Stock Return, Consumer Confidence, Purchasing Manager's Index And Economic Fluctuations

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ABSTRACT

This paper empirically investigates, in the context of vector autoregression and error-correction methodology, the link between three confidence measures of consumers, investors, businesses, and economic fluctuations. Using quarterly data for the United Sates from 1980 to 2005, we found that the hypothesis that these confidence measures do not Granger-cause GDP was rejected, even after controlling for other macroeconomic variables. Forecast Variance decompositions of GDP suggest that consumer confidence, stock return, and purchasing manger's index, account for large variations in GDP. Overall, the results reconfirm the views that these measures play important roles in economic fluctuations.

INTRODUCTION

Researchers have been in search of identifying some economic indicators that can show early signals of changes in the economy. Among these indicators consumer confidence index, which measures consumers' attitudes and sentiment, and stock price index, which measures investors' attitudes and confidence, have been subject to extensive investigations. The investigations of the impact of these two indexes on the level of economic activity and their potential forecasting abilities have still been an area of continued interests in the literature. The Purchasing Manager's Index (PMI), is used by industrialized economies to assess businesses confidence, which is viewed widely as a major leading indicator of both manufacturing and overall economic growth, has not been subject to our knowledge to any formal investigations as the other two have.

The aim of this paper is to investigate the causal link between these confidence measures and the level of economic activity. This is important because the usefulness of these indexes for economic forecasting, policy making, and business planning depends crucially on the assumption that the indexes lead (cause) aggregate economic conditions.

The literature of consumer confidence is divided into two groups of studies: the first group has focused on confidence-consumption studies which have attempted to explain the link between the confidence, total consumption, and different categories of consumption. The results of these studies have produced varied results for U.S. and other countries. The most recent studies in this group are Garner (2002), Ludvigson (2004), Desroches and Gosselin (2004), Kawn and Cotsomitis (2004, 2006), Cotsomitis and Kawn(2006), Dunn and Mirzie (2006). The second group, which is the focus of this study, has investigated the confidence-GDP relationship.

Matsusaka and Sbordone (1995) used the U.S. quarterly data from 1953 to 1988 to examine the link between index of consumer confidence (sentiment) and Gross National Product (GNP). They found that confidence did Granger caused GNP for 1, 2, 3, and 4-quarter lags models. Their results of causality were robust to different model specifications[1].They applied the forecast variance decomposition technique to the model of GNP, the index of consumer sentiment, and the index of leading indicators and concluded that 13% to 26% of variation in GNP can be attributed to consumer confidence.

Utaka (2003), using the data from first quarter of 1980 to third quarter of 2000 and following the same methodology of Matsusaka and Sbordone, reconfirmed the U.S. confidence-GDP connection for Japan and found the confidence explained 9% to 11% of the variation in GDP. This shows smaller impact for Japan than the U.S.

The two recent studies in investigating the link between stock market and real activity have produced conflicting evidence. Binswanger (2000) connected the U.S. stock returns to production growth rate and real GDP growth rate and found no evidence of relationship for the sample period 1980 to 1995.The reason for the lack of evidence, as pointed out by the author, was the sample period considered was small. Morley (2002) examined the link between stock returns, output and consumption for the U.S and major European countries. In the case of the U.S., the evidence of long-run (co-integrating) relationship was found and the direction of Granger causality was predominantly from stock returns to both output and consumption. Both studies conducted bivariate investigations and their results could be questioned. Bivariate analysis provides no compelling case for true relationship due to the omission of other variables. Omitted variables may not reveal or may overstate the linkage. The more appropriate approach is to conduct a multivariate approach and that will be examined in our paper.

This study conducts three separate investigations. The first two investigations reexamine the confidence-GDP and stock return-GDP relationships by including the most recent observations to produce additional evidence. The third is to examine the link between purchasing manger's index and GDP to produce fresh evidence. To our knowledge no formal study has ever been conducted to investigate this link which will be the first attempt in that direction. The main focus of this paper is to analyze the usefulness of these confidence measures and to compare which measure(s) is important quantitatively in predicting GDP.

The paper proceeds as follows. Section II describes the methodology of this study. The data and empirical results are presented in Section III. The concluding section summarizes our findings.

METHODOLOGY

To analyze the causal relationship, in the context of Granger-causality, and specify an appropriate model for empirical investigation, it is necessary to determine the stationary properties of the variables of the model. The unit root test or the test of order of integration is conducted using the Augmented Dickey-Fuller (ADF). The ADF test is a two-step procedure. The first step is to test the null hypothesis that the variables in their un-differenced (level) form are non-stationary, integrated order of one, I (1). Rejection of the null indicates that the variables are stationary and non-rejection indicates they are non-stationary and will be subject to further testing. The second step tests the null hypothesis that the variables in their first differenced form are stationary, integrated of order zero, I (0).

The results of the test may lead to two possibilities. One possibility is that the variables are integrated of different orders, for example, if one variable is integrated of order one and the other variable is integrated of order zero, then the two variables cannot be co-integrated (implying the lack of long- run relationship between the variables). However, short-run relationship can be investigated by standard Granger-causality test in the context of Vector-Autoregressive (VAR) model. Another possibility is the variables have the same order of integration, for example, they are integrated of order one, which requires a further test for existence of co-integration. If co-integration exists among the variables, then a vector of error-correction model (ECM), which requires stationary variables, is used for causality test.

According to The standard Granger causality test a stationary variable x is said to Granger cause a stationary variable y if and only if y (t) is predicted better by using the past changes of x, together with the past changes of y itself, rather than by using only the past changes of y. To determine whether causality runs from y to x, one simply repeats the exercise, but with y and x interchanged. Three findings are possible: 1) neither variable Granger causes the other; 2) unidirectional causality, x causes y only; y causes x only; and 3) bidirectional causality, x and y Granger cause each other.

The vector autoregressive standard Granger causality model is presented below:

$$\Delta Y_t = \alpha + \sum_{i=1}^{\rho} \alpha y_i \, \Delta Y_{t-i} + \sum_{i=1}^{\rho} \alpha x_i \, \Delta X_{t-i} + \varepsilon_t \tag{1}$$

$$\Delta X_t = \beta + \sum_{i=1}^{\rho} \beta x_i \, \Delta X_{t-i} + \sum_{i=1}^{\rho} \beta y_i \, \Delta Y_{t-i} + \mu_t \tag{2}$$

Where Δ is the first-difference operator and ΔX and ΔY are stationary time series. The null hypothesis that X does not Granger-cause Y is rejected if the coefficients, αx_i, in equation (1) are jointly significant. The null hypothesis that Y does not Granger-cause X is rejected if the βy_i are jointly significant in equation (2). These two-variable vector autoregressive equations can be expanded to multivariate equations by including more variables.

In addition to the standard Granger causality test which captures the short-run causality. A new channel of causality can be emerged from the evidence of co-integration which captures the long-run causality. If there a co-integrating (long-run) relationship exists between two variables then, as Granger (1988) points out, there is causality among these variables at least in one direction. The direction of causality is revealed by application of following vector error-correction model (VECM).

$$\Delta Y_t = \alpha + \sum_{i=1}^{\rho} \alpha y_i \, \Delta Y_{t-i} + \sum_{i=1}^{\rho} \alpha x_i \, \Delta X_{t-i} + \lambda \, EY_{t-1} + \varepsilon_t \tag{3}$$

$$\Delta X_t = \beta + \sum_{i=1}^{\rho} \beta x_i \, \Delta X_{t-i} + \sum_{i=1}^{\rho} \beta y_i \, \Delta Y_{t-i} + \gamma EX_{t-1} + \mu_t \tag{4}$$

Where ΔY and ΔX are first difference stationary and co-integrated variables, and EY_{t-1} and EX_{t-1} are the lagged values of the error correction terms, defined by the following cointegration equations:

$$EY_{t-1} = Y_t - vX_t \tag{5}$$

$$EX_{t-1} = X_t - wY_t \tag{6}$$

From equation (3) the null hypothesis that ΔX does not Granger-cause ΔY is rejected if the coefficients αx_i are jointly significant and the error-correction coefficient λ is significant. The inclusion of error-correction term EY_{t-1}, in contrast to the standard Granger causality, introduces another channel of causality even if the coefficients αx_i are not jointly significant. The above can be reversed for equation (4). These bivarite vector error-correction models can also be modified to multivariate error-correction models by adding more variables.

If Granger-causality exists among variables then a forecast variance decomposition technique is utilized to assess the quantitative importance of these variables. Sims (1982) points out that the strength of Granger-cause relation can be measured by variance decomposition. For example, if a variable explains a small portion of the forecast error variance of another variable, this could be interpreted as a weak Granger-causal relation. The technique is simply to use the vector autoregression residuals of a variable to decompose the forecast variance of that variable into contributions by each of the variables in the system. For example, for a vector autoregression equations of three variables, say X, Y, and Z, the vector autoregression residuals of X is used to decompose the forecast variance of X into contributions by Y and Z. The procedure can be repeated for other variables. The percentage contribution can be obtained for any arbitrary length forecasts, and it is sensitive to relative ordering of variables in the equation. The usual practice is to report the results for different orders of the variables in the vector autoregression equations. For example, if variable Y is placed first in the vector autoregression residuals of X then the best scenario case of percentage contribution for variable Y is obtained for variable X. If it is placed last then Y variable has the worst scenario case of percentage contribution for variable X. In other words, the percentage is reported between the lowest (worst case) and the highest (best case) contributions. A detailed discussion of the methodology described in this section can be found in Enders (2004).

DATA AND EMPIRICAL RESULTS

Data

The U.S. data for the variables in this study are obtained from the Federal Reserve of Bank of St. Louis and www.economagic.com. The sample period runs from the first quarter of 1980 to the fourth quarter of 2005. The variables are measured as follows:

1. CCI: is the log of the consumer confidence index. It is measured by the index of consumer sentiment constructed by the Survey Research Center at the University of Michigan[2]. The index is not seasonally adjusted at the source because it does not appear to have seasonal component.
2. SPI: is the log of stock return. It is measured by the Standard and Poor's 500 stock price index.
3. GDP: is the log of seasonally adjusted real gross domestic product.
4. PMI: is the log of seasonally adjusted purchasing manager's index[3].
5. CPI: is the log of seasonally adjusted consumer price index. The CPI is included to serve as a control variable to conduct multivariate investigations and it is also considered important variable affecting GDP.

All estimations were conducted using Microfit 4.0 (Pesaran and Pesaran 1997).

Tests Of Order Of Integration

The empirical investigation starts by examining the order of integration for the variables in the study. To determine the order of integration, as explained in the previous section, we apply the Augmented Dickey-Fuller (ADF) test to the level and the first difference of the variables. The optimal lag length in ADF tests are chosen based on the Akaike Information Criterion (AIC). The test is based on a null hypothesis of a unit root (non-stationary), or I (1), against an alternative hypothesis of a zero root (stationary), I (0). The results are reported in Table 1. For the level of the variables, the ADF statistics rejects the null hypothesis for CCI and PMI, and fails to reject the null for GDP, SPI, and CPI. In other words, CCI and PMI are stationary in levels. For the first difference of the variables, the ADF rejects the null hypothesis for GDP, SPI, and CPI. Therefore, we can conclude that these variables are integrated of order one, I (1). In other words, they are stationary in first difference.

Table 1- The results of ADF test

Variable	Level	First Difference
CCI	-3.0493	--------
PMI	-3.1604	--------
GDP	0.0758	-4.6930
SPI	-1.0331	-8.7746
CPI	-1.1537	-4.3448
5% critical values	-2.8906	-2.8909

Note: We also carried out the ADF test with trend and the results were the same.

Confidence-GDP Relationship

Our empirical strategy is as follows. First, we estimate a bivariate Granger causality model, equations (1) and (2), to demonstrate that causality exists from consumer confidence to GDP or from GDP to consumer confidence. Second, multivariate models are estimated by incorporating the CPI or SPI into equations (3) and (4) to show that the relation is robust to inclusion of a number of alternative specifications. There are several statistics to test formally the direction of causality. These are the Lagrange Multiplier (LM) statistic, the Likelihood Ratio (LR) statistic, and the Wald statistic which are all asymptotically equivalent and distributed as χ^2, and the usual F-statistic. Among these statistics the LR statistic is used to test the causality. After selecting the optimal lag based on the Akaike Information Criterion (AIC), then the adequacy of all estimated equations were evaluated for serial correlation, heteroscedasticity, normality, and functional form[4]. Finally, the results of forecast error variance decomposition method are reported to determine the quantitative importance of consumer confidence.

To investigate that Granger causality exists from consumer confidence (CCI) to GDP, several vector autoregression models are considered for estimations. We begin by estimating a simple two-variable, output (GDP) and consumer confidence (CCI), given by equations (1) and (2). In this bivariate model there is a possibility that the presumed correlation between GDP and CCI may be driven by a third variables acting on their behalf. To address this, the model is augmented with the consumer price inflation (CPI) or the stock return (SPI). The optimal lag selected by the (AIC) is two for all models. The results are presented in table 2.

From the table we can conclude that the hypothesis that CCI does not Granger-cause is rejected at 1% level of significance and it is robust to different model specifications. This shows that the CCI helps to predict GDP. In addition, the hypothesis that GDP does not Granger-cause CCI is reject at less than 10% level of significance which shows the condition of the economy affects the consumer confidence.

Table 2- Granger –Causality Test

Model	Null Hypothesis	χ^2- Statistic
VAR (ΔGDP, CCI)	H0	19.44(0.000)
	H1	6.14(0.046)
VAR (ΔGDP, CCI, ΔCPI)	H0	18.95(0.000)
	H1	14.08 (0.009)
VAR (ΔGDP, CCI, ΔSPI)	H0	11.21(0.004)
	H1	5.99(0.050)

Note: H0: CCI does not Granger cause GDP. H1: GDP does not Granger cause CCI.
Numbers in parentheses are the significance levels.

From the table we can conclude that the hypothesis that CCI does not Granger-cause is rejected at 1% level of significance and it is robust to different model specifications. This shows that the CCI helps to predict GDP. In addition, the hypothesis that GDP does not Granger-cause CCI is reject at 5% level of significance which shows the condition of the economy affects the consumer confidence.

The quantitative impact of consumer confidence on GDP can be investigated by using the forecast variance decomposition. As was noted earlier the percentage contributions are sensitive to the ordering of variables in the equation. To compare our results with the results of Matsusaka and Sbordone (1995), we follow their practice of using three different orders. Since concern is especially with the quantitative effect of CCI on GDP and to conserve space, only summary results for GDP decomposition are presented for one quarter ahead, four quarters ahead, eight quarters ahead and they are reported in table 3.

From the table the variance of consumer confidence index in the first model explains approximately between 8% and 23% of the one-quarter-ahead forecast variance of GDP. The second model has about the same percentage contributions between 8% and 26%. For the eight-quarter-ahead the approximate percentage contributions are 10% to 21% in the first model and over 7% to 24% in the second model. The investigation of Matsusaka and Sbordone (1995) which included GNP, the index of leading indicators and consumer sentiment in their model, concluded that between 13% and 26% of the variance of GNP was explained by the consumer confidence for the eight-quarter-ahead[5]**.** Utaka (2003) used Japanese data and found for the eight-quarter-ahead the consumer confidence's contribution was between 9% and 11%. However, our results produce more evidence to conclude that changes in consumer confidence are quantitatively important in explaining the GDP fluctuations.

Table 3- Forecast variance decomposition of GDP
Percentage of forecast variance of GDP explained by Consumer Confidence

Forecast horizon (quarter)	1	4	8
VAR model I (ΔGDP, CCI, ΔCPI)			
Order (CCI, ΔGDP, ΔCPI)	22.80	19.91	20.68
Order (ΔGDP, CCI, ΔCPI)	10.91	9.95	10.37
Order (ΔGDP, ΔCPI, CCI)	7.77	9.15	9.91
VAR model II (ΔGDP, CCI, ΔSPI)			
Order (CCI, ΔGDP, ΔSPI)	25.79	23.44	23.59
Order (ΔGDP, CCI, ΔSPI)	12.60	11.01	11.16
Order (ΔGDP, ΔSPI, CCI)	7.63	7.09	7.31

Stock Return-GDP Relationship

Since the variables GDP, Stock return (SPI), and consumer price index (CPI) are confirmed by the ADF test to be integrated order one then, we can apply the Johansen's (Johansen, 1991) co-integration approach to test for co-integration among these variables. The approach uses two likelihood ratios test, the **Trace** and **Maximum Eigenvalue** to determine **r**, which is the number of co-integrating vectors. The null hypothesis of no co-integration is tested by comparing the trace and maximum eigenvalue statistics with their critical values.

The Johansen cointegration test is performed on two different models. The first model is a bivariate model which tests the co-integrating relationship between GDP and SPI. The second model is a trivariate model which includes GDP, SPI, and CPI. In order to implement the test, a lag length must be specified for the Vector Autoregression (VAR) model. For both models the lag order is two using the Akaike Information Criterion (AIC). Table 4 reports the co-integration test results.

Both trace and maximum eigenvalue tests suggest that there is a single cointegrating vector for both models. The results indicate that there is a long-run relationship between GDP and SPI in the first model and among the three variables in the second model.

Given the existence of cointegration then the causality tests can be carried out by vector error correction models. The two models considered for the causality tests are: (1) Model I (ECM1)-an error correction model which includes GDP and SPI, is estimated by equations (3) and (4). In those equations the error correction terms are estimated by the cointegrating equations (5) and (6). (2) Model II (ECM2)-it includes GDP, SPI, and CPI and it is estimated by incorporating the consumer price index variable into those equations. From error correction model, the causality can be derived through: (a) the χ^2-test of the joint significance of lags of SPI or GDP-a short-run causality, (b) the t-test of significance of the lagged error correction term coefficient (ECT)-long-run causality. Table 5 presents the results of Granger causality tests for Stock return (SPI) and GDP[6].

Table 4- Cointegration Test Results

	Trace	Trace (5%) critical value	Max. Eigenvalue	Max.Eigen (5%) critical value
VAR model I (GDP, SPI)				
H0: r = 0	20.09	11.03	30.75	12.36
H0: r < 1	1.65	4.16	1.65	4.16
VAR model II (GDP, SPI, CPI)				
H0: r = 0	43.39	17.68	51.17	24.05
H0: r < 1	5.10	11.03	7.78	12.36
H0: r < 2	2.68	4.16	2.68	4.16

Note: r denotes the number of co-integration vectors.

Table5- Causality test on Error Correction Models

	χ^2- test		T-test
Model	ΔSPI	ΔGDP	ECT
EMC1 (GDP, SPI)			
ΔGDP equation	11.76 (0.001)		-5.33 (0.000)
ΔSPI equation		0.05 (0.821)	-2.15 (0.034)
EMC2 (GDP, SPI, CPI)			
ΔGDP equation	6.89 (0.009)		-5.64 (0.000)
ΔSPI equation		0.15 (0.701)	-1.18 (0.242)

Note: Numbers in parentheses are the significance levels.

The results from the table show the evidence of short-run and long -run causality from SPI to GDP. There is no evidence of causality from GDP to SPI in both models with the exception of long-run causality in the bivariate model which is significant at the 0.034 level. We also carried out the standard granger causality tests on equations (1) and (2) and arrived at the same conclusion. We can conclude that the stock return (SPI) is an important factor in predicting the economic fluctuations. The quantitative importance of SPI on GDP, using the GDP forecast variance decomposition of ECM2 model, is summarized as follows. The percentage of forecast variance of GDP explained by the stock return for one-quarter-ahead is between 2.86 and 5.43 and for eight-quarter-ahead is between 8.07 and 17.09. This shows that the stock return is quantitatively important in explaining the GDP fluctuations.

Purchasing Manager's Index –GDP Relationship

Since the Purchasing Manager's Index (PMI) found to be stationary in the previous section therefore, we estimate equations (1) and (2) to carry out the standard Granger causality tests. We repeat the confidence-GDP procedures discussed earlier to report the test results for the PMI-GDP relationship in table 6. From the table we can conclude that the hypothesis that PMI does not Granger-cause is rejected at 1% level of significance and it is robust to different model specifications. This indicates that the PMI helps to predict GDP. Moreover, the hypothesis that GDP does not Granger-cause PMI is rejected approximately at 5% level of significance.

Table 6- Granger–Causality Test

Model	Optimal lag	Null Hypothesis	χ^2- Statistic
VAR (ΔGDP, PMI)	2	H0	30.92 (0.000)
		H1	5.76 (0.056)
VAR (ΔGDP, PMI, ΔCPI)	3	H0	16.76 (0.001)
		H1	10.51 (0.015)
VAR (ΔGDP, PMI, ΔSPI)	2	H0	25.19 (0.004)
		H1	6.04 (0.049)

Note: H0: CCI does not Granger cause GDP. H1: GDP does not Granger cause CCI. The optimal lag is selected by the AIC. Numbers in parentheses are the significance levels.

The quantitative impact of PMI on GDP growth, using the forecast variance decomposition of GDP for two alternative models, is summarized in table 7. The results show the PMI is important in explaining the GDP fluctuations.

Having conducted separate investigation of the direction of Granger causality of the consumer confidence index, the stock price index, the purchasing manager's index, and their quantitative importance, we thought it would be a good idea to compare the impact of these indexes on GDP and conclude which index accounts for the largest variations in GDP. The summary results are reported in table 8.

Table 7- Forecast variance decomposition of GDP

Percentage of forecast variance of GDP explained by Purchasing Manager's Index

Forecast horizon (quarter)	1	4	8
VAR model I (ΔGDP, PMI, ΔCPI)			
Order (PMI, ΔGDP, ΔCPI)	22.42	20.37	23.28
Order (ΔGDP, PMI, ΔCPI)	10.54	8.92	11.62
Order (ΔGDP, ΔCPI, PMI)	9.86	8.37	11.32
VAR model II (ΔGDP, PMI, ΔSPI)			
Order (PMI, ΔGDP, ΔSPI)	30.16	29.53	29.97
Order (ΔGDP, PMI, ΔSPI)	18.73	17.10	17.54
Order (ΔGDP, ΔSPI, PMI)	16.75	14.98	15.45

Table 8- Forecast variance decomposition of GDP

Percentage of forecast variance of GDP explained by Consumer Confidence Index,Stock Return and Purchasing Manager's Index

Forecast horizon (quarter)	1	4	8
VAR model			
Consumer Confidence (GDP, CCI, CPI)	7.77-22.80	9.15-19.91	9.91-20.68
Stock Return (GDP, SPI, CPI)	2.86-5.43	6.61-13.54	8.07-17.09
Purchasing Manager's Index (GDP, PMI, CPI)	9.86-22.42	8.38-20.37	11.32-23.28

Note: The results are based on three different orders as explained earlier.

Several observations can be made from the table. First, for one-quarter-ahead, the percentage contributions for the consumer confidence (CCI), the stock return (SPI) and purchasing manager's index (PMI) are between 7.77 to 22.80, 2.86 to 5.43, and 9.86 to 22.42, respectively. Second, the SPI accounts for more variations in GDP with longer forecast horizon. Finally, for one, four, eight-quarter-ahead, the CCI and PMI account for about the same variations in GDP which are evidently higher than the SPI.

The evidence of similar effect of the CCI and PMI on GDP was obtained from the estimated VAR model in which the consumer price index (CPI) was included as a control variable. Whether the same evidence can be found under different model specification, is investigated by using a VAR model that the SPI replaces the CPI as a control variable. The estimated results which were reported in the bottom portions of tables 3 and 7 are reproduced in table 9.

Table 9- Forecast variance decomposition of GDP

Percentage of forecast variance of GDP explained by Consumer Confidence Index and Purchasing Manager's Index

Forecast horizon (quarter)	1	4	8
VAR model			
Consumer Confidence (GDP, CCI, SPI)	7.63-25.79	7.09-23.44	7.31-23.59
Purchasing Manager's Index (GDP, PMI, SPI)	16.75-30.16	14.98-29.53	15.45-29.97

It is evident from the table that the PMI is more quantitatively important than the CCI. For example, for eight-quarter-ahead, the CCI accounts for 7.31% to 23.59% variations in GDP and the PMI accounts for 15.45% to 29.97% variations. However, the results of the horse-race contest produced new evidence that the businesses confidence, as measured by the PMI, is an important key economic indicator in predicting the economic fluctuations and this variable should be included as an argument in the GDP model. Therefore, the policy makers should pay close attention to this indicator.

CONCLUSION

In this paper, the causal links between consumer confidence and economic growth (GDP), and stock return-GDP, have been re-examined to provide additional evidence by including the most recent observations. We have also examined for the first time the connection between Purchasing Manager's Index and GDP to provide fresh evidence. This is the first attempt to include three measures of confidence, consumers, investors, and businesses in a single investigation and analyze their impacts on economic growth.

Our horse-race contest of these confidence measures has produced the following findings. First, our empirical estimates of the United States data reject the hypotheses that the consumer confidence index (CCI), the stock price index (SPI), and the purchasing manager's index (PMI), do not Granger-cause GDP and the results are robust to alternative model specifications. We conclude from the causality tests that the changes in the confidence measures help to predict GDP. Second, according to the forecast variance decomposition of GDP, we found that the CCI, SPI, and PMI are quantitatively important in explaining the fluctuations in GDP. For eight-quarter-ahead, the CCI accounts for between 10% to 21% in VAR model with the consumer price inflation and between over 7% to 24% in VAR model with the stock price index, the SPI accounts for 8% to 17%, the PMI accounts for between 11% to 23% and over 15% to 30% in both models. Lastly, the overall results of our investigations reconfirm the views that these confidence measures play prominent roles in economic fluctuations.

ENDNOTES

1. They included the control variables such as the Index of Leading Indicators, government spending and "default risk" in their investigation.
2. Another widely recognized measure of consumer confidence is the Conference Board's Index of Consumer Confidence. Both indexes focus on consumer perception of overall business and economic conditions. We decided to use the Michigan's index in order to compare our results with the results of Matsuaka and Sbordone (1995) paper.
3. Purchasing Manager's Index (PMI) is a composite index based on the seasonally adjusted diffusion indexes. The index measures such factors as new orders, production, supplier delivery times, backlogs, inventories, prices, employment, import orders and exports
4. To conserve space, those diagnostic tests are not reported but they are available upon request.
5. Their period of study was from 1953 to 1988. After 1989 the index of leading indicators was expired. Therefore we could not include the index in our investigation to make a comparison.
6. All estimated coefficients of the vector error correction models, though not presented here due to space constraints, are available on request from the authors.

REFERENCES

1. Atsuo Utaka. Confidence and the Real Economy-the Japanese Case. *Applied Economics*, 35, 2003, 337-342.
2. Bruce Morley. Output, Consumption and the Stock Market: Implications for European Convergence. *Applied Economics*, 34, 2203, 317-323.
3. Costsomitis, J. A., and Kwan A. C. C. Can Consumer Confidence Forecast Household Spending? Evidence from the European Commission Business and Consumer Surveys, *Southern Economic Journal*, 72 (3), 2006, 597-610.
4. Desroches B. and Gosselin M.A. Evaluating Threshold Effects in Consumer Sentiment *Southern Economic Journal*, 70 (4), 2004, 942-952.
5. Dunn L.F. and Mirzaie I.A. Turns in Consumer Confidence: An Information Advantage Linked to Manufacturing *Economic Inquiry*, 44 (2), 2006, 343-351.
6. Enders Walter. *Applied Econometrics Time Series* New York, Wiley Pub. 2004.
7. Garner C. A. Consumer Confidence after September 11 *Economic Review*, 87 (2), 2004, 5-25.
8. Granger C. W. J. Some Recent Development in a Concept of Causality *Journal of Econometrics*, 39, 1988, 199-211.
9. Johansen S. Estimation and Hypothesis Testing of Co-integration Vectors in Gaussian Vector Autoregressive Models *Econometrica*, 59, 1991, 1551-1580.
10. Kwan A. C. C. and Cotsomitis J. A. Can Consumer Attitudes Forecast Household Spending in the United States? Further Evidence from the Michigan Surveys of Consumers *Southern Economic Journal*, 71 (1), 2004, 136-144.
11. Kwan A. C. C. and Cotsomitis J. A. The Usefulness of Consumer Confidence in Forecasting Household Spending in Canada: A National and Regional Analysis. *Economic Inquiry*, 44 (1), 2006, 185-197.
12. Ludvigson S. C. Consumer Confidence and Consumer Spending *Journal of Economic Perspectives*, 18 (2), 2004, 29-50.
13. Mathias Binswanger. Stock Returns and Real Activity: Is There Still a Connection? *Applied Financial Economics*, 10, 2000, 379-387.
14. Matsusaka J. G. and Sbordone A. Consumer Confidence and Economic Fluctuations *Economic Inquiry*, 33 (2), 1995, 296-318.
15. Pesaran M. H. and Pesaran B. *Working With Microfit 4.0: Interactive Econometric Analysis* Oxford University Press, Oxford. 1997.
16. Sims C. A. Policy Analysis with Econometric Model Brookings Paper on Economic Activity, 1, 1982, 107-152.