\tau)\pi_t + \delta_2(\tau)SYS_t \qquad (2)$$

where $\tau \in (0,1)$, and $Q_{\pi_{t+h}}(\tau)$ represents the τth percentile of the inflation distribution conditional on lagged inflation rate π_t and systemic risk indicator SYS_t. Therefore, by changing the value of quantile τ, we can obtain the value of future inflation rate at multiple quantiles, and draw the conditional distribution image of future inflation rate.

In the context of Equation (2), by selecting appropriate regression coefficients $\delta_0(\tau)$, $\delta_1(\tau)$ and $\delta_2(\tau)$, make sure that the sum of the weighted absolute values of the error terms is minimized:

$$\hat{\eta}(\tau) = \text{argmin}_{\eta_\tau \in R^k} \sum_{t=1}^{T-h} \left(\tau * I_{(\pi_{t+h} \geq X_t)} |\pi_{t+h} - X_t| + (1-\tau) * I_{(\pi_{t+h} < X_t)} |\pi_{t+h} - X_t| \right) \qquad (3)$$

where $X_t = \delta_0(\tau) + \delta_1(\tau)\pi_t + \delta_2(\tau)SYS_t$, $\hat{\eta}(\tau) = \{\widehat{\delta_0}(\tau), \widehat{\delta_1}(\tau), \widehat{\delta_2}(\tau)\}$. Indicator function $I_{(\cdot)}$ is equal to 1 on the condition that $(\cdot)$ is satisfied, otherwise $I_{(\cdot)}$ is equal to 0. Plugging the estimators $\hat{\eta}(\tau)$ into Equation (2), we can get the fitted values.

$$\hat{Q}_{\pi_{t+h}}(\tau) = \widehat{\delta_0}(\tau) + \widehat{\delta_1}(\tau)\pi_t + \widehat{\delta_2}(\tau)SYS_t \qquad (4)$$

2.1.2 Out-of-Sample Forecast Accuracy

In order to evaluate the predictive power of conditional quantile regression model based on systemic risk, we draw on Giglio et al. (2015)[v], who propose out-of-sample quantile R^2 to examine whether the systemic risk indicators provide important information about the distribution of future inflation rate.

$$R^2 = 1 - \frac{\frac{1}{T}\sum_t[\rho_\tau(\pi_{t+h} - \widehat{\delta_0}(\tau) - \widehat{\delta_1}(\tau)\pi_t - \widehat{\delta_2}(\tau)SYS_t)]}{\frac{1}{T}\sum_t[\rho_\tau(\pi_{t+h} - \hat{q}_\pi(\tau))]} \qquad (5)$$

where $\rho_\tau(\cdot)$ represents a loss function. $\hat{q}_\pi(\tau)$ represents the fitted value of unconditional quantile regression, in which the effect of systemic risk on the inflation rate is not considered. In Equation (5), the numerator represents the loss sequence of quantile regression model based on the conditional information of systemic risk, and the denominator represents the loss sequence of quantile regression model based on the unconditional information. Therefore, if the prediction accuracy of the conditional quantile regression is better than the unconditional quantile regression, the out-of-sample quantile R^2 is positive and in the interval of $(0,1)$. While if the prediction effect of conditional quantile regression is relatively poorer, its value can be negative. Therefore, the comparatively stronger prediction effect based on the conditional quantile regression of systemic risk indicators is that after the systemic risk indicator is added to the regression model, R^2 significantly improves and $\widehat{\delta_2}(\tau)$ is statistically significant.

2.1.3 Impact Direction on Different Quantiles

We focus on the critical coefficient $\delta_2(\tau)$, which measures the changing level of inflation rate at τ^{th} percentile, when the systemic risk indicator lagged h months varies 1 unit. The systemic risk indicators selected are CoVaR and ΔCoVaR. The smaller of these two indicators, the higher the systemic risk is. Therefore, when $\tau = 0.1$, if $\widehat{\delta_2}(\tau) > 0$, it indicates that after the index decreases, that is, the overall financial system risk rises, the future inflation rate at 10% quantile will fall, which means that the risk of deflation will increase. On the contrary, when

$\tau = 0.9$, if $\widehat{\delta_2}(\tau) < 0$, it suggests that as index decreases, the future inflation rate on 90% quantile will increase, that is, the possibility of future inflation rate above a certain level rises, which implies that the inflation risk increases in the future.

According to the different symbols and numerical sizes of $\delta_2(\tau)$ at multiple quantile, we can study the changing direction and degree with the exposure to ascending systemic risk.

2.2 Data Description

2.2.1 Systemic Risk

The systemic risk index selected in this paper is conditional value at risk (CoVaR). Adrian and Brunnermeier (2016) proposed a measure for systemic risk called CoVaR, which represents that the value at risk of the overall financial system conditional on the return of a single institution m, that is $CoVaR^m$. It is defined as:

$$Pr(R^{sys} \leq CoVaR^m | R^m = VaR^m) = q \qquad (6)$$

where $q \in (0,1)$. R^m is the return on assets of the representative institution m. R^{sys} denotes the overall level of returns in financial market, by averaging the yields of all institutions. Equation (7) suggests that the probability that whole financial market yields R^{sys} less to $CoVaR^m$ is q, conditional on the ROA of institution m being equal to VaR^m.

Furthermore, $\Delta CoVaR^m$ represents the difference between the value-at-risk of financial market conditional on the distress of a particular institution m and the value-at-risk of financial market conditional on the median state of the institution m. $\Delta CoVaR^m$ measures how much the institution m adds to overall systemic risk.

$$\Delta CoVaR^m = CoVaR^m(q) - CoVaR^m(50\%) \qquad (7)$$

We select publicly traded financial institutions in Shanghai Composite and Shenzhen Component, a total of 239 institutions, including four categories of the financial sectors: banks, insurance companies, security broker-dealers and real estate companies. Our sample starts from January 1990 to September 2019. The data used comes from the Wind database, including daily data of financial institutions' closing price and market value. Different from Adrian and Brunnermeier (2016)[vi], we propose CoVaR by rolling window with a 252-days window.

2.2.2 Inflation

In the existing literature, the year-on-year changes in the consumer price index (CPI), producer price index (PPI), and GDP deflator are often used to calculate Chinese inflation rate. This article uses the consumer price index and the producer price index to calculate China's inflation rate for comparison. The difference between the two indexes is that the CPI is based on the perspective of consumer consumption and represents the price level of the final consumer goods and services purchased by residents. It measures the income level of midstream and downstream companies and the price changes on the demand side; while the PPI is based on the perspective of enterprise manufacturers, which measures the level of profit of midstream and upstream companies and changes in supply-side costs. By comparing the intensity and duration of financial market risks to the two types of inflation risks, we can examine the distinction between the impact of systemic risk on the supply side and the demand side, in order to formulate relevant policies more specifically.

The data is collected from April 1992 to September 2019, containing Chinese monthly consumer price index (CPI) and producer price index (PPI). We also remove seasonal trends. Data are taken from the Federal Reserve Economic Database (FRED). The specific calculation formula is as follows:

$$\pi_t = ln\left(\frac{P_t}{P_{t-12}}\right) \qquad (8)$$

where P_t represents the current CPI or PPI index, while P_{t-12} denotes 12-months-lagged price index.

2.3 Summary Statistics

The descriptive statistical results are shown in Table 1. It can be seen that the skewness of CPI inflation is positive, referring that its distribution is skewed to the right and it has a large kurtosis value, indicating that during the sample period, the CPI inflation rate has a fat-tail characteristic. The skewness of PPI inflation rate, CoVaR andΔCoVaRare less than 0, and the mean value of CoVaR is negative, suggesting that the probability of extremely small values for these two indicators is low.

Table1: **Summary Statistics.** The producer price index of the sample interval starts from January 1999.

Variable	Observations	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
CPI inflation	330	-2.616	27.665	4.126	5.884	2.162	7.500
PPI inflation	248	-8.257	10.003	1.254	4.166	-0.108	2.074
CoVaR	330	-4.540	-2.480	-3.181	0.480	-0.927	3.110
ΔCoVaR	330	-2.817	-0.815	-1.486	0.483	-0.999	3.270

Table 2 shows the correlation between the systemic risk indicators and the two types of inflation rate under different lag periods. As can be seen from the table, for the CPI inflation, regardless of the length of the lag, it has a negative correlation with the systemic risk indicators. However, the PPI inflation is different. When the lag period is prolonged from 1 to 6, it has a positive correlation with financial indicators; when lagging 12 months, there is a negative correlation.

Table 2: **Correlation between systemic risk indicators and inflation.** h is the lag horizon. $h = 1, 6, 12$ respectively represent lags of 1 month, 6, and 12 months.

Variable	CoVaR (h=0)	ΔCoVaR (h=0)	CoVaR (h=1)	ΔCoVaR (h=1)	CoVaR (h=6)	ΔCoVaR (h=6)	CoVaR (h=12)	ΔCoVaR (h=12)
CPI inflation	-0.4	-0.3	-0.4	-0.3	-0.3	-0.2	-0.3	-0.2
PPI inflation	0.1	0.1	0.1	0.1	0.1	0.0	-0.1	-0.2

I.   Empirical Analysis

3.1 Forecast Accuracy

3.1.1 CPI-Based Inflation

Table 3 and Table 4 show the out-of-sample quantile $R^2$of the CPI inflation. Table 3 is about lower quantile, while Table 4 is about higher quantile. The larger the R^2, the better the predictive power of the indicators.

From the results in Table 3, it can be seen that at low quantiles, for different out-of-sample starting times, the out-of-sample quantile R^2increases with the extension of the lag period, which indicates that CoVaR and ΔCoVaR indicators have a strong predictive power for the future inflation at lower quantiles. According to Table 4, when lagging 12 months, the out-of-sample quantile R^2 becomes the largest, indicating that these two indicators have strong predictive effects on the high quantile level of future inflation.

Table 3: **Out-of-Sample Forecast Accuracy (CPI): lower quantile.** The table reports out-of-sample quantile R^2 (in percentage) relative to the historical quantile model.

(a)$\tau = 0.1$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	0.061	0.093	3.747	3.896	11.390	10.890	13.633	13.350
2013	0.589	0.555	4.586	4.465	13.092	12.329	13.911	13.385
2014	0.770	0.701	4.089	3.978	15.660	14.857	7.172	6.865
2015	0.825	0.682	7.692	7.469	29.016	28.237	24.459	24.998
2016	0.020	0.028	18.612	18.385	36.505	36.486	27.306	28.026
2017	6.410	4.743	8.948	8.527	2.172	2.428	1.423	1.519

(b)$\tau = 0.2$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	0.467	0.485	0.068	0.054	4.997	4.525	6.051	6.129
2013	0.248	0.264	0.144	0.069	6.937	5.722	8.940	8.628
2014	0.573	0.617	0.179	0.133	7.723	6.922	7.176	6.918
2015	0.233	0.250	1.569	1.602	17.656	16.407	20.227	20.337
2016	0.450	0.482	6.752	6.600	26.714	26.362	29.490	30.058
2017	0.980	0.755	9.209	8.740	6.279	6.571	3.988	4.093

Table 4: Out-of-Sample Forecast Accuracy (CPI): higher quantile.

(a)$\tau = 0.8$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	0.096	0.126	1.114	1.275	3.963	3.951	3.604	4.363
2013	0.051	0.106	0.252	0.344	4.494	4.123	5.519	5.519
2014	0.010	0.009	0.350	0.358	6.442	6.037	7.142	6.769
2015	0.032	0.000	0.726	0.857	9.506	9.010	7.193	6.960
2016	0.614	0.786	2.271	2.354	9.174	9.014	12.927	12.737
2017	1.472	2.545	21.771	22.620	0.188	0.172	11.125	11.985

(b)$\tau = 0.9$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	0.896	1.334	4.479	5.050	4.362	4.798	3.452	3.939
2013	0.823	1.172	5.175	5.709	5.163	5.054	6.981	6.681
2014	0.001	0.071	2.368	2.790	7.139	6.808	8.081	7.827
2015	0.351	0.316	8.041	8.720	12.630	12.481	13.332	13.353
2016	2.506	2.273	8.183	8.380	10.259	10.189	9.740	9.537
2017	3.214	4.809	9.375	10.139	0.261	0.364	3.482	5.582

3.1.2 PPI-Based Inflation

Table 5 and Table 6 show the results of out-of-sample R^2 tests using PPI inflation. Table 5 is about lower quantile, while Table 6 is about higher quantile. Similarly, as the lag time increases, the out-of-sample prediction effect gradually rises. For lower quantiles, lagging 12 months has the strongest predictive effect; at higher quantiles, lagging 9 months is optimal. Secondly, the R^2 on the higher quantiles is generally greater, so the predictability of systemic indicators for the high quantiles is stronger than lower quantiles. Except for the difference that R^2 based on PPI inflation is generally greater than CPI inflation, indicating that CoVaR and ΔCoVaR indicators have stronger predictive power for changes in the producer price index.

Table 5: **Out-of-Sample Forecast Accuracy (PPI): lower quantile.** The table reports out-of-sample quantile R^2 (in percentage) relative to the historical quantile model.

(a)$\tau = 0.1$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	8.596	8.715	16.699	18.053	36.179	36.375	40.829	43.374
2013	10.305	9.871	26.713	26.606	43.176	43.436	42.236	45.441
2014	11.706	11.653	30.697	31.190	51.092	51.626	46.846	50.685
2015	13.218	12.724	31.292	31.331	46.929	48.334	53.206	54.411
2016	8.591	8.780	23.140	22.124	54.875	53.396	27.274	28.937
2017	5.227	4.731	2.180	2.474	0.863	0.746	10.057	10.673

(b)$\tau = 0.2$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	6.918	6.954	23.125	22.757	39.353	39.542	41.271	44.662

2013	8.178	7.379	30.852	29.561	44.486	45.033	43.456	47.253
2014	10.177	9.640	32.800	32.806	51.720	52.638	47.761	52.299
2015	7.781	7.398	36.647	35.978	49.391	50.052	56.514	57.770
2016	6.679	6.671	23.349	22.447	54.346	53.191	31.974	33.444
2017	0.738	1.003	3.369	4.092	0.247	0.716	9.152	9.855

Table 4: **Out-of-Sample Forecast Accuracy (PPI): higher quantile.**

(a)$\tau = 0.8$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	10.489	10.177	34.369	32.222	69.088	68.064	60.962	62.493
2013	12.426	11.967	38.656	36.537	70.177	68.548	59.039	60.538
2014	11.630	11.313	40.406	38.663	69.561	70.718	52.970	55.353
2015	14.906	14.755	36.453	35.006	66.302	65.583	46.324	46.780
2016	6.936	6.960	15.073	14.943	49.838	49.804	3.636	3.696
2017	0.344	0.380	9.118	9.426	1.402	2.128	1.188	1.452

(b)$\tau = 0.9$

Lags	h=1		h=6		h=9		h=12	
Out of sample starting time	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR	CoVaR	ΔCoVaR
2012	9.180	8.122	46.913	45.842	71.952	71.540	57.996	60.313
2013	11.709	10.699	48.322	46.915	70.814	69.612	55.282	57.725
2014	10.071	8.956	46.303	45.385	68.748	69.659	48.858	50.706
2015	14.616	14.149	37.075	35.963	64.996	64.423	39.406	39.419
2016	12.553	12.597	14.522	14.556	50.757	51.133	2.636	2.617
2017	0.024	0.027	5.983	7.066	15.394	16.474	7.202	7.972

3.2 Significance Test

3.2.1 CPI-Based Inflation

Table 7 shows the estimators of both quantile and OLS regression model under various lag time. Among them, both CoVaR and ΔCoVaR have been standardized.

As we can see, under the same lag, OLS regression results are generally positive, and not statistically significant, different from the quantile regression results. Therefore, compared with the OLS model, quantile regression can obtain the distribution information of future inflation rate, which is more suitable for exploring the impact of systemic risk on inflation risk.

Secondly, at lower quantiles, the coefficient $\delta_2(\tau)$ of two indicators is positive, indicating that these two indicators have fallen, that is, when the overall risk of the financial system rises, the low percentiles of the inflation distribution will get down, suggesting deflation risk appears to be driven up. However, when it comes to higher quantiles, $\delta_2(\tau)$ turns to be negative, indicating that the high percentiles of the inflation distribution will go up as systemic risk raises, and the risk of inflation increases. For example, $\delta_2(\tau)$ = -0.93 means that as CoVaR lagged 6 months goes down *1* standard deviation, the 95th percentile of the inflation distribution will significantly rise by 0.93%, indicating a higher risk of future inflation.

Furthermore, with the lag period extending from 1 month to 12 months, except for median level, the coefficient $\delta_2(\tau)$ first increases and then decreases, and it reaches a maximum at the lag of 9 months. This shows that the intensity of the impact of indicators on the risk of inflation gradually increases with time and then decreases. Besides, it is observed that $\delta_2(\tau)$ of high quantiles is larger than that of low quantiles, therefore, the systemic risk has greater influence on inflation risk than deflation risk.

Table 7: **t-Statistics of Systemic Indicators Exposures – CPI Inflation.** Parentheses show the standard error of $\delta_2(\tau)$. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

(a) CoVaR

Lags	h=1	h=3	h=6	h=9	h=12
Quantiles	CoVaR	CoVaR	CoVaR	CoVaR	CoVaR
τ=0.1	0.14	0.46***	0.88***	1.01***	0.91***
	(0.09)	(0.12)	(0.18)	(0.11)	(0.25)
τ=0.3	0.06**	0.37***	0.75***	0.78***	0.25
	(0.03)	(0.11)	(0.16)	(0.23)	(0.27)
τ=0.5	0.06	0.08	0.06	0.03	0.01
	(0.05)	(0.10)	(0.17)	(0.22)	(0.18)
τ=0.7	0.01	-0.05	-0.32*	-0.66**	-0.86***
	(0.04)	(0.09)	(0.18)	(0.29)	(0.30)
τ=0.9	0.01	-0.27*	-0.96***	-1.29***	-1.27***
	(0.13)	(0.14)	(0.17)	(0.33)	(0.25)
τ=0.95	-0.20*	-0.38***	-0.93***	-1.08**	-0.81
	(0.11)	(0.09)	(0.12)	(0.45)	(0.60)
OLS	0.08*	0.20**	0.24	0.13	-0.13
	(0.04)	(0.09)	(0.15)	(0.21)	(0.26)

(b) ΔCoVaR

Lags	h=1	h=3	h=6	h=9	h=12
Quantiles	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
τ=0.1	0.12	0.47***	0.78***	1.05***	0.98***
	(0.11)	(0.08)	(0.16)	(0.14)	(0.24)
τ=0.3	0.06*	0.20*	0.67***	0.68***	0.25
	(0.03)	(0.11)	(0.18)	(0.23)	(0.26)
τ=0.5	0.05	0.06	0.02	0.03	0.01
	(0.05)	(0.10)	(0.16)	(0.19)	(0.17)
τ=0.7	-0.01	-0.05	-0.35**	-0.62**	-0.84**
	(0.04)	(0.07)	(0.15)	(0.27)	(0.34)
τ=0.9	0.01	-0.22	-0.79***	-1.17***	-1.15***
	(0.11)	(0.17)	(0.22)	(0.22)	(0.19)
τ=0.95	-0.10	-0.23	-0.78***	-0.83***	-0.74***
	(0.08)	(0.15)	(0.12)	(0.16)	(0.23)
OLS	0.06	0.16*	0.22	0.16	0.00

| | (0.04) | (0.09) | (0.15) | (0.20) | (0.24) |

3.2.2 PPI-Based Inflation

Table 8 shows the significance test based on PPI inflation, and CoVaR and ΔCoVaR have been standardized. There is some distinction from Table 7. Firstly, at the median level, $\delta_2(\tau)$ goes negative and statistically significant, and so does the 30th percentile. We can tell that the probability of high inflation risk in future drives up as systemic risk rises.

Secondly, compared with CPI inflation, the absolute value of $\delta_2(\tau)$ based on PPI inflation is generally larger, contending that the producer price index will suffer a greater impact after the financial system is exposed to risk. In addition, for CPI inflation, $\delta_2(\tau)$ starts to be generally significant at all quantiles when the lag is 6 months; while PPI inflation rate are statistically significant from the 1st lag time. This shows that upon systemic risk increasing, the producer price index will change first, and then the consumer price index will fluctuate. Lv Jie et al. (2015)[vii] constructed a three-sector DSGE model that includes the basic industrial production sector, basic agricultural production sector, and processing service sector. The processing service sector is the final consumer sector. Combining this model framework, according to the empirical results of this article, it can be speculated that systemic risk affects the industrial products of upstream firms, causing the cost of service sectors to rise, and eventually promote consumer-side prices, which will increase inflation risks.

It is found from Table 7 and Table 8 that if systemic risk rises, the risk of inflation or deflation will increase, and the impact on the producer price index will be greater and faster. Therefore, it can be speculated that systemic financial risks first cause an increase in supply-side inflation risk, which is then passed on to the consumer goods market, leading to increasing price. The increased risk of the financial system directly affects the company's asset prices on the one hand; on the other hand, it will trigger a credit crunch, which will cause enterprises to reduce investment, demand and output. Thus, midstream and upstream companies are more sensitive to systemic risk. Ex-factory prices of products fluctuate severely, and the risk of inflation measured by PPI rises. As far as the consumer price index is concerned, a rise in the producer price index increases costs and affects selling prices. On the other hand, financial risk changes consumer spending decisions by affecting consumer expectations, and the combination of the two triggers inflation perceived by residents.

Table 8: **t-Statistics of Systemic Indicators Exposures - PPI Inflation.** Parentheses show the standard error of $\delta_2(\tau)$. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

(a) CoVaR

Lags	h=1	h=3	h=6	h=9	h=12
Quantiles	CoVaR	CoVaR	CoVaR	CoVaR	CoVaR
τ=0.1	0.32**	0.90**	1.13**	1.38**	1.39***
	(0.15)	(0.36)	(0.49)	(0.55)	(0.33)
τ=0.3	-0.08	-0.32	-0.7	-0.31	-1.19*
	(0.10)	(0.31)	(0.55)	(0.70)	(0.69)
τ=0.5	-0.12**	-0.48***	-0.95***	-1.63***	-2.04***
	(0.06)	(0.16)	(0.27)	(0.43)	(0.50)
τ=0.7	-0.17***	-0.52***	-1.39***	-2.11***	-1.90***
	(0.06)	(0.12)	(0.36)	(0.26)	(0.24)
τ=0.9	-0.21	-0.65***	-1.57***	-1.67***	-1.12***
	(0.17)	(0.19)	(0.39)	(0.26)	(0.23)
τ=0.95	-0.24	-0.89	-1.29***	-0.94***	-1.00***
	(0.30)	(0.68)	(0.34)	(0.20)	(0.29)
OLS	0.02	0.01	-0.11	-0.36	-0.58**
	(0.06)	(0.14)	(0.22)	(0.26)	(0.27)

(b) ΔCoVaR

Lags	h=1	h=3	h=6	h=9	h=12
Quantiles	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
τ=0.1	0.32**	0.65*	1.17***	1.43***	1.30***
	(0.14)	(0.35)	(0.38)	(0.50)	(0.38)
τ=0.3	-0.08	-0.39	-0.63	-0.51	-1.02
	(0.09)	(0.29)	(0.53)	(0.67)	(0.65)
τ=0.5	-0.12**	-0.44***	-0.87***	-1.62***	-1.85***
	(0.06)	(0.14)	(0.28)	(0.42)	(0.46)
τ=0.7	-0.13**	-0.49***	-1.40***	-1.95***	-1.73*
	(0.06)	(0.11)	(0.31)	(0.23)	(0.21)
τ=0.9	-0.16	-0.48	-1.35***	-1.71***	-1.09***
	(0.16)	(0.36)	(0.30)	(0.24)	(0.23)
τ=0.95	-0.40	-1.05*	-1.08***	-1.03***	-0.83***
	(0.28)	(0.57)	(0.21)	(0.23)	(0.24)
OLS	-0.01	-0.07	-0.23	-0.45*	-0.60**
	(0.05)	(0.14)	(0.21)	(0.24)	(0.25)

3.3 Transmission Mechanism of Systemic Risk to Inflation Risk
3.3.1 Systemic Risk and Inflation Risk

When the financial market is very prosperous, more and more investors are willing to enter the market and make additional investments. With the excessive increase in investment, many bad loans have been created to meet the ever-expanding investment demand, causing the fake phenomenon of extreme prosperity in financial market. In the process, systemic risk has started to accumulate. Such financial bubbles will burst when bad-loans lenders have difficulties in meeting their repayment obligations. Due to the high uncertainty of asset prices in the future, the disappearance of confidence in financial institutions, and negative expectations of market prospects, investors and depositors would stop investing and quickly withdraw funds, causing phenomena such as bank runs and widespread market panic, resulting in a sharp decline in liquidity throughout the financial system. Due to the high correlation among financial institutions, risk has begun to spread and spread between various sectors, causing systemic risk to accelerate. To avoid risk at this time, some financial institutions, such as commercial banks, will choose to raise credit standards and reduce credit supply. Lack of capital injection from investors and loan support from banks, the companies immediately face financing difficulties and even a shortage of liquidity. In this case, corporate investment is blocked and it's necessary to reduce the scale of production to maintain its own survival, resulting in low corporate sales. Under the condition that the company's existing debt remains unchanged, its net assets have decreased, which has reduced the company's ability to borrow, making it more difficult to obtain loans from banks, which forms a vicious circle. As more and more companies in the market have a similar dilemma, the total output of the market will greatly reduce, leading to a total market supply that cannot meet the total market demand, thus, prices will continue to rise. At the same time, the central bank is willing to implement a loose monetary policy to stimulate investment, causing the amount of money in circulation to exceed the actual demand for currency. As a result, hyperinflation follows.

3.3.2 Systemic Risk and Deflation Risk

Different from the mechanism of high inflation caused by the decrease in credit supply, the increase in deflation risk caused by systemic risk may depend on the demand side of credit activities. Firstly, after the financial system exposed to risk, asset values would suddenly shrink. Due to the wealth effect, the fall in asset prices will directly promote the marginal consumption propensity of residents declined. Li Bo (2015)[viii] added household credit constraints and asset structure to the optimal consumer choice model, and examined the risk effect and wealth effect of financial risk assets on household consumption levels. The study found that when financial assets take up the weight of total household assets, the marginal propensity to consume assets will increase. Secondly, according to Tobin's q theory, the continuous decline of the market value of the enterprise may cause the Tobin's q value to be less than 1, which means that capital investment cannot bring profits to the enterprise at this time, and this will directly result in a decline in corporate investment demand. In addition, systemic risk can influence their investment and consumption decisions by changing public expectations. As financial market bubble continuing to inflate, a large number of non-performing loans exist in the market. However, due to information asymmetry and the winner's curse, investors don't know about it. Once a debt default occurs, the financial system will be exposed to risk, and uncertainty will rise. At this time, public confidence in financial institutions and financial markets has declined, market risk appetite has decreased, and people have pessimistic expectations of the future economy, which will directly reduce investment. As a result, overall market demand has weakened and the risk of deflation will increase.

3.4 Robustness Test

The measurement of systemic risk can be divided into four categories, which are based on credit, linkage and contagion, individual institutional risk, volatility and instability. We select the index *Volatility*, which measures the fluctuations of the financial system, in order to test the robustness of the results.

Volatility indicator is calculated by the rolling standard deviation of value-weighted equity portfolio returns for all financial institution stocks. All of the data come from Wind database, and the sample interval starts from April 1992 to September 2019.

Table 9 is about the out-of-sample quantile R^2 at 90th percentile, based on *Volatility* index. As can be seen from the table, when the lag period is 12 months, R^2 is the largest. Besides, *Volatility* index has a stronger predictive power of inflation risk than deflation risk.

The greater the *Volatility*, the higher the systemic risk, which is different from the results of CoVaR and ΔCoVaR. Therefore, if the coefficient $\delta_2(\tau)$ is positive, it means that as systemic risk rising, the value of the inflation rate at a specific quantile will

135

increase. Table 10 shows the significance test of the quantile regression and OLS regression estimators based on *Volatility* index. The inflation rate is calculated by CPI and the *Volatility* index has been standardized. As can be seen from the table, when the lag extends from 9 to 12 months, at high quantiles, $\delta_2(\tau)$ is significantly positive, indicating that as *Volatility* increases, that is, the systemic risk rises, higher percentiles of the inflation distribution will significantly shift to the right.

Table 9: **Out-of-Sample 90th Percentile CPI Inflation Forecasts.** The table reports out-of-sample quantile forecast R^2 (%) relative to the historical quantile model.

Lags	h=1	h=3	h=6	h=9	h=12
Out of sample starting time	Volatility	Volatility	Volatility	Volatility	Volatility
2012	0.099	0.303	1.718	1.380	4.531
2013	0.087	1.214	3.806	0.091	4.144
2014	0.500	1.102	2.522	0.081	4.122
2015	0.984	1.875	5.126	0.268	8.210
2016	7.733	7.051	0.149	0.810	2.200
2017	15.786	13.593	1.278	2.087	0.938

Table 10: **t-Statistics of *Volatility* index Exposures - CPI Inflation.** Parentheses show the standard error of $\delta_2(\tau)$. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Lags	h=1	h=3	h=6	h=9	h=12
Quantiles	volatility	volatility	volatility	volatility	volatility
τ=0.1	0.036	-0.335**	-0.572*	-0.930***	-0.930***
	(0.13)	(0.14)	(0.33)	(0.31)	(0.23)
τ=0.3	0.005	0.062	0.091	0.047	0.041
	(0.06)	(0.14)	(0.25)	(0.30)	(0.33)
τ=0.5	0.036	0.071	0.183	0.278	0.283
	(0.07)	(0.13)	(0.14)	(0.21)	(0.30)
τ=0.7	0.095*	0.238**	0.484***	0.751*	1.101**
	(0.05)	(0.12)	(0.16)	(0.44)	(0.56)
τ=0.9	0.135	0.088	0.824**	1.195***	1.627***
	(0.13)	(0.18)	(0.35)	(0.37)	(0.36)
τ=0.95	0.227	0.197	1.003***	1.038***	0.868*
	(0.14)	(0.12)	(0.32)	(0.36)	(0.52)

| OLS	0.091**	0.13	0.276*	0.473**	0.572**
	(0.05)	(0.10)	(0.16)	(0.21)	(0.26)

II.   Forecast Inflation Risk

Based on model (2), we forecast both CPI and PPI inflation risk from March 2020 to March 2021, with systemic risk indicator used as CoVaR. The predicted values of the inflation rate distribution are shown in Table 11 and Table 12.

In addition, referring to the inflation forecast reports of the Bank of England, we draw Chinese inflation forecasting fan charts, as shown in Figure 1. Forecast fan charts are images of a set of time series centered on the mean or median, with shadow bands as probabilities, and are used to describe the future distribution trend of the series. Its more common application is to characterize the confidence interval of prediction results and display the results of risk prediction. In Figure 1, the colored bands in different depths indicate the possibility of varying degrees. The dark shaded areas, from the inside out, represent 40%, 60%, 80% and 90% probability, respectively. Therefore, there is 90% probability of future inflation falling into overall shaded bands shown in the figure, and only 10% may exceed the shaded range. The larger the area of the shaded band, the greater the possibility it is. From the figure, it can be found that, the possibility of higher inflation significantly increases. Therefore, according to the prediction of this article, inflation risk in China will rise in the next year.

Figure 1: **Inflation Forecasting Fan Charts.** The forecast range is from March 2020 to March 2021. The grey dotted line is the predicted value at median level, and the grey solid line from bottom to top represents the predicted values of $\tau = 0.05$, 0.1, 0.2, 0.3, 0.7, 0.8, 0.9, and 0.95, respectively. The shaded area indicates that there is a 40% probability that the future inflation falls into the darkest middle interval; a 90% probability that it will fall within the fan-shaped interval; the probability of the fan-shaped interval from deep to shallow is 40%, 60%, 80% and 90%.
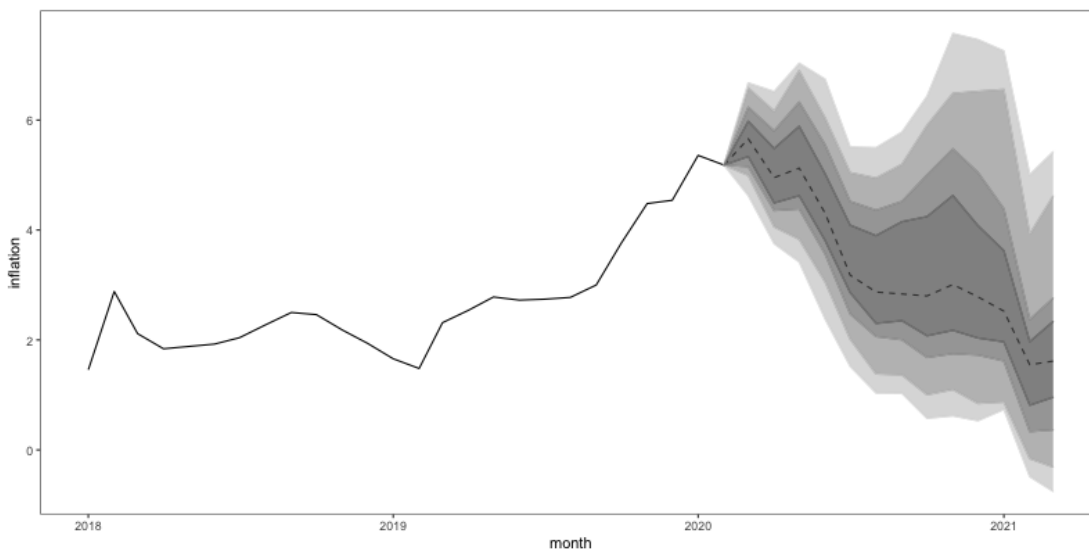
(a) CPI Inflation
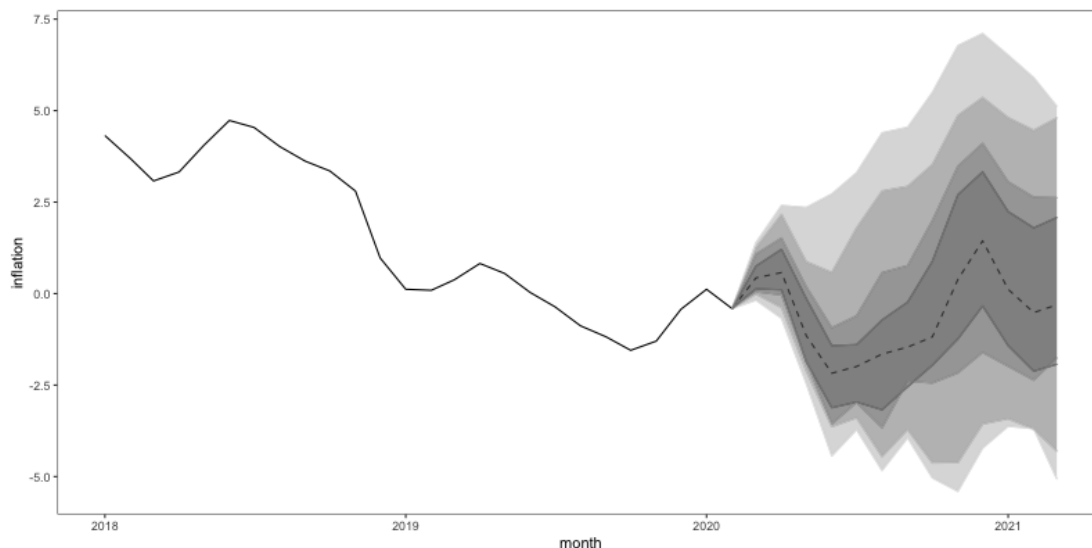
(b) PPI Inflation

Table 11: **CPI Inflation Risk (%) Forecast.**

Forecast Horizon	τ = 0.05	τ = 0.1	τ = 0.2	τ = 0.3	τ = 0.5
2020.3	4.626	4.993	5.152	5.336	5.660
2020.4	3.751	4.057	4.353	4.492	4.953
2020.5	3.418	3.830	4.381	4.623	5.126
2020.6	2.382	3.055	3.562	3.808	4.306
2020.7	1.520	2.014	2.473	2.862	3.178
2020.8	1.034	1.380	2.061	2.301	2.872
2020.9	1.029	1.363	2.003	2.350	2.836
2020.10	0.573	1.001	1.680	2.076	2.801
2020.11	0.618	1.096	1.748	2.175	3.008
2020.12	0.530	0.844	1.724	2.035	2.783
2021.1	0.734	0.870	1.618	1.965	2.524
2021.2	-0.488	-0.160	0.333	0.812	1.549
2021.3	-0.755	-0.313	0.364	0.957	1.615
Forecast Horizon	τ = 0.7	τ = 0.8	τ = 0.9	τ = 0.95	
2020.3	5.979	6.234	6.585	6.677	
2020.4	5.483	5.804	6.164	6.519	
2020.5	5.887	6.329	6.902	7.035	
2020.6	5.023	5.553	6.041	6.744	
2020.7	4.088	4.520	5.045	5.510	
2020.8	3.898	4.362	4.946	5.498	

2020.9	4.152	4.521	5.197	5.782	
2020.10	4.244	5.004	5.905	6.434	
2020.11	4.628	5.477	6.488	7.575	
2020.12	4.080	5.048	6.526	7.465	
2021.1	3.625	4.386	6.559	7.258	
2021.2	1.969	2.373	3.928	5.008	
2021.3	2.337	2.760	4.618	5.424	

Table 12: **PPI Inflation Risk (%) Forecast.**

Forecast Horizon	$\tau = 0.05$	$\tau = 0.1$	$\tau = 0.2$	$\tau = 0.3$	$\tau = 0.5$
2020.3	-0.180	-0.014	0.049	0.129	0.429
2020.4	-0.675	-0.381	-0.038	0.104	0.575
2020.5	-2.455	-2.116	-1.845	-1.865	-1.150
2020.6	-4.438	-3.641	-3.565	-3.119	-2.176
2020.7	-3.721	-3.395	-2.978	-2.963	-1.992
2020.8	-4.835	-4.454	-3.668	-3.176	-1.652
2020.9	-3.942	-3.719	-2.392	-2.545	-1.461
2020.10	-5.037	-4.629	-2.444	-1.958	-1.184
2020.11	-5.405	-4.623	-2.169	-1.239	0.387
2020.12	-4.223	-3.566	-1.608	-0.340	1.444
2021.1	-3.626	-3.422	-1.987	-1.423	0.117
2021.2	-3.693	-3.705	-2.365	-2.120	-0.519
2021.3	-5.061	-4.306	-1.759	-1.931	-0.307
Forecast Horizon	$\tau = 0.7$	$\tau = 0.8$	$\tau = 0.9$	$\tau = 0.95$	
2020.3	0.752	1.081	1.256	1.394	
2020.4	1.211	1.518	2.166	2.409	
2020.5	-0.133	0.188	0.874	2.355	
2020.6	-1.420	-0.932	0.577	2.725	
2020.7	-1.397	-0.608	1.794	3.303	
2020.8	-0.720	0.573	2.804	4.395	
2020.9	-0.233	0.766	2.932	4.547	
2020.10	0.884	1.998	3.528	5.497	
2020.11	2.702	3.484	4.869	6.779	
2020.12	3.327	4.106	5.360	7.108	
2021.1	2.241	3.057	4.809	6.516	
2021.2	1.796	2.635	4.464	5.902	
2021.3	2.079	2.620	4.802	5.121	

Conclusions

In the framework of the quantile regression model, we explore the impact of systemic risk on future inflation risk. Specifically, we use data from Chinese financial institutions to calculate the conditional value-at-risk (CoVaR), ΔCoVaR, and Volatility as indicators measuring Chinese systemic risk. We study these indicators' impacts on the

inflation risk, including direction, intensity, as well as predictability. Finally, we forecast the inflation risk in China from March 2020 to March 2021 and draw forecast fan charts.

Results of this study can be summarized as the following four aspects: Firstly, based on out-of-sample quantile R^2, we find that the systemic risk indicators can significantly increase the predictive power of the quantile model. Secondly, as overall risk of the financial system rises, the inflation rate at different quantiles will change in different directions and to different degrees, which is obviously different from OLS regression model. OLS estimations show that the rising risk of financial system doesn't have significant impact on the average level of inflation rate. However, the results based on the quantile regression model show that systemic risk has a significant influence on inflation rates at high and low quantiles. Specifically, when systemic risk goes up, the higher percentile of the inflation distribution will shift significantly to the right, while the lower percentile of the inflation distribution will shift significantly to the left, which is mainly reflected in the lag of 6 to 12 months, suggesting the ascending risk of future inflation or deflation. Thirdly, the value of the estimator shows that compared with the CPI inflation, the impact of systemic risk on PPI inflation risk is greater. In addition, it is found that there is a time difference in the impact of systemic financial risk on the two types of inflation risk. Specifically, as risk of the financial system increasing, the PPI inflation responds to it faster. Finally, we predict Chinese inflation risk from March 2020 to March 2021. The results show that during the prediction interval, the inflation risk in China will dramatically boost.

Based on the results of this study and the actual conditions in China, the following policy recommendations are proposed: Firstly, after financial system exposed to risk, policy formulation should be mainly focused on enterprise manufacturers to avoid disruption of their capital flows and appropriate rescue measures should be given. According to the analysis results of this paper, after the rise of systemic risk, the change range of producer price index (PPI) exceeds that of consumer price index, and the response is more rapid. Therefore, in order to prevent systemic risk from overflowing the inflation risk, policy formulation should pay more attention to the supply side and avoid the accelerated rise in production costs of enterprises.

Secondly, based on the transaction data and the overall financial market risk, the central bank should regularly release the forecast results of Chinese inflation risk, so as to better monitor systemic risk and improve the information disclosure. So far, most of the relevant forecast information in China is a point estimate of the conditional average of macroeconomic variables, and there is no prediction of distribution information. From the quantile regression results in this article, we can see that when risk of financial market rises, inflation rate has distinctive changing directions and degrees at various quantiles, and systemic risk doesn't have a significant impact on the average level. Forecasting based on OLS regression model is likely to underestimate the risk of future inflation. In recent years, some countries have begun to forecast the distribution of inflation rate, such as the Bank of England and the US Federal Open Market Committee. Referring to the methods of these countries, China can regularly publish the forecast of the inflation distribution.

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