FORECASTING HOUSEHOLD EXPENDITURES USING THE CONSUMER CONFIDENCE INDEX: A MEAN-VARIANCE APPROACH*

Note: 5th Paper

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Abstract

This paper refines the way consumer confidence survey data are used in forecasting models. The refinement is easy to describe: it extends existing models by controlling for statistically significant changes in consumer confidence index values. The motivation behind this refinement is simply that not all changes in the confidence index are statistically significant, and mean index values alone provide a noisy signal. Controlling for significant versus insignificant changes in the consumer confidence index materially enhances the explanatory power of household expenditure forecasting models.

JEL Classification: E270, D84, D120, C83

KEYWORDS: consumer confidence index, forecasting consumer spending, mean-variance approach

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I. Introduction

Decision-makers and analysts in the public and private sectors show keen interest in measures of consumer attitudes, generically referred to as 'consumer confidence.' As a quick illustration, a Google search of 'Index of Consumer Sentiment' (the University of Michigans measure) and 'Consumer Confidence Index' (the Conference Boards measure) returned over a quarter million results in July 2013. Devotees of consumer confidence metrics are evidently driven by the perception that these indices reveal information about the future: the path of economic variables such as consumer spending; financial market trends such as movements in stock prices; and even the outcome of elections and other political events.

Academic researchers have scrutinized this perception about the forecasting capacity of consumer confidence indices.[1] This research program goes beyond the raw forecasting power of consumer confidence indices. It also investigates whether consumer confidence indices convey information about the future that is not already contained in other indicators. For example, does a consumer confidence index merely reflect conditions in the labor market, interest rates, stock prices, and so on? If it does, the consumer confidence index per se is not adding any independent forecasting power; instead, it merely serves as a proxy for these other underlying economic dimensions. This would mean that consumer confidence metrics convey redundant information in forecasting models that take these other economic variables into account.

The consensus in the literature is that consumer confidence indices do enhance econometric forecasts of consumer spending, but only modestly.[2] For example, the recent survey article by Ludvigson (2004) reports that adding lagged values of the Michigan Index of Consumer Sentiment to a baseline regression model increases the adjusted R^2 by 5 percentage points, from 0.45 to 0.50. While a 5-percentage point improvement might represent a meaningful value-added for some forecasting purposes, the modest gain is generally disappointing in light of the huge following and media attention given to the monthly releases of the Michigan index.

The purpose of this paper is to introduce a refinement in the way the consumer confidence index is used in forecasting models. The novelty of the refinement is easy to describe: we

[1]For example see Lovell (2001).

[2]For recent studies that examine the forecasting power of consumer confidence, see Fuhrer (1993), Bram and Ludvigson (1998), Lettau and Ludvigson (2001), Howrey (2001), Ludvigson (2004), Croushore (2005), and Dees and Soares Brinca (2011).

add a variable to the existing regression models that controls for statistically significant changes in the consumer confidence index from one period to the next. The motivation is simply that not all changes in the consumer confidence index are statistically significant, and our refined forecasting model captures the distinction between significant and insignificant changes. To put this distinction another way, prior forecasting models control for the mean of the consumer confidence index, and our model takes into account whether changes in this mean over time are significant. While a change in the index may be due to random sampling, a significant change is much more likely to be due to a change in true consumer confidence. When significant changes in the confidence index are accounted for in the forecasting model for consumer spending, the adjusted R^2 increases by 10 percentage points, from 0.45 to 0.55. In other words, a mean-variance approach almost doubles the forecasting enhancement.

The remainder of the paper is organized into three sections. Section II describes the variance in the consumer confidence index and why this dimension is important. We begin with a simple, one-question case, and then proceed to the slightly more complex case where multiple questions are aggregated into a single confidence index. Section III presents the forecasting results for total household expenditures and for the major sub-components. Finally, Section IV summarizes the findings and their importance.

II. Computing Significant Changes in the Consumer Confidence Index

This central purpose of the paper is to add a qualitative dimension to forecasting models that use a consumer confidence index. For this purpose, we derive a variable to control for whether changes in the index from one period to the next are statistically significant. In this section we describe the derivation of this variable. The exact method used depends on whether the index is based on survey responses to a single question, or based on responses to multiple questions. We start with the simplest, one-question index case and then proceed to the multiple question index.

Method 1: statistically significant changes in a one-question confidence index

The simplest case is an index based on a single question, which we illustrate using the following question asked by the Michigan survey:

'About the big things people buy for their homes – such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?'

The index calculated from this question is referred to as DUR (for 'durable purchases'). The DUR index is calculated in the following way by Michigan's Survey Research Center:

$$DUR = (\% \text{ 'good time to buy'}) - (\% \text{ 'bad time to buy'}) + 100 \tag{1}$$

To simplify the exposition we define the following variables:

y The percent that answered 'Now is a good time to buy'

n The percent that answered 'Now is a bad time to buy'

m The percent that answered 'Uncertain' or 'It depends'

Of course, these categories sum to 100 percent, so we can re-write Equation (1) as:

$$DUR = y - n + 100 = y - n + (y + n + m) = 2 * y + 1 * m + 0 * n \tag{2a}$$

$$DUR = \frac{200y + 100m + 0n}{100} \tag{2b}$$

The following examples provide a useful illustration of our basic point. Suppose a survey asking the DUR question obtains the following results: 30% respond 'Now is a good time to buy' (y) and 20% respond 'Now is a bad time to buy' (n). This means 50% respond 'Uncertain' or 'It depends' (m). So:

$$DUR = 30 - 20 + 100 = 110, \text{ or} \tag{3a}$$

$$DUR = \frac{200 * 30 + 100 * 50 + 0 * 20}{100} = 110 \tag{3b}$$

The DUR Index equals 110 based on this survey, which we label Survey A.

Now suppose we get a different set of survey results for the DUR question, labeled Survey B: 50% respond 'Now is a good time to buy' (y) and 40% respond 'Now is a bad time to

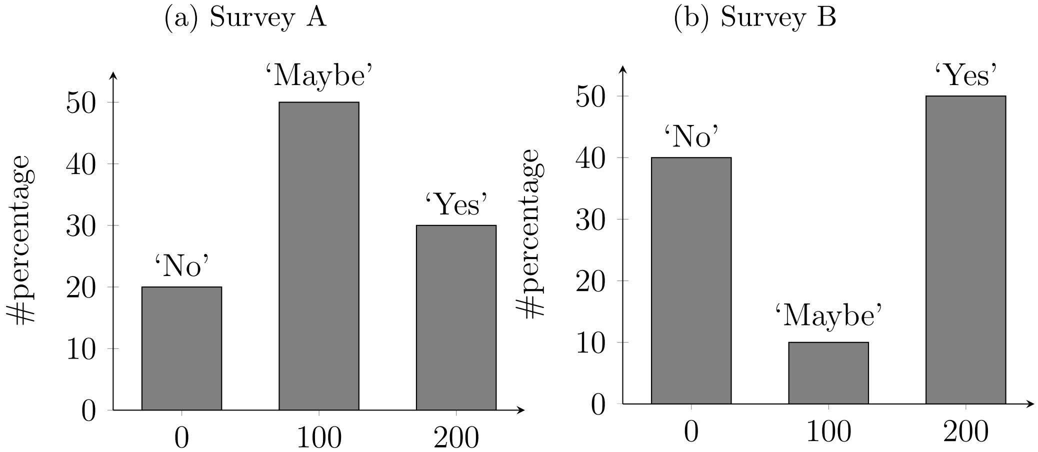

FIGURE 1
Index with equal means and different dispersions

buy' (n). In this survey, 10% respond 'Uncertain' or 'It depends' (m). So, for Survey B:

$$DUR = 50 - 40 + 100 = 110, \text{ or} \tag{4a}$$

$$DUR = \frac{200 * 50 + 100 * 10 + 0 * 40}{100} = 110 \tag{4b}$$

$$\tag{4c}$$

Importantly, as these examples illustrate, two different sets of polling results can yield exactly the same index value (here, $DUR = 110$).

These two sets of results are shown graphically in Fig. 1. Again, Survey A and Survey B yield the same DUR Index score but have two entirely different distributions.[3] As this illustration indicates, we can enhance the information contained in the consumer confidence survey responses by introducing a qualitative dimension that captures the dispersion, and then use this dispersion to compute significant changes in the index over time.[4]

[3]Survey B indicates a split among households that is in line with the framework posited by Campbell and Mankiw (1989). In their model, half of households follow a rule of thumb of consuming their current income and half are forward-looking and consume their permanent income.

[4]Dominitz and Manski (2004) looked at the transitions between 'yes', 'no', and 'maybe' in the index and found a transition matrix. They concluded that the transitions between 'yes', 'no', and 'maybe' was also volatile between months, which also shows that there can be big differences between months with the same aggregate ICS.

In the one-question index case, the dispersion in the responses is derived by first computing the standard deviation, as shown in Equation (5):[5]

$$\sigma = \sqrt{\frac{1}{100}\left(y*(200-DUR)^2 + n*(0-DUR)^2 + m*(100-DUR)^2\right)} \tag{5}$$

Recall that the DUR Index in Survey A = 110, which means that the standard deviation for Survey A is:

$$\sigma = \sqrt{\frac{1}{100}\left(30*(200-110)^2 + 20*(0-110)^2 + 50*(100-110)^2\right)} = 70 \tag{6}$$

Similarly, the standard deviation using the response data from Survey B is:

$$\sigma = \sqrt{\frac{1}{100}\left(50*(200-110)^2 + 40*(0-110)^2 + 10*(100-110)^2\right)} = 94 \tag{7}$$

The results in Equations (6) and (7) serve to emphasize that two sets of responses with exactly the same mean DUR index can have different standard deviations.

We derive a variable to control for significant changes in the confidence index by first converting the standard deviation into a standard error and then computing the probability that index scores from one period to the next in fact reflect the same actual score.[6] Again we rely on an example to illustrate the methodology, in this instance using actual data for the Michigan DUR survey from 1985. In the third quarter of 1985, the DUR index is 154, its standard deviation is 78, and the number of persons surveyed is 1,945. Thus, the standard error is:

$$\text{Standard error } (s_{1985:3}) = \frac{\sigma_{DUR}}{\sqrt{N}} = \frac{78}{\sqrt{1945}} = 1.769 \tag{8}$$

In the fourth quarter of 1985, the DUR index is 148, its standard deviation is 81.8 and the number surveyed is 1,955. So:

[5]Equation (5) scales the standard deviation to conform to the specific formula used by the University of Michigan in computing their various indices of consumer attitudes. In their computations, if $y = 100\%$ then the DUR index would be 200. If $n = 100\%$ then the DUR index would be 0. And if $m = 100\%$ then the DUR index would be 100. In each of these cases the standard deviation would obviously be zero, since there is no deviation. Thus Equation (5) adjusts the typical standard deviation formula to conform to the values assigned by the University of Michigan and the fact that the sum of all response shares must equal 100 percent. See the Appendix for further details on how the Michigan indices are computed.

[6]Curtin et al. (2000) examined the error of the consumer sentiment tied to an increasing refusal rate (of interviews). In a more complex model, the standard error might take this into account. For the purposes of the analysis in this paper we assume such effects are negligible.

$$\text{Standard error } (s_{1985:4}) = \frac{81.8}{\sqrt{1955}} = 1.851 \tag{9}$$

Assuming that the underlying consumer sentiment for durable purchases is continuous and normal, the probability that the third and fourth quarters of 1985 reflect the same actual durable consumer sentiment would be:[7]

$$\frac{1}{2\pi * 1.769 * 1.851} * \frac{\sqrt{2\pi} * e^{-\frac{(158-148)^2}{2*(1.769^2+1.851^2)}}}{\sqrt{\frac{1}{1.769^2}+\frac{1}{1.851^2}}} = 0.00\overline{9} \tag{10}$$

This yields about a one percent chance that the survey results for the third and fourth quarters of 1985 reflect the same value for the DUR index. In the subsequent analysis, we define a significant change from one quarter to the next when the probability that the two indices are the same is less than 5 percent.[8] We create two dummy variables to examine index changes over time: one that measures significant changes up and another that measures significant changes down. As a final illustration of this procedure, the variables created to measure significant changes in the DUR for 1967 and 1968 are shown in Table 1.

TABLE 1
Significant changes in the DUR Index: illustration using 1967-68 data

Year	Quarter	DUR Index	Prob($DUR_t = DUR_{t-1}$)	Significant Change Up Indicator Variable	Significant Change Down Indicator Variable
1967	1	121	–	–	–
1967	2	147	2.3 E-27	1	0
1967	3	144	0.080	0	0
1967	4	142	0.110	0	0
1968	1	149	0.002	1	0
1968	2	141	0.001	0	1
1968	3	141	0.134	0	0
1968	4	129	1.4 E-05	0	1

[7]Equation (10) derives from the total area under the product of the heights of two normal error curves determined by the means and standard errors. This area approximates the sum of the probabilities that both means reflect parameters within the same index point.

[8]In alternative specifications, not reported in the paper, we examined other critical cutoff values such as the one-percent and 10 percent confidence levels. The results were largely unchanged, and the five-percent confidence level is of course a commonly used convention.

Method 2: statistically significant changes in a multiple question index

The method for finding statistically significant changes in a multiple question index, such as the well-known Michigan Index of Consumer Sentiment, is slightly more complex than for a single question index as described above. In a nutshell, a multiple question index computation requires the covariances between the individual questions.

The Michigan Index of Consumer Sentiment (ICS) consists of an aggregation of the responses to five questions (see the Appendix for details). Because the survey response data are not available at the level of an individual respondent, we estimate the covariances among the five questions in the ICS.[9] This is done by first finding the correlation coefficients between the indices using quarterly data from 1960 through 2002. These correlation coefficients are shown in Table 2.[10]

TABLE 2
Correlation coefficients for the five components of the Michigan Index of Consumer Sentiment

Index	PAGO	PEXP	BUS12	BUS5	DUR
PAGO	–	0.816	0.835	0.825	0.822
PEXP	0.816	–	0.799	0.852	0.661
BUS12	0.835	0.799	–	0.906	0.675
BUS5	0.825	0.8523	0.906	–	0.672
DUR	0.822	0.661	0.675	0.672	–

The time series correlations are then used to compute the covariances with the standard formula:

$$cov(X, Y) = \rho_{XY} * \sigma_X \sigma_Y \tag{11}$$

The covariances and the standard deviations of each individual index are used to find the

[9] Alternatively, if the survey results for the five questions were available at the level of the individual respondent, we could compute the covariances as follows: $cov(A, B) = 400P(y_A, y_b) + 200P(y_A, m_b) + 200P(m_A, y_b)$, where $P(1, 2)$ is the number of occurrences that someone polled answered both 1 in Index A and 2 in Index B. This is based on the standard formula $cov(X, Y) = E(XY) - E(X)E(Y)$ and the values for y, n and m discussed in Note 5. Because this information is not reported on the individual basis, we are forced to assume that the correlation coefficients are constant over time. This assumption makes the correlation coefficients between variables over time equal to the correlation coefficients between variables at every survey level.

[10] Dominitz and Manski (2004) also looked at correlations among the indices across time. They also found a high correlation between the expected business condition variables (in our case BUS12 and BUS5).

TABLE 3
Covariances among the five components of the Michigan Index of Consumer Confidence

Index	PAGO	PEXP	BUS12	BUS5	DUR
PAGO	–	3542.221	4573.740	4570.540	4725.424
PEXP	3542.221	–	3604.538	3885.276	3124.864
BUS12	4573.740	3604.538	–	5208.248	4026.839
BUS5	4570.540	3885.276	5208.248	–	4054.583
DUR	4725.424	3124.864	4026.839	4054.583	–

standard deviation of the sum of the five indices. The formula for this is Equation (12a):

$$\sigma^2_{I_1+I_2+I_3+I_4+I_5} = \sum_{i=1}^{5} \sigma^2_{I_i} + \sum_{i \neq j}\sum cov(I_i, I_j) \tag{12a}$$

This standard deviation is scaled to fit the Index of Consumer Sentiment with Equation (12b):[11]

$$\sigma_{ICS} = \frac{\sigma_{I_1+I_2+I_3+I_4+I_5}}{6.7558} \tag{12b}$$

The covariances among the five components of the ICS are computed using the quarterly data starting in 1960 through the particular quarter being analysed. For example, the covariances for the first quarter in 1967 are shown in Table 3.
These covariances change as the series is updated for each successive quarter.

In this manner we calculate all the standard deviations for all the quarters of the Index of Consumer Sentiment from 1960 through 2002. Finally, we create two indicator variables to reflect significant increases in the ICS and significant decreases in the ICS.

III. Does a Mean-Variance Approach Improve Household Expenditure Forecasts?

The basic method we use to assess whether significant changes in the consumer confidence index enhance the predictive ability is to examine the adjusted R-squares ($\overline{R}^2$) from regressions of the growth of various measures of household spending. We adopt the model specification

[11] Michigan computes the index as follows: $ICS = 2.0 + \frac{I_1+I_2+I_3+I_4+I_5}{6.7558}$. We divide the standard deviation of the sum of the Indices by 6.7558 to transform the standard deviation into the same units as the Index of Consumer Sentiment.

used in prior studies such as Campbell and Mankiw (1989), Carroll et al. (1994), Bram and Ludvigson (1998), and Ludvigson (2004). The form of the model is shown in Equation (13):

$$\Delta \ln(C_t) = \alpha_0 + \sum_{i=1}^{4} \beta_i S_{t-i} + \sum_{i=1}^{4} \phi_i \text{Sig\_Up}_{t-i} + \sum_{i=1}^{4} \psi_i \text{Sig\_Down}_{t-i} + \sum_{i=1}^{4} \gamma_i \mathbf{Z}_{t-i} + \epsilon_t \quad (13)$$

where:

the subscript t denotes an observation in quarter t,

C_t	=	household consumption expenditures (total or sub-component as indicated),
S_{t-i}	=	lagged values of the consumer confidence index (i = 1,..., 4),
Sig_Up_{t-i}	=	lagged values of the indicator variable denoting that an increase in consumer confidence is statistically significant (i = 1,...,4),
Sig_Down_{t-i}	=	lagged values of the indicator variable denoting that a decrease in consumer confidence is statistically significant (i = 1,...,4),
$\mathbf{Z}_{t-i}$	=	a vector of control variables, and
ϵ_t	=	the regression error term.

All the independent variables include four lags in the quarterly data, which follows the methodology used in studies by Carroll et al. (1994), Bram and Ludvigson (1998), and Ludvigson (2004). We reiterate that the results reported below use the 5 percent level of statistical significance as the critical cutoff for the two indicator variables, Sig_Up and Sig_Down.[12]

The vector of control variables, **Z**, includes: lagged dependent variables, growth of real labor income, the (log) first difference of the real stock price, and the first difference of the three-month Treasury Bill rate.[13] We also include an indicator variable to control for

[12] We examined other critical cutoff values, as explained in Note 8, and the results are not materially different from those reported in the text.

[13] Labor income is wages and salaries plus transfers minus personal contributions for social insurance, as is appears in the quarterly components from the Department of Commerce's National Income and Product Accounts. Stock prices are quarterly averages based on the Standard and Poor's 500. The interest rate is the quarterly average based on the three-month Treasury bill rate, reported monthly by the Board of Governors of the Federal Reserve System. Nominal labor income and the Standard and Poor's 500 index are deflated by the personal consumption expenditure implicit price deflater, as reported quarterly in the National Income and Product Accounts.

TABLE 4
Comparison of Adjusted-R^2s to a Baseline Model of Consumer Spending

Category of Household Consumption	Baseline Model	Plus ICS Index	Plus ICS Index, Sig_Up, and Sig_Down Indicator Variables
Total	0.445	+0.053	+0.098 (.87)
Goods, excluding motor vehicles	0.271	+0.028	+0.046 (.40)

Notes: The Baseline Model column reports the total adjusted R^2 from the Baseline Model, which includes the lagged values of the vector of control variables (i.e., without the Index of Consumer Sentiment or the Significant Change indicator variables). The successive columns report the increment in the adjusted R^2 in models that add the ICS index and so forth (compared with the adjusted R^2 in the Baseline Model). The values in parenthesis show the p-values for joint marginal significance of the lags of each variable listed in the column heading.

the 1990-91 recession.[14] As a final specification issue, we model the error term as a MA(1) process, following the procedure in Ludvigson (2004).[15]

Table 4 presents the relevant statistics from estimating Equation (13), with which we can assess the predictive power of alternative model specifications.

The adjusted R^2 ($\overline{R}^2$) for the baseline model is 0.445 for Total Consumption Spending. When the ICS Index is added to the baseline model, the increases by 0.053.[16] When the ICS Index and the Sig_Up and Sig_Down variables are added to the model, the adjusted R-square increases by 0.098, raising the to 0.543. This means that controlling for significant changes in the ICS roughly doubles the enhancement to the baseline Total Household Consumption

[14] Several studies, including Leeper (1992), Carroll and Dunn (1997), and Bram and Ludvigson (1998), posit that the 1990-91 recession gives consumer sentiment too much forecasting credit. Carroll and Dunn (1997) examined the theory that debt weakened consumption during the recession, complicating the typical influence of consumer sentiment.

[15] Mankiw (1982) suggests that the growth in spending on durable goods may be passively autocorrelated, with the error term following a first order moving average process. Such first-order autocorrelation may cause the error to be correlated with the one-period-lagged endogenous variable, a condition that could skew in-sample statistical tests of joint marginal significance of the explanatory variables (the reported p-values).

[16] We note that the results in Table 4 for the Baseline Model and the Plus ICS Index model replicate those in Ludvigson (2004).

model.

The three other models reported in Table 4 examine sub-components of household consumption. For the 'Goods, excluding motor vehicles' model, the adjusted R-square for the baseline model is 0.271. When the ICS Index is added, thethe adjusted R-square increases by 0.028. When the ICS Index and the Sig_Up and Sig_Down variables are added to this model, the adjusted R-square increases by 0.046, raising the adjusted R-square to 0.317.

Table 5 provides a similar comparison looking at household consumption of durable goods, excluding motor vehicles, and spending on motor vehicles. We use the same model described in Equation (13) with a more basic vector of control variables. In this case, the vector of control variables, $\mathbf{Z}$, is the lagged values of the dependent variable and the dummy controlling for the 1990-01 recession. We use two different survey indices in these models, which we denote DUR and VEH following the labels applied by the University of Michigan.[17]

The adjusted R-square for the baseline model is 0.284 for Durable Consumption, excluding motor vehicles. When the DUR Index is added to the baseline model, the adjusted R-square increases by 0.018. When the DUR Index and the Sig_Up and Sig_Down variables are added to the model, the the adjusted R-square increases by 0.161, raising the adjusted R^2 to 0.445. In this analysis, controlling for significant changes in the DUR index raises by nine fold the enhancement to the baseline model for Durable Consumption.

Regarding Motor Vehicle spending, the the adjusted R-square for the baseline model is 0.419. When the VEH Index is added to the baseline model, the adjusted R^2 increases by 0.005, adding virtually nothing to the model's explanatory power. When the VEH Index and the Sig_Up and Sig_Down variables are added to the model, the adjusted R^2 increases by 0.063, raising the adjusted R^2 to 0.482.

IV. Concluding Remarks

Despite the apparently wide interest in surveys of consumer confidence, rigorous analysis suggests that these indicators add only slightly to the explanatory power of forecasting models of household consumption expenditures. This paper provides a refinement in the way consumer confidence indices are assessed. Specifically, we simply compute whether the

[17]The DUR Index question asks: 'About the big things people buy for their homes – such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?' The VEH Index question asks: 'do you think now is a good or bad time for people to buy a motor vehicle?'

TABLE 5
Comparison of Adjusted-R^2s to a Baseline Model of Durable Spending

Category of Household Consumption	Baseline Model	Plus ICS Index	Plus ICS Index, Sig_Up, and Sig_Down Indicator Variables
Durable Goods, excluding motor vehicles	0.284	+0.018	+0.161 (.030)
Motor Vehicle Consumption	0.419	+0.005	+0.063 (.12)

Notes: The Baseline model column reports the total adjusted R^2 from the Baseline Model, which includes the lagged values of the dependent variable and the 1990-01 recession dummy variable. The successive columns report the increment in the adjusted R^2 in models that add the survey index and so forth (compared with the adjusted R^2 in the Baseline Model). The values in parenthesis show the p-values for joint marginal significance of the lags of each variable listed in the column heading. The model for Durable Consumption, excluding motor vehicles, uses the DUR Index, and Motor Vehicle Consumption model uses the VEH Index.

change in an index from one period to the next is statistically significant. This refinement is straight forward, and certainly one that squares with standard notions of statistical inference.

The findings in the paper indicate that this approach offers considerable promise as a technique to enhance consumer spending forecasts. In models of total household consumption, controlling for significant changes in the Index of Consumer Sentiment roughly doubles the explanatory power added by the Index of Consumer Sentiment alone. Moreover, the relative enhancement from controlling for significant changes in consumer confidence is even greater in forecasting models for durable goods and motor vehicles. As a final comment, the mean-variance methodology developed in this paper and the idea of controlling for significant changes in a survey index value has applications well beyond the topic of consumer confidence. This would include political opinion surveys, television ratings, and so forth.

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. Appendix: How the University of Michigan Survey Research Center Calculates the Index of Consumer Sentiment

As described in Curtin (2005) the Survey Research Center at the University of Michigan surveys over five hundred persons a month and asks about fifty questions. The answers to almost all of these questions fit into four categories: positive, negative, same, and dont know/not applicable. An index for each question is computed as follows:

$$\text{Index} = (\%\ \text{Positive}) - (\%\ \text{Negative}) + 100$$

The Index of Consumer Sentiment (or ICS, is sometimes called the Michigan Survey or the American Consumer Sentiment Index) is calculated using five of these questions. These five questions are concerned with:

PAGO:	Personal Finance Current
PEXP:	Personal Finance Expected
BUS12:	Business Conditions 12 Months Out
BUS5:	Business Conditions 5 Years Out
DUR:	Buying Conditions Current

The Survey Research Center computes the ICS by aggregating these five questions using the following formula:

$$\text{ICS} = 2.0 + \frac{I_1 + I_2 + I_3 + I_4 + I_5}{6.7558}$$