Empirical Analysis and Forecasting of CPI Based on VECM Modeling

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Abstract—The Consumer Price Index (CPI) is closely related to people's daily life, which not only affects the economic operation of a country, but also relates to the happiness of residents. Over the years, many scholars have studied the CPI from different perspectives and have drawn many useful conclusions. In the past two years, due to the impact of the new coronary pneumonia epidemic and the rise in pork prices, China's CPI has experienced a relatively large increase, especially the rise in pork prices has a greater degree of impact on the CPI. Therefore, it is particularly important to study the changing law of CPI and predict its future trend under the new circumstances. This paper starts from the factors affecting the CPI, utilizes the monthly data of China's consumer price index from January 2010 to March 2021, establishes the VECM model, conducts an empirical study on the relationship between the CPI and the influencing factors of the CPI, such as the MPI, M2, and PPI, and utilizes the VECM model to forecast the CPI from April to December 2021, which provides a certain reference basis for the governmental departments to formulate economic policy provides a certain reference basis. Finally, this paper concludes that China's CPI will show an upward trend in the next six months or so, but the magnitude of the increase is not large, and the VECM model has a better forecasting effect, and corresponding policy recommendations are put forward based on the empirical results of this paper.

Keywords—Consumer Price Index (CPI), Vector Error Correction Model (VECM), impulse response, variance decomposition

I. INTRODUCTION

In China, the Consumer Price Index that (CPI) reflects the changes in the price level, is an important indicator in the economy to maintain stable operation, while the CPI is also a very important factor affecting economic development. 2020, due to the impact of the new crown epidemic on the global economy, the Federal Reserve began to open the floodgates dramatically, and the central banks of all countries can only follow the expansion of the table, which is to the future of the price level to maintain stable brought a lot of pressure.

The level of prices is closely related to the daily life of the population, and it not only affects public well-being but also economic development. Moderate and mild inflation is conducive to economic development, aligning with Friedman's (1968) argument that monetary policy plays a key role in stabilizing inflation within acceptable ranges to promote growth. However, too high an inflation rate or deflation will have a negative impact on economic development. For China's economic sector, CPI is an important indicator to monitor the fluctuation of the price level, and the relevant decision-making departments can adjust their fiscal and monetary policies according to the future trend of CPI, so as to keep prices within a reasonable range, thus allowing the economy to maintain stable development. At the same time, CPI also provides an important reference for market players to carry out various economic activities.

The consumer price index is very responsive to changes in market prices and can quickly reflect changes in price levels. If the CPI rises sharply on a sustained basis, it indicates that the price level has risen, the purchasing power of the currency held by residents has fallen, and the cost of living has risen sharply; conversely, it indicates that the price level has declined, the purchasing power of the currency held by residents has risen, and the cost of living has fallen.

Promoting economic growth, full employment of the population and stabilizing the price level are the three major policy objectives of macro-control. Sims (1980) emphasized that these objectives require dynamic modeling techniques, such as VAR models, to capture the intricate interdependencies in macroeconomic indicators. In order to realize the above objectives at the same time, the decisionmaking body will often consider the reasonable combination of fiscal policy and monetary policy, and time must be taken into account the impact of the level of inflation, and the CPI is an important reference indicator of the level of inflation. Therefore, it is of great theoretical and practical significance to study the influencing factors and future trends of CPI.

II. LITERATURE REVIEW

Domestic scholars Ye and Li (2000) collected China's monthly CPI data from April 1993 to November 1998 and used the GARCH model to study and compare conclusions drawn from the study with the results obtained using the regression model. Their study concluded that the prediction effect of the GARCH model is better than that of the regression model, but the constraints imposed by the GARCH model could result in parameter estimation oscillations, thus increasing prediction inaccuracies. Building on this, Engle and Granger (1987) developed the co-integration framework, which provides a more robust method for studying long-term relationships between economic variables like CPI and its influencing factors. Hu and Luo (2006) first studied the movement of the consumer price index in China over the past decade or so, and used a multiple regression model to quantitatively analyze several variables affecting the price level in China.

Hu and Luo (2006) conducted a quantitative analysis using a multiple regression model to study the impact of several variables affecting the price level in China over a decade. Later, He and Tian (2007) utilized the VAR model to analyze the main factors affecting CPI. They concluded that internal factors, such as food prices and housing, play a dominant role in driving CPI changes. Building on these methodologies, Sims (1980) introduced VAR models as a critical tool for interdependencies among capturing macroeconomic indicators, thereby advancing the analysis of CPI trends. Xie, et al. (2008) employed the ARIMA model with 80 months of CPI data from 2001 to August 2007 to analyze the fluctuation law of China's CPI. Their research demonstrated the effectiveness of ARIMA in capturing CPI trends, but noted its limitations due to the small sample size. Furthermore, Johansen (1991) expanded on traditional time-series approaches by proposing a maximum likelihood framework for cointegration vectors, which allowed for the analysis of multiple equilibrium relationships. Similarly, Stock and Watson (1988) made significant contributions by testing for common trends in time-series data, further enhancing the ability to forecast economic variables like CPI. Zha (2009) utilized the monthly CPI data from 1990 to June 2009, and used the ARIMA model to fit and forecast the CPI index and other studies, with better results.

III. RESEARCH DESIGN

In this paper, the monthly data (135 sets in total) from January 2010 to March 2021 are selected for the study, and the four variables of Consumer Price Index (CPI), the growth rate of money and quasi-money over the same period (M2), the purchasing price index of raw materials, fuels, and power (MPI), and the ex-factory Price Index of Industrial products (PPI) are selected for the empirical study by using the VECM model, and the prediction of the the VECM model belongs to the category of time series analysis, which is mainly used to study the dynamic characteristics of the economic system. The sample data used in this paper is larger and contains more comprehensive information, which makes the model more accurate when used for forecasting.

All of the above data were obtained from the CCER Economic and Financial Research Database in the school library. In order to make the data smoother, the natural logarithm was taken for the above four variables, and the results of the data processing were noted as: lncpi, lnm2, lnmpi, and lnppi.

IV. EMPIRICAL FINDINGS

A. Serial Smoothness Test



The time series plot of lncpi is shown in Fig. 1, according to the time series plot, it can be initially judged that lncpi has only intercept and no trend. Therefore, in the ADF test for the

horizontal sequence and the first-order difference sequence test, check the box INTERCEPT. The ADF test results of the sequence lncpi and its first-order difference sequence are shown in Figs. 2 and 3.

Augmei	nted Dickey-Fuller U	nit Root Test on LI	
Null Hypothesis: LNCI Exogenous: Constant Lag Length: 0 (Automa	PI has a unit root atic - based on SIC, ma	axlag=12)	
		t-Statistic	Prob.'
Augmented Dickey-Fu	ller test statistic	-1.746684	0.4056
Test critical values:	1% level	-3.479656	
	5% level	-2.883073	
	10% level	-2.578331	

*MacKinnon (1996) one-sided p-values

Fig. 2. ADF unit root test on LNCPI.

Augment	ed Dickey-Fuller Uni	t Root Test on D(L	NCPI)
Null Hypothesis: D(LN Exogenous: Constant Lag Length: 0 (Automa	ICPI) has a unit root atic - based on SIC, ma	axlag=12)	
		t-Statistic	Prob.*
Augmented Dickey-Fu	ller test statistic	-11.73409	0.0000
Test critical values:	1% level	-3.480038	
	5% level	-2.883239	
	10% level	-2 578420	

*MacKinnon (1996) one-sided p-values.

Fig. 3. ADF unit root test on D (LNCPI).

According to the test results in Figs. 2 and 3, it can be seen that at a significance level of 0.05, the lncpi test statistic corresponds to a *p*-value of 0.4056>0.05, which does not reject the original hypothesis, i.e., there is a unit root in the sequence lncpi and the sequence is not smooth. Whereas, the test result for the first order difference series shows a *p*-value of 0 < 0.05, rejecting the original hypothesis that there is no unit root in the series D (lncpi) and the series is smooth.



The timing diagram of lnm2 is shown in Fig. 4, according to the timing diagram, it is judged that the sequence lnm2 has both intercept and obvious trend, so the trend and intercept is checked in the ADF test. the ADF test results of the sequence lnm2 as well as D (lnm2) are shown in Figs. 5 and 6.

Augme	nted Dickey-Fuller U	nit Root Test on L	NM2
Null Hypothesis: LNM: Exogenous: Constant, Lag Length: 2 (Automa	2 has a unit root Linear Trend atic - based on SIC, ma	axlag=12)	
		t-Statistic	Prob.*
Augmented Dickey-Fu	ller test statistic	-1.675721	0.7567
Test critical values:	1% level	-4.029041	
	5% level	-3.444222	
	10% level	-3.146908	

Fig. 5. ADF unit root test on LNM2.

Augmented Dickey-Fuller Unit Root Test on D(LNM2)

Null Hypothesis: D(LNM2) has a unit root	
Exogenous: Constant, Linear Trend	
Lag Length: 1 (Automatic - based on SIC, maxlag=12)	

Augmented Dickey-Fuller te	est statistic	-12.77261	0.0000
Test critical values: 19	% level	-4.029041	
5	% level	-3.444222	
10	% level	-3.146908	

Fig. 6. ADF unit root test on D (LNM2).

According to the test results in Figs. 5 and 6, the *p*-value of the test statistic corresponding to lnm2 is 0.7567 > 0.05, which does not reject the original hypothesis, i.e., there is a unit root in lnm2 and the series is not smooth; the *p*-value of the test statistic corresponding to D (lnm2) is 0 < 0.05, which rejects the original hypothesis, i.e., there is no unit root in D (lnm2) and the series is smooth.

And the timing diagram of lnmpi is shown in Fig. 7, according to the image, it can be seen that lnmpi has no trend, only intercept. In the ADF test, only need to check the INTERCEPT, the test results are shown in Figs. 8 and 9.



^{*}MacKinnon (1996) one-sided p-values.

According to the test results in Figs. 8 and 9, it can be seen that the sequence lnmpi has a unit root and the sequence is not smooth; while D (lnmpi) does not have a unit root and the sequence is smooth. That is, lnmpi is a first-order single-integrated sequence.

The time series plot of Inppi is shown in Fig. 10, i.e., the

sequence Inppi contains only intercept and no trend. the ADF test is checked INTERCEPT and the test results are shown in Figs. 11 and 12.



Augmented Dickey-Fuller Unit Root Test on LNPPI

Null Hypothesis: LNPPI has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Ful	ler test statistic	-2.345849	0.1594
Test critical values:	1% level	-3.480425	
	5% level	-2.883408	
	10% level	-2.578510	
*MacKinnon (1996) on	e-sided p-values.		
Fig.	11. ADF unit root to	est on LNPPI.	
Augment	ed Dickey-Fuller Uni	t Root Test on D(Ll	NPPI)
Null Hypothesis: D(LN Exogenous: Constant	PPI) has a unit root		
Lag Length: 1 (Automa	auc - based on SIC, ma	axiag=12)	
		t-Statistic	Prob.*
Augmented Dickey-Fu	ller test statistic	-5.069727	0.0000
Test critical values:	1% level	-3.480425	
	5% level	-2.883408	
	10% level	-2.578510	

*MacKinnon (1996) one-sided p-values.

Fig. 12. ADF unit root test on D (LNPPI).

According to the test results in Figs. 11 and 12, i.e., the sequence lnppi has a unit root and the sequence is not smooth; while D (lnppi) does not have a unit root and the sequence is smooth. That is, lnppi is also a first-order single-integrated series.

Sequence Smoothness Test Summary: That is, the four sequences lncpi, lnm2, lnmpi, and lnppi are all first-order single-integrated sequences, i.e., the sequences themselves are not smooth, but the sequences are smooth after first-order differencing.

B. Determine the Optimal Lag Order P

The four variables lncpi, lnm2, lnmpi and lnppi are used as endogenous variables, the constant term is used as exogenous variable, and the lag order is selected as 2 to establish the VAR model, and then according to the criteria for the selection of the lag order, the maximum order has been experimentally adjusted from the 8th order to the 1st order, and it is found that when the lag order is 2, the corresponding 5 selection indexes are all at the minimum, so the 2nd order is selected as the VAR model's lag order. The test results are shown in Fig. 13 below.

Fig. 9. ADF unit root test on D (LNMPI).

VAR Lag Order Selection Criteria Endogenous variables: LNCPI LNMPI LNMPI LNM2 Exogenous variables: C Date: 07/16/21 Time: 17:12 Sample: 2010M01 2021M03 Included observations: 133						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	1061.332	NA	1.46e-12	-15.89973	-15.81280	-15.86440
1	1824.843	1469.615	1.92e-17	-27.14049	-26.70586	-26.96387
2	1900.596	141.2547*	7.82e-18*	-28.03904*	-27.25669*	-27.72113

indicates lag order selected by the criterior

Fig. 13. VAR lag order selection.

C. Johansen Cointegration Test

The Johansen cointegration test is performed on the basis of the VAR model, and the test type is chosen as hypothesis 2 (i.e., with intercept term and without trend term), because the intercept term is found to be significant while the trend term is not significant in the ADF test of the four series, and combined with the analysis of the series' time series plot, hypothesis 2 is chosen, the optimal lag order is chosen as 1 (the optimal lag order for the VAR model is -1), the test the results are shown in Fig. 14.

		Jonansen	Contegration Te	est
Date: 07/16/21 Sample (adjuste ncluded observa Trend assumptio Series: LNCPI L	Time: 17:23 d): 2010M03 202 ations: 133 after on: No determinis NPPI LNMPI LNM first differences):	21M03 adjustments tic trend (restri v12 : 1 to 1	cted constant)	
_ags interval (in				
ags interval (in	,			
Jnrestricted Coi	ntegration Rank	Test (Trace)		
Jnrestricted Coi	ntegration Rank	Test (Trace) Trace	0.05	
Jnrestricted Coi Hypothesized No. of CE(s)	ntegration Rank Eigenvalue	Test (Trace) Trace Statistic	0.05 Critical Value	Prob.**
Jnrestricted Coi Hypothesized No. of CE(s)	ntegration Rank Eigenvalue 0.353797	Test (Trace) Trace Statistic 105.5589	0.05 Critical Value 54.07904	Prob.**
Jnrestricted Coi Hypothesized No. of CE(s) None * At most 1 *	ntegration Rank Eigenvalue 0.353797 0.181785	Test (Trace) Trace Statistic 105.5589 47.48564	0.05 Critical Value 54.07904 35.19275	Prob.** 0.0000 0.0015
Ags interval (in Jnrestricted Coi Hypothesized No. of CE(s) None * At most 1 * At most 2 *	ntegration Rank Eigenvalue 0.353797 0.181785 0.098410	Test (Trace) Trace Statistic 105.5589 47.48564 20.80183	0.05 Critical Value 54.07904 35.19275 20.26184	Prob.** 0.0000 0.0015 0.0421

denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Fig. 14. Johansen cointegration test.

The test results in Fig. 14 show that, at a significance level of 0.05, when the original hypothesis is that there is no cointegration, the *p*-value is 0 < 0.05, which rejects the original hypothesis, indicating that there is at least one cointegration relationship; while when the original hypothesis is that there is at most one cointegration relationship, the *p*-value is 0.0015 < 0.05, which rejects the original hypothesis, indicating that there is more than one cointegration relationship; and when the original hypothesis is that there are at most When the original hypothesis is that at most two cointegration relationships exist, the p value is 0.0421 < 0.05, rejecting the original hypothesis, indicating that there are at least two or more cointegration relationships; and when the original hypothesis is that at most three cointegration relationships exist, the p value is 0.1252 > 0.05, not rejecting the original hypothesis, i.e., there are three cointegration relationships. That is, there are three cointegration relationships among lncpi, lnm2, lnmpi, and Inppi, and there is a long-term equilibrium relationship among the four variables.

D. Granger Causality Test

Granger causality test is performed on the VAR model and the test results are shown in Fig. 15, indicating that mpi is the Granger cause of ppi changes.

Dependent va	ariable: LNPPI
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Excluded	Chi-sq	df	Prob.
LNCPI	0.760239	2	0.6838
LNMPI	62.31665	2	0.0000
LNM2	3.746693	2	0.1536
All	73.72915	6	0.0000

Fig. 15. Granger causality test.

E. Construction of VECM Model

Since all four variables are non-stationary series and are smooth after first-order differencing, i.e., they are all firstorder single-integrated series and there is a cointegration relationship, they are suitable for VECM modeling. Choose lncpi, lnm2, lnmpi, lnppi as endogenous variables, the lag order is 1 (the same order as Johansen's cointegration test), the number of cointegration relationships is 3, and the basic assumptions of the model choose assumption 2 (the same as the assumptions of Johansen's cointegration test), to establish the VECM model. The tabular output of the VECM consists of four parts, namely, the first part is the coefficients of the cointegration equations, the second part is the coefficient of the cointegration equations, and the third part is the coefficients of the cointegration equations. The first part is the estimated values of the coefficients of the cointegration equations, as shown in Fig. 16; the second part is the parameter estimation results of the VECM, as shown in Fig. 17; and the last two parts are the test results of the individual equations and the VECM model as a whole, as shown in Fig. 18.

Vector Error Correction E Date: 07/16/21 Time: 0 Sample (adjusted): 2010 Included observations: 1 Standard errors in () & t	Estimates 0:00 M03 2021M03 33 after adjustme -statistics in []	ents		
Cointegrating Eq:	CointEq1	CointEq2	CointEq3	
LNCPI(-1)	1.000000	0.000000	0.000000	
LNPPI(-1)	0.000000	1.000000	0.000000	
LNMPI(-1)	0.000000	0.000000	1.000000	
LNM2(-1)	-0.107066 (0.04826) [-2.21845]	0.175458 (0.08790) [1.99599]	0.261898 (0.12250) [2.13800]	
С	-2.984321 (0.67992) [-4.38925]	-7.349492 (1.23841) [-5.93461]	-8.675057 (1.72575) [-5.02684]	
Fig. 16.	Estimated v	alues of the	coefficients.	

Error Correction:	D(LNCPI)	D(LNPPI)	D(LNMPI)	D(LNM2)
CointEq1	0.010194	-0.014670	-0.071962	0.047689
	(0.01487)	(0.02696)	(0.02039)	(0.06400)
	[0.68541]	[-0.54422]	[-3.52879]	[0.74513]
CointEq2	-0.017197	-0.436349	0.040963	-0.038105
	(0.07176)	(0.13005)	(0.09839)	(0.30879)
	[-0.23965]	[-3.35515]	[0.41633]	[-0.12340]
CointEq3	0.016592	0.307255	-0.056269	0.008351
	(0.05412)	(0.09809)	(0.07421)	(0.23289)
	[0.30657]	[3.13251]	[-0.75828]	[0.03586]
D(LNCPI(-1))	-0.080190	-0.075284	0.025261	-0.256343
	(0.09519)	(0.17252)	(0.13052)	(0.40963)
	[-0.84239]	[-0.43637]	[0.19353]	[-0.62579]
D(LNPPI(-1))	0.001040	-0.169342	0.102337	0.236427
	(0.06523)	(0.11822)	(0.08944)	(0.28069)
	[0.01595]	[-1.43245]	[1.14422]	[0.84230]
D(LNMPI(-1))	0.084395	0.706304	0.658873	0.061140
	(0.06129)	(0.11107)	(0.08403)	(0.26373)
	[1.37706]	[6.35890]	[7.84070]	[0.23183]
D(LNM2(-1))	0.010077	-0.030235	-0.005830	-0.438899
	(0.01852)	(0.03356)	(0.02539)	(0.07968)
	[0.54421]	[-0.90097]	[-0.22963]	[-5.50830]

Fig. 17. Parameter estimation results.

R-squared	0.034081	0.400850	0.612965	0.222259
Adj. R-squared	-0.011915	0.372319	0.594535	0.185224
Sum sq. resids	0.002303	0.007566	0.004330	0.042652
S.E. equation	0.004276	0.007749	0.005862	0.018399
F-statistic	0.740960	14.04967	33.25871	6.001290
Log likelihood	540.3691	461.2833	498.3886	346.2750
Akaike AIC	-8.020589	-6.831327	-7.389302	-5.101879
Schwarz SC	-7.868465	-6.679204	-7.237179	-4.949755
Mean dependent	-0.000127	-7.10E-05	-0.000353	0.009587
S.D. dependent	0.004250	0.009781	0.009207	0.020383
Determinant resid covariance (dof adi.)		5.95E-18		
Determinant resid covariance Log likelihood Akaike information criterion Schwarz criterion		4.79E-18		
		1897.085		
		-27.88097		
		-26.94650		
Number of coefficients		43		

Fig. 18. VECM test results.

From the estimation results, the joint equation of the VECM model is obtained as:

D(LNCPI) = 0.0101940747382*(LNCPI(-1) -

0.107066413503*LNM2(-1) -2.98432139351) -

0.0171967556114*(LNPPI(-1) +

0.175457549489*LNM2(-1) -7.34949213755) +

0.0165915719314*(LNMPI(-1) +

0.26189805163*LNM2(-1) -8.67505692498) -

0.0801900405884*D(LNCPI(-1)) +

0.00104029522155*D(LNPPI(-1)) +

0.0843949965445*D(LNMPI(-1)) +

0.0100768097186*D(LNM2(-1))

D(LNPPI) = -0.0146696040147*(LNCPI(-1) -

0.107066413503*LNM2(-1) -2.98432139351) -

0.436348876305*(LNPPI(-1) +

0.175457549489*LNM2(-1)-7.34949213755)+

0.307255072143*(LNMPI(-1) +

0.26189805163*LNM2(-1) -8.67505692498) -

0.0752835181425*D(LNCPI(-1)) -

0.169342178791*D(LNPPI (-1)) +

0.70630404486*D(LNMPI(-1))

-0.0302351117642*D(LNM2(-1))

```
D(LNMPI) = -0.0719624918185*( LNCPI(-1)
-0.107066413503*LNM2(-1) -2.98432139351 ) +
0.0409632426277*( LNPPI(-1) +
0.175457549489*LNM2(-1) -7.34949213755 ) -
0.0562691672793*( LNMPI(-1) +
0.26189805163*LNM2(-1) -8.67505692498 ) +
0.0252607516045*D(LNCPI(-1)) +
0.102336941577*D( LNPPI(-1)) +
0.658872801829*D(LNMPI(-1))
```

-0.00583006871693*D(LNM2(-1))

$$\begin{split} D(LNM2) &= 0.0476893096966^*(\ LNCPI(-1) - \\ 0.107066413503^*LNM2(-1) - 2.98432139351) - \\ 0.03810491203^*(\ LNPPI(-1) + \\ 0.175457549489^*LNM2(-1) - 7.34949213755) + \\ 0.0083508198399^*(\ LNMPI(-1) + \\ 0.26189805163^*LNM2(-1) - 8.67505692498) - \\ 0.256343008415^*D(LNCPI(-1)) + \\ 0.236427296106^*D(LNPPI (-1)) + \\ 0.0611404130535^*D(LNMPI(-1)) - \\ 0.43889949903^*D(LNM2(-1)) \end{split}$$

The error correction term reflects the stable relationship between the variables in long-term equilibrium, and the coefficients in front of the error correction term describe the strength of the adjustments to bring CPI, M2, MPI, and PPI to the equilibrium state when a disturbance occurs that causes them to deviate from their long-term equilibrium state in the short term. And all the difference terms on the right side of the VECM linkage equation used as explanatory variables reflect all the short-term changes of the explanatory variables affected by the short-term fluctuations of each explanatory variable.

Therefore, the CointEq1 coefficient estimates of 0.010194, -0.014670, -0.071962, and 0.047689 in the operational results indicate that when short-term fluctuations deviate from the long-run equilibrium, the system composed of lncpi, lnm2, lnmpi, and lnppi will adjust toward the equilibrium with this deviation (error) of 0.010194, -0.014670, -0.071962, and 0.047689 strength to adjust toward the equilibrium in the next period.

F. VECM Model Stability Test

The AR root diagram and table are shown in Figs. 19 and 20.



Root	Modulus
0.991281	0.991281
0.890763 - 0.076335i	0.894027
0.890763 + 0.076335i	0.894027
0.850477	0.850477
0.665297	0.665297
-0.406852 - 0.070018i	0.412833
-0.406852 + 0.070018i	0.412833
-0.057344	0.057344

No root lies outside the unit circle.

Fig. 20. AR root table.

The test results in Figs. 19 and 20 show that the inverse of the modes of all the roots are within the unit circle. This indicates that the established VECM model system is stable.

G. Impulse Response Function

Impulse response functions are a mainstream method for

analyzing VECM models and can be used to describe the response of an endogenous variable to a shock brought about by an error term, i.e., the extent of the impact on the current and future values of the endogenous variable after a shock of one standard deviation in size is applied to the random error term. Impulse response analysis provides a more comprehensive picture of the dynamic impact of the relationship between the variables. The prerequisite for conducting impulse response analysis is to test the stability of the constructed VECM modeling system; if the VECM modeling system is not stable, the impulse response function analysis process may be unstable. From the above, it can be seen that the constructed VECM model system is stable and impulse response analysis can be performed.

The impulse response function of the VECM model system is shown in Fig. 21.



Fig. 21. Impulse response diagrams.

Since the data is monthly, the impulse response period is set to 30 periods. Fig. 21 is a synthetic plot of four impulse response functions output using the EVIEWS software, the first of which is a plot of the impulse response of the CPI. As can be seen from the graph, the effect of CPI on itself has been positive, and the degree of its effect is gradually decreasing, and after the 6th period it rapidly decreases to 0.003645 in the 30th period. This indicates that one accidental increase in CPI may cause the consumer price index to increase in all the following 30 periods, but with decreasing magnitude of the increase. Secondly the impact of m2 on the CPI is gradually increasing over the 30 periods and the impact is changing from negative to positive. Again the effect of MPI on CPI is great in the first two periods, gradually weakening after the 2nd period and 0 in the 8th period, then the negative effect is gradually increasing, and remaining stable after the 25th period. Finally the degree of

PPI's effect on CPI is similar to that of MPI.

H. Variance Decomposition

Variance decomposition is also a commonly used method to analyze the VECM model, and its basic idea is to decompose the fluctuation of all endogenous variables in the system into K components associated with the new information of each equation according to the causes, and get the relative importance of the stochastic new information to the endogenous variables of the model. The results of the variance decomposition obtained with Eviews10 are shown in Fig. 22.

According to Fig. 22, it can be seen that the prediction error of consumer price index mainly comes from the influence of its own information, which accounts for a large and decreasing proportion in the previous periods, and stabilized at 92.57% in the 10th period, which fully explains that the prediction error of CPI mainly comes from the influence of its own information. According to the graph, the influence of the other three variables on the CPI is relatively small, that is, the CPI itself can well predict the future short-term trend. The degree of influence of the three variables on CPI is in the following order: mpi > ppi > m2, mpi has the relatively strongest degree of effect on cpi, and m2 is the weakest.



Fig. 22. Variance decomposition diagrams.

To visualize the results more, Fig. 23 presents the variance decomposition of the 25-period lncpi.

Variance Decomposition of LNCPI:							
Period	S.E.	LNCPI	LNPPI	LNMPI	LNM2		
1	0.004276	100.0000	0.000000	0.000000	0.000000		
2	0.005935	99.24546	0.183931	0.471117	0.099492		
3	0.007334	98.16185	0.702461	1.055056	0.080630		
4	0.008566	96.99582	1.205720	1.717457	0.081003		
5	0.009679	95.88389	1.721821	2.317705	0.076589		
6	0.010692	94.91131	2.166576	2.847718	0.074394		
7	0.011620	94.09835	2.542304	3.286846	0.072502		
8	0.012472	93.44608	2.840936	3.641660	0.071321		
9	0.013256	92.94101	3.069928	3.918436	0.070629		
10	0.013979	92.56512	3.236725	4.127789	0.070371		
11	0.014648	92.29888	3.350836	4.279816	0.070471		
12	0.015269	92.12354	3.421275	4.384322	0.070867		
13	0.015848	92.02203	3.456446	4.450021	0.071506		
14	0.016389	91.97938	3.463735	4.484537	0.072344		
15	0.016897	91.98283	3.449472	4.494360	0.073341		
16	0.017377	92.02166	3.418944	4.484933	0.074465		
17	0.017831	92.08707	3.376485	4.460756	0.075685		
18	0.018264	92.17193	3.325579	4.425508	0.076979		
19	0.018677	92.27053	3.268985	4.382159	0.078324		
20	0.019074	92.37836	3.208850	4.333088	0.079703		
21	0.019456	92.49190	3.146819	4.280178	0.081100		
22	0.019826	92.60845	3.084132	4.224910	0.082503		
23	0.020184	92.72595	3.021709	4.168435	0.083902		
24	0.020532	92.84286	2.960214	4.111639	0.085288		
25	0.020871	92.95803	2.900119	4.055196	0.086654		
Fig. 23. Variance decomposition of LNCPI.							

I. Out-of-sample Prediction

The purpose of doing various empirical analysis and research is to try to derive the objective law of the interaction between variables, and then be able to well predict the trend of the variables in the coming period of time, to provide reference for economic decision-making. In this paper, on the basis of the above sample, we make a forecast of the trend of

the consumer price index from April to December 2021, and the results are shown in Fig. 24.



Fig. 24. Consumer price index forecast.

According to Fig. 24, i.e., the CPI from April to December 2021 shows a clear upward trend, but the rate of increase is getting slower and slower, and remains stable after November. This indicates that in the next six months or so, China's economy faces the pressure of rising inflation levels, and the relevant governmental decision-making departments should take appropriate preparatory measures in stabilizing price levels.

V. CONCLUSIONS AND INSIGHTS

First, the main factor causing changes in the price level is the movement of the consumer price index itself. Imposing a standard deviation size shock on the CPI, the impact of this shock on the consumer price index itself is the largest, and the role of the speed is very fast, the impact is positive. If the CPI continues to rise, the relevant government departments should quickly take measures to suppress prices, to maintain stable and healthy economic operation; on the contrary, if the CPI continues to fall, then it should be taken as soon as possible to stimulate the policy, to avoid the formation of deflation, the situation of economic recession.

Secondly, the impact of the mpi and ppi on the consumer price index is still relatively significant, although it is still much smaller than the CPI's impact on itself. This also corresponds to the actual situation in China, which is still in a state of weak domestic demand. And the impact of m2 on the CPI is gradually increasing, after a certain period of time to remain stable.

Once again, the degree of influence of the three variables on the CPI is in the following order: mpi > ppi > m2, with mpi having the relatively strongest degree of effect on the cpi and m2 the weakest.

Finally, by forecasting the consumer price index from April to December 2021, the prediction results show that the CPI shows an upward trend in six months' time, but the rise is not very large and the speed is getting slower and slower. Due to the impact of the new crown epidemic, the country experienced a severe economic recession in 2020, and this year, with the widespread vaccination, the epidemic has been effectively controlled and the economy has begun to recover. Therefore, a moderate rise in CPI is favorable to economic recovery, but government departments should take measures to prevent a sharp rise in CPI.

The price problem has been one of the most important issues in China's macroeconomic operation, and the macroeconomic goal is to maintain economic growth while keeping prices within a reasonable and bearable range. Strengthening the monitoring of CPI and the study of its relationship with MPI, PPI and M2 is of great significance in preventing economic shocks caused by drastic price increases.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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