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Do sentiment indicators help to assess and predict actual developments of the Chinese economy?

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Aaron Mehrotra and Jouko Rautava[1]

Do sentiment indicators help to assess and predict actual developments of the Chinese economy?

Abstract

This paper evaluates the usefulness of business sentiment indicators for forecasting developments in the Chinese real economy. We use data on diffusion indices collected by the People's Bank of China for forecasting industrial production, retail sales and exports. Our bivariate vector autoregressive models, each composed of one diffusion index and one real sector variable, generally outperform univariate AR models in forecasting one to four quarters ahead. Similarly, principal components analysis, combining information from various diffusion indices, leads to enhanced forecasting performance. Our results indicate that Chinese business sentiment indicators convey useful information about current and future developments in the real economy. They also suggest that the official data provide a fairly accurate picture of the Chinese economy.

Keywords: forecasting, diffusion index, VAR, China.
JEL: E32, E37, P27

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Aaron Mehrotra and Jouko Rautava

Do sentiment indicators help to assess and predict actual developments of the Chinese economy?

Tiivistelmä

Tutkimuksessa tarkastellaan yritysbarometrimuuttujien käytön hyödyllisyyttä Kiinan reaalitalouden ennustamisessa. Työssä käytetään Kiinan keskuspankin julkaisemia diffuusioindeksejä teollisuustuotannon, vähittäiskaupan ja viennin ennustamiseksi. Yritysbarometrimuuttujasta ja reaalitalouden muuttujasta koostuvat kahden muuttujan vektoriautoregressiiviset mallit ennustavat reaalitalouden kehitystä paremmin kuin yhden muuttujan autoregressiiviset mallit, kun ennustehorisontin pituus ulottuu yhdestä neljään vuosineljännekseen. Myös pääkomponenttianalyysi auttaa ennustamisessa kokoamalla informaatiota eri diffuusioindekseistä. Tulosten mukaan Kiinan yritysbarometrimuuttujat välittävät hyödyllistä tietoa talouden tämänhetkisestä ja tulevasta kehityksestä. Tulokset vahvistavat näkemystä, että virallinen data antaa kohtalaisen tarkan kuvan Kiinan talouden kehityksestä.

Asiasanat: ennustaminen, diffuusioindeksi, vektoriautoregressiivinen malli, Kiina
JEL: E32, E37, P27

1 Introduction

In 2005, China surpassed France and the UK in nominal GDP to become the fourth largest economy in the world after Germany, Japan and the US. If we apply GDP in PPP terms, only the US outranks China. China's global role is accentuated by the fact that foreign trade plays a more prominent role in the Chinese economy than in most other large economies, as the exports-to-GDP ratio in China is about 34%. In recent years, China's contribution to global economic growth has been particularly noteworthy.

The increasing importance of China for the world economy assures a growing demand for information on its macroeconomic developments. However, from the standpoint of economic monitoring and research, major problems remain regarding basic economic statistics. This is evidenced by the upward revision of GDP by 17% at the end of 2005, based on improved information on the role of the service sector in China's booming economy. Moreover, even with the improvements in GDP data, their usefulness is still impaired by a lack of quarterly series on GDP components in real terms. On the expenditure side of GDP, the problems are even more formidable. Thus, quarterly consumption and investment data are available only as cumulative nominal data, which do not enable direct computation of actual quarterly figures.[2]

While one could in principle use some other indicator to proxy a national account item, there is also a lack of satisfactory proxies. For example, it has been argued that the monthly indicator on retail sales poorly captures trends in household consumption. The same applies to capital formation, as investment data published on a monthly basis (fixed asset investment) differ conceptually from the internationally comparable national account measure (gross fixed capital formation).[3] Besides problems with real sector data, the lack of proper price indices hinders the evaluation of actual developments.

To deal with concerns about the availability and reliability of the data one can use various survey indicators to gain insights into current developments and future trends in the real economy. While business sentiment indicators are widely used in developed industrial countries, their role in assessing Chinese developments has so far been very modest. Nevertheless, the National Bureau of Statistics (NBS) and the People's Bank of China

[2] In order to overcome problems with the quarterly Chinese GDP data, Curran and Funke (2006) use some simple assumptions and time series techniques to construct a quarterly GDP series in real terms.
[3] See World Bank's China Quarterly Update August 2005.

(PBoC) have for several years been publishing a number of survey indicators for the consumer and business sectors.

In this paper, we consider various business condition indicators reported by the PBoC so as to evaluate their usefulness in assessing and forecasting actual developments in the Chinese economy. We are not aware of any earlier studies focusing on the forecasting properties of the PBoC's business condition indicators in China. Our paper provides a first attempt to fill this gap in the literature. We find that our estimated bivariate VARs, each composed of one diffusion index and one real sector variable, usually lead to an improvement in forecasting performance compared with a univariate AR process. Similarly, principal components analysis, combining information from various diffusion indices, leads to enhanced forecasting performance. These results indicate that Chinese business sentiment indicators provide useful information about current and future developments in the Chinese real economy. They also suggest that the official data provide a relatively accurate picture of the Chinese economy.

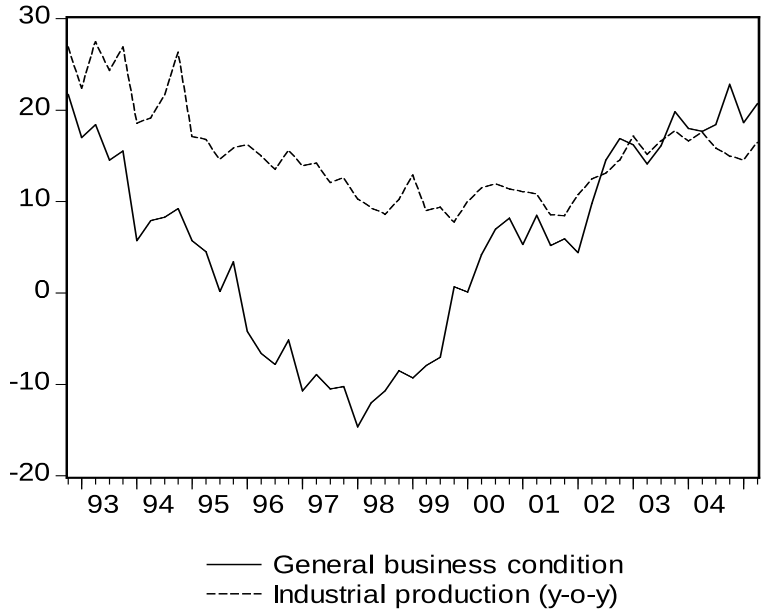
The paper is organised as follows. In the next section, we briefly discuss the availability of business condition indicators in China and the main characteristics of the indicators chosen for this study. Section 3 deals with the analytical framework, providing details about the empirical methodology used in our exercise. Section 4 reports the results of our estimations. The concluding section provides a summary of our findings.

2 Data

The classification of various leading and business confidence (sentiment, climate) indicators seems to be somewhat arbitrary. However, leading indicators are often based on regularly published 'hard' data (money supply, asset prices, exports, etc) while confidence indicators build on particular consumer and enterprise surveys. Sometimes composite leading indicators include both hard and soft data. Nevertheless, both types of indicators are expected to contain some useful information about future developments. This paper focuses on the forecasting properties of enterprise survey-based indicators.[4]

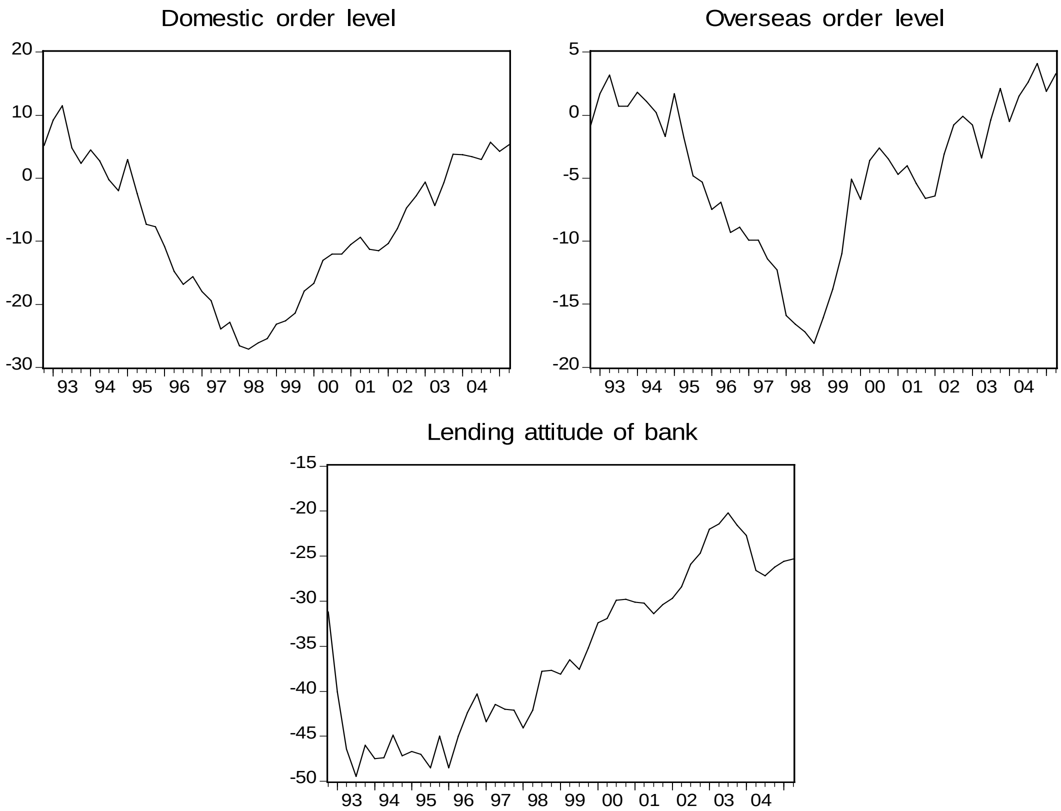
[4] Regarding composite leading indicators for China, see Nilsson and Brunet (2006) and Curran and Funke (2006).

Figure 1 General business condition and industrial production (y-o-y growth rate)



Given the above considerations, in this paper we consider the GBC and three other diffusion indices (overseas and domestic order level, and lending attitude of bank) compiled by the PBoC to evaluate their ability to forecast actual developments in the Chinese economy. Overseas and domestic order level were chosen due to their presumably direct demand-pull link with our real sector variables, while lending attitude of bank should indicate the role of financial factors on actual developments. These three other diffusion indices are illustrated in Figure 2.

Figure 2 Domestic and overseas order level, and lending attitude of bank



Due to the aforementioned problems with GDP data and the fact that quarterly real GDP series are available only since 1998, we evaluate forecasting performances of the diffusion indices for developments in industrial output, retail sales and Chinese exports. These three series feature prominently in public discussion and news about Chinese economic developments.[5] Consequently, it would be interesting to know whether diffusion indices could be used to provide forecasts for these three real sector indicators.

In order to obtain stationary time series data for econometric inference, the following transformations were applied. All the diffusion index variables were differenced once. Real exports and real retail sales in levels were first-differenced and transformed to logarithms.[6] The year-on-year growth rate of industrial production was differenced once, with-

[5] Holz (2004) notes that the regular data reporting system is most highly developed for the industrial sector. Industrial statistics have moved to a two-class compilation system where industrial firms with accurate data report directly to the NBS (accounting for 60% of industrial output) and all other firms are covered by sample surveys.

[6] Real retail sales was constructed by deflating nominal retail sales by a proxy for the CPI index (which is not available directly and was thus built by the authors). Real exports was obtained by deflating US dollar export figures by the US CPI.

out a logarithmic transformation.[7] Augmented Dickey-Fuller (ADF) tests for unit root generally suggest that the resulting series are stationary, as displayed in Table 1. The lag length is that suggested by the commonly-used information criteria, setting the maximum number of lags to 8. While Schwarz criteria always reject the null of unit root, for three series longer lag lengths indicated by the Akaike and Hannan-Quinn criteria indicate the existence of a unit root. As the KPSS test for unit roots is not able to reject the null of level stationarity in these cases at the 5% level (depending on choice of lag truncation parameter; results available on request), we continue with the assumption that all series are stationary.

Table 1 Augmented Dickey-Fuller tests on final series used in estimation

Series	Lags	Test statistic
Domestic order level	3 (AIC, HQ)	-1.40
	0 (SC)	-5.72***
Exports	8 (AIC, HQ)	-0.42
	3 (SC)	-5.31***
Overseas order level	0 (AIC, HQ, SC)	-6.16***
General business condition	7 (AIC)	-1.20
	3 (HQ)	-1.88
	0 (SC)	-7.85***
Industrial production	0 (AIC, HQ, SC)	-9.71***
Lending attitude of bank	0 (AIC, HQ, SC)	-6.35***
Retail sales	4 (AIC, HQ)	-3.04**
	0 (SC)	-5.98***

Note: Constant included as deterministic term in all models.
Information criteria in parentheses: AIC=Akaike, HQ=Hannan-Quinn, SC=Schwarz criteria.
* indicates significance at 10% level, ** at 5% and *** at 1%.

[7] It would have been preferable to use as the raw series the industrial production in levels, similarly to real retail sales and real exports, as the year-on-year growth rates are by definition affected by historical developments, which may not be optimal in a forecasting exercise. However, the estimated systems did not per-

3 Methodology

Our approach for analyzing the information content of the different diffusion indices is based largely on the vector autoregressive (VAR) framework. The formal presentation that follows draws on Lütkepohl (2004). A reduced form VAR representation can be written as

$$x_t = A_1 x_{t-1} + ... + A_p x_{t-p} + CD_t + u_t \tag{1}$$

where p denotes the order of the model. In our VAR with K endogenous variables, $x_t = (x_{1t}, ..., x_{Kt})'$ is a $(K\times1)$ random vector, the A_i are fixed $(K\times K)$ coefficient matrices and D_t is a vector of deterministic terms. C is the coefficient matrix associated with the deterministic terms. $u_t = (u_{1t}, ..., u_{Kt})'$ is assumed to follow a K-dimensional white noise process with $E(u_t) = 0$.

We commence by discussing bivariate vector autoregressions (BVARs). Every BVAR in the first part of the empirical study is composed of one indicator of the real economy (industrial production, retail sales, or exports) and one diffusion index (overseas/domestic order levels, general business condition, or lending attitude of bank). The exact pair of variables depends on the suitability of the series, eg lending attitude of bank could *a priori* be considered appropriate to provide information about future growth in industrial production. All VARs are estimated for the time period 1993Q1-2004Q2. [8]

The estimated BVARs are then utilized in a forecasting exercise. After specifying a VAR model that passes the necessary tests for misspecification, we use it to obtain out-of-sample forecasts for the real sector variable 1, 2 and 4 periods ahead, so that forecasts are generated for the period 2004Q3-2005Q2. An h-step forecast based on estimated coefficients yields

$$\hat{x}_{T+h|T} = \hat{A}_1 \hat{x}_{T+h-1|T} + ... + \hat{A}_p \hat{x}_{T+h-p|T}\ , \tag{2}$$

where $\hat{x}_{T+j|T} = x_{T+j}$ for $j \leq 0$ and the $\hat{A}_i$ $(i = 1, \ldots, p)$ are estimated parameters. The goodness of the forecasts is assessed by comparing them to those from a univariate AR model in terms of the ratio of their root mean squared forecast errors (RMSE). In the uni-

form satisfactorily in the misspecification tests using the industrial output series in levels terms (again constructed by the authors).

[8] Period 1993Q2-2004Q2 is used in the VARs with retail sales due to data availability.

variate AR model, the past development of the real sector variable alone is used in order to obtain forecasts for this variable.

One obvious criticism of the BVAR approach is that more information could be obtained by using combinations of the diffusion indices. Therefore, we also estimate trivariate VAR models, each including one real sector variable and two diffusion indices, and compare the forecasting performance of these with the simple AR models. A problem here with multivariate VAR models is the extremely high correlation between three diffusion indices (general business condition and domestic and overseas order levels), as shown in Figures 1 and 2. This militates against using any combination of two of these in multivariate VAR models – or indeed all three of them. Therefore, we additionally use principal components analysis, where we generate new variables (the principal components) as linear combinations of the original variables (the diffusion indices). These principal components, obtained from an orthogonalization of the sample correlation matrix, are uncorrelated. In general, the use of principal component can also be seen as a way of summarizing information extracted from a large number of predictors.[9] This analysis allows us to determine the component that has the highest variance proportion in the principal components analysis. In the BVAR framework, we estimate a model including this principal component and the real sector variable, and compare the forecasts provided by this model with univariate autoregressions.

A note on cointegration is in order. Our BVARs are estimated by using the stationary first-differenced variables. However, as the original (untransformed) variables are integrated of order one, possible cointegrating relations cannot be ruled out. If the variables are cointegrated, estimating a VAR in first differences would be equivalent to estimating a misspecified equation. Acknowledging that tests for cointegration are likely to have weak power in our short sample, we find little robust evidence of common stochastic trends utilizing the Johansen trace test. Importantly, while estimating the VAR models in levels would allow for possible cointegration relations, in the context of single equation estimates we could then encounter problems of spurious regressions. We therefore proceed on the assumption that no cointegration relationships exist among the untransformed (levels) data for the diffusion indices and real sector variables.

4 Empirical evidence

In this section, we present the results from the estimated models. We commence with evidence provided by the bivariate and trivariate VAR models using the individual business sentiment indicators. Finally, we look at results from principal components analysis.

4.1 Forecasts with individual indicators

The order of the VAR model is predominantly based on the Akaike information criterion, specifying a maximum number of lags of 8. In the case where misspecification tests provide evidence against the indicated order, another lag length is used. A constant was included as a deterministic term for all systems, whereas a linear trend was only included when statistically significant. Appendix A displays information on the chosen BVAR orders, as well as results from tests for model adequacy. The chosen systems using the business sentiment indicators perform quite satisfactorily in the conducted tests.[10]

We next compare the h-step out-of-sample forecasts of the real sector variables yielded by our BVARs to simple AR models involving only the past process of the real sector variable. The forecasting ability of the model is determined by the ratio of the root mean square forecast error (RMSE) of the BVAR process to the AR model 1, 2 and 4 quarters ahead. The lag length of the AR model is based on the same considerations as the VAR model above. The results of this exercise are presented in Table 2 below.

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[9] Principal components analysis is utilized in Stock and Watson (2002), where diffusion indices are used to forecast US macroeconomic time series. Their forecasts outperform univariate autoregressions, small vector autoregressions, and leading indicator models.

[10] There is very weak evidence of autocorrelation (only at 10% significance level) in the models consisting of overseas order level and industrial production, and domestic order level and industrial production. The performance of the models with the OECD composite leading indicator instead of the diffusion indices was somewhat poorer. There is now evidence of autocorrelation at certain lag orders even at 5% level (and at 1% level when exports are used as the real sector variable). However, the composite indicator is not the focus of our study.

Table 2 Relative RMSE of forecasts. BVAR, trivariate VAR and AR models, 2004Q3-2005Q2.

Predictor	Exports			Retail sales			Industrial production		
	h = 1	*h* = 2	*h* = 4	*h* = 1	*h* = 2	*h* = 4	*h* = 1	*h* = 2	*h* = 4
General business condition	0.62	0.52	0.36	1.00	0.52	0.45	0.70	0.69	0.75
Domestic order level	-	-	-	1.86	0.55	0.57	0.86	0.84	0.86
Overseas order level	0.33	0.63	0.52	-	-	-	0.77	0.72	0.78
Lending attitude of bank	0.24	0.14	0.20	-	-	-	0.06	0.36	0.70
OECD leading indicator	0.07	0.36	0.43	2.73	1.09	0.73	0.41	1.08	1.04
General business condition, Lending attitude of bank	1.65	1.16	0.91	-	-	-	0.05	0.30	0.78
Domestic order level, lending attitude of bank	-	-	-	-	-	-	0.13	0.28	1.01
Overseas order level, lending attitude of bank	0.59	0.39	0.35	-	-	-	0.79	0.84	1.11

The first four rows in Table 2 show that in 7 cases out of 9, the BVAR models including a diffusion index outperform forecasts from a univariate AR-process, with forecasts conducted 1, 2 and 4 quarters ahead. This is suggested by values below the magnitude of 1 in the table. Specifically, in the case of exports and industrial production, the forecasting performance of the BVAR model is always superior to that of an AR-process. For retail sales, a simple AR-process produces the best forecast one quarter ahead, whereas the forecasting ability of the BVARs improves substantially when forecasts 2 and 4 quarters ahead are considered. Lending attitude of bank seems to provide information that improves forecasts quite substantially, at least in the short run.

A comparison of the forecasting performance of the enterprise survey indicators with other plausible leading indicators is complicated in the Chinese case by the paucity of data. However, the OECD publishes a composite leading indicator for China, which is available at a monthly frequency.[11] The component series used in the compilation of this indicator are cargo handled at ports, enterprise deposits, chemical fertilizer production, non ferrous metal production, monetary aggregate M2 and imports from Asia. Even if this composite variable is not designed to provide information on the series for retail sales and exports considered in our study, it does provide a benchmark against which the enterprise survey indicators can be examined. The fifth row of Table 2 shows the results from BVARs utilizing the OECD composite leading indicator.[12] The BVAR model outperforms the univariate AR model for all forecast horizons only in the case of exports. This is perhaps not surprising given that two of the components of the OECD indicator are directly linked to trade. As in the models with enterprise survey indicators, retail sales seems to be the most difficult variable to forecast. [13]

The vector autoregressive setup further allows us to examine the dynamics between the diffusion indices and real sector variables by the use of impulse response analysis. In this framework, we introduce a shock to the diffusion index and trace the effects of this shock on the real sector variable in the BVAR setup. In most of our estimated BVARs, the model residuals are not contemporaneously correlated, permitting the use of forecast error impulse responses (for discussion on impulse response analysis, see Breitung et al., 2004). However, in only three BVAR systems do we obtain a statistically significant impact of the diffusion index shock on the real sector variable. Acknowledging that the 'shocks' to the diffusion indices are difficult to justify from a theoretical viewpoint, and the statistical sig-

[11] For the purpose of our study, we aggregated this series from monthly to quarterly frequency by calculating the average value for every quarter. To ensure stationarity, the resulting quarterly series was included in the analysis in logarithms and differenced once.

[12] It should be noted that our series for industrial production differs in construction from the one used as a reference series for China's composite leading indicators by Nilsson and Brunet (2006). We use the y-o-y real growth rate of the value added of industry provided by China Monthly Economic Indicators from 2002Q3 onwards and the IMF's series until 2002Q2. Nilsson and Brunet (2006) consider a series constructed by combining the series for gross industrial output before 1994 and industrial value added over 1995-2004, and then recalculated to constant prices of 1995.

[13] To again compare the Chinese diffusion indices with their Japanese counterparts, we constructed a BVAR model with the Japanese industrial production (y-o-y growth rate) and the Tankan index (business conditions, manufacturing). However, in this brief analysis for Japan, the BVAR forecasts were not markedly different from a univariate AR model.

nificance of these shocks may be limited in our short sample, we leave further causality analysis to future research.

The forecasting performance of the trivariate VAR models is evaluated in the last three rows of Table 2. We consider only combinations of those diffusion indices that are not closely correlated. In order to disregard a large number of statistically insignificant coefficients in these larger systems, we used subset models where the coefficients with *t*-values below the threshold of one were eliminated from the system. The trivariate models outperform the univariate autoregressions at all forecast horizons only in 2 out of 5 systems examined. Both systems include the lending attitude of bank, but this variable is also included in those cases where the multivariate systems are found to provide poorer forecasts than the AR models. Overall, the BVAR models seem to perform better in relative terms than the trivariate ones.

4.2 Forecasts with principal components

Finally, we use the principal components methodology to examine the forecasting ability of the variables created by this approach. Here, new variables are generated as linear combinations of the original diffusion index variables. The weights of the linear combinations – the factor loadings - are chosen so that the new principal components are uncorrelated. Thus, we are able to use all information derived from the diffusion indices, even when those indices are highly correlated. Table 3 below depicts the results from the principal components analysis. The eigenvalues result from orthogonalization of the sample correlation matrix, whereas the variance proportion indicates the share of a principal component in the total variance of the diffusion index.

Table 3 Principal components of diffusion index variables, 1993Q1-2004Q2

	PC1	PC2	PC3	PC4
Eigenvalue	2.19	1.20	0.40	0.22
Variance proportion	0.55	0.30	0.10	0.05
Loadings:				
Domestic order level	-0.57	0.36	0.38	0.64
Overseas order level	-0.59	0.32	0.07	-0.74
General business condition	-0.52	-0.38	-0.74	0.18
Lending attitude of bank	-0.24	-0.79	0.55	-0.10

We do not give much detail here on the structure of the estimated principal components. The first principal component has high negative factor loadings on all components, perhaps reflecting weak domestic demand conditions. As most of the information from the diffusion indices can be summarized by the first principal component (55% of the total variance proportion), we use this first component in the BVAR setup with real sector variables, again comparing the resulting forecasts to the univariate AR models. The results are displayed in Table 4 below, with misspecification tests for the models reported in Appendix C. Our BVAR models with the first principal component pass all of our misspecification tests.

Table 4 Relative RMSE of forecasts, BVARs with first principal component and AR models, 2004Q3-2005Q2.

Predictor	Exports			Retail sales			Industrial production		
	$h = 1$	$h = 2$	$h = 4$	$h = 1$	$h = 2$	$h = 4$	$h = 1$	$h = 2$	$h = 4$
1st Principal component	0.57	0.78	0.88	0.46	0.61	0.47	0.65	0.78	0.79
1st Principal component (excl. GBC)	0.48	0.74	0.81	0.38	0.63	0.47	0.75	0.84	0.86

Table 4 shows that summarizing information from all four diffusion indices by the first principal component results in an improvement in the forecasting exercise as compared with the univariate model. Notably, the relative RMSE values are less than one for all forecasting horizons and for all real sector variables, as shown in the first row of the table. As a robustness check, we re-estimated the first principal component by excluding general business condition (GBC).[14] One can argue that the inclusion of general business condition in the principal components analysis is unnecessary, as this variable may already act as a summary variable of the different diffusion indices. Nevertheless, this robustness check does not change the conclusions from the principal components analysis, as shown in the second row of Table 4. It seems that the information content of the various diffusion indices can be meaningfully combined by principal components to form forecasts of the real sector variables.

5 Conclusion

While business condition indices are regularly published in China, their role in economic monitoring is still very modest compared with the use of similar indicators in developed countries. In this paper, we used various econometric techniques to study whether the diffusion indices published by the PBoC could actually be useful in assessing the short-term prospects of the Chinese economy. To our knowledge, while composite leading indicators have been constructed for China, no previous studies have evaluated the forecasting power of business sentiment indicators in the Chinese context.

We find that forecasts from our bivariate vector autoregressive models, each composed of one diffusion index and one real sector variable, generally outperform forecasts from univariate AR models one to four quarters ahead. In particular, the forecasts for industrial production and exports in the BVAR framework always beat the AR forecasts. These results suggest that the individual diffusion indices considered in our paper could be meaningfully applied in a BVAR setup to predict future economic developments in China. Similarly, principal components analysis, summarizing information from various diffusion indices, always outperforms the univariate AR models. However, the forecasting performance of trivariate VAR models, including two individual business sentiment indicators, does not differ markedly from the univariate models.

Finally, the results could be taken as support for the reliability of the 'hard' macroeconomic time series considered in our paper. As the trends in both soft and hard data are similar and the former can be meaningfully used to predict the latter, it is likely that both series reflect the same underlying economic dynamics.

[14] The variance proportion of the new first principal component amounts to 0.59 (excluding GBC).

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APPENDIX A. Misspecification tests for BVAR models

Model	Lags	Portmanteau	LMF (5, 4, 1 lags)	Nonnormality (skewness, kurtosis)	ARCH-LM
General business condition, Exports	5	45.63 (0.40)	0.83 (0.66) 0.84 (0.81) 0.70 (0.59)	0.40 (0.82) 0.57 (0.75)	18.74 (0.28) 15.11 (0.52)
Overseas order level, Exports	4	45.75 (0.57)	0.39 (0.99) 0.28 (1.00) 0.32 (0.86)	0.54 (0.77) 1.42 (0.49)	9.36 (0.90) 12.50 (0.71)
Lending attitude of bank, Exports	7	45.59 (0.13)	1.10 (0.41) 1.44 (0.19) 0.50 (0.73)	0.33 (0.85) 0.24 (0.89)	14.97 (0.53) 17.90 (0.33)
General business condition, Retail sales	1	69.72 (0.18)	1.54 (0.10) 1.57 (0.10) 1.59 (0.19)	1.25 (0.54) 0.48 (0.79)	12.10 (0.74) 14.87 (0.53)
Domestic order level, Retail sales	3	42.26 (0.83)	1.27 (0.25) 1.32 (0.22) 1.56 (0.20)	2.82 (0.24) 1.09 (0.58)	15.06 (0.52) 11.82 (0.76)

Note: Portmanteau refers to the adjusted Portmanteau test statistic for autocorrelation at 16 lags; LMF is the LM-F test for autocorrelation at 5, 4 and 1 lags; Nonnormality is the Doornik & Hansen (1994) test for skewness and kurtosis; ARCH-LM test is conducted with 16 lags; *p*-values in parentheses.

Misspecification tests for BVAR models (continued)

Model	Lags	Portmanteau	LMF (5, 4, 1 lags)	Nonnormality (skewness, kurtosis)	ARCH-LM
Overseas order level, Industrial production	1	50.91 (0.79)	1.45 (0.14) 1.76 (0.06*) 2.01 (0.10)	1.07 (0.59) 2.68 (0.26)	9.44 (0.89) 18.30 (0.31)
General business condition, Industrial production	1	64.04 (0.34)	1.29 (0.22) 1.46 (0.14) 0.36 (0.84)	0.24 (0.89) 2.15 (0.34)	10.41 (0.84) 16.14 (0.44)
Lending attitude of bank, Industrial production	5	48.14 (0.31)	1.07 (0.42) 1.46 (0.14) 0.36 (0.84)	0.31 (0.86) 0.42 (0.81)	20.59 (0.19) 15.24 (0.51)
Domestic order level, Industrial production	3	44.20 (0.77)	0.83 (0.66) 1.22 (0.29) 2.20 (0.08*)	1.99 (0.37) 1.15 (0.56)	9.68 (0.88) 16.43 (0.42)
OECD leading indicator, Exports	8	73.83 (0.00***)	0.42 (0.97) 0.56 (0.88) 0.95 (0.45)	0.66 (0.72) 2.07 (0.36)	17.02 (0.38) 11.37 (0.79)
OECD leading indicator, Retail trade	3	40.12 (0.89)	1.08 (0.40) 0.93 (0.54) 1.79 (0.14)	0.99 (0.61) 0.31 (0.86)	14.42 (0.57) 18.05 (0.32)
OECD leading indicator, Industrial production	4	48.98 (0.43)	1.53 (0.12) 1.30 (0.24) 3.00 (0.03**)	2.21 (0.33) 0.56 (0.76)	20.01 (0.22) 9.19 (0.91)

Note: Portmanteau refers to the adjusted Portmanteau test statistic for autocorrelation at 16 lags; LMF is the LM-F test for autocorrelation at 5, 4 and 1 lags; Nonnormality is the Doornik & Hansen (1994) test for skewness and kurtosis; ARCH-LM test is conducted with 16 lags; *p*-values in parentheses.

APPENDIX B. Misspecification tests for trivariate VAR models

Model	Lags	Portmanteau	LM (5, 4, 1 lags)	Nonnormality (skewness, kurtosis)	ARCH-LM
General business condition, Lending attitude of bank, Exports	4	125.59 (0.47)	52.99 (0.19) 43.49 (0.18) 8.36 (0.50)	0.59 (0.90) 0.69 (0.88)	19.85 (0.23) 10.83 (0.82) 11.56 (0.77)
Overseas order level, lending attitude of bank, Exports	2	138.24 (0.45)	51.23 (0.24) 41.32 (0.25) 6.36 (0.70)	0.49 (0.92) 0.40 (0.94)	11.39 (0.78) 9.27 (0.90) 9.24 (0.90)
General business condition, Lending attitude of bank, Industrial production	5	125.51 (0.47)	59.64 (0.07*) 41.80 (0.23) 9.04 (0.43)	0.16 (0.98) 0.79 (0.85)	15.72 (0.47) 16.32 (0.43) 13.23 (0.66)
Domestic order level, Lending attitude of bank, Industrial production	5	117.23 (0.50)	47.88 (0.36) 31.99 (0.66) 10.34 (0.32)	5.26 (0.15) 3.45 (0.33)	15.62 (0.48) 10.74 (0.83) 13.59 (0.63)
Overseas order level, Lending attitude of bank, Industrial production	4	114.56 (0.76)	54.07 (0.17) 41.76 (0.23) 4.50 (0.88)	1.59 (0.66) 0.58 (0.90)	11.82 (0.76) 15.50 (0.49) 12.62 (0.70)

Note: Portmanteau refers to the adjusted Portmanteau test statistic for autocorrelation at 16 lags; LM is the LM test for autocorrelation at 5, 4 and 1 lags; Nonnormality is the Doornik & Hansen (1994) test for skewness and kurtosis; ARCH-LM test is conducted with 16 lags; *p*-values in parentheses.

Appendix C. Misspecification tests for principal components models

Model	Lags	Portmanteau	LM (5, 4, 1 lags)	Nonnormality	ARCH-LM
Exports, 1st principal component	4	42.13 (0.71)	0.54 (0.93) 0.35 (0.99) 0.60 (0.67)	0.03 (0.99) 0.77 (0.68)	9.58 (0.89) 9.61 (0.89)
Retail sales, 1st principal component	1	38.92 (0.98)	1.10 (0.37) 1.20 (0.29) 1.34 (0.26)	0.05 (0.98) 0.69 (0.71)	17.30 (0.37) 14.32 (0.58)
Industrial production, 1st principal component	3	35.09 (0.97)	0.66 (0.85) 0.70 (0.79) 0.91 (0.46)	0.33 (0.85) 1.27 (0.53)	18.58 (0.29) 11.53 (0.78)
Exports, 1st principal component (excl. GBC)	4	42.22 (0.71)	0.40 (0.99) 0.32 (0.99) 0.29 (0.88)	1.01 (0.60) 1.80 (0.41)	10.53 (0.84) 15.94 (0.46)
Retail sales, 1st principal component (excl. GBC)	1	38.84 (0.98)	1.15 (0.33) 1.17 (0.31) 1.20 (0.32)	0.99 (0.61) 0.07 (0.97)	14.31 (0.58) 16.39 (0.43)
Industrial production, 1st principal component (excl. GBC)	3	37.63 (0.93)	0.88 (0.61) 0.83 (0.64) 0.91 (0.46)	0.07 (0.97) 1.27 (0.53)	17.77 (0.34) 14.15 (0.59)

Note: Portmanteau refers to the adjusted Portmanteau test statistic for autocorrelation at 16 lags; LM is the LM-F test for autocorrelation at 5, 4 and 1 lags; Nonnormality is the Jarque-Bera test; ARCH-LM test is conducted with 16 lags; *p*-values are in parentheses; GBC refers to general business condition.

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