DO CONSUMER CONFIDENCE INDEXES HELP

FORECAST CONSUMER SPENDING IN REAL TIME?

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ABSTRACT

Could a researcher or policy analyst use data reported from surveys of consumer confidence to improve forecasts of consumer spending? This issue has been examined in the literature previously, which reached the conclusion that consumer confidence data helped improve the forecasts slightly, but not statistically significantly. But that research was based on latest available data and thus did not use the data that would have been available to forecasters in real time. This paper remedies that shortcoming, using the Real-Time Data Set for Macroeconomists to analyze the quality of forecasts made with indexes of consumer confidence. We conjecture that using real-time data might show greater marginal significance for consumer confidence because the surveys might capture effects that will not appear in the data until they are revised. The main finding is that the indexes of consumer confidence are not of significant value in forecasting consumer spending. In fact, in some cases, they make the forecasts significantly worse, suggesting that consumer confidence surveys are no better than government data agencies in capturing information about consumer spending.

(*JEL* classification: E27)

DO CONSUMER CONFIDENCE INDEXES HELP FORECAST CONSUMER SPENDING IN REAL TIME?

A recent symposium held at Princeton University, "How Confident Can We Be in Consumer Confidence?" (May 10, 2002) examined the ways in which indexes of consumer confidence were gathered and used. The *New York Times* reported that "whatever the shortcomings of the consumer confidence indexes, nearly all the researchers agree that when combined with other data, they provide some additional information in forecasting consumption." (Uchitelle, 2002)

The idea that indexes of consumer confidence may be useful in forecasting consumption was first proposed by Eva Mueller (1963), who used ten years of data from the Michigan survey of consumers. She found that consumer confidence was a significant explanatory variable for consumption spending in a regression that included lagged consumption in the equation. Frederic Mishkin (1978) found that the significance of the Michigan consumer confidence measure depended on what else was included on the right-hand-side of the equation for predicting spending on durable consumer goods—adding financial variables to the equation greatly reduced the explanatory power of consumer confidence. Christopher Carroll, Jeffrey Fuhrer, and David Wilcox (1994) confirmed Mishkin's finding for overall personal consumption expenditures, noting that the explanatory power of the confidence index declined after 1978. Yash Mehra and Elliot Martin (2003) showed that consumer confidence matters in regression equations for consumer spending because it helps predict future changes in income and the real interest rate. Thomas Garrett, Rubén Hernández-Murillo, and Michael T. Owyang (2004) used regional data to show that consumer confidence helps predict retail spending in U.S. states. However, this literature bases its results entirely on in-sample results and does not ask the question of whether the consumer confidence indexes could be used to forecast consumer spending out-of-sample.

The first paper to perform out-of-sample forecasting experiments for consumer confidence was Jason Bram and Sydney Ludvigson (1998), who tested the Michigan index against the Conference Board index and found greater explanatory power in the Conference Board's index. In their out-of-sample forecasting exercises, they found that the Conference Board's index reduced the root-mean-squared forecast error (RMSFE) relative to a baseline forecasting equation in which consumption spending growth is forecast with its own lags, and lags of income growth, growth in real stock prices, and the change in the interest rate, while the Michigan survey increased the RMSFE. However, neither change in RMSFE was statistically significant.[1]

Several papers have examined the ability of the confidence indexes to influence variables other than consumption spending. For example, Eric Leeper (1992) showed that the Michigan index helps explain movements in industrial production and unemployment, but the explanatory power disappears when real stock prices and the interest rate are added to the system of equations. Forecasts are not improved by using the Michigan index. He concludes that the Michigan index does not include information not already available to financial markets.

More recently, Philip Howrey (2001) tested whether the Michigan survey helps predict business cycle turning points and consumption spending. He found that the

[1] A similar exercise was conducted on UK data by Joshy Easaw and Saeed Heravi (2004).

monthly information in the confidence index helps improve quarterly forecasts, so the high-frequency information in the Michigan index appears useful. The last paragraph of his paper indicates directions for further research: "Most of these conclusions are based on models that were estimated over the entire sample period. It would be interesting to see whether these results also hold for recursive estimates of the forecasting equations. In addition, no attempt has been made to deal with issues of measurement error and data revision that accompany real-time forecasts." (p. 205) This is the point of departure for the current paper.

All of the research that examines whether indexes of consumer confidence help to forecast consumer spending are based on latest available data (the data available to the researcher), rather than data that were available to forecasters in real time. As a result, the regression exercises and forecasts that are contained in this research are not indicative of the value of the consumer confidence indexes in actual forecasting. A conjecture that arose at the Princeton symposium was that the confidence indexes might prove to be even more useful in real time than they were with latest available data, because the data revisions are based on information not known to government data collectors until after the fact, but people know about their own incomes and their own spending plans when they respond to the surveys of consumer confidence. So, the question to be answered is: are indexes of consumer confidence valuable for forecasting consumer spending in real time? And are they more valuable when combined with real-time data than if combined with latest available data?

I. Data on Consumer Confidence and Real-Time Macroeconomic Data

To examine whether indexes of consumer confidence have any value in real time, we need data on consumer confidence and real-time macroeconomic data. This section describes the available data.

The Confidence Indexes

We examine two different indexes of consumer confidence: the Surveys of Consumers taken at the University of Michigan (hereafter called the Michigan survey), and the Conference Board survey of consumer attitudes.

The Michigan survey began in 1946. Currently, each monthly survey asks approximately 500 telephone respondents about 50 questions, covering many different aspects of consumer attitudes and expectations. Economists have focused on a subset of questions relating to current and future economic conditions. The responses to three questions concerning future economic conditions (on national business conditions in the next year, on national business conditions in the next five years, and on family financial conditions in the next year) are added together to obtain an Index of Consumer Expectations (which we will call M-future). The responses to two questions concerning current economic conditions (on whether it is a good time for people to buy major consumer goods and on the family's financial condition relative to one year ago) are averaged to arrive at a Current Conditions Index (M-current). The responses to all five of those questions are combined to calculate an Index of Consumer Sentiment (M-overall).[2]

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[2] For more information on the Michigan survey, see the survey's web site at: www.sca.isr.umich.edu/main.php. Economists have investigated some of the other questions in the survey as well, such as the expectations of inflation; see Croushore (2005) for an analysis of inflation forecasts from the Michigan survey compared with other forecast surveys.

The M-future index is one of the components of the Conference Board's index of leading indicators and the M-overall index is widely reported in the financial media on its release its month.

The Conference Board survey began in 1967 on a bi-monthly basis and has been conducted monthly since June 1977. Questionnaires are mailed to 5,000 households, with a response rate of about 70 percent. The consumer confidence index comes from the answers to five questions, which are similar to the Michigan survey. The responses to three questions concerning future economic conditions (on business conditions six months ahead, on employment conditions six months ahead, and on family income six months ahead) are added together to obtain an Expectations Index (which we will call CB-future). The responses to two questions concerning current economic conditions (on current business conditions and on current employment conditions) are averaged to arrive at a Present Situation Index (CB-current). The responses to all five of those questions are combined to calculate a Consumer Confidence Index (CB-overall).[3]

Figure 1 shows the two overall indexes, plotted over time from January 1978 to December 2002. In the graph, the gray shaded bars indicate recessions. Prior to the 1980 recession, the Michigan and Conference Board indexes had been declining steadily, then fell sharply before the recession began. Consumer confidence rebounded a bit when that recession ended, then fell during the 1981–1982 recession. In the remainder of the 1980s, the consumer confidence indexes remained fairly high, with a few twists and turns. In 1987, the stock-market crash in October caused consumer confidence to fall,

[3] For more information on the Conference Board survey, see their web site at: www.consumerresearchcenter.org/consumer_confidence/methodology.htm

but it rebounded shortly thereafter. Other than that, the Michigan index was fairly stable over most of 1984–1990, though with a slight downward trend. However, the Conference Board index, after declining slightly from 1984 to 1987, jumped up to a higher level in 1987, where it remained until about 1990. In the recession of 1990–1991, both indexes fell sharply. With slow economic growth after the recession, the indexes remained fairly low for some time. Both the Michigan and Conference Board indexes were more erratic in the period from 1991 to 1993 than they had been earlier. Consumers fared well in the remainder of the 1990s, and the confidence indexes rose to their highest levels ever. Confidence remained at a high level until 2000. The indexes all fell in late 2000 and early 2001, even before the recession began in March 2001.

From Figure 1, it is difficult to ascertain whether the consumer confidence indexes are likely to be helpful in forecasting recessions. In some cases, the indexes declined steadily well before a recession began. Mostly, the indexes fell after recessions began, except for the recession that began in March 2001.

However, even if indexes of consumer confidence are not too useful in predicting recessions, they may help in forecasting consumption spending. To illustrate this possibility, Figure 2 plots the Michigan overall index against the growth rate of consumption spending each month relative to one year earlier. The general movements of the two series correspond fairly closely. They declined together from 1978 to 1980, rose sharply together after the recession ended in 1982, drifted slowly downward together in the 1980s. In the 1990s, the Michigan index rose earlier than the growth rate of consumption spending, but both were very high in the late 1990s and fell together in the early 2000s. Similar patterns hold for the other indexes of consumer confidence.

Real-Time Macroeconomic Data

Our empirical procedure will be to test forecasts to see if including the confidence indexes reduces the root-mean-square-forecast error (RMSFE) significantly. We begin with a forecasting equation that does not include a consumer confidence index as a right-hand-side variable. Using the baseline equation, we generate a series of forecasts, just as if we were making those forecasts in real time. To do so, we must have, at each date for which we make a forecast, the exact data set available to a forecaster in real time. Such data are available in the Croushore-Stark (2001) Real-Time Data Set for Macroeconomists (RTDSM), which is available on the web at: http://www.phil.frb.org/econ/forecast/reaindex.html. We make a set of forecasts in a recursive fashion and then calculate the forecast errors. Then, we modify the forecasting equation by adding an index of consumer confidence and repeat the forecast exercise. Finally, we examine whether the RMSFE has increased or decreased significantly from the addition of the confidence index in the regression. Significance is determined using the Harvey-Leybourne-Newbold (1997) modification of the Diebold-Mariano (1995) procedure.[4]

Why do we need real-time macroeconomic data, as opposed to the data available in today's data bank? We need such data because we wish to investigate whether consumer confidence would help us forecast. If data revisions were small and inconsequential, we would not worry about using real-time data, but instead could rely on

[4] Note that the models tested here are nested, so this test may not be appropriate and the critical values are likely to be lower than we use. However, the problem of testing nested models with real-time data has not been fully solved (thanks to Todd Clark for discussions about this issue). Some ideas are contained in Clark and West (2004).

data that have been revised many times. However, data revisions may be large and may be systematic, so our empirical results could be biased if we did not use real-time data.

Research by Tom Stark and Dean Croushore (2002) illustrates how much the use of real-time data affects forecasts, especially short-term forecasts, which have been the focus of the literature on forecasting using consumer-confidence indexes. To get a feel for how much difference it makes to use real-time data as opposed to latest available data, we look briefly at the revisions to consumption growth in Figure 3; they are described in greater detail in Croushore-Stark (2001). The figure shows the revision from the initial release of consumption spending growth to its latest available value, both in terms of its quarterly growth rate (labeled "Quarterly") and the growth rate over the preceding four quarters (labeled "Four Quarters"). The revisions are quite large at times for personal consumption and for personal income (not shown), suggesting that the use of real-time data may make a significant difference. The revisions are not large for the real stock price, as only revisions in the consumption deflator would cause a revision in that variable, as deflator revisions tend not to be too large in most cases. But for personal consumption spending, many revisions are two percent or larger for a quarter, and sometimes one percent or more for the four-quarter average, while revisions to personal income (not shown) are even larger in many cases.

The forecasting equation that we will use in our empirical work is based on research by Carroll-Fuhrer-Wilcox and Bram-Ludvigson. The baseline equation is:

$$\Delta c_t = a_0 + \sum_{i=1}^{4} a_1^i \Delta c_{t-i} + \sum_{i=1}^{4} a_2^i \Delta y_{t-i} + \sum_{i=1}^{4} a_3^i \Delta r_{t-i} + \sum_{i=1}^{4} a_4^i \Delta s_{t-i} + e_t, \qquad (1)$$

where c is the logarithm of real consumption spending, y is the log of real personal income, r is the interest rate on three-month Treasury bills, s is the log of real stock prices (measured by the S&P 500 index). Real values are obtained from nominal values by deflating by the personal consumption expenditures price index. The error term, e_t, follows an MA(1) process because of time aggregation, as consumption decisions are made continuously, while the data are observed quarterly (see Carroll-Fuhrer-Wilcox).

We test forecasts made using equation (1) against forecasts that add to equation (1) the values of a measure of consumer confidence:

$$\Delta c_t = a_0 + \sum_{i=1}^{4} a_1^i \Delta c_{t-i} + \sum_{i=1}^{4} a_2^i \Delta y_{t-i} + \sum_{i=1}^{4} a_3^i \Delta r_{t-i} + \sum_{i=1}^{4} a_4^i \Delta s_{t-i} + \sum_{i=1}^{4} b^i C_{t-i} + e_t, \quad (2)$$

where we include some measure of consumer confidence, C_t.

Previous researchers estimating this equation used latest available data, which is easily obtained from a standard data base. However, consumption spending and personal income are revised over time, as is the deflator used to construct real values of the variables. So, we need real-time data on real consumption spending, personal income, and the deflator. Only real consumption spending currently exists in the Croushore-Stark (2001) real-time data set for macroeconomists, so we collected real-time data on nominal personal income and nominal consumption spending. From the real-time data on nominal and real consumption spending, we created a series for the personal consumption expenditures price deflator.

II. Comparing Real-Time Results With Results From Latest Available Data

Our experiments differ from those of Bram-Ludvigson by extending the sample period (hoping for greater ability to test the hypothesis that the confidence indexes matter), by using real-time data to estimate the model for each forecast date (beginning with the same sample starting date), and by using several alternative choices for the actual value of consumption growth.

Researchers in the forecasting literature must always make a choice about what they think forecasters are attempting to forecast. Such choices include data released shortly after the period in question, data available just prior to a benchmark revision, and the latest available data. Generally, we think that forecasters using real-time data do not forecast methodological changes by the government in constructing the data, so the data available just prior to a benchmark revision (which we label "last-benchmark data") make sense to use as actuals. However, the "best" measure of data is probably the latest available data, so we will also consider that possibility. Figure 4 highlights the differences in the quarterly growth of consumption spending in each of the forecast periods. The latest-available data show somewhat higher growth rates in the 1980s than the last-benchmark data and are a bit smoother in the 1990s than the last-benchmark data.

Forecasting Experiments

In all the forecasting experiments that follow, we use the following procedure:

1. Using real-time data with a sample period of 1968Q1 to 1981Q4, estimate the forecasting equation (1), then generate a forecast for 1982Q1. Do the same for equation (2) for each consumer confidence index. The estimation procedure is by non-linear least squares because of the MA(1) error term.
2. Increase the sample period from the previous step by one period (1968Q1 to 1982Q1 the first time), and estimate forecasts for the next quarter

(1982Q2 the first time) for the baseline from equation (1) without a consumer confidence index and equation (2) for each different consumer confidence index. Repeat this recursive forecasting procedure until the sample is exhausted, so the final forecasts are for 2002Q4, based on data from 1968Q1 to 2002Q3.

3. Calculate the root-mean-square-forecast error (RMSFE) from the out-of-sample forecasts and the relevant actual values.

Figure 5 shows that the use of the different consumer confidence indexes leads to somewhat different forecasts for consumption growth, compared with the baseline forecast that does not include on consumer confidence index. This is especially true in the 1980s, where the use of each of the consumer confidence indexes leads to persistent forecast differences compared with not using either index. (Forecasts for M-overall and CB-overall are shown; the M-current, M-future, CB-current, and CB-future forecasts are broadly similar and are thus not shown.)

Figure 6 illustrates how a forecast (CB-current, chosen because it has the poorest forecasts) for the consumption growth rate compares with the actual value, as measured by the last-benchmark data, and the baseline forecast generated without using a consumer confidence index.

Table 1 reports the results of formal tests for differences in RMSFEs, comparing the RMSFE of the baseline model from equation (1) that does not include a consumer confidence index, with the RMSFE of the model from equation (2) for each different consumer confidence index. The column labeled "Relative RMSFE" divides the RMSFE for the forecast using a consumer confidence index by the RMSFE for the baseline forecast that does not use a consumer confidence index, so a relative RMSFE greater than 1 means the forecast is worse than the baseline, while a relative RMSFE less than 1 means a better forecast than the baseline. The column labeled "p-value" is the result of the Harvey-Leybourne-Newbold modification of the Diebold-Mariano procedure; a p-value less than .05 shows a significantly different RMSFE for the forecast using a consumer-confidence index compared with the baseline forecast, while p-values greater than .05 indicate that there is not a statistically significant difference between the forecasts.

The results show that none of the consumer confidence indexes reduce the RMSFE significantly, and in many cases the RMSFE is significantly worse. Although in-sample results showed that the Conference Board indexes entered the regression equation significantly, using those measures in real time would have significantly worsened the forecasts made using the CB-current index and last-benchmark data as actuals, or using the M-current, CB-current, or CB-future indexes and latest-available data as actuals. Only the M-future index reduces the RMSFE relative to using an equation without confidence indexes, but does not do so enough that the difference is statistically significant.

III. Sensitivity Analysis: Improving the Forecasts with Alternative Specifications

How sensitive are the results of this study to alternative choices of the model we used? One way that we could modify the model to test for robustness is to use a linear estimation procedure instead of a non-linear one. A second way is to look at changes in the confidence indexes instead of their levels. Third, we may want to investigate if alternative actuals change the results. Finally, we may want to investigate changes in the forecasting model.

Experienced forecasters know that in practice a simpler procedure for forecasting often leads to more robust results than a more complicated procedure, especially one that is non-linear. In our case, this suggests trying to estimate the model using OLS instead of estimating the model with an MA(1) error term, which was recommended for theoretical reasons by Carroll-Fuhrer-Wilcox but which might cause poor out-of-sample forecast performance. In fact, after running regression (1) or (2), an examination of the residuals shows no evidence of an MA(1) process.[5] The results of estimating the model with OLS instead of estimating an MA(1) error process via non-linear-least squares (NLS) are reported in Table 2. First, note that every reported RMSFE is lower in the OLS case than the NLS case, except for M-future with last-benchmark actuals, suggesting that the increased parsimony gained from using OLS is valuable. Under the linear estimation procedure, every RMSFE is higher when using a consumer-confidence index in the equation than the baseline. But only the CB-current forecast has an RMSFE that is significantly higher than the RMSFE from not using consumer-confidence indexes in the equation.

Studying the pattern of coefficients in the estimates suggests that another alternative is to use changes in the consumer-confidence indexes instead of their levels, because in the level model, the coefficients sometimes have a pattern with alternating signs. Doing so yields the results in Table 3. In this table, every RMSFE is lower than the corresponding entry in Table 2, with the exception of CB-future compared with latest-

[5] I thank Tom Stark for discovering this.

available data as actuals. The results in Table 3, however, show no significant improvement in the forecasts from using any of the consumer-confidence measures.

Because the results of Table 3 have lower RMSFEs for the most part than other models, and we wish to investigate the sensitivity of the results, we extend the tests to include some additional alternatives as actuals: using data available one quarter, two quarters, and four quarters after the period in question. The results of those tests are shown in Table 4. The table shows that there are more cases in which the forecasts are improved by the use of consumer confidence indexes, but never significantly.

Finally, one final idea of forecasters is that often a model with many parameters to estimate leads to worse forecasts than a model with fewer parameters. With that idea in mind, one might argue that the baseline model should be simplified by eliminating variables.[6] Tests suggest that both the interest rate and personal income may be dropped from the model, leaving lagged consumption spending and the change in real stock prices as the only explanatory variables. However, the number of lags of each variable should remain 4, which is fairly typical with quarterly data (based on SIC evaluation).

Table 5 shows the results of simplifying the model by dropping the interest rate and personal income. Doing so lowers the RMSFE, using last benchmark actuals, significantly from 0.005894 to 0.004976, and from 0.005507 to 0.004835 using latest available actuals. So, in this case a more parsimonious model is superior. Adding any of

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[6] I thank Lucrezia Reichlin for this suggestion.

the consumer confidence measures makes the forecasts worse, though only for M-overall and M-current are the forecasts significantly worse.[7]

IV. Do the Results Derive from Recursive Estimation versus Full-Sample Estimation, or from Real-Time Data versus Latest Available Data?

Given the best forecasting model used to generate the results in Table 5, we ask: what leads to the lack of explanatory power from the consumer-confidence indexes?[8] The key difference between the results in this paper and those of Bram-Ludvigson is the use of real-time data (which I used) instead of latest available data (which they used). But every researcher finds that consumer-confidence indexes are significant in-sample, which suggests that it might be the recursive nature of the forecasting exercise that generates the lack of significance of the consumer-confidence indexes, instead of the use of real-time data. To investigate this, we repeat our recursive forecasting exercise using latest-available data instead of real-time data, and compare these results to the real-time results reported in Table 5 and to the in-sample residuals from estimating equations (1) and (2) using latest-available data.

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[7] Following the methods in Bram-Ludvigson and Carroll-Fuhrer-Wilcox, all the forecasting equations used four lags of each right-hand-side variable. To see if the number of lags mattered, I investigated the number of lags of each variable that would have minimized the RMSFE for each forecasting equation. Finding the optimal number of lags would have reduced the RMSFE somewhat, but would not change the qualitative results in Table 5—again, none of the confidence indexes significantly improved the forecasts, and at least one index made the forecasts significantly worse.

[8] I thank a referee for suggesting this comparison.

The results of this exercise are shown in Table 6. The results for the real-time estimation are identical to those reported in Table 5. Whenever a consumer confidence measure is included in the estimation equation, we find that the RMSFE is lowest for the in-sample estimation, next lowest for the recursive estimation on latest-available data, and highest for the real-time estimation. In the real-time estimation, the Michigan-overall and Michigan-current indexes lead to significantly worse forecasts, while in the in-sample estimation and recursive estimation, the Michigan-current index leads to a significantly worse forecast. In most cases, the recursive estimation with latest-available data has an RMSFE not too different from the in-sample estimation, but there is usually a bigger gap between the RMSFE from real-time estimation and the RMSFE from the recursive estimation. These results suggest that it is the nature of the real-time data that is leading to the deterioration of the forecasts, more so than the recursive estimation.

V. Summary and Conclusions

In this paper, we have used existing methods to investigate whether or not indexes of consumer confidence are helpful in improving forecasts of consumption spending. Though consumer confidence indexes in some specifications are significant in sample using latest-available data, we find no evidence in any specification that the use of such indexes improves forecasts significantly.

These results suggest that forecasters can ignore consumer-confidence indexes in forecasting consumption spending. But the results are not definitive because they depend on the quality of the forecasting model being used. In our exercises, we have used only models that other researchers in the literature have used. It may be that using better forecasting methods could show that consumer confidence indexes do indeed have marginal significant explanatory power, if any such methods can be found.

In addition, there may yet be a role for consumer confidence indexes to add value in forecasting. The indexes are released monthly and the monthly data could be used to help predict current-quarter consumption growth. Testing this hypothesis will require the use of quite different methods and models, however. A good current-quarter forecasting model would look like that of Stark (2000), Trehan (1989), or Howrey (2001).

Table 1
RMSFEs for Various Forecasts
Model: With Levels of Consumer Confidence Indexes
Estimation by Non-linear Least Squares
Sample: 1982Q1 to 2002Q4

	Actuals = last benchmark			Actuals = latest available		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.006082	1.000	NA	0.005635	1.000	NA
M-overall	0.006249	1.027	0.61	0.005815	1.032	0.52
CB-overall	0.006578	1.082	0.15	0.006002	1.065	0.25
M-current	0.006834	1.124	0.07	0.006496	1.153	0.04
CB-current	0.006913	1.137	0.02	0.006320	1.122	0.05
M-future	0.005920	0.973	0.59	0.005578	0.990	0.80
CB-future	0.006736	1.108	0.10	0.006482	1.150	0.02

Table 2
RMSFEs for Various Forecasts
Model: With Levels of Consumer Confidence Indexes
Estimation by OLS
Sample: 1982Q1 to 2002Q4

	Actuals = last benchmark			Actuals = latest available		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.005894	1.000	NA	0.005507	1.000	NA
M-overall	0.006142	1.042	0.39	0.005764	1.047	0.32
CB-overall	0.006332	1.074	0.17	0.005789	1.004	0.94
M-current	0.006258	1.062	0.29	0.006062	1.101	0.11
CB-current	0.006427	1.090	0.05	0.005931	1.077	0.10
M-future	0.005986	1.016	0.70	0.005567	1.011	0.76
CB-future	0.006141	1.042	0.46	0.005631	1.023	0.69

Table 3
RMSFEs for Various Forecasts
Model: With Changes in Consumer Confidence Indexes
Estimation by OLS
Sample: 1982Q1 to 2002Q4

	Actuals = last benchmark			Actuals = latest available		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.005894	1.000	NA	0.005507	1.000	NA
M-overall	0.005961	1.011	0.77	0.005546	1.007	0.85
CB-overall	0.006122	1.039	0.37	0.005597	1.016	0.72
M-current	0.005910	1.003	0.95	0.005654	1.027	0.49
CB-current	0.006218	1.055	0.18	0.005752	1.045	0.30
M-future	0.005896	1.000	1.00	0.005451	0.990	0.79
CB-future	0.006083	1.032	0.43	0.005671	1.030	0.54

Table 4
RMSFEs for Various Forecasts
Model: With Changes in Consumer Confidence Indexes
Estimation by OLS
Sample: 1982Q1 to 2002Q4

	Actuals = one-quarter later			Actuals = two-quarters later		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.006712	1.000	NA	0.006806	1.000	NA
M-overall	0.006665	0.993	0.82	0.006742	0.991	0.76
CB-overall	0.006975	1.039	0.32	0.006991	1.027	0.50
M-current	0.006719	1.001	0.98	0.006787	0.997	0.93
CB-current	0.007034	1.048	0.19	0.007103	1.043	0.23
M-future	0.006606	0.984	0.62	0.006684	0.982	0.56
CB-future	0.006857	1.021	0.58	0.006882	1.011	0.77

	Actuals = four-quarters later		
Forecast	RMSFE	Relative RMSFE	p-value
No confidence measure	0.006517	1.000	NA
M-overall	0.006517	0.992	0.80
CB-overall	0.006676	1.016	0.70
M-current	0.006665	1.014	0.69
CB-current	0.006791	1.033	0.36
M-future	0.006403	0.974	0.43
CB-future	0.006518	0.992	0.83

Table 5
RMSFEs for Various Forecasts
Model: With Changes in Consumer Confidence Indexes
Forecasting Model Includes Only Consumption and Stock Prices
Estimation by OLS
Sample: 1982Q1 to 2002Q4

	Actuals = last benchmark			Actuals = latest available		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.004976	1.000	NA	0.004835	1.000	NA
M-overall	0.005594	1.124	0.04	0.005402	1.117	0.03
CB-overall	0.005300	1.065	0.14	0.004958	1.025	0.55
M-current	0.005719	1.149	0.01	0.005579	1.154	0.01
CB-current	0.005505	1.106	0.06	0.005326	1.102	0.06
M-future	0.005384	1.082	0.12	0.005198	1.075	0.14
CB-future	0.005392	1.083	0.14	0.005154	1.066	0.28

Table 6
RMSFEs for Various Forecasts
Model: With Changes in Consumer Confidence Indexes
Forecasting Model Includes Only Consumption and Stock Prices
Estimation by OLS; Actuals = Latest Available
Sample: 1982Q1 to 2002Q4

	Real-Time Estimation			**In-Sample Estimation**		
Forecast	RMSFE	Relative RMSFE	p-value	RMSFE	Relative RMSFE	p-value
No confidence measure	0.004835	1.000	NA	0.004895	1.000	NA
M-overall	0.005402	1.117	0.03	0.005058	1.033	0.26
CB-overall	0.004958	1.025	0.55	0.004762	0.973	0.24
M-current	0.005579	1.154	0.01	0.005233	1.069	0.04
CB-current	0.005326	1.102	0.06	0.004880	0.997	0.88
M-future	0.005198	1.075	0.14	0.004954	1.012	0.66
CB-future	0.005154	1.066	0.28	0.004832	0.987	0.66

Recursive Estimation with Latest-Available Data

Forecast	RMSFE	Relative RMSFE	p-value
No confidence measure	0.004902	1.000	NA
M-overall	0.005204	1.062	0.20
CB-overall	0.004828	0.985	0.71
M-current	0.005547	1.132	0.02
CB-current	0.005035	1.027	0.52
M-future	0.005011	1.022	0.62
CB-future	0.004891	0.998	0.96

Figure 1
Consumer Confidence Indexes, January 1978 to December 2002

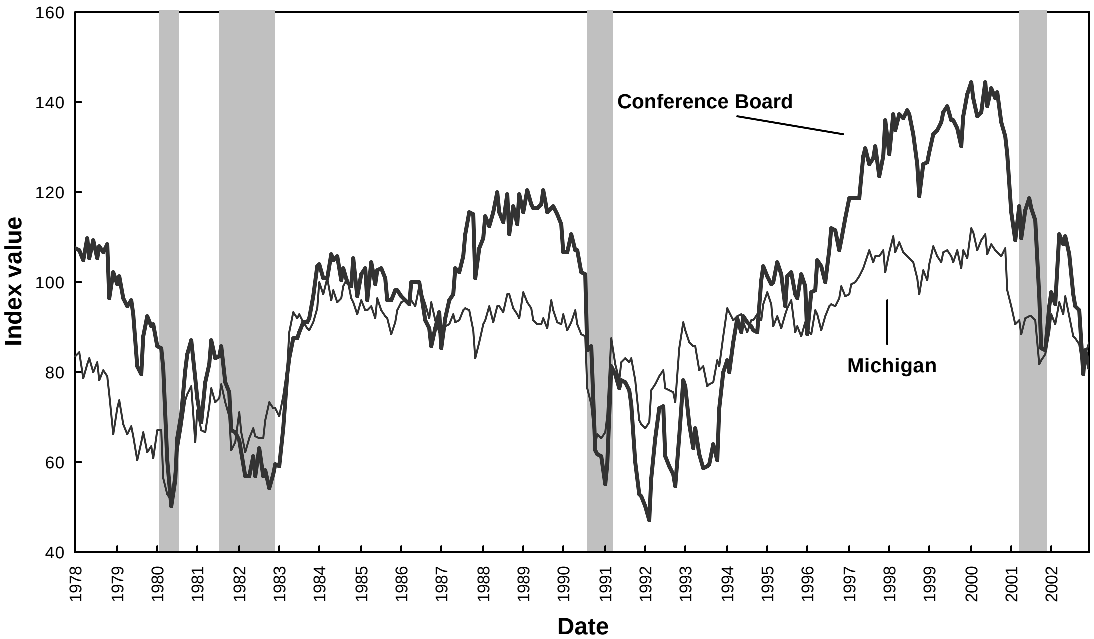


Figure 2
Michigan Overall Index and Consumption Spending
January 1978 to December 2002

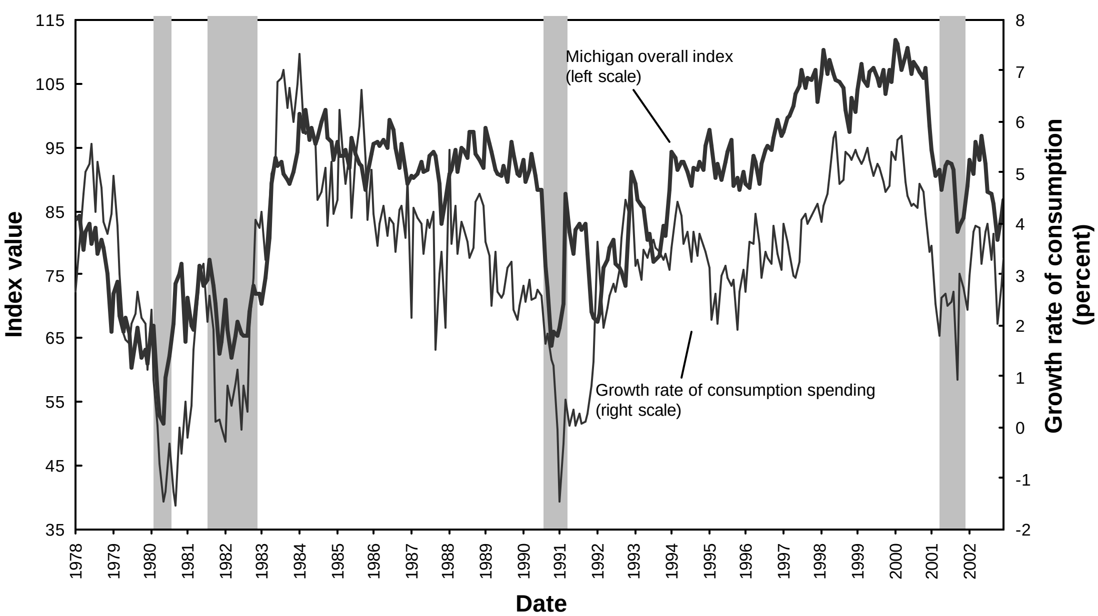


Figure 3
Revisions to Real Consumption Growth
Initial to Latest Available, 1969Q4 to 2002Q4

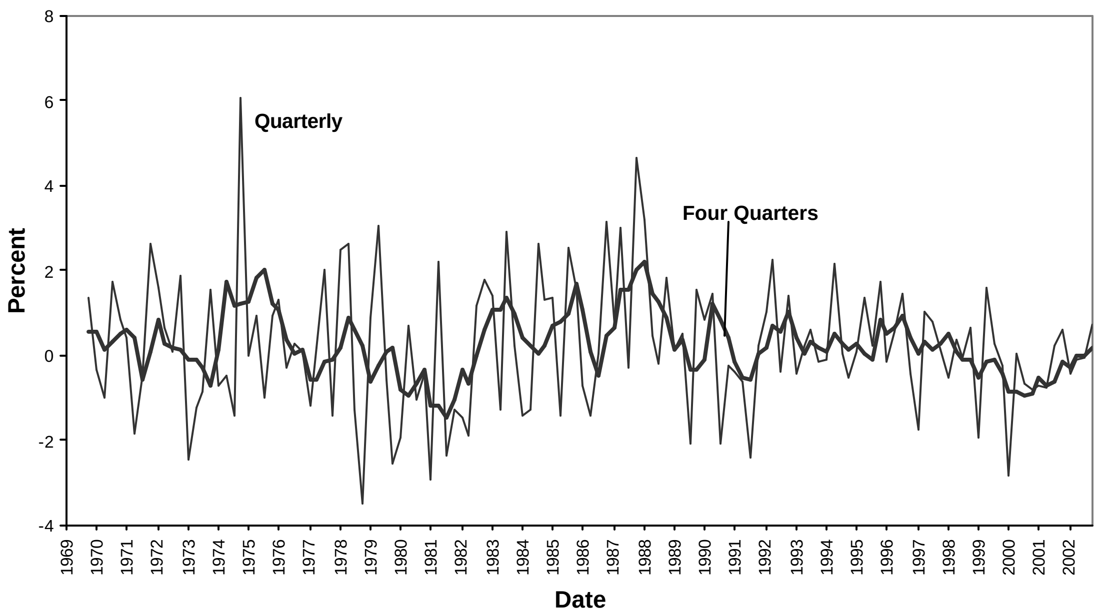


Figure 4
Alternative Actuals, 1982Q1 to 2002Q4

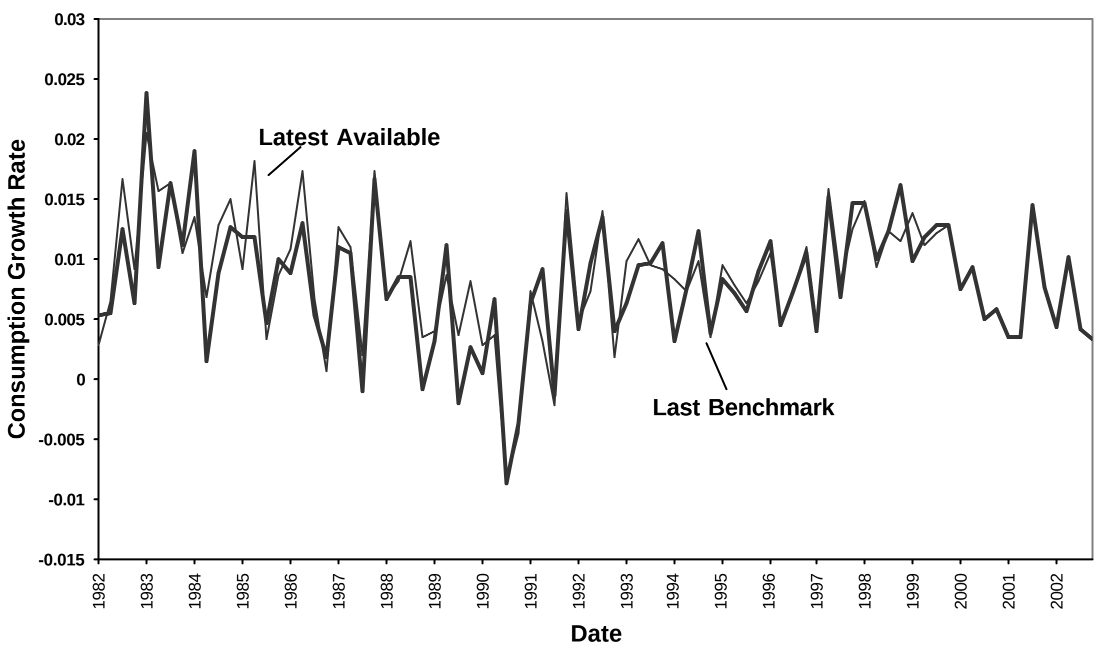


Figure 5
Comparing Forecasts Over Time, 1982Q1 to 2002Q4

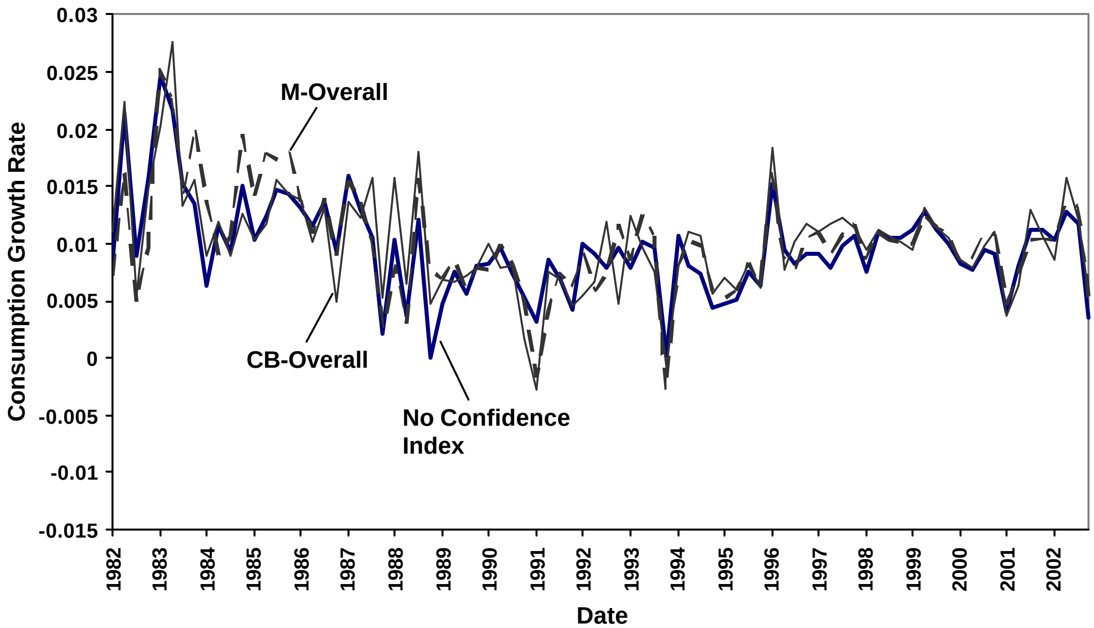
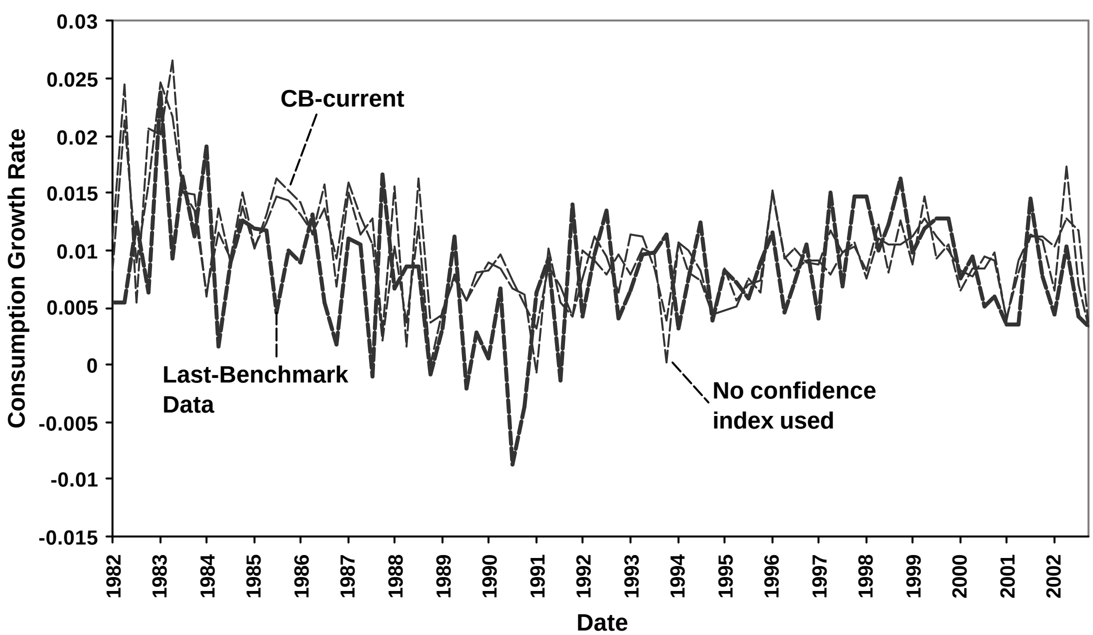


Figure 6
Comparing Forecasts Over Time, 1982Q1 to 2002Q4



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