Consumer Confidence and the Unemployment Rate in New York State: A Panel Study

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Abstract

This paper explores the short-term and long-run relationship between the unemployment rate and the consumer confidence index in five metropolitan statistical areas (MSAs) of New York State. The paper utilizes a unique dataset collected by the Siena Research Institute (SRI) between 2001 and 2010. We use panel cointegration and panel error-correction models (ECM) to explore the causal relationship between these two variables. The short-run coefficients indicate a negative causality from consumer sentiment to unemployment and vice versa, indicating that unemployment and consumer sentiment reinforce each other in the short run. In the long-run, we find significant negative causality from consumer confidence to unemployment. However, the direction of causality from unemployment to consumer confidence is not significant.

1. Introduction

The purpose of this study is to explore the short-run and long-run relationship between the New York State (NYS) unemployment rate and consumer sentiment as measured by the Index of Consumer Sentiments (ICS) and its sub-indices - Index of Current Economic Conditions (ICC) and Index of Consumer Expectations. The paper utilizes a unique panel dataset collected by the Siena College Research Institute (SRI) from 2001-2010 documenting the quarterly NYS consumer sentiment across five Metropolitan Statistical Areas (MSAs) of the state. The idea and purpose of the SRI Consumer Sentiment Survey is to replicate for NYS the national level Survey of Consumers conducted by the University of Michigan. The NYS Consumer Sentiment Survey not only reports consumer sentiment for NYS, but also for five Metropolitan Statistical Areas (MSAs) throughout NYS. This enables us to exploit variations in data across time and cross section to explore the relationship between the unemployment rate and consumer sentiment. We use panel cointegration and panel error-correction models (ECM) to explore the causal relationship between these two variables. Our study finds convincing evidence that in the short-run there is negative causality between unemployment rate and consumer confidence, which runs both ways. However, in the long-run though there is negative causality from consumer sentiment to unemployment rate but the reverse causality is not statistically significant.

In the 1940s, George Katona developed the Consumer Sentiment Index as a direct measure of expectations in models of savings and investment behavior (Katona, 1975; Curtin, 1983). The Consumer sentiment surveys are based on the premise that data on consumer sentiments both predict and are predicted by a wide range of economic variables (Curtin, 2007). Katona hypothesized that

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consumer spending depends on both their “ability and willingness to buy.” By spending, he meant discretionary purchases; by ability, he meant consumers’ current income and by willingness, he meant consumers’ assessment of their future income prospects (Curtin, 2007). Based on Katona’s ideas, modern day consumer sentiment surveys are designed to measure the psychological aspect of consumer wellbeing by asking respondents a series of subjective questions.

However, the usefulness of the consumer sentiment index to forecast or explain the economy in general and consumer behavior in particular has often been challenged. In the second half of the fifties, the Board of Governors appointed a committee to evaluate the usefulness of consumer surveys in anticipating consumer behavior. The broad outcome of the committee report was that consumer surveys were not useful (Board of Governors, 1955). The subsequent work by Tobin (1959) and Juster (1964) supported the conclusion of the Board of Governor’s report. From a theoretical point of view, given the rational expectations hypothesis, it can be surmised that consumer sentiment indices are not supposed to have additional information if they are based on expected macroeconomic variables. However, subsequent empirical research has shown mixed results. In some cases it was shown that these indices were useful as explanatory variables in the consumption function. See: Mueller, 1963; Suits and Sparks, 1965; Fair, 1971a and 1971b; Adams and Klein, 1972. In other studies they were seen as nothing more than a synthesis of macroeconomic indicators. See: Friend and Adams, 1964; Adams and Green, 1965; Hymans et al., 1970; Juster and Wachtel, 1972 and Juster et al. 1972; Shapiro, 1972; McNeil, 1974; Lovell, 1975. The prevailing opinion now seems to be that it may help predict the evolution of economic activity. See: Garner, 1991; Fuhrer, 1993; Carrol et al., 1994; Kumar et al., 1995; Matsusaka and Sbordone, 1995; Eppright et al., 1998, Bram and Ludvigson, 1998.

Prior studies exploring the relationship between the unemployment rate and consumer confidence assumed that causality ran from the unemployment rate to consumer confidence (Mueller, 1966, Calerio, 2007). However, the relationship between the unemployment rate and consumer sentiment may not be straightforward. Consumer sentiment is affected by an individual’s general feeling of optimism or pessimism. Therefore periods of economic growth and low unemployment are typically expected to have a positive impact on consumer sentiment. Similarly the labor market is also intimately linked to general economic conditions. Therefore it may not be inappropriate to assume an intrinsic link between the unemployment rate and consumer sentiment, but the direction of causation between these two variables may not be that obvious. In this paper we are particularly interested in exploring the long-run and short-run relationship between the unemployment rate and consumer sentiment in NYS. The focus of the study is to explore the direction of causality between these two variables. The rest of the paper is organized as follows. Section 2 discusses the data. The results of the panel unit root tests and the error correction models are presented in section 3. Section 4 concludes.

2. Data description

Each month, the Siena Research Institute (SRI) publishes a Consumer Confidence index number for New York State consumers. The survey is comparable with the similar national survey conducted by the University of Michigan's Consumer Sentiment index. Current consumer confidence is measured by the Index of Current Economic Conditions, whereas future consumer confidence is measured by the Index of Consumer Expectations. These two indices are combined to calculate the Index of Consumer Sentiments. SRI also produces a quarterly consumer confidence index that looks at five regions (MSAs) of New York State: Albany, Binghamton, New York City, Rochester and Syracuse. The survey also collects data for the Mid-Hudson, Long Island and Utica regions. However, for these regions data are available only from 2007 onwards. Therefore these regions are not included in the study. The quarterly Consumer Confidence index provides regional measures of the state's economic health. The index is constructed based on random telephone calls to at least 2400 NYS residents across various MSAs and over the age of 18 years. The sample is selected based on a random digit dialing (RDD) sample obtained from Sample Survey International (SSI).

The Index of Consumer Sentiment (ICS) is derived from the following five questions:

- "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"
- "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?"
- "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?"
- "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 will have periods of widespread unemployment or depression, or what?"
- "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?"

Time series for unemployed and employed are obtained from the Local Area Unemployment Statistics survey conducted monthly by the U.S. Bureau of Labor Statistics. The monthly data are converted into quarterly data using a simple average. All the data have been converted to natural logarithms to stabilize the variance.

Though monthly state level data are available from January 1999, MSA data is only available quarterly from the fourth quarter of 2001. Hence the period under study is 2001:IV-2010:IV. The MSAs considered in this study are Albany, Binghamton, New York City (NYC), Rochester and Syracuse. We look at the consumer confidence index (Index of Consumer Sentiment (ICS), Index of Consumer Expectations (ICE) and Index of Current Economic Conditions (ICC)), and the unemployment rate. The extent of study and the frequency of data are primarily guided by the availability of the data. The data are deseasonalized using the Census Bureau's X-12-ARIMA seasonal adjustment procedure.

The descriptive statistics in Table 1 show substantial variation in the unemployment rate ranging from 4.09 percent to 9.38 percent. Some of these variations are due to changes in demographic factors rather than business cycle fluctuations. The distribution of the unemployment rate does vary from area to area in the state. We find substantial variation in ICS, ICC and ICE also.

Table 1: Descriptive Statistics – New York State

	Index of Consumer Sentiments (ICS)*	**Index of Current Economic Conditions (ICC)***	**Index of Consumer Expectations (ICE)***	**Unemployment Rate**
Mean	73.11	77.05	70.57	6.09%
Median	77.00	80.00	72.00	5.77%
Maximum	87.00	91.00	88.00	9.38%
Minimum	54.00	54.00	53.00	4.09%
Std. Dev.	9.2580	11.2841	8.4838	0.0146
Skewness	-0.5311	-0.5742	-0.2803	0.7114
Kurtosis	2.1715	1.9595	2.4868	2.3544
Jarque-Bera	2.7975	3.7021	0.8905	3.7631
Observations	37	37	37	37

Notes:
* Index Value (1966=100)

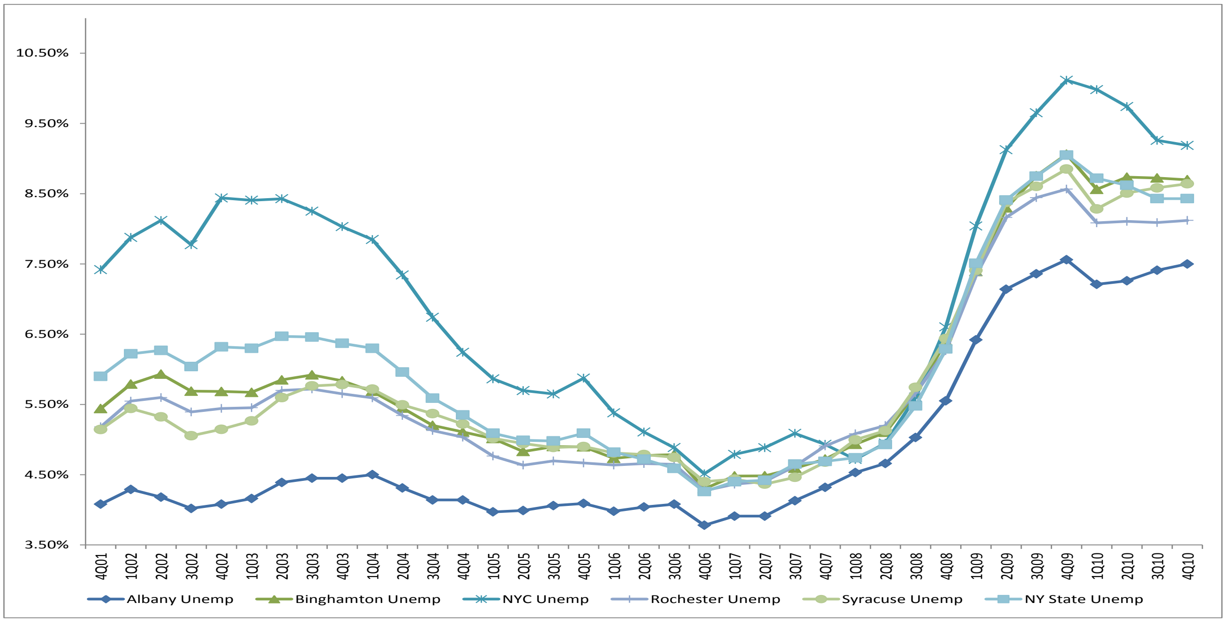
Figure 1 shows the unemployment rate in New York State and the MSAs under study. New York City has both a relatively higher unemployment rate and more volatility in its unemployment rate as compared to the rest of the state. On the other hand Albany typically has a lower unemployment rate as compared to the rest of the state. The unemployment rates in the rest of the state follow each other closely.

Among the MSAs, Albany consistently has the lowest unemployment rate and the highest consumer sentiments. The unemployment rate in Binghamton follows the average trend in New York State. However, it has the lowest consumer sentiment as measured by all the three indices.

3. Estimations

The point of departure for our study is the use of panel data to explore the long-run and short-run relationship between consumer sentiment and the unemployment rate. To our knowledge this is the only

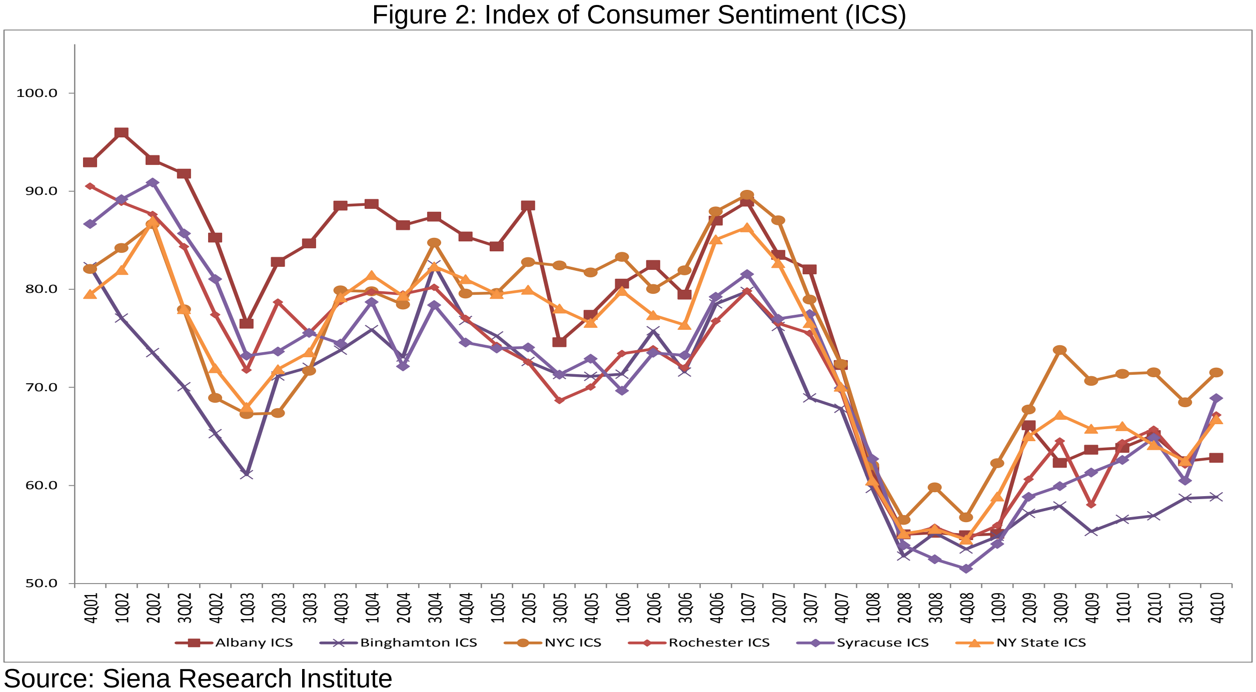
Figure 1: Unemployment Rate



Source: Local Area Unemployment Statistics

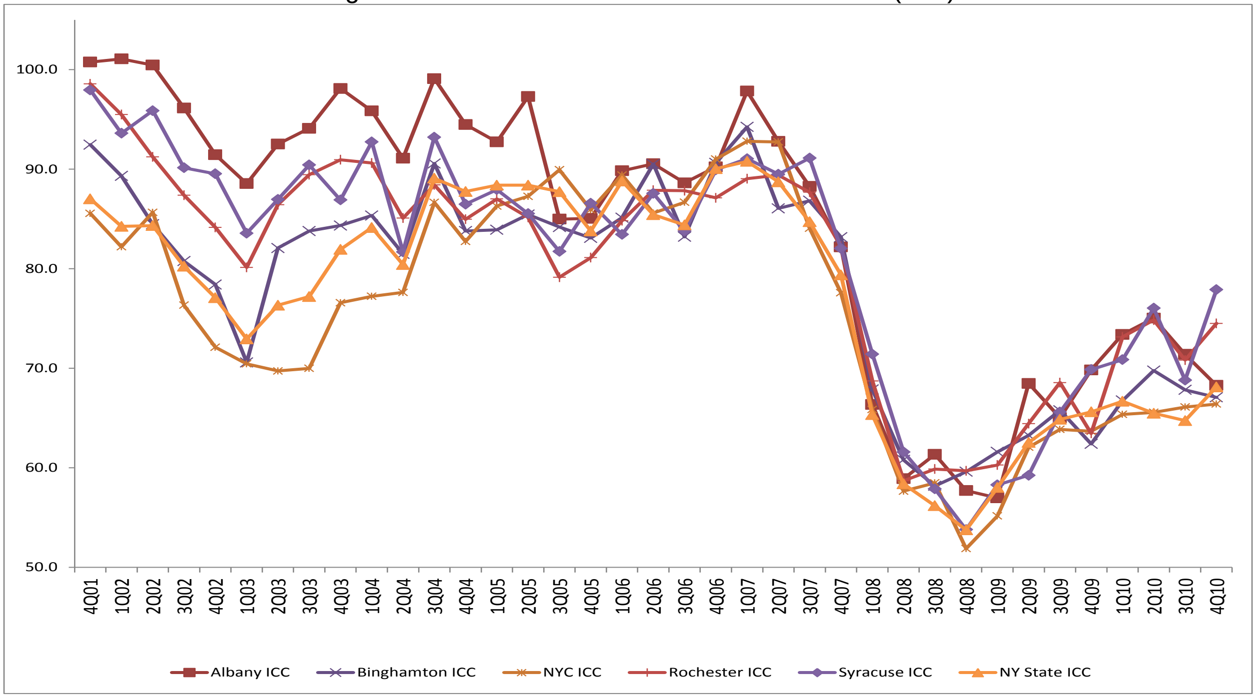
Figure 2,3 and 4 show the behavior of the consumer sentiment indices.

Figure 2: Index of Consumer Sentiment (ICS)



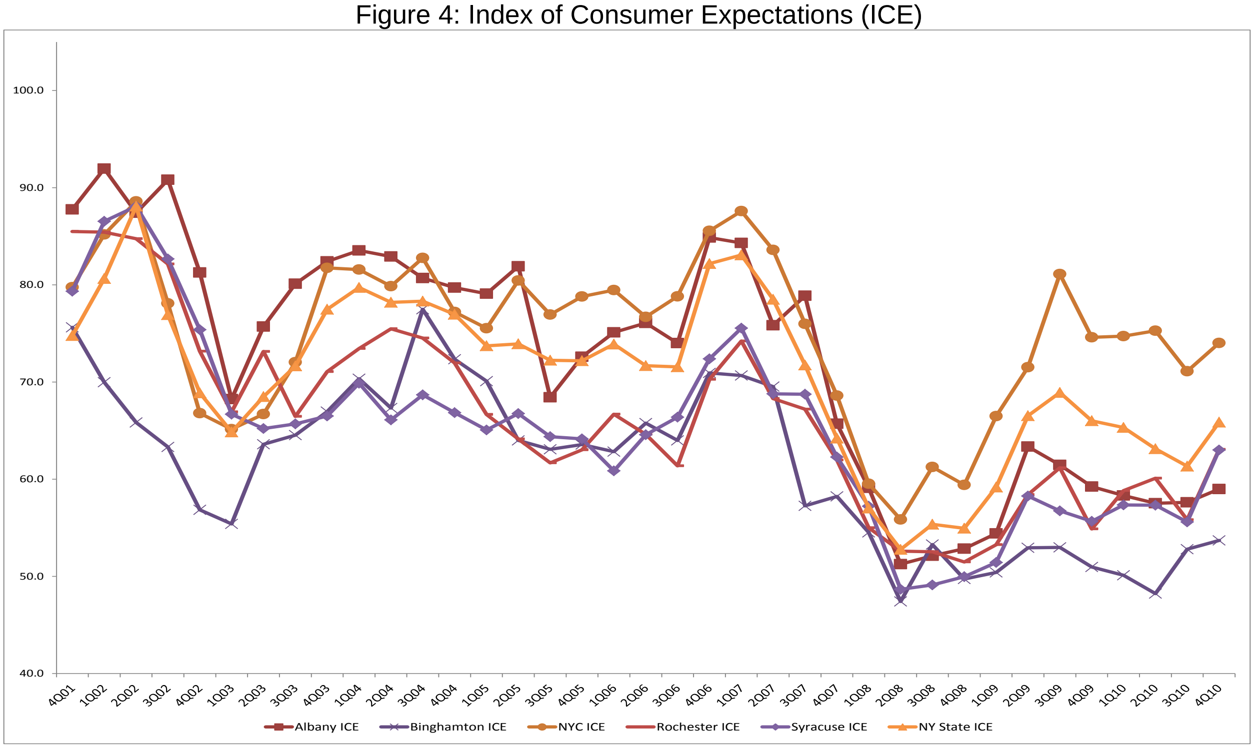
Source: Siena Research Institute

Figure 3: Index of Current Economic Conditions (ICC)



Source: Siena Research Institute

Figure 4: Index of Consumer Expectations (ICE)



Source: Siena Research Institute

study exploiting the panel features of the consumer sentiment data produced by the Siena Research Institute to explore its relationship with the unemployment rate. In addition, by combining the time series dimension with the cross-sectional dimension, the panel data help to reduce collinearity among the explanatory variables, increase the degrees of freedom, take care of the omitted variable problem, and give more variability and efficiency.

3.1 Estimation Technique

Based on the methods developed by Granger (1969) and popularized by Sims(1972), we can test causality, in the Granger sense, by using *F*-tests to determine whether lagged information on a stationary variable *Y* provides any statistically significant information about a stationary variable *X* in the presence of lagged *X*. If not, then "*Y* does not Granger-cause *X*." So we can test Granger causality using the following bivariate autoregressive-distributed lag model

$$y_{it} = \alpha_0 + \sum_{j=1}^{t} \alpha_j \, y_{it-j} + \sum_{j=0}^{t} \delta_j \, x_{it-j} + f_i + u_{it}$$

$$x_{it} = \beta_0 + \sum_{j=1}^{t} \beta_j \, y_{it-j} + \sum_{j=0}^{t} \gamma_j \, x_{it-j} + \mu_i + \varepsilon_{it}$$

where index i=1…N refers to the MSAs and t=1…T to the time periods. The disturbances u_{it} and ε_{it} are assumed to be independently and identically distributed with a zero mean. MSA specific effects are captured by f_i and μ_i. In the above model x Granger causes y if all δ_j are not equal to zero. Using the same argument y Granger causes x if all γ_j are not equal to zero. However, Engle and Granger (1987) have shown that, if the series *x* and *y* are cointegrated, the standard Granger causality test is misspecified. Also a cointegrating regression considers only the long-run property of the model, and does not deal with the short-run relation explicitly. To account for short-run dynamics and the long-run equilibrium simultaneously, we need to use an error correction model (ECM) (Engle and Granger, 1987). Our first step is to apply a unit root test to check for the stationarity of our data set. Based on our stationarity test results, we will test for the existence of a cointegrating relationship. In the presence of a cointegrating relationship, we would use an ECM model to explore short run dynamics and the long-run relation between variables.

3.2 Panel Unit Root Test

We check panel stationarity by using a panel unit root test using the LLC test developed by Levin et al. (2002). Though there are other panel unit root tests notably the IPS test by Im et al. (2003) and Fisher type tests by Maddala and Wu(1999) and Choi(2001), however, we are using the LLC test since our data set has only five MSAs and 37 time periods and Levin et al. requires $\frac{N}{T} \to 0 \; as \; T \to \infty$. Following Levin et al. (2001), in order to mitigate the impact of cross-sectional dependence, cross-sectional means are subtracted from the series. The panel unit root test results are shown in the table 2.

Table 2: Panel Unit Root Test Results for Unemployment rate, ICC, ICS and ICE

Variable	LLC Panel Unit root test	P-value	First Difference LLC Panel Unit root test	P-value
Unemployment Rate	-0.2977	0.3830	-4.9733***	0.0000
ICC	-0.1683	0.4332	-7.0349***	0.0000
ICS	-1.4750*	0.0701	-6.4866***	0.0000
ICE	-0.3402	0.3668	-4.8896***	0.0000

Notes:
* Rejects the null of a unit root at the 10% level
** Rejects the null of a unit root at the 5% level
*** Rejects the null of a unit root at the 1% level

Based on the LLC panel unit root test, we reject the null hypothesis of no unit root for the unemployment rate, the ICC and the ICE at the 1 percent level of significance; however, for the ICS it is not rejected at a 10 percent level of significance. On the other hand, using first differences we find all the series are stationary. Hence, the following analysis is based on first differenced data.

3.3 Panel Cointegration Test

Since the panel unit root tests presented above indicate that the variables are integrated of order one I(1), we test for cointegration using the panel cointegration test developed by Westerlund (2007) and Persyn and Westerlund (2008). It is an error correction based panel cointegration test and the tests are general enough to allow for a large degree of heterogeneity, both in the long-run cointegrating relationship and in the short-run dynamics, and dependence within as well as across the cross-sectional units. The results of the Westerlund panel conitegration tests between the unemployment rate and confidence indices using the optimal lag length selected by the Akaike Information Criterion (AIC) are presented below in table 3.

The test contains four cointegrations statistics, the first two (G_τ, G_α) are called group mean tests and the last two (P_τ, P_α) are called panel tests. The tests (G_τ , P_τ) are computed with the standard errors of the intercept term, estimated in a standard way and the tests (G_α , P_α) are based on the Newey and West

Table 3: Panel Cointegration Tests

	ICC		ICE		ICS	
Statistic	**Z-Value**	**P-Value**	**Z-Value**	**P-Value**	**Z-Value**	**P-Value**
G_τ	-4.671***	0.000	-1.352*	0.088	-3.319***	0.001
G_α	-2.746***	0.003	0.126	0.550	-1.182	0.119
P_τ	-4.701***	0.000	-1.372*	0.085	-3.278***	0.001
P_α	-5.142***	0.000	-1.247	0.106	-3.148***	0.001

Notes:
* Rejects the null of no cointegration at the 10% level
** Rejects the null of no cointegration at the 5% level
*** Rejects the null of no cointegration at the 1% level

(1994) adjusted standard errors for heteroscedasticity. Based on panel unit root cointegration tests, we convincingly reject the null hypothesis at 1 percent level of significance, indicating that the unemployment rate and ICC exhibit a cointegration relationship. We can draw similar conclusions about the relationship between the unemployment rate and the ICS. However, we failed to reject one of the null hypotheses. We failed to reject the null hypothesis for the cointegration test between the unemployment rate and the ICE, indicating that perhaps no significant cointegrating relationship exists between these two variables.

3.4 Error Correction Estimations

Engle and Granger (1987) showed that if two variables are cointegrated of the same order, then one needs to model the short-run dynamics and long-term relation between these two cointegrated variables using an error correction model. However, following Banerjee et al. (1993) it is advisable to use a generalized one step error correction model rather than the two step error correction model suggested by Engle and Granger. Banerjee et al.(1993) show that the one step error correction model is asymptotically equivalent to more complex full-information maximum-likelihood and fully modified estimators when the processes are weakly exogenous. Therefore the one step error correction model is efficient and unbiased, as well as consistent. The generalized error correction model is estimated in one step using the following equation.

$$\Delta y_{it} = \alpha_0 + \beta_0 \Delta x_{it} - \beta_1 (y_{i,t-1} - \beta_2 x_{i,t-1}) + \varepsilon_{i,t} \qquad (1)$$

The error correction term is given by $(y_{i,t-1} - \beta_2 x_{i,t-1})$ and its estimated coefficient β_1 gives the estimated error correction rate. If $(y_{i,t-1} - \beta_2 x_{i,t-1})$ equals 0, then x and y are in their equilibrium state. Any increase in x will cause a deviation from equilibrium and cause y to be too low. As a result y will increase a total of β_2 points in the long-run to correct for this disequilibrium, and β_1 percent of the deviation would be corrected in each subsequent time period. The short term contemporaneous adjustment is captured by β_0.

Following De Boef (2000), it can be shown by simple algebra that equation (1) can be estimated by the following equation.

$$\Delta y_{it} = \alpha_0 + \alpha_1 \Delta x_{it} - \gamma(y_{i,t-1} - x_{i,t-1}) + \theta x_{i,t-1} + \varepsilon_{i,t}$$

where the short-run adjustment, β_0 in equation (1), is measured by α_1 and the long-run equilibrium, β_2 in equation (1), is estimated by $(1 - \frac{\theta}{\gamma})$. However, the standard error for $\beta_2 = (1 - \frac{\theta}{\gamma})$ is not obtained directly from the one step error correction regression. The standard error is obtained by a Bewley transformation (Bewley, 1979, De Boef and Keele, 2008). It is computationally convenient for calculating the standard error for the long-run multiplier and is not meant to serve as a representation of the underlying dynamics. The Bewley transformation requires estimating the following regression

$$y_{it} = \alpha_0 + \alpha_1 \Delta y_{it} + \alpha_2 x_{i,t} - \alpha_3 \Delta x_{i,t} + u_{i,t}$$

where α_2 is the estimated long-run effect. However, Δy_{it} appears on the right side of above equation. Therefore we need to proxy Δy_{it} as

$$\Delta y_{it} = \alpha_0 + \beta_1 y_{it-1} + \beta_2 x_{it} + \beta_3 \Delta x_{i,t} + \epsilon_{i,t}$$

and we use the predicted value of Δy_{it} from above equation in the Bewley transformation regression.

The results of the corresponding error correction regressions between the unemployment rate and ICC and the unemployment rate and ICS are summarized in tables 4 and 5. They include coefficients of the regressions, the short-run effects and the calculated long-run effects along with the corresponding standard errors in brackets and the level of significance denoted by asterisks. The first column under dependent variables explores the impact of the confidence indices on the unemployment rate and the second column explores the other direction of causality.

The coefficients of the error-correction term give the adjustment rate at which a short-run disequilibrium converges to a long-run equilibrium. With respect to our model, it is the rate at which the gap between the unemployment rate and the confidence index is closed. All of these error-correction coefficients are negative and highly significant indicating that there exists a long-run relationship between these two variables and providing evidence of a the existence of a cointegrating relationship between the variables.

Table 4 : Short Run and Long-run Relationship between Unemployment Rate and ICC

Model	Dependent Variables	
	Δ ln unemp	**Δ ln ICC**
Constant	1.4277*** (0.09653)	0.52488** (0.147342)
Δ ln ICC	-0.11740*** (0.02039)	
Δ ln unemp		-0.29262** (0.074719)
($\ln unemp_{t-1}$ - $\ln ICC_{t-1}$)	-0.09898*** (0.00642)	
($\ln ICC_{t-1}$ - $\ln unemp_{t-1}$)		-0.13235*** (0.02831)
$\ln ICC_{t-1}$	-0.38371*** (0.02527)	
$\ln unemp_{t-1}$		-0.10386** (0.04229)
Short-run Coefficient (α_1)	-0.11740*** (0.02039)	-0.29262*** (0.07472)
Long-run Coefficient (1-θ/ϒ)	-2.87647*** (0.01405)#	0.21522*** (0.02188)#
F-test (model)	114.92*	26.63**
R^2 (within)	0.4483	0.1132
R^2 (between)	0.2847	0.4171
R^2 (overall)	0.4470	0.1014
Observations	180	180

Notes:

(1) Robust standard errors reported in parentheses
(2) *, ** and *** denote significance at 10%, 5% and 1% level
(3) # denotes standard errors are estimated by Bewley transformation.

3.5 Results

In the panel econometric literature there are debates about which particular panel technique to use. Often the choice is between fixed effect, random effect and dynamic panel models. Clearly in our dataset we have a dynamic relationship and hence it is reasonable to use dynamic panel estimations. However, dynamic panel estimations popularly developed by Arellano and Bond (1991) are designed for panels with relatively large cross-sections and small time series. But in our dataset we have large time series and relatively small cross-sections. Beck and Katz (2011) and Judson and Owen (1999) suggests that for cases with large time series and small cross-section it is advisable to use fixed effect panel estimations

Table 5: Short Run and Long-run Relationship between Unemployment Rate and ICS

Model	Dependent Variables	
	Δ ln unemp	**Δ ln ICS**
Constant	1.27481*** (0.09381)	0.45378*** (0.11216)
Δ ln ICS	-0.08141* (0.03605)	
Δ ln unemp		-0.15644 (0.08299)
($\ln unemp_{t-1}$ - $\ln ICS_{t-1}$)	-0.07399*** (0.00862)	
($\ln ICS_{t-1}$ - $\ln unemp_{t-1}$)		-0.11919*** (0.02183)
$\ln ICS_{t-1}$	-0.3393*** (0.02342)	
$\ln unemp_{t-1}$		-0.09012* (0.03315)
Short-run Coefficient (α_1)	-0.08141* (0.03605)	-0.15644 (0.08299)
Long-run Coefficient (1-θ/ϒ)	-3.58555*** (0.03725)#	0.24395*** (0.01845)#
F-test (model)	75.62***	27.59**
R^2 (within)	0.3561	0.0938
R^2 (between)	0.4954	0.1852
R^2 (overall)	0.3226	0.0863
Observations	180	180

Notes:

(1) Robust standard errors reported in parentheses
(2) *, ** and *** denote significance at the 10%, 5% and 1% level
(3) # denotes standard errors are estimated by Bewley transformation.

rather than dynamic panel estimations. The large time series takes care of the biases caused by the lagged dependent variable on the right side of the panel regressions. Therefore all of our results in this study are based on fixed effect panel estimations. The regression results are presented in tables 4 and 5. Table 4 regression results are obtained by estimating the following equations:

$$\Delta \ln unemp_{i,t} = \alpha_0 + \alpha_1 \Delta \ln ICC_{i,t} - \beta_1\left(\ln unemp_{i,t-1} - \beta_2 \ln ICC_{i,t-1}\right) + \theta ln\ ICC_{i,t-1} + \varepsilon_{i,t}$$

$$\Delta \ln ICC_{i,t} = \alpha_0 + \alpha_1 \Delta \ln unemp_{i,t} - \beta_1\left(\ln ICC_{i,t-1} - \beta_2 \ln unemp_{i,t-1}\right) + \theta ln\ unemp_{i,t-1} + \varepsilon_{i,t}$$

Similarly Table 5 results are obtained by estimating following equations:-

$$\Delta \ln unemp_{i,t} = \alpha_0 + \alpha_1 \Delta \ln ICS_{i,t} - \beta_1(\ln unemp_{i,t-1} - \beta_2 \ln ICS_{i,t-1}) + \theta ln\ ICS_{i,t-1} + \varepsilon_{i,t}$$

$$\Delta \ln ICS_{i,t} = \alpha_0 + \alpha_1 \Delta \ln unemp_{i,t} - \beta_1(\ln ICS_{i,t-1} - \beta_2 \ln unemp_{i,t-1}) + \theta ln\ unemp_{i,t-1} + \varepsilon_{i,t}$$

Based on first columns under the dependent variables heading in tables 4 and 5, we find that all the coefficients are highly significant at the 1 percent level of significance except for the coefficient on the change in the ICS in table 5 which is significant at 10 percent level. As expected the error correction terms are negative and significant, indicating that there is a long-run relationship between consumer confidence and the unemployment rate. It implies that whenever there are deviations from long-run equilibrium, the short-run adjustments in ICC and ICS would reestablish the long-run equilibrium. The speed of adjustment is given by the coefficients of the error-correction term. In the case of the causality from ICC to the unemployment rate, the adjustment rate is (-0.09898) or -9.8 percent, whereas from ICS to the unemployment rate the adjustment rate is (-0.07399) or -7.3 percent. The corresponding short-run effects are measured by the coefficients of (ΔlnICC) and (ΔlnICS). In our estimation results, the short-run coefficients (-0.11740) for ΔlnICC and (-0.08141) for ΔlnICS, are both negative and significant. It implies that in the short-run, both ICC and ICS have negative effects on the unemployment rate. It implies the higher the consumer confidence, either measured by ICC or ICS, the lower the unemployment rate is in the short-run. The long-run effects are measured by taking the ratio of the coefficients of the lagged independent variable and of the error correction term and then subtracting it from one. The long run effect of the ICC on the unemployment rate is (-2.87647) and for ICS on unemployment rate is (-3.58555). We find that the long-run effect of the ICC and the ICS are both negative and significant. Intuitively it means in the long-run, consumer confidence reflects general wellbeing in the economy, and hence it results in a reduction of the unemployment rate.

The results of the analysis of causality from the unemployment rate to the confidence indices are given in the second columns under the dependent variables heading in tables 4 and 5. In case of the causality from the unemployment rate to ICC, all the coefficients in table 4 are significant at the 5 percent level of significance at least. The results for causality from the unemployment rate to the ICS presented in table 5 are much more mixed. Though all the coefficients are negative, the coefficient of the change in the unemployment rate (Δlnunemp) is not significant and the coefficient of the lag unemployment rate (lnunemp_{t-1}) is significant only at the 10 percent level of significance. The rate of adjustment given by the coefficients of the error-correction term are (-0.13235) or -13.23 percent for causality from unemployment rate to ICC and (-0.11919) or -11.91 percent for causality from unemployment rate to ICS. The rate of adjustment, however, is faster than the reversed model. The short-run effect of the unemployment rate on confidence indices are negative for ICC and ICS, however, it is significant only for ICC. However, to our surprise the long-run effect is significant but positive. It is hard to interpret the positive long-run effect. One possible interpretation is that higher unemployment creates positive future expectations that eventually will cause unemployment to decrease to its natural rate in the long-run. Hence the unemployment rate has a positive impact on confidence.

4. Conclusion

The paper explores the short-run and long-run causal relationship between the New York State (NYS) unemployment rate and the consumer sentiments as measured by the Index of Consumer Sentiments (ICS) and its sub-indices the Index of Current Economic Conditions (ICC) and the Index of Consumer Expectations. The study uses a unique dataset collected by the Siena Research Institute (SRI). The SRI provides quarterly data for confidence indices across NYS MSAs and hence in the study we have been able to exploit both the cross-section and the time series aspects of the dataset and as a result we are able to reduce collinearity among the explanatory variables, increase the degrees of freedom, take care of the omitted variable problem, and obtain more variability and efficiency. The results suggest that there are strong causal relationships between the unemployment rate and the ICC and the ICS, however, the study failed to find any relationship between the unemployment rate and the ICE. With respect to the ICC and the ICS, the relationship between the unemployment rate and the ICC is much stronger than the relationship between the unemployment rate and the ICS. The effect of ICS is diluted by the fact that the ICE is not causally related with unemployment rate. The short-run causality between the unemployment rate and the ICC runs both ways and is negative. However, in the long-run the causality from the unemployment rate to the ICC is negative but the reverse causality is positive. We find a similar relationship between the unemployment rate and the ICS; however, the short run relationship between the ICS and the unemployment rate is not significant. Based on the results, both long-run and short-run causality from the ICS to the unemployment rate is much stronger than the reverse causality. We believe that the causal relationship between the unemployment rate and the confidence indices have important policy implications, especially for forecasting purposes. Both the unemployment rate and confidence indices can help us to predict the behavior of each other. We believe that the dataset collected by the SRI is underutilized and in the future perhaps the SRI dataset can be used for understanding the behavior of the NYS economy, especially the behavior of the unemployment rate.

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