Does Consumer Confidence Forecast Economic Fluctuations? The Case of China

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Abstract: This study evaluates the predictive power of China's consumer confidence indicators for macroeconomic fluctuations. First, using the framework of vector autoregression models, we find that the expectation component of consumer confidence index, either alone or in conjunction with a set of macroeconomic predictors, tends to Granger cause the monthly growth rates of gross industrial output. Nonetheless, the associated forecast error variance decomposition analysis suggests that the expectation index plays only a minor role in predicting output growth. Next, it is shown that the self predictive power of the expectation index in identifying discrete business cycle phases seems weak, but its coefficients are generally significant and robust across various settings. More importantly, its forecasting ability does not vanish after controlling for other economic fundamentals.

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The current economic crisis provides a rare opportunity both for the general public and economists to revive the old statement of Keynes (1936) that emotional factors or ‘animal spirits’ can influence the decision-making of economic agents (see, for example, Blanchard, 1993, and Akerlof and Shiller, 2009). Indeed, few people doubt today that the global recession can be partially explained by the spread of economic gloom, and thus re-establishing the confidence is one of principle objectives of the stimulus policies adopted by many countries around the world. Clearly, how can we imagine a recovery when our hopes for that are fading?

Nonetheless, numerous empiric studies show rather mixed results for the role of the confidence indicators in forecasting consumption expenditure or aggregate output. The main disagreement among several authors is whether the attitudes of economic actors contain independent predictive information about future changes in real economy, as found in Carroll et al. (1994) for US household spending, Acemoglu and Scott (1994) for UK household spending, Matsusaka and Sbordone (1995) for US GNP, Berg and Bergström (1996) for Swedish household spending, Howrey (2001) for US GDP, Utaka (2003) for Japanese GDP, Kwan and Cotsomitis (2004) for US household spending, and Taylor and McNabb (2007) for European countries’ GDP, or they are only a rational assessment of economic prospects based on fundamentals and thus, have no or modest incremental forecasting power once other predictors are captured, as evidenced in Fan and Wong (1998) for Hong Kong household spending, Howrey (2001) for US household spending, Goh (2003) for New Zealand household spending, Ludvigson (2004) for US household spending, and Barsky and Sims (2009) for US household spending.

Our study expends this literature by examining the case of China, where the survey-based Consumer Confidence Index (CCI) has been issued monthly since December 1997. However, up to our knowledge, the effect of mass psychology of China’s agents on the real economic activity remains an important yet rarely discussed issue. Specifically, the main objectives of this paper are twofold. Relying on vector autoregression (VAR) models, we first seek to investigate whether China’s overall CCI and its component, the Consumer Expectation Index (CEI), cause the changes in aggregate output in Granger’s sense (Granger, 1969). In other words, the question of interest is whether the lagged values of confidence indicators help predict output growth after holding other things constant. Next, using a framework of binary choice model, we attempt to evaluate the predictive power of confidence indicators over discrete economic upturns and downturns. As stressed in Sensier et al. (2004) and Taylor and McNabb (2007), for policymakers and private agents, such qualitative measures of the regimes of output fluctuations might be more meaningful than the quantitative point forecasting.

The remainder of the paper is structured as follows. The next section presents how China's CCI is measured. Section 3 addresses the Granger causality between the confidence indicators and growth rates of output. Both bivariate and multivariate VAR are considered to assess the independent predictive capacity of consumer sentiment. Section 4 turns to the qualitative forecasting of the discrete turning points in business cycles. Various specifications are used to check the sensitivity of the regression outcomes. The last section draws a few conclusions.

2. China's Consumer Confidence Index

China's CCI is built on the Consumer Confidence Survey conducted by China Economic Monitoring & Analysis Center (CEMAC), an affiliate of the National Bureau of Statistics. Because the details on the measure of China's CCI, such as survey questionnaire design and sampling method, have not been released, we can merely summarize the information currently available and thus offer a fairly brief overview.

Apparently, the compilation of China's CCI draws on the US experience. Like the University of Michigan's Consumer Sentiment Index and the Conference Board's Consumer Confidence Index, it is a composite index including an expectation component, CEI, and a present situation component, Consumer Satisfactory Index. The former is based on a subset of forward-looking questions about the respondents' future economic situation and the overall economic trend; the latter index is based on a subset of present conditions questions about the consumers' attitudes for the current overall economic situation and the purchasing time for major durable consumer goods. The overall index is then obtained by averaging the two components with a certain weight for each.

Regarding the scoring procedure, both overall index and its components are graded on a scale of '0' to '200'. These two extreme values correspond to 'very pessimistic' situation and 'very optimistic' situation, respectively, and then the value of '100' reflects a neutral position. When CCI is higher than 100, it implies that consumers are becoming optimistic. Symmetrically, when CCI is lower than 100, it shows that consumers are becoming pessimistic. According to the CEMAC, the data published before December 2009 are subject to some technical adjustments. In particualr, the raw index directly given by the survey was benchmarked to June 1996 = 100, where China's economic indicators were relatively stable[2]. It should be noted that in the following econometric analysis, such standardized data[3] have been restored to their original form.

[2] The confidence index in 1996 came from the survey carried out by another organization, China Economic Monitoring Center.
[3] Namely the published data for the period of December 1997 to November 2009.

Finally, the survey has an acceptably large sample size. Indeed, the total number of respondents is likely to exceed 3400. Thus it might be smaller than the sample size for the Conference Board's Index, roughly 3500, but much bigger than the one for Michigan's index, roughly 500. Nonetheless, the survey covers only the urban residents of 70 major cities of China, while the rural households' opinions are ignored. Obviously, it casts doubt over whether the two heterogeneous groups of consumers have consistent sentiments about economic conditions[4].

3. Granger causality between output growth and confidence indicators

This section addresses the Granger causality between confidence indicators described above and output growth. Given the fact that the most appealing measure of aggregate economy, Gross Domestic Product (GDP), has only quarterly and annual series in China, we draw on the monthly gross industrial output. Specifically, after some treatment presented in Data appendix, and then taking the log difference, we obtain the approximate monthly real growth rates of industrial output, denoted by OUTPUT. It should be stressed that as point out Zhang and Wan (2005) in their study on Chinese business cycles, gross industrial output can serve as a good indicator of economic activity on the grounds that the agricultural output, especially in China, often exhibits climatically-driven fluctuations, and the service sector depends heavily on the industrial sector. Indeed, industrial output series are widely used in the related literature, such as Tang (1998), and Poncet and Barthélemy (2008).

In the first step, the pairwise causality is tested through the following bivariate VAR model, with k indicating the lag order:

$$OUTPUT_t = c_y + \alpha_{yi} \sum_{i=1}^{k} OUTPUT_{t-i} + \beta_{yi} \sum_{i=1}^{k} Confidence_{t-i} + \varepsilon_{yt}, \qquad (1)$$

$$Confidence_t = c_c + \alpha_{ci} \sum_{i=1}^{k} OUTPUT_{t-i} + \beta_{ci} \sum_{i=1}^{k} Confidence_{t-i} + \varepsilon_{ct}, \qquad (2)$$

Looking at the output growth equation (1), the procedure proposed in Granger (1969) amounts to testing the null hypothesis that the coefficients associated with the lagged confidence indicators: $\beta_{y1},\ \beta_{y2},\ ...\ \beta_{yk}$ are jointly insignificant. If the null is rejected at conventional level, Confidence is said to Granger cause OUTPUT.

[Table 1 around here]

[4] A recent improvement in this concern seems noteworthy. Since the fourth quarter of 2009, CEMAC cooperating with Nielson Company has conducted a new consumer survey extending to rural areas. Nonetheless, given the time span covered here, this extension is likely to have little effect on the current study.

Table 1 contains the outcomes of the Granger causality tests for this parsimonious model. On the one hand, the *p*-values associated with the *Chi*-squared statistic for estimates of CCI and CEI in the OUTPUT equation are 0.096 and 0.100, respectively, driving us to reject the null hypothesis of no Granger causality at 10% level. In other words, it means that the preceding growth performance is helpful for the consumers to form their attitudes toward the current and future economic situation. On the other hand, as illustrated in the table, the causal link is also run from CEI to output growth, indicating that the lagged values of CEI contain useful information to forecast present growth rates. Nonetheless, with the *p*-value equal to 0.20, the statistical evidence for the causality from CCI to output growth is weak. Because the CEI reflects solely consumers' perception of future economic conditions, while the overall CCI contains also the satisfaction component reflecting the attitudes about the current economy, the findings that the CEI does a better job in economic forecasting do not appear to be staggering. As a matter of fact, Lovell (2001) suggests a similar proposition for the case of US, which has been empirically confirmed by Kwan and Cotsomitis (2004)[5]. Due to this reason, the subsequent analysis will focus only on the CEI.

Table 1 also reports the estimates of the sum of coefficients for lagged variables, which can be viewed as a rough indicator of the direction of the relationship among variables involved. Looking at the CEI-OUTPUT system, the *t*-statistic suggests that despite the bi-directional causal link between CEI and output growth, the sum of lagged terms of CEI is estimated to be statistically indifferent from zero, but with a negative sign. It implies that the effect of expectation index on output seems to be trivial at longer time horizons. However, as discussed later, the insignificance of the sum of coefficients for CEI will no longer hold in the multivariate VAR framework.

After discussing the self predictive power of confidence indicators, we turn to the key question whether the confidence index, in conjunction with other variables, provides meaningful independent information for forecasting economic activity.

A straightforward way to address the above question is to augment the bi-variate VAR model by introducing a set of economic fundamentals. Unfortunately, there is no clear theoretical guidance to enable us to identify appropriate candidate variables. In fact, it is a major difficulty facing the researchers working in this line of literature. As argues Ludvigson (2004), 'we don't know what those other fundamentals might be'. In the current study, we merely consider the following variables whose monthly series are available: total freight volume (denoted by FV; in log difference), sales rate of

[5] Probably for the same reason, in their work, Berg and Bergström (1996), and Barsky and Sims (2009) focus mainly on the expectation index, rather than overall confidence index.

industrial products (SR; in level), freight volume handled in major coastal ports (PORT; in log difference) and money and quasi-money (M2; in log difference). The reason behind this choice is due to CEMAC, which documents that these variables, along with CEI, change before the economic mass has changed, and thus defines them as ‘leading indicators’. In addition, because the stock price is commonly viewed as a useful macroeconomic predictor (see, for example, Howrey, 2001, and Ludvigson, 2004), the closing price of the Shanghai Stock Exchange Composite Index on the last trading day of each month (STOCK; in log difference) is also embodied in the VAR system. Details on these variables are also given in Data appendix.

Table 2 shows the results based on the augmented VAR. The CEI, along with SR, PORT and STOCK, are found to be causal for the output growth. However, as illustrated in the lower part of the table, we fail to establish the Granger causal link from output growth, and most other controls, to the expectation index. Plainly, little is known about the underlying determinants of the consumers’ attitudes.

Another result of interest from Table 2 is that capturing other fundamentals, the estimated sum of coefficients for lagged CEI remains negative but, in this case, become significant at 5% level. This finding is in contrast with those evidenced by Matsusaka and Sbordone (1995) and Utaka (2003), where the estimates of the sum of coefficients for lagged confidence indicators are found to be significant and positive. Our results are, however, consistent with the hypothesis of precautionary saving. As point out Carroll et al. (1994), Acemoglu and Scott (1994), and Ludvigson (2004), if the consumer sentiment is, in part, a measure of uncertainty about the future economic conditions, a rise in the level of confidence about tends to reduce the precautionary saving and thus stimulates today’s consumption expenditure. As a result, it turns out that the present values of the expectation index might be negatively correlated with the future values of consumption growth. In fact, even though this proposition is not borne out by most previous work (see, for example Ludvigson, 2004), there is a noticeable exception: Using micro data of US household, Souleles (2004) provides supportive evidence that higher confidence is associated with less contemporaneous saving (so it can translate into lower consumption growth in the next period). It seems reasonable to extend this logic to the relationship between consumer attitudes and broader economic measures, such as the aggregate industrial output. In particular, the assumption of precautionary saving has special relevance in the case of China, where the vagaries of structural reform and underdevelopment of social safety net lead to precautionary motive playing an important role in household saving behavior (see Meng, 2003, and Chamon and Prasad, 2008).

[Table 2 around here]

To further gauge the predictive capacity of the expectation index within the framework of multivariate VAR, we next conduct an analysis on the forecast error variance decomposition. Table 3 reports the percentage contributions of innovations in CEI to the forecast error variance of OUTPUT. The three control variables that are previously shown to be Granger causal for output growth are also captured in this innovation accounting. Different forecast horizons and orderings of variables are considered to check the robustness of the results.

[Table 3 around here]

Clearly, it is shown that about 85% of the forecast error variance of the output growth can be attributed to its own variations, while only 2% to 3 % accounted for by variations in CEI. At this juncture, it is worthwhile to compare our results to those found in previous work on other countries. For instance, Matsusaka and Sbordone (1995) show that the variations in the Michigan's Consumer Sentiment Index explain about 13% to 26% of forecast variance of US GNP. Utaka (2003) finds that in the Japanese economy, the variations in the Japanese counterpart of CCI explain about 9% to 11% of forecast variance of GDP. Hence, the forecasting power of China's CEI seems underwhelming.

4. Forecasting the regimes of economic activity

The above empirical strategy involves the quantitative point estimation of the output growth. However, as pointed out in Sensier et al. (2004) and Taylor and McNabb (2007), because of the stochastic characteristics of the economic activity, knowing the directional change in future trend, namely the business cycle regimes, seems more meaningful and important for both policymaker and private agents. Accordingly, this section will discuss the usefulness of the CEI in forecasting the discrete turning points in industrial output.

In the related literature, a recessionary event is typically defined as the occurrence of two or more consecutive quarters of decline in real GDP. Because of the monthly frequency of our data series, this two-quarter rule cannot be followed here and, thus, we have to address the short term economic fluctuations. Specifically, an expansion (or a recession) of three consecutive months above (or below) the period average of the growth rates of industrial output is considered. Alternatively, the criteria of two-month and one-month are equally employed. In Table 4, we describe the summary statistics for the business cycle regimes. Given the fact that the expansion events are more frequent than recession events[6], the following econometric investigation centers on the prediction of the former[7].

[6] Thus it gives more non-zero values to the dependent binary variable in the Probit model explored later.

[Table 4 around here]

Let define the binary indicator, E, which equals 1 if the expansion event occurs, and 0 otherwise. The Probit model estimating the probability of an expansion at time $t+k$, can be expressed as follows:

$$\text{Prob}(E_{t+k} = 1) = F(\mathbf{x}_t \boldsymbol{\beta}), \qquad (3)$$

where $F(.)$ is the cumulative distribution function based on the matrix of independent variables available at time t, $\mathbf{x}_t$, with corresponding coefficient vector, $\boldsymbol{\beta}$. Here, the Probit estimator means that $F(.)$ is assumed to be normal.

We first gauge the forecasting capacity of CEI by itself for three-month expansions. Table 5 shows the regression outcomes through maximum likelihood procedure. Huber-White robust standard errors are used in the inference to cope with the possible heteroskedasticity. Under various forecast horizons, CEI appears to be a significant predictor with negative sign on its coefficient. However, the goodness-of-fit is fairly poor judged by pseudo R-squared. Indeed, if 0.5 is used as the critical value of the probability, the model has not correctly predicted any three-month expansion events, which occur 32 times over the entire period involved.

[Table 5 around here]

Tables 6 and 7 show the results for the two-month and one-month expansions. Notwithstanding the modest explanatory power, the coefficients associated with lagged values of CEI remain significant and negative in most regressions.

[Table 6 around here]

[Table 7 around here]

Next, the Probit model is augmented by including the five control variables discussed previously. The results are illustrated in Tables 8, 9, and 10 corresponding the three-month, two-month, and one-month expansions, respectively.

[Table 8 around here]

[Table 9 around here]

[Table 10 around here]

As can be seen from the tables, although the pseudo R-squared has been greatly increased, the predictability of the independent variables appears to be mixed. On the one hand, the coefficients of the

[7] For the sake of brevity, the outcomes of Probit forecasting models for the recession phases are not reported. However, the findings are mainly consistent with those for expansion models.

three CEMAC-defined leading indicators, FV, PORT, and M2, as well as STOCK are generally insignificant and rather sensitive to the forecast horizons and expansion lengths. On the other hand, judged by the robustness of the signs and magnitudes of their coefficients, both CEI and SR are useful predictors for the expansion phases. For concreteness, let take the three-month expansion equation displayed in Table 8 as an example. Under one-month-ahead setting, the Probit estimate of CEI is -0.0863, and its corresponding marginal effect is -0.0212, holding other explicative variables equal to sample averages. It means that a one-point increase in expectation index will reduce the probability of the occurrence of three-month expansion event by about 0.0212 (or 2.12 percent).

Eventually, it turns out that the signs of the Probit estimates associated with CEI remain convincingly negative. Obviously, such findings are consistent with those provided in Section 3, and thus further support the argument of precautionary saving.

5. Conclusions

This study sought to evaluate the predictive power of China's consumer confidence indicators for macroeconomic fluctuations. The empirical findings are somewhat mixed. Relying on the VAR framework, we first find that the expectation component of consumer confidence index, either alone or in conjunction with other economic indicators, tends to Granger cause the monthly growth rates of gross industrial output over the period of December 1997 to March 2010. Nonetheless, the associated innovation accounting analysis suggests that only a minor proportion of forecast error variance of output growth can be accounted for by innovations in expectation index. Next, turning to the qualitative estimation, we employ a Probit model with binary expansion (or recession) indicator as dependent variable, and find that the self predictive power of the expectation index in identifying discrete business cycle phases is rather poor, but its coefficients in the forecasting regression are generally significant and robust across various settings. More importantly, its forecasting ability does not vanish after controlling for other macroeconomic predictors.

In short, the evidence we have presented shows that China's confidence indicators might provide additional information about the future path of output growth, with the caveat that its marginal effect on real economy should not be exaggerated. Further research is sorely needed to construct a forecasting model with other relevant economic fundamentals, which are motivated by theory and empirical feasibility. Moreover, to better understand what are actually measured in China's consumer confidence index, the details on the attitude survey remain to be revealed and the underlying determinants of the index seem worth investigating.

Data appendix

Gross industrial output. The data are from the website: mac.hexun.com. The raw series are first deflated by Producer Price Index (PPI) released in *China Monthly Economic Indicators* (CEMAC, various issues). It should be noted that the reported monthly PPI is relative to the same month in the previous year. To obtain the output data in constant price, we choose the 12 months of 1997 as the base time and, by consequence, the price variations within the year of 1997 are ignored. Such deflated series are then deseasonalized by the US Census Bureau's X-12 seasonal adjustment procedure.

Other variables. The consumer confidence index (CCI), consumer expectation index (CEI), and the five control variables also come from *China Monthly Economic Indicators* . Among them, the total freight volume (FV), sales rate of industrial products (SR), freight volume handled in major coastal ports (PORT), and money and quasi-money (M2) have been seasonally adjusted through X-12 procedure.

Because the statistical inference after estimating VAR requires variables involved are stationary series, we carry out the Augmented Dickey-Fuller (ADF) unit root tests and show the MacKinnon approximate *p*-value associated with ADF statistic in Table 11.

[Table 11 around here]

As can be seen from the table, with different lag orders, the null hypothesis of a unit root is overwhelmingly rejected for all the variables under consideration. Indeed, the alternative Phillips-Perron unit root tests yield similar results. For the sake of brevity, their outcomes have not been reported here.

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Table 1
Pairwise Granger causality tests for industrial output and confidence index

	Chi2-Statistic	*p*-value	Sum of coefficients	Standard errors
Lags of CCI in OUTPUT equation	3.2218	0.200	-0.0003	0.0007
Lags of OUTPUT in CCI equation	4.6925	0.096	11.1036	5.9725*
Lags of CEI in OUTPUT equation	5.7115	0.058	-0.0007	0.0006
Lags of OUTPUT in CEI equation	4.6119	0.100	13.1788	7.0425*

Notes: 1. Number of observations equals 145.
2. Both the Akaike information criterion (AIC) and Schwarz information criterion (SIC) suggest that the appropriate lag order in the VAR is two.
3. * significant at the 10% level.

Table 2
Pairwise Granger causality tests for industrial output, expectation index, and all control variables

	Chi2-Statistic	*p*-value	Sum of coefficients	Standard errors
- OUTPUT model				
Lags of CEI	7.0003	0.030	-0.0011	0.0006**
Lags of FV	0.6405	0.726	-0.0073	0.0783
Lags of SR	13.0570	0.001	0.0133	0.0043***
Lags of PORT	5.4361	0.066	-0.2584	0.1415*
Lags of M2	0.9023	0.637	0.1816	0.1917
Lags of STOCK	6.4220	0.040	0.0728	0.0355**
- CEI model				
Lags of OUTPUT	3.3786	0.185	12.3189	8.0382
Lags of FV	3.3882	0.184	-7.1322	4.1912*
Lags of SR	5.3813	0.068	0.3130	0.2287
Lags of PORT	0.6399	0.726	6.0329	7.5745
Lags of M2	1.4736	0.479	-5.5366	10.2589
Lags of STOCK	0.0683	0.966	0.2726	1.8985

Notes: 1. Number of observations equals 145.
2. Results reported here are based on the VAR with two lags, as suggested by AIC. Although SIC tends to choose model with only one lag, the causal link running from CEI to output still exists.
3. *** significant at the 1% level;
** significant at the 5% level;
* significant at the 10% level.

Table 3
Forecast variance decomposition of output growth (in percentage)

Month	**CEI**	OUTPUT	SR	PORT	STOCK
1	**0.3**	99.7	0	0	0
6	**2.4**	85.1	4.4	4.3	3.9
12	**2.5**	84.9	4.4	4.3	3.9

Month	OUTPUT	**CEI**	SR	PORT	STOCK
1	100	**0**	0	0	0
6	84.6	**2.9**	4.4	4.3	3.9
12	84.4	**3.0**	4.4	4.3	3.9

Month	OUTPUT	SR	**CEI**	PORT	STOCK
1	1	0	**0**	0	0
6	84.6	4.8	**2.4**	4.3	3.9
12	84.4	4.9	**2.6**	4.3	3.9

Month	OUTPUT	SR	PORT	**CEI**	STOCK
1	1	0	0	**0**	0
6	84.6	4.8	4.7	**2.0**	3.9
12	84.4	4.9	4.7	**2.2**	3.9

Month	OUTPUT	SR	PORT	STOCK	**CEI**
1	1	0	0	0	**0**
6	84.6	4.8	4.7	3.9	**2.0**
12	84.4	4.9	4.7	3.9	**2.2**

Note: It is found that the modulus of each eigenvalue of the coefficient matrix is strictly less than one, indicating that the VAR system is stable.

Table 4
Frequency of expansionary /recessionary events in industrial output

	1-month expansion	2-month expansion	3-month expansion	1-month recession	2-month recession	3-month recession
Yes	79	45	27	68	34	23
No	68	101	118	79	112	122
Total observations	147	146	145	147	146	145

Table 5
Forecasting three-month expansions: Probit model without control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0665	-0.0640	-0.0563
	(0.0293)**	(0.0296)**	(0.0297)*
Log-likelihood value	-66.3857	-66.3868	-66.8482
Pseudo R-squared	0.0447	0.0418	0.0322
Percent correctly predicted (expansion)	-	-	-
Percent correctly predicted (no expansion)	81.25%	81.12%	80.99%
Overall percent correctly predicted	81.25%	81.12%	80.99%

Notes: 1. Huber-White robust standard errors are in parentheses, with
** significant at the 5% level;
* significant at the 10% level.
2. Predicted probability is compared to the conventional benchmark 0.5.

Table 6
Forecasting two-month expansions: Probit model without control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0539	-0.0607	-0.0518
	(0.0260)**	(0.0260)**	(0.0261)**
Log-likelihood value	-87.4708	-86.4880	-86.9241
Pseudo R-squared	0.0260	0.0330	0.0240
Percent correctly predicted (expansion)	50.00%	80.00%	66.67%
Percent correctly predicted (no expansion)	69.50%	72.39%	69.29%
Overall percent correctly predicted	68.97%	72.92%	69.23%

Notes: 1. Huber-White robust standard errors are in parentheses, with
** significant at the 5% level.
2. Predicted probability is compared to the conventional benchmark 0.5.

Table 7
Forecasting one-month expansions: Probit model without control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0338	-0.0464	-0.0479
	(0.0243)	(0.0239)*	(0.0241)**
Log-likelihood value	-99.7691	-98.3831	-97.5090
Pseudo R-squared	0.0093	0.0170	0.0182
Percent correctly predicted (expansion)	54.72%	54.65%	55.68%
Percent correctly predicted (no expansion)	47.50%	47.46%	48.21%
Overall percent correctly predicted	52.74%	51.72%	52.78%

Notes: 1. Huber-White robust standard errors are in parentheses, with

** significant at the 5% level;

* significant at the 10% level.

2. Predicted probability is compared to the conventional benchmark 0.5.

Table 8
Forecasting three-month expansions: Probit model with control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0863	-0.0865	-0.0924
	(0.0307)***	(0.0321)***	(0.0332)***
FV	-1.0600	-4.9178	3.3674
	(1.9281)	(2.7506)*	(2.7371)
SR	0.5852	0.7106	0.7451
	(0.2167)***	(0.2523)***	(0.2565)***
PORT	0.3361	5.4799	3.0625
	(3.9225)	(3.7403)	(3.6191)
M2	-5.4137	-4.5556	-21.2502
	(7.2722)	(6.6726)	(15.5297)
STOCK	1.6418	1.5488	2.0024
	(1.4584)	(1.3785)	(1.4236)
Log-likelihood value	-62.5152	-59.8955	-59.3970
Pseudo R-squared	0.1004	0.1355	0.1401
Percent correctly predicted (expansion)	25.00%	50.00%	50.00%
Percent correctly predicted (no expansion)	81.43%	82.01%	82.35%
Overall percent correctly predicted	79.86%	81.12%	80.99%

Notes: 1. Huber-White robust standard errors are in parentheses, with

*** significant at the 1% level;

* significant at the 10% level.

2. Predicted probability is compared to the conventional benchmark 0.5.

Table 9
Forecasting two-month expansions: Probit model with control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0810	-0.0783	-0.0784
	(0.0276)***	(0.0292)***	(0.0273)***
FV	-1.9990	-3.8876	-0.9871
	(1.7645)	(2.2118)*	(2.5333)
SR	0.6805	0.6739	0.7298
	(0.2065)***	(0.2233)***	(0.2131)***
PORT	-2.0044	2.5096	1.9881
	(3.3568)	(3.9097)	(3.6053)
M2	-8.7021	12.8138	-4.7692
	(7.2475)	(6.4011)**	(6.6203)
STOCK	1.2486	0.9778	1.1101
	(1.2504)	(1.2717)	(1.2693)
Log-likelihood value	-81.1420	-78.5535	-80.2559
Pseudo R-squared	0.0965	0.1217	0.0989
Percent correctly predicted (expansion)	61.90%	52.38%	53.85%
Percent correctly predicted (no expansion)	74.19%	72.36%	73.50%
Overall percent correctly predicted	72.41%	69.44%	69.93%

Notes: 1. Huber-White robust standard errors are in parentheses, with

*** significant at the 1% level;

** significant at the 5% level;

* significant at the 10% level.

2. Predicted probability is compared to the conventional benchmark 0.5.

Table 10
Forecasting one-month expansions: Probit model with control variables

	1 month ahead	2 months ahead	3 months ahead
CEI	-0.0688	-0.0637	-0.0741
	(0.0255)***	(0.0271)**	(0.0287)***
FV	1.3205	-3.5237	-0.5055
	(1.7578)	(1.8862)*	(2.0444)
SR	0.6565	0.5893	0.7308
	(0.2114)***	(0.2039)***	(0.1977)***
PORT	-4.0296	2.1373	-1.5997
	(3.8647)	(3.7193)	(4.0778)
M2	-9.5292	7.1691	9.0214
	(8.0473)	(6.3059)	(6.2509)
STOCK	3.2822	-0.8572	1.3334
	(1.3380)**	(1.2021)	(1.2078)
Log-likelihood value	-88.4899	-91.3174	-88.7904
Pseudo R-squared	0.1213	0.0876	0.1060
Percent correctly predicted (expansion)	67.03%	63.41%	65.88%
Percent correctly predicted (no expansion)	67.27%	58.73%	62.71%
Overall percent correctly predicted	67.12%	61.38%	64.58%

Notes: 1. Huber-White robust standard errors are in parentheses, with
*** significant at the 1% level;
** significant at the 5% level;
* significant at the 10% level.
2. Predicted probability is compared to the conventional benchmark 0.5.

Table 11
ADF unit root tests for variables under consideration: MacKinnon approximate *p*-value

Variables	**Lag=1**	**Lag=2**	**Lag=3**	**Lag=4**	**Lag=5**	**Lag=6**
OUTPUT (log difference)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004
CCI (level)	0.0343	0.1058	0.0904	0.0575	0.1127	0.1202
CEI (level)	0.0215	0.0807	0.0924	0.0335	0.0906	0.0998
FV (log difference)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
SR (level)	0.0134	0.0174	0.0082	0.0069	0.0119	0.0083
PORT (log difference)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
M2 (log difference)	0.0000	0.0000	0.0000	0.0000	0.0002	0.0024
STOCK (log difference)	0.0000	0.0000	0.0004	0.0019	0.0005	0.0071

Note: All the tests have been performed with a constant, but without time trend.