THE USEFULNESS OF CONSUMER CONFIDENCE INDICES IN THE U.S.

Marc-André Gosselin and Brigitte Desroches*

Bank of Canada
234 Wellington
Ottawa, ON K1A 0G9
CANADA

Abstract

The purpose of this research is to assess the usefulness of consumer confidence indices in forecasting aggregate consumer spending in the U.S. The literature generally gives little intrinsic value to these indices. However, without formal modelling, some researchers (Garner (1991), and Throop (1992)) suggested that these indices could be helpful during periods of major economic or political shocks. Such periods are usually associated with high volatility of consumer confidence, suggesting that large swings in confidence could be useful indicators of consumption. Our work distinguishes itself from previous research in that we provide a rigorous assessment of this possibility by estimating a consumption function in which only large variations of confidence can affect spending. Our results show that economists and forecasters should be concerned with consumer confidence, especially in times of elevated economic or political uncertainty.

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“In normal times, these measures, in my view, offer relatively little predictive power for household spending. During the Gulf War, however, we learned (...) that in extraordinary times consumer confidence can change abruptly in a way not foreshadowed by the incoming economic indicators. Another way of saying this is that sometimes the equations we use to predict consumer confidence make dramatic forecast errors. Such errors may indicate an “exogenous” psychological shock and thus provide additional information to forecasters.”

Laurence Meyer, former Federal Reserve Governor (November 27, 2001)

1. Introduction

The Consumer Sentiment Index published by the University of Michigan (hereafter UM index) and the Consumer Confidence Index issued by the Conference Board (hereafter CB index) are the two most commonly monitored measures of consumer confidence in the U.S.¹ These indices, which are constructed from answers to survey questions, are popular with the media, as journal articles and commentaries abound following their release. The analysis often confers a primary role to consumer confidence in determining economic fluctuations. The view among economists is, however, more equivocal. As early as 1965, Adams and Green showed that the information contained in the UM index overlaps the information included in standard government statistics on employment and financial conditions. Many economists think that consumer confidence is endogenous and is a reflection of current macroeconomic conditions whereas others, in line with Keynes’ animal spirits, argue that psychological factors can impact consumers’ decisions. According to the latter, willingness to consume may be an important factor affecting consumption.

Few studies have found that confidence indices have significant explanatory power once fundamental economic factors are taken into account. However, some researchers (Gartner (1991), and Throop (1992)) performed event studies and suggested that these indices could be helpful during major economic or political events, as they then tend to diverge from a path consistent with other macroeconomic variables. Adopting a practical approach, our study attempts to take into account the existing literature, and to provide a new, and formal evaluation of consumer confidence indices as predictors of aggregate consumer spending.

Periods of high economic or political uncertainty are usually associated with high volatility of consumer confidence, suggesting that large swings in confidence influence consumption. We provide a formal assessment of this possibility by estimating a consumption function in which only large variations of confidence affect spending. We find consumer confidence is a statistically important determinant of consumption in periods of elevated uncertainty.

The remainder of this paper is organized as follows: Section 2 describes two competing views of consumer behaviour, Section 3 reviews the relevant empirical literature, Section 4 introduces our econometric model, data, and estimation methods, Section 5 summarizes the estimation and forecasting results, and Section 6 presents a conclusion. A documentation of the UM and CB indices can be found in the Appendix.

¹ Other surveys, such as that conducted by ABC/Washington Post, are issued on a sporadic basis.
2. Theory

This section reviews two theories of consumer behaviour and links each to consumer confidence. We present an economic approach of consumption based on the life cycle-permanent income hypothesis, followed by a psychological view of consumer expenditures.

2.1 Economic Theory of Consumption: The Permanent Income Hypothesis

Friedman (1957) postulated that consumption was determined on the basis of an individual’s income over his or her lifetime. The permanent income hypothesis (PIH), as this theory is known, argues that consumers’ expenditures are financed from their permanent income. Temporary gains in income do not affect consumption. This could explain why temporary tax cuts appear to have much smaller effects than permanent cuts (Steindel, 2001). Formally, we can write

\[ C_t = \frac{1}{T} \left( A_0 + \sum_{t=1}^{T} Y_t \right) \quad \forall t \]

where \( C_t \) is consumption during period \( t \), \( A_0 \) is the individual’s initial wealth, and \( Y_t \) is income earned in period \( t \). The term in parenthesis is the individual’s total lifetime resources. Thus (1) states that an individual divides is or her entire lifetime resources equally among each period of life. Consequently, a rise in income will increase consumption only to the extent that this rise reflects a gain in permanent income.

Hall (1978) finds that, under perfect capital markets, the PIH can be approximated by a random walk, thus concluding that no past information other than consumption can help predict current consumption. Campbell and Mankiw (1990) assessed the random walk hypothesis by separating consumption into two types of consumers: life-cyclers and rule-of-thumbers. The former consume from their permanent income whereas the latter consume from their current income. The authors find a share of about 0.5 for each type of consumers, thereby questioning the PIH. This shortcoming of the PIH is not attributable to data aggregation. Indeed, Shea (1995) uses micro data to find that predictable changes in income produce predictable changes in consumption, a feature referred to as excess sensitivity of consumption relative to income (Flavin, 1981).

Excess sensitivity can be explained by liquidity constraints and precautionary savings. If individuals are unable to borrow as desired (because access to credit is limited or interest rates are too high), their consumption may be weaker in the advent of low current income compared to permanent income. Also, uncertainty relative to future income can be such that individuals attain higher expected utility by reducing current consumption and building reserves in the advent of a drop in income. Precautionary savings can be affected by liquidity constraints. Even if the constraint does not bind currently, the possibility that it will bind in the future reduces consumption.

According to the above theory, the fact that consumer confidence can help forecast consumption is, in itself, a violation of the PIH. Such a result can be justified by the presence
of liquidity constraints. If predictable changes in income produce predictable changes in consumption, the usefulness of consumer confidence indices can only come from the fact that they capture information relative to expected income, but that current consumption cannot react because of liquidity constraints. Therefore, confidence indices can be seen as indicators of liquidity constraints.

If confidence anticipates income, then high confidence today should signal higher income in the future. If liquidity constraints bind, the consumer will be unable to immediately react to this improvement in permanent income and will increase consumption only when the rise in income will have materialized. Consequently, under liquidity constraints, the PIH supports the inclusion of a confidence index in a consumption function.

2.2 Psychological View
The psychological approach of consumption was pioneered by Katona (1975). In Katona’s view, consumer expenditures are a function of both capacity and willingness to consume. In this paradigm, consumption depends on the confidence that individuals have regarding their future financial condition. The cornerstone of the psychological theory is that willingness to consume cannot be explained only by the reaction of consumers to economic variables. Their willingness to buy is also influenced by unquantifiable or non-economic factors such as political crises or wars. According to this view, a drop in confidence can, by itself, cause a decline in consumption in a way not foreseen by economic variables (i.e. without a decrease in income).

The main factor behind the psychological approach is uncertainty (present or expected). The concept of willingness to consume must be negatively related to uncertainty (Acemoglu and Scott (1994)). More precisely, even if consumers’ financial position is unchanged, higher perceived uncertainty relative to that position can lead to a drop in consumption, as higher uncertainty lowers marginal propensity to consume. In this context, the usefulness of confidence comes from its ability to convey consumers’ assessment of risk. This assessment should affect spending plans only to the extent that this uncertainty translates into economic uncertainty. The psychological view’s justification thus boils down to the need for precautionary savings.

Consumer confidence indices comprise three components: current conditions, future conditions, and total (current+future) indices (see Appendix 3). This decomposition could be helpful in determining the relative relevance of the two competing views if current conditions reacted only to a change in willingness to consume, and future conditions reacted only to a change expected income. However, it is difficult to empirically distinguish the source of changes in confidence as each component can potentially react to a change in both expected income and willingness to consume or uncertainty. An assessment of whether confidence proxies expected income, or whether it provides additional information can be done, for instance, by regressing confidence on future income.3

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2. This can be helpful given that permanent income is difficult to measure. Under the pure PIH, the fact that confidence anticipates expected income means confidence can be useful to explain current consumption.

3. This has been done for Canada by Côté and Johnson (1998), who found that about a third of the movement in confidence can be explained by its correlation with changes in leads of income.
3. Review of Empirical Fit

The publication of the UM index started on a quarterly basis in 1952 whereas the publication of the CB index began on a bimonthly frequency in 1967. Perhaps because of its longer sample period, most academic research is devoted to the UM index. The first research pertaining to confidence indices was performed during the 1960s. Thereafter, the bulk of papers on confidence appeared in times of economic weakness or geopolitical turmoil, such as the early 1990s. Our investigation is thus part of a new flow of research that could emerge given the recent economic and geopolitical events in the U.S.

3.1 Determinants of Consumer Confidence

In order to evaluate the informational content unique to confidence indices, they must be purged of information that could come from their determinants. The explanatory variables presented herein are based on economic theory. The use of these variables in a consumption equation will then ensure that the addition of confidence indices provide further explanatory power only to the extent that the indices capture information relative to expected income, or willingness to consume or uncertainty, or at least information not found in standard macroeconomic data.

The method commonly used is to evaluate the goodness of fit of the following regression equation

\[ CCI_t = \lambda + \beta \partial_t + \nu_t \]  

(2)

where \( CCI \) stands for a consumer confidence index, and \( \partial \) is a vector containing the determinants. Using disposable income, unemployment rate, inflation, interest rates, the S&P500 index and household net wealth as determinants, we find that about 72 per cent of the variation in confidence indices can be explained by these determinants. With a similar framework, Fuhrer (1993) finds that disposable income, the unemployment rate, inflation and stock prices explain 72 per cent of the variation in the UM index. Thus, some of the variations in confidence cannot be explained by standard macro variables, suggesting that \( \nu_t \) could be used in a consumption equation to assess the intrinsic explanatory power of confidence. However, in our empirical model, we chose to use confidence itself with the addition of \( \partial \) since it involves only one estimation step.

i) Disposable Income:
The correlation between consumer confidence and the four-quarter moving average of consumption growth is 0.68. As shown in Figure 1, variations in consumption are often accompanied, and sometimes preceded, by movements in confidence. At 0.77, the correlation between disposable income and consumption is even higher, reflecting the possibility that the strong link between confidence and consumption is actually stemming from the fact that they both respond to expected disposable income.
As can be seen from the graph on the left, the link between confidence and consumption has deteriorated since the mid-1990s. This fact is confirmed by Bram and Lugvigson (1998), who find that the performance of confidence in forecasting consumption has diminished during the last decade. Consumer confidence has increased much more firmly than consumption since 1995. This could be explained by the fact that the large increases in the stock market in the late 1990s have had a stronger effect on confidence than on consumption. The graph on the right shows that stock market wealth gains have had an impact on the link between income and consumption during that period.

ii) Unemployment Rate:
Consumers can interpret an increase in the unemployment rate as an increase in uncertainty, even though they are not themselves unemployed. This can stimulate precautionary savings. Hence, a negative relationship between consumer confidence and unemployment is expected.

iii) Inflation:
Rising inflation is a sign of erosion of purchasing power that can lower consumer confidence. As the volatility of inflation increases with its level, one can also think of higher inflation as generating uncertainty around expectations of real wage gains. Lovell and Tien (2000) analyse the link between the Economic Discomfort Index (EDI) and the UM index. The EDI, which is the sum of the unemployment rate and the inflation rate, gives a measure of economic malaise or uncertainty. The authors obtain a correlation coefficient of about -0.80 between the UM index and the EDI. In line with the psychological approach, this would suggest that confidence indices are good proxies for uncertainty.

iv) Interest Rate:
To the extent that consumers are forward-looking, a tightening in monetary policy will negatively affect consumer confidence because of its expected effect on economic activity, and income growth.
v) Stock Prices:
There are two general ways in which movements in the stock market can affect consumer confidence: 1) an increase in the stock market may increase wealth, boosting confidence directly; and 2) confidence and stock prices can be correlated because stock markets are leading indicators of output. In this case, rising stock markets act as a leading indicator of higher expected labour income, and thus boost confidence. For instance, using data at the consumer level to control for stock ownership, Otoo (1999) finds that relationship 2 is valid. She finds that an increase in the stock market yields an increase in confidence for those who do not own stocks. This suggests that a portion of the surge in consumption in the late 1990s is attributable to relationship 1, whereas the increase in confidence comes from both 1 and 2. This can explain why confidence increased more firmly than consumption during that period (Figure 1, left graph), as consumption increased only for those who owned stocks.4

Otoo also estimates impulse response functions based on a VAR model of consumer confidence (UM Index) and the Wilshire 5000 index. She finds that a shock to confidence has essentially no impact on the behaviour of stock prices. Moreover, the variance decomposition gives a share of only 2 per cent to confidence after 8 months. However, an innovation to the stock market initiates a temporary (2 months) response of confidence. In this case, the variance decomposition gives a share of 6 per cent to the stock market shock, a percentage comparable to those of the unemployment rate, inflation, and real interest rates.

vi) Household Wealth:
Mishkin (1978) analyses the link between consumer confidence and balance sheet variables. He assumes that confidence indices measure the perceived probability of financial distress. Arguing that this probability is a function of changes in households’ balance sheet variables, he estimates a contemporaneous equation between confidence, financial assets, and debt.5 He obtains that confidence is positively affected by assets, and negatively affected by debt with an explanatory power of 88 per cent. However, Hall and Shoven (1978) stressed that the variables used by Mishkin are not exogenous, and that consequently the estimated correlations probably stem from the influence of a common factor.

Some variations in consumer confidence cannot be explained by fundamental macroeconomic variables. This suggests that one can expect to find at least some intrinsic explanatory power within these indices to explain consumption.

3.2 Forecasting Value of Consumer Confidence
Numerous approaches to analysing consumer confidence indices within a consumer spending forecasting equation are found in the literature. In-sample performance is usually evaluated by calculating the increment to the goodness of fit of the model (R²) resulting from the addition of the indices to the equation or by looking at the change in significance statistics (t,F) following the inclusion of controls. Out-of-sample performance

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4. Approximately 50 per cent of U.S. households own stocks directly or indirectly.
5. This decomposition is essential: replacing assets and liabilities by wealth changes the results.
is assessed by the reduction in forecasting errors as measured by the root mean squared error statistics (RMSE). The generally considered equations are of the following form:

\[ \Delta C_t = \alpha + \Delta L^{j+1}(C_t) + \sum_{i=1}^{n} \beta_i \Delta L^i(X_{it}) + \Delta L^i(CCI_t) + \epsilon_t \quad j=0, ..., m. \]  

(3)

where \( C \) represents consumption, \( X \) represents a vector of control variables (the aforementioned determinants), \( CCI \) stands for a consumer confidence index, and \( L \) is a polynomial lag operator.\(^6\) In more sophisticated studies, cointegrating vectors between consumption, income, and wealth are added as long-run anchors.

The literature can be divided into three groups. Consumer confidence indices: 1) are of negligible value because they lose their explanatory power with the addition of control variables; 2) have an intrinsic value since they contain information over and above that held in the controls; and 3) are useful because they improve forecasts of consumption during exceptional periods. Garner (1991) concludes that these diverging results are attributable to 3 factors:

- The information set used is different. Some studies link consumption to confidence and to only one or two variables whereas others consider a broader set of control variables.
- The lag structure and the forecasting horizon is different. Some focus on a contemporaneous relationship between the variables whereas others give much more importance to the dynamic effect of explanatory variables.
- The sample period is different. Since confidence appears to be especially useful to forecast consumption during extraordinary periods, the likelihood of concluding that confidence indices are helpful is greater when such periods are covered.

3.2.1 Negligible Value

The analysis of a consumption equation such as (3) frequently leads authors to give negligible value to consumer confidence indices. Fuhrer (1993) finds that the UM index is a statistically significant predictor of consumer spending, but that its explanatory power fades in the presence of income in the equation. Hymans (1970), Mishkin (1978), Burch and Gordon (1984), and Garner (1991) also find that confidence indices lose their significance with the addition of controls. Only Carroll et. al. (1994) find a predictive value for the UM index once controls are taken into account, but their results are dismissed by Ludvigson (1996) on the basis that their residuals are misspecified.

3.2.2 Intrinsic Value

Other researchers (Matsusaka and Sbordone (1995), Bram and Ludvigson (1998), Howrey (2001), and Mourougane and Roma (2002)) found that consumer confidence indices depict idiosyncratic variations useful to explain consumption or economic activity.

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6. Zero order \((j=0)\) can be used to assess coincident indicator properties.
The analysis of Bram and Ludvigson contains a few results worth mentioning. They use a simple linear equation relating consumption to four lags of consumption, labour income growth, the change in the S&P500 index, and the change in the 3-month T-bill rate. As in Leeper (1991), they add a dummy variable to capture the effects of the Gulf War.

Their key results are that: 1) contrary to Huth et. al. (1994), the addition of the CB index increases the R² by more than the addition of the UM index does; 2) the indices contain complementary information since the use of both indices simultaneously improves the R²; 3) the CB (UM) index reduces (increases) the forecasting error by 10 per cent (1.4 per cent) between 1982 and 1996. The forecast accuracy has deteriorated since 1990 as the addition of the CB and UM index raises the RMSE by 4.2 per cent and 3.7 per cent respectively; and 4) looking at the explanatory power of each survey questions, they find that some questions are more useful than others to forecast consumption. This last result means that a closer look at the source of the changes in the indices could help to better infer implications for consumption.7

The value of consumer confidence indices might come from the timeliness of their release. The indices are available with almost no time lag. The UM index, for example, is typically released at the end of the month for which data are collected. By contrast, statistics that measure economic activity such as output, consumption, and inflation are released weeks after the end of the reporting month or quarter.

This advantage has been found to be relatively small. Indeed, Fuhrer (1993) compares the forecasting value of the current month’s UM index (when other macroeconomic variables are available only up to the previous month) to the value of financial variables (such as stock prices and interest rates; for which data is available on an almost continuous basis), and to the value of past economic variables. He finds that the incremental value in any contemporaneous data (consumer confidence or financial data) is relatively small compared to the information contained in the lagged data. Contemporaneous data increases forecast accuracy by only 2 to 3 per cent while the exclusion of macroeconomic data for the previous month reduces forecast accuracy by 36 per cent.

As a result, financial variables can be used to control for any effects that could stem from the timeliness of the release of confidence indices. This is a fact confirmed by Leeper (1992), who finds that a statistically significant correlation between economic activity and confidence actually fades with the inclusion of financial variables. However, his result was dismissed by Souleles (2001). Using data at the consumer level, he finds forecasting power in confidence over and above the information held in financial variables.

7. In a related study for Canada, Côté and Johnson (1998) find that the addition of a consumer confidence measure increases the explained variation in consumption by 18 percentage points.
3.2.3 Value in Extraordinary Times

Consistent with the psychological approach, consumer confidence indices could be useful during periods of elevated uncertainty such as wars. For example, to quote Garner (1991):

“Had the Gulf crisis been widely anticipated, uncertainty might have risen before the actual invasion. As a result, consumer spending might have weakened, and past macro-economic data might have foreshadowed further declines in consumer spending. But in actuality, past economic data probably did not reflect greater uncertainty because the invasion surprised nearly all U.S. households. The abrupt decline in confidence after the invasion provided potentially useful information to forecasters about the reaction of consumers.”

In line with Garner, Throop (1992) finds that, in times of major economic or political events (the Gulf War and the 1987 stock market crash), consumer confidence can move independently from current economic conditions. At such times, he argues that confidence provides useful information about future consumer expenditures that is not otherwise available. Using a VECM framework, he finds that the variables that usually explain confidence fail to do so during the Gulf war. During this period, confidence dropped markedly, and did not follow a path consistent with that given by a cointegration relation among confidence, unemployment, inflation, and interest rates. This behaviour of confidence was helpful since consumer spending followed the path of confidence during that period.8 This fact is supported by Santero and Westerlund (1996) who argue that strong variations in confidence, which are likely driven by major events, are often followed by fluctuations in GDP.

Periods of high economic or political uncertainty are often associated with high volatility of consumer confidence, suggesting that large swings in confidence are particularly important for consumption. Using the standard controls, Garner (1991) finds that the addition of consumer confidence worsens the forecasting performance during “normal” times, and improves the forecasting accuracy during the Gulf war. This suggests that we should ignore consumer confidence indices during “normal” periods. However, Leeper (1992) finds that large shocks to consumer confidence are not systematically linked to economic activity as measured by the unemployment rate and industrial production. He confirms Throop’s results for the Gulf war period, but not for other periods during which marked changes in consumer confidence were observed.9

Analyses of the usefulness of consumer confidence during these exceptional times of high uncertainty are scant. Moreover, they are always focused on predetermined periods, often the Gulf war period. But can we really conclude that confidence indices are valuable in times of major shocks based only on event studies? In the next section, we provide a formal assessment of the usefulness of confidence indices during extraordinary periods. We do this by estimating a consumption function in which only strong variations in confidence can affect spending.

8. Decreasing interest rates and inflation led the model to forecast an increase in consumption at that time.
4. Empirical Framework

Our model is based on Garner and Throop’s finding that consumer confidence indices are useful to forecast aggregate consumption in periods of major shocks. However, instead of focusing on periods of major economic or political events that are documented in the literature, we estimate endogenous periods of high volatility within a consumption function framework. Periods of high uncertainty are then inferred. Before turning to the modelling of confidence, we introduce our benchmark model.

4.1 Benchmark Model: A Consumption Function

In order to evaluate the usefulness of confidence indices in explaining and forecasting consumption, we need to estimate a realistic consumption equation. A typical consumption function contains a long-run anchor determined by a cointegrating vector including the level of consumption, income, and wealth (all in real per capita terms). Moreover, short-run dynamics provide information coming from variables that affect consumption within the business cycle. These variables are the first difference of nominal interest rates, inflation, stock prices, unemployment, and of the variables included in the cointegrating vector.\(^{10}\) We estimate the following dynamic consumption function:

\[
\Delta C_t = \alpha + \pi \Delta L^j(C_t) + \sum_{i=1}^{n} \beta_i \Delta L^j(X_{it}) + \gamma[C_{t-1} - \lambda_1 Y_{t-1} - \lambda_2 W_{t-1}] + \epsilon_t \quad j=1, ..., m. \quad (4)
\]

where \(C_t\) is total consumer outlays, \(Y_t\) is disposable income, \(W_t\) is households’ net worth (financial and non-financial), and \(X_{it}\) represents a vector containing the \(n\) short-run dynamic variables. Given that this is a forecasting equation, the variables and lags kept for the final specification are chosen with the general-to-specific method as in Hendry and Ericsson (1991). This is the same type of equation as (3) except that we explicitly introduce an error-correction term. Note that this equation does not include any measure of consumer confidence at this stage.

4.2 Threshold Specification

Since periods of major shocks that elevate uncertainty are frequently associated with strong variations in confidence, we postulate that the value of the indices comes from their strong variations. In this context, we build a model in which only large swings in confidence can affect consumption. If our thinking is correct, the explanatory and forecasting power of our model should be maintained by focusing on large changes in the indices. Moreover, if in-sample and out-of-sample properties are improved by doing so, we may conclude that small variations in the indices should be ignored.

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\(^{10}\)More precisely, we use quarterly NIPA time series from 1967Q1 to 2001Q4. This sample is conditioned by the availability of both confidence indices and covers a fairly large number of high volatility periods. The dependent variable is the change in the log of real consumption per capita, and the following set of control variables is considered: lagged dependent variable, 90-day commercial paper rate (nominal), CPI inflation, unemployment rate, S&P500 stock market index, real disposable income per capita, and real households’ net worth per capita (see Appendix 1 for a complete description of the variables). Income, wealth, and stock market variables can be seen as proxies for credit conditions or liquidity constraints. Separating wealth into assets and liabilities did not improve the fit.
Thus, we estimate a threshold conditioning the inclusion of confidence in the consumption function (4). More precisely, we estimate \( \theta, \theta > 0 \), in the following equality:

\[
\Delta CCI_{tr} = \begin{cases} 
\Delta CCI & \text{if } |\Delta CCI| > \theta \\
0 & \text{otherwise.} 
\end{cases} \tag{5}
\]

The threshold \( \theta \) is given by a grid search minimizing the sum of squared errors of (4) with \( \Delta CCI_{tr} \) added. This symmetric criterion stipulates that the change in consumer confidence will enter the regression at time \( t \) only if its absolute value is larger than \( \theta \). It tells us at which magnitude of variation it is worthwhile to include confidence in the regression in terms of lower empirical errors. However, to ensure the estimation of a threshold confidence variable with minimal noise (such that positive shocks are not immediately followed by negative shocks, or vice-versa), we choose to use a somewhat smoother criterion for the estimation of \( \theta \). The following condition for \( \theta \) is used in place of (5):

\[
\Delta CCI_{tr} = \begin{cases} 
\Delta CCI & \text{if } |CCI_t - \text{average}(CCI_{t-1}, CCI_{t-2})| > \theta \\
0 & \text{otherwise.} 
\end{cases} \tag{6}
\]

This criterion stipulates that the change in consumer confidence will enter the regression at time \( t \) only if the absolute value of the difference between its level and the average level over the two previous quarters exceeds \( \theta \). This restriction therefore imposes that the shock to confidence must be “minimally” persistent.

5. Results

We first present our base case model which will be our benchmark for measuring the usefulness of consumer confidence indices. Various models based on different threshold specifications are then analysed.

5.1 Benchmark Models

After testing for cointegration with the Johansen-Juselius approach, we use the Phillips and Loretan (1991) nonlinear least squares methodology to estimate (4) and obtain long-run parameters over the sample period 1959-2001 for the level of consumption, income, and net wealth (Table 1, Appendix 2).\(^{11}\) Although the estimated parameters should not be interpreted as marginal propensities to consume out of income or wealth (since this is a reduced form, Wickens (1996)), the values are in line with theory as the coefficients are positive, significant, and the income parameter is larger than the wealth parameter.

Given that the CB index series starts in 1967, we then use OLS to reestimate our consumption function over the 1967-2001 period with the long-run parameters values imposed by the 1959-2001 estimation. Using the general-to-specific method, we obtain a

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\(^{11}\)This is the same methodology as that used by Amano and Van Norden (1995) to estimate the Bank of Canada’s exchange rate equation.
final specification (Model 1). Unfortunately, this specification excludes income from the short-run dynamics.\textsuperscript{12} Since we want to assess the information content of consumer confidence indices especially over and above that of income, we consider an alternative equation (Model 2) in which income is significant. More specifically, this model is based on the exclusion of consumption from the equation during the general-to-specific process.\textsuperscript{13} Table 2 in Appendix 2 contains the estimation results for both models. In addition, it summarizes various diagnostic tests on the residuals of these equations.

Both equations perform reasonably well in explaining movements in consumption over the last three decades. Indeed, the $R^2$s are relatively high given that the equations are not contemporaneous relations. About 37.3 and 29.9 per cent of the variations in consumption can be explained by our explanatory variables for Model 1 and 2, respectively. As well, apart from inflation, which has a positive sign when lagged four periods, all short-run coefficients are statistically significant, and of the expected sign. Moreover, the error-correction term depicts a negative coefficient in both models, a feature consistent with further evidence of cointegration.

5.2 Augmented Models
We begin our assessment by reproducing the analysis commonly found in the literature, measuring the improvement to the goodness of fit and forecasts of a consumption equation that result from the addition of confidence indices. In order to give confidence maximum chances of success, we add four lags of that variable (in first difference, since we are interested in changes in confidence). The sum of the coefficients on these lags is positive and statistically significant for both indices. In-sample performance is assessed with the increment in the $R^2$s while out-of-sample performance is examined using the root mean squared error (RMSE) over the 1990s.\textsuperscript{14} We compute one-step ahead forecasts as we do not provide forecasts for explanatory variables.\textsuperscript{15}

Results are found in the first and second lines of Table 3 for the UM index and Table 4 for the CB index (Appendix 2). The RMSEs are shown in parentheses and expressed relative to the benchmark’s RMSEs. The results are broadly consistent with the literature’s view that, taken on their own, consumer confidence indices have a small value. Indeed, the addition of the UM index yields virtually identical $R^2$ and RMSEs. The conclusion is however more ambiguous for the CB index, as the increment to the goodness of fit is somewhat larger, but the out-of-sample performance is unchanged or worsened.

5.3 Threshold Models
We present two models for volatility thresholds. First, we estimate a model as in (6). Second, we turn to a volatility criterion defined in terms of conditional variance. The focus of the analysis is to evaluate the improvement of our consumption function when we

\textsuperscript{12}This probably reflects the fact that income and consumption are colinear.
\textsuperscript{13}The explanatory power of S&P500 however fades.
\textsuperscript{14}RMSEs are calculated using rolling regressions starting with 1967-1990 as the sample period, moving up one quarter each time to generate a new forecast.
\textsuperscript{15}This is a reasonable forecasting horizon since we use quarterly data and we do not expect confidence to affect consumption more than one quarter out.
replace consumer confidence with the threshold variable in the augmented models. The core of our analysis is consequently to compare the threshold models’ performance to that of the augmented models.

5.3.1 Basic Thresholds
The estimation of (6) over the 1967-2001 period produces interesting results for the parameter θ. For the UM index, values of 10.51 for Model 1 and 10.69 for Model 2 are found. However, the CB index yields lower results: 0.77 for Model 1 and 1.59 for Model 2, suggesting that our hypothesis is more plausible in the case of the UM index. The lower values found for the CB index could be attributed to the fact that, by construction, this series is relatively smooth and consequently depicts very few large variations (see Appendix 3).

With these estimates, we can construct series that contain only values that meet the criterion (6). Given that the estimated thresholds are small for the CB index, the original series and the transformed one are virtually identical. On the other hand, the transformed UM series contrasts more with the original series. Figure 2 depicts the transformed UM series actually replacing the confidence index in our consumption equation. Coefficients for the threshold variables remain positive and become even more significant than in the augmented models. The threshold identifies high volatility periods.

![Figure 2: Transformed UM Index (Model 2)](image)

The graph on the left shows the confidence variable entering in the augmented models, and the graph on the right shows the confidence variable entering in the threshold models. With this threshold, we identify a relatively small number of periods, which is intuitive. These estimated periods are often consistent with major economic or political events. Moreover, in 4 of the last 5 recessions, marked positive variations in confidence were useful to explain consumption during early recovery periods, thereby suggesting that confidence could be a good proxy for pent-up demand. Although the UM index dropped markedly following September 11, this drop was not large enough to meet our criterion. It is interesting to note that the adjusted series coincides with several turning
points in the U.S. economy. This is consistent with the theoretical view that consumer confidence proxies uncertainty as turning points are, by definition, periods of elevated uncertainty.

The third line of Tables 3 and 4 summarizes the results with the threshold models. For both indices, the in-sample performance is significantly improved relative to the benchmark and augmented models. The increment to the \( R^2 \) varies from 4 to 6 percentage points relative to the benchmark models and from 1 to 6 percentage points relative to the augmented models. Thus, replacing the confidence indices by the threshold variables increases the explanatory power, confirming that the relevant information for future consumption coming from confidence is indeed found in its strong variations.\(^{16}\)

This conclusion would still have been true had the \( R^2 \) only been maintained. Furthermore, as in Garner (1991), our results suggest that small fluctuations should be ignored. The fact that confidence is especially helpful in periods of high uncertainty is consistent with our interpretation of the psychological approach. This is evidence suggesting that the indices convey consumers' assessment of economic risk, and that this assessment can potentially affect spending. Still, our results can also be interpreted as showing that confidence captures expectations relative to income better than other variables do in times of high uncertainty.

Results with respect to the out-of-sample performance are however less obvious. In this case, the RMSE decreases only in the model including income (Model 2). Still, the improvement to the forecasting errors is impressive with the UM index as the relative RMSE falls by more than 7 percentage points. It is finally worth mentioning that our results are not sensitive to a change in the sample period for the estimation of the thresholds. Indeed, changing the threshold estimation period from 1967-2001 to 1967-1980 with estimation of the consumption function over the 1980-2001 and rolling forecasts over the 1990s yields similar results.

5.3.2 Alternative Thresholds

Another method can be used to identify periods of high volatility in consumer confidence indices. In addition to the above threshold specification, we present a method based on conditional variance estimation as in Worrell (2001). In this case, the criterion is:

\[
\Delta CCI_{tr} = \begin{cases} 
\Delta CCI & \text{if } \sigma(CCI_t) > \theta \\
0 & \text{otherwise.}
\end{cases}
\] (7)

where \( \sigma \) is an estimate of the volatility of confidence given by the conditional variance of ARCH(1) or GARCH(1,1) models. Figure 3 depicts maximum likelihood estimates of \( \sigma \) for the CB index.\(^{17}\)

\(^{16}\)Another improvement pertains to the increased significance of the error-correction term under the threshold models. This shows that we are able to keep a richer specification with the thresholds, a feature that was absent from the augmented models.
Periods of high volatility are easily traceable with these estimates. As in the previous case, they often coincide with recessions. Estimates from the GARCH(1,1) are more persistent since squared residuals follow an ARMA(1,1) in this case. For example, estimated values for $\theta$ are of 60 and 126 for the ARCH and GARCH models with the CB index (Model 1). Points above the horizontal lines, depicting values where $\sigma(CCI)$ meets the criterion, indicate when confidence was useful in explaining consumption.

Estimation and forecasting results are found in lines 4 and 5 of Tables 3 and 4 for the UM and CB indices, respectively. In-sample performance depicts its strongest improvement in these models as the $R^2$ rises by as much as 9 percentage points. Out-of-sample performance is also reasonably good, especially for the GARCH models of the CB index. In this case, the relative RMSE falls to 0.95. These results reinforce our premise that large swings in consumer confidence are particularly useful.

Finally, looking at the overall results for the augmented, basic threshold, and alternative threshold models, we find that an increase in the $R^2$ is more frequent than a decrease in the forecast errors as the RMSEs are lowered in only 50 per cent of the times. This shows that in-sample properties can be more easily improved than out-of-sample properties.

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17. We also looked at different models based on the standard deviation of consumer confidence indices. Whether including the 8-quarter rolling standard deviation of confidence itself or estimating a threshold based on this variable, we found some improvement in the in-sample and out-of-sample performance. Still, the best results were found with our basic or alternative thresholds. Moreover, our results are not very sensitive to small changes in $\theta$.

18. Overall, the lowest relative RMSEs are obtained with the threshold models: 0.928 for the basic threshold and 0.951 for the alternative threshold (GARCH). Upon performing standard statistical tests for the equality of the forecasting errors, we find that these two models provide statistically significant lower forecasting errors.
6. Conclusion

Few studies have found that confidence indices have significant explanatory power once fundamental factors of the economy are taken into account. In line with the literature, we find that, taken on their own, confidence indices contain relatively little information to forecast aggregate consumer spending in the U.S.

However, some researchers suggested that these indices could be helpful during major economic or political events, as they tend to diverge from a path consistent with other macroeconomic variables in such periods. These periods of high uncertainty are usually associated with strong volatility of consumer confidence, suggesting that large swings in confidence matter for consumption.

We construct a simple threshold model that takes into account the magnitude of variation of consumer confidence indices for forecasting consumption. Whether using our basic thresholds or thresholds founded on conditional variance estimates, in-sample and out-of-sample properties of a consumption equation are generally improved relative to equations in which confidence is included as it is. This shows that strong variations in confidence matter for consumption as confidence is a significant predictor of consumption during high volatility periods. Importantly, these results hold when disposable income is included in the specification, suggesting that confidence contains some information over and above that of income in times of major events.

Whether consumer confidence indices are useful in explaining and forecasting consumption because of the information they convey relative to consumers’ expected income or assessment of present or expected economic uncertainty remains an open question. Our contribution is to formally show that these indices are helpful because of the strong variations that they register during exceptional periods. It is during periods of high uncertainty that confidence indices are most likely to affect spending. Echoing Meyer’s comments, we therefore conclude that economists and forecasters should be concerned with these indices especially in times of high uncertainty.
References


Appendix 1: Sources and Definitions of Variables

Dependent variable


Explanatory variables

• Change in the log of real disposable personal income (U.S. Department of Commerce, Bureau of Economic Analysis, Personal Income & Outlays) per capita.

• Change in the log of Standard & Poor’s Stock Price Index (Standard & Poor’s Corporation, Trade and Securities Statistics), divided by the GDP deflator (U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts).

• First difference of the nominal short-term interest rate (U.S. 90-day commercial paper rate, AA-nonfinancial closing rate, Federal Reserve Website).

• First difference of the unemployment rate (U.S. Department of Labor, Bureau of Labour Statistics, Household Data).

• Inflation calculated as the change in the log of the CPI - all items (U.S. Department of Labor, Bureau of Labour Statistics).

• Change in the log of net worth per capita (Balance Sheets for the U.S. Economy, Flow of Funds data (C.9)), divided by the GDP deflator.

(Consumer confidence variables are added in first difference. Please refer to Appendix 3 for more details on these series. Source: DRI)
Appendix 2: Estimation and Forecasting Results

Table 1: Cointegration Tests (1959-2001)

<table>
<thead>
<tr>
<th>Long-run parameter estimates&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Unit root tests&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Johansen test&lt;sup&gt;c&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ADF dflags</td>
<td>λ-Trace</td>
</tr>
<tr>
<td>-0.3413+0.3146w&lt;sub&gt;t&lt;/sub&gt;+0.6637y&lt;sub&gt;t&lt;/sub&gt;</td>
<td>-5.1013 19</td>
<td>30.20 (H&lt;sub&gt;0&lt;/sub&gt;: r=0) 11.48 (H&lt;sub&gt;0&lt;/sub&gt;: r=1)</td>
</tr>
</tbody>
</table>

Notes:

a. t-statistics are reported below the parameters estimates.

b. The ADF statistic tests the null hypothesis of non-cointegration (H<sub>0</sub>: unit root in the residuals).

Critical values for the 1 per cent, 5 per cent, and 10 per cent level are: -3.75, -3.00, and -2.63 (Hamilton (1994)).

Choice of the optimal lag length for the ADF regression using the Akaike and Bayesian Information Criteria.

c. Critical Values for the 5 per cent level are 26.79 and 13.33 for r=0 and r=1, respectively.

Table 2: Base Case Error-Correction Models (without confidence indices)

<table>
<thead>
<tr>
<th>Dependent variable: total consumption (1967Q1 to 2001Q4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
</tr>
<tr>
<td>---------</td>
</tr>
<tr>
<td>ect&lt;sub&gt;-1&lt;/sub&gt;</td>
</tr>
<tr>
<td>Income&lt;sub&gt;-1&lt;/sub&gt;</td>
</tr>
<tr>
<td>Consumption&lt;sub&gt;-2&lt;/sub&gt;</td>
</tr>
<tr>
<td>Consumption&lt;sub&gt;-3&lt;/sub&gt;</td>
</tr>
<tr>
<td>S&amp;P500&lt;sub&gt;-1&lt;/sub&gt;</td>
</tr>
<tr>
<td>Int. rate&lt;sub&gt;-1&lt;/sub&gt;</td>
</tr>
<tr>
<td>Int. rate&lt;sub&gt;-2&lt;/sub&gt;</td>
</tr>
<tr>
<td>Int. rate&lt;sub&gt;-4&lt;/sub&gt;</td>
</tr>
<tr>
<td>Unemployment rate&lt;sub&gt;-2&lt;/sub&gt;</td>
</tr>
</tbody>
</table>
Table 2: Base Case Error-Correction Models (without confidence indices)

<table>
<thead>
<tr>
<th>Dependent variable: total consumption (1967Q1 to 2001Q4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Unemployment rate</strong>&lt;sub&gt;t-3&lt;/sub&gt;</td>
</tr>
<tr>
<td><strong>CPI</strong>&lt;sub&gt;t-1&lt;/sub&gt;</td>
</tr>
<tr>
<td><strong>CPI</strong>&lt;sub&gt;t-4&lt;/sub&gt;</td>
</tr>
<tr>
<td>**R&lt;/sup&gt;²</td>
</tr>
<tr>
<td><strong>ARCH(4)</strong></td>
</tr>
<tr>
<td><strong>Jarque-Bera</strong></td>
</tr>
<tr>
<td><strong>Breusch-Godfrey</strong></td>
</tr>
<tr>
<td><strong>Q-stat(8)</strong></td>
</tr>
</tbody>
</table>

Notes:
1. The figures in parentheses are t-statistics.
2. The ARCH test is an LM statistic used to test for the presence of autoregressive conditional heteroskedasticity. Jarque-Bera is a test for normality, the Breusch-Godfrey test is a test for serial correlation in the residuals, The Q-statistic is the Ljung–Box statistic used to test for the presence of autocorrelation. The numbers shown for those tests are p-values.
Table 3: In-Sample and Out–of–Sample Performance  
Adjusted $R^2$ and Relative RMSE  
University of Michigan Index

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base case</strong></td>
<td>0.373 (1.00000)</td>
<td>0.299 (1.00000)</td>
</tr>
<tr>
<td><strong>Augmented</strong></td>
<td>0.372 (0.99776)</td>
<td>0.301 (0.99433)</td>
</tr>
<tr>
<td><strong>Threshold</strong></td>
<td>0.431 (1.02908)</td>
<td>0.363 (0.92817)</td>
</tr>
<tr>
<td><strong>ARCH(1)</strong></td>
<td>0.466 (1.02685)</td>
<td>0.357 (1.13043)</td>
</tr>
<tr>
<td><strong>GARCH(1,1)</strong></td>
<td>0.410 (1.04027)</td>
<td>0.369 (0.96408)</td>
</tr>
</tbody>
</table>

Notes:  
(1) Numbers in parentheses represent relative RMSEs (i.e., divided by the Base case model’s RMSE).  
(2) Shaded cells indicate lower relative RMSE.  

Table 4: In-Sample and Out–of–Sample Performance  
Adjusted $R^2$ and Relative RMSE  
Conference Board Index

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base case</strong></td>
<td>0.373 (1.00000)</td>
<td>0.299 (1.00000)</td>
</tr>
<tr>
<td><strong>Augmented</strong></td>
<td>0.397 (1.05593)</td>
<td>0.355 (0.99622)</td>
</tr>
<tr>
<td><strong>Threshold</strong></td>
<td>0.413 (1.05145)</td>
<td>0.369 (0.98866)</td>
</tr>
<tr>
<td><strong>ARCH(1)</strong></td>
<td>0.450 (1.02461)</td>
<td>0.359 (1.00189)</td>
</tr>
<tr>
<td><strong>GARCH(1,1)</strong></td>
<td>0.409 (0.97092)</td>
<td>0.364 (0.95085)</td>
</tr>
</tbody>
</table>

Notes:  
(1) Numbers in parentheses represent relative RMSEs (i.e., divided by the Base case model’s RMSE).  
(2) Shaded cells indicate lower relative RMSE.  
Appendix 3: Documenting Consumer Confidence Indices

The University of Michigan Index of Consumer Sentiment (UM index) began as an annual survey in the late 1940s. It became a quarterly survey in 1952 before being converted to a monthly survey in 1978. The publication of the Conference Board Consumer Confidence Index (CB index) on the other hand started in 1967 on a bimonthly basis and was transformed to a monthly survey in 1977.

Conceptually, those indices are used to evaluate the confidence that households have in the economy. They are composed of different questions and can sometimes convey conflicting signals. That was the case during the 1990-91 recession when the UM index reached a low point in October 1990 whereas the CB index did not bottom out until January 1991. Nevertheless, the indices generally fluctuate at the same time. Furthermore, the turning point of the last expansion was hit by both attitudinal measures in January 2000. Each survey contains five specific questions from which three indices are constructed: the present conditions index, the expectations index and the overall consumer confidence index (with a weight of 40 per cent attached to the current conditions index, and 60 per cent to the expectations index).

Because of the nature of the questions, the CB current conditions index reflects the labour market conditions, whereas the UM current conditions index depicts the recent changes in the economy. Therefore, the UM current conditions index tends to lead the
economic cycle while the CB current conditions index tends to follow it. In contrast, the three forward-looking questions about the future conditions are comparable for both indices and consequently the prospective indicators for both measures are strongly correlated ($\rho=0.80$).

There are key differences in the survey methodologies with respect to the sample size, construction method, timing and release schedules. The University of Michigan conducts a monthly telephone survey of about 500 households and has a preliminary midmonth release based on 250 phone interviews. The final results are announced by the end of the month.

At the end of the prior month, the Conference Board sends out a mail survey to 5,000 households, with an average response of about 3,500.\(^ {19} \) On the last Tuesday of the survey month, the Conference Board releases preliminary figures (based on about 2,500 responses). The final results are published along with the release of the preliminary results of the ensuing month.

The construction method of the attitudinal measures is similar to that employed in the construction of the diffusion indices such as the ISM indices. For the UM index, the procedure consists in adding the number of “positive” responses to 100 and to subtract the number of “negative” replies. On the other hand, the CB index expresses the number of “positive” responses as a percentage of the sum of “positive” and “negative” responses. Those different methodologies in constructing the indices from the raw response data explain why the CB index takes a wider range of values while the UM index is more volatile. To obtain an index, the current value is simply divided by a base-period level.

\(^ {19} \) A selection bias could arise in the case where households dissatisfied with the economic conditions would have a greater probability of responding to the survey. That is plausible since the confidence indices constitute a tribune for the consumers given their importance in the media.
Appendix 4: Survey Questions

Each survey is composed of five specific questions about current and expected economic conditions, both personal and national. Three indices are then constructed: the current conditions index, the expectations index and the overall index.

University of Michigan
Survey participants must provide qualitative answers to questions about their personal present and future financial conditions (within one year), expected general business conditions (in one year and in five years) as well as the current conditions for purchases of large household appliances.

Present Conditions Questions:
1. Do you think now is a good or bad time for people to buy major household items? [good time to buy/uncertain, depends/bad time to buy]
2. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago? [better/same/worse]

Expectations Questions:
3. Now turning to business conditions in the country as a whole - do you think that during the next twelve months, we’ll have good times financially or bad times or what? [good times/uncertain/bad times]
4. Looking ahead, which would you say is more likely - that in the country as a whole we’ll have continuous good times during the next five years or so or that we’ll have periods of widespread unemployment or depression, or what? [good times/uncertain/bad times]
5. Now looking ahead - do you think that a year from now, you (and your family living there) will be better off financially, or worse off, or just about the same as now? [better/same/worse]

Conference Board
Respondents must provide qualitative responses to questions about current and future general business conditions (in 6 months), current and future job availability as well as their income prospects.

Present Conditions Questions:
1. How would you rate present general business conditions in your area? [good/normal/bad]
2. What would you say about available jobs in your area right now? [plentiful/not so many/hard to get]

Expectations Questions:
3. Six months from now, do you think business conditions in your area will be [better/same/worse]?
4. Six months from now, do you think there will be [more/same/fewer] jobs available in your area?
5. How would you guess your total family income to be six months from now? [higher/same/lower]