Time Series Estimates of the Italian Consumer Confidence Indicator

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Abstract

This work shows that Italian consumer confidence indicator (*CCI*) is non-stationary and, therefore, can be estimated with the time series methods. It is found that a long-run relationship exists between *CCI*, short-term interest rate, industrial production index and the difference between perceived and measured inflation. The use of time series methods to estimate *CCI* for Italy is a novelty in the literature.

Keywords: Consumer confidence indicator, Short-term interest rate, Perceived rate of inflation, Cointegration.

JEL: C22, C32, D12.

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1. Introduction

The consumer confidence indicator (*CCI*) released by the EU Commission[1] for the Euro Area is widely used by economists and pratictioners to forecast private consumption. Monitoring future paths of consumption spending is important because it is more than 50% of the GDP. However, there is no consensus on the actual contribution of the *CCI* to predict private consumption spending; see Malgarini and Margani (2007) for a review. Although predicting consumer confidence measures appears dubious, *CCI* for Italy seems to have good forecasting performance for consumption spending.

Dreger and Kholodilin (2010) have examined the role of *CCI* in predicting private consumption expenditure for various countries and found that the gains for Italy is about 20%. Malgarini and Margani (2007) have provided evidence that lagged values of *CCI* can improve short-run behaviour of Italian consumption expenditure. For this reason, it appears interesting to explain the main factors driving *CCI*.

This paper examines a neglected issue concerning the time series properties of the key variables explaining *CCI* for Italy and in our specification these are the short-term interest rate (i), industrial production index (IP) and the gap between perceived and measured inflation ($DINF$). The justification for our selection is as follows. An increase in the rate of interest raises the cost of capital, increases liqidity constraints and the tightness in the credit markets. Therefore, confidence of individuals decrease as interest rates go up; see for example Praet and Vuchelen (1989). Industrial production is used as a proxy for GDP since we use monthly data and monthly data on GDP are not available. The idea is that a rise in GDP or its growth rate increases consumer confidence because of higher expected employment, incomes and optimism on the future prospects of the economy. On the other hand, as Golinelli and Parigi (2005) have noted, Italian households are very much concerned with

[1] See European Commission (2007) for details.

systematic perceptions of inflation rates exceeding the expted official rates. When inflation is perceived to be high relative to the official rate, the confidence of consumers declines because of the decline in the purchasing power of incomes. Therefore, the general specification of our model is $f(CCI, i, IP, DINF) = 0.$ Unit root tests with Italian data for 1985m1-2010m10 show that these four variables are I(1) in their levels[2]. Therefore, it is necessary to estimate the *CCI* with the time series methods. Thus, the main issue of this paper is whether there is a well defined cointegrating equation between these variables.

A word of caution is in order at the outset. Explaining consumer confidence is not simple because attitutdes depend on both objective and valotaile subjective factors. According to Mueller (1963) and Dion (2007) economic factors, at best, can explain about half of any consumer confidence measure because attitudes are influenced by non-economic factors. Therefore, our estimates are unlikely to give high adjusted R-bar squares. The remainder of the paper is organised as follows. Section 2 specifies the long and short run equations. Section 3 presents empirical estimates. Section 4 concludes.

2. Specification

Unit root tests with ADF and KPSS tests are in appendix (Table 1A) and show that *CCI*, *i*, *IP*, and *DINF* are I(1) in levels and I(0) in first differences. Therefore, we can estimate the long run relationship between them using the standard cointegration methods. In particular, we shall use four alternative methods: Phillips and Hansen's (1990) fully modified OLS (FMOLS), Park's (1992) canonical cointegrating regression (CCR), Stock and Watson's (1993) dynamic OLS (DOLS), and Johansen's (1998) maximum likelihood (JML). If these alternative methods give similar results, then, confidence in their estimates will increase.The long and short run relationships can be specified as:

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[2] Our sample period is based on the ready availability of data on *CCI*.

$$CCI = \alpha + \beta i + \gamma IP + \delta DINF + \phi DUM_{92-93} + \tau TREND + \varepsilon_t \\ \varepsilon_t \sim N(0,\sigma^2) \tag{1}$$

$$\Delta CCI_t = \lambda ECM_{t-1} + \sum_{i=1}^{n1} \varpi_i \Delta i_{t-i} \\ + \sum_{j=1}^{n2} \theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m} + \sum_{h=1}^{n4} \mu_h \Delta CCI_{t-h} \tag{2}$$

where DUM_{92-93} = dummy for 1992-1993 recession and *ECM* = residuals from equation (1). The exogenous deterministic trend is a part of the cointegrating equation and retained there because its coefficient is always significant. It is expected that $\beta < 0$, $\gamma > 0$, $\delta < 0$, $\phi < 0$, and $\tau < 0$. This last one emerges from the fact *CCI* historically shows a decreasing trend (see Figure 1A in appendix). It is also expected that in the dynamic equation (2), $\lambda < 0$ and statistically significant to enable the negative-feedback mechanisms to function.

3. Empirical Results

Equations (1) and (2) are estimated with the monthly Italian data from 1985m1-2010m10 for which data on *CCI* are available. Details on the definitions of variables and data sources are in the appendix. Table 1 presents estimates of equation (1) with FMOLS, CCR, DOLS, JML.

Table 1

Cointegrating Equations 1985m1-2010m10

$$CCI = \alpha + \beta i + \gamma IP + \delta DINF + \phi DUM_{92-93} + \tau TREND + \varepsilon_t$$

	FMOLS	*CCR*	*DOLS*	*JML*
Intercept	-38.528***	-38.662***	-41.029***	-27.797***
TREND	-0.091***	-0.091***	-0.082***	-0.121***
DINF	-2.139**	-2.142**	-2.159**	-2.178**
i	-1.123***	-1.120***	-0.951***	-1.815***
IP	0.501***	0.502***	0.501***	0.486***
DUM_{92-93}	-13.565***	-13.472***	-14.150***	-20.962***
EG Test		-4.931**		-
SL test				
None				61.46***
At most 1	-	-	-	30.14**
At most 2				5.28
At most 3				0.01

Notes: *** Significance at 10%; **Significance at 5%. EG = Engle-Granger *t*-test for cointegration. SL = Saikkonen and Lutkepohl (2000a, b, c) test for the cointegrating rank of a VAR process. FMOLS and CCR use the Newey-West automatic bandwith selection in computing the long-run variance matrix. In DOLS leads and lags are selected according to SIC criteria. The standard errors for DOLS are Newey-West corrected.

The estimates with the four alternative methods are somewhat similar. There are only small difference in the estimates of the coefficients γ and δ between various estimation techniques, whereas JML exhibits a larger value for the interest rate coefficient (β)[3]. The Engle and Granger cointegrating test (EG) shows that there is cointegration in the estimation with FMOLS, CCR and DOLS. Saikkonen and Lutkepohl test (2000a, b, c) indicates two cointegration relationships depending on the chosen level of statistical significance. If we consider the more restrictive (1

[3] The use of time series cointegration technique of *CCI* for Italy is a novelty in literature. For this reason our estimation results cannot be compared with other studies.

percent level), then SL test confirms the existence of only one cointegrating relationship.

Estimates of the short-run dynamic equations in (2), with the lagged ECM from four methods in Table 1, are in Table 2. All the estimates pass the diagnostic tests on residuals (normality (JB test), absence of heteroskedasticity (BPG test) and serial correlation (DW and BG)). In addition, it can be seen that the adjustment coefficient (λ) has the correct negative sign and is statistically significant in all the estimates. λ is very similar with ECMs from FMOLS, CCR and DOLS but a bit lower when the JML estimate is used. In conclusion, we can say that all the estimates confirm the existence of a long run relationship between *CCI*, *i*, *IP* and *DINF*.

Table 2

Summary: Dynamic Equations 1985m1-2010m10

$$\Delta CCI_t = \lambda ECM_{t-1} + \sum_{i=1}^{n1} \varpi_i \Delta i_{t-1} + \sum_{j=1}^{n2} \theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m}$$

	(1)	*(2)*	*(3)*	*(4)*
	FMOLS	*CCR*	*DOLS*	*JML*
ECM_{t-1}	-0.174 (0.045)***	-0.175 (0.045)***	-0.168 (0.045)***	-0.100 (0.036)***
$\bar{R}^2$	0.106	0.104	0.110	0.103
JB test	4.509 [0.105]	4.450 [0.108]	4.804 [0.091]	4.329 [0.115]
DW	2.00	1.99	2.00	1.98
BG test	2.19 [0.07]	2.18 [0.07]	2.20 [0.07]	2.07 [0.08]
BPG test	0.989 [0.4811]	0.991 [0.479]	0.987 [0.484]	1.096 [0.341]

Notes: Standard errors are below the coefficients in the paratheses and *p*-values are in square brackets. *** and ** signify significance at 1% and 5% levels, respectively. JB = Jarque Bera test for normality; DW = Durbin-Watson test for first order serial correlation of residuals; BG = Bresuch-Godfrey test for serial correlation of order p (in our case p = 4); BPG = Breusch-Pagan-Godfrey test for heteroskedasticity.

4. Conclusion

This paper has estimated the CCI for the Italy with time series methods and this is a novelty in the literature. Our estimates found a cointegrating relationship between *CCI*, *i*, *IP* and *DINF*. A possible development could be to extend similar time series methods to estimate the consumer confidence indicies for other countries for international comparisons.

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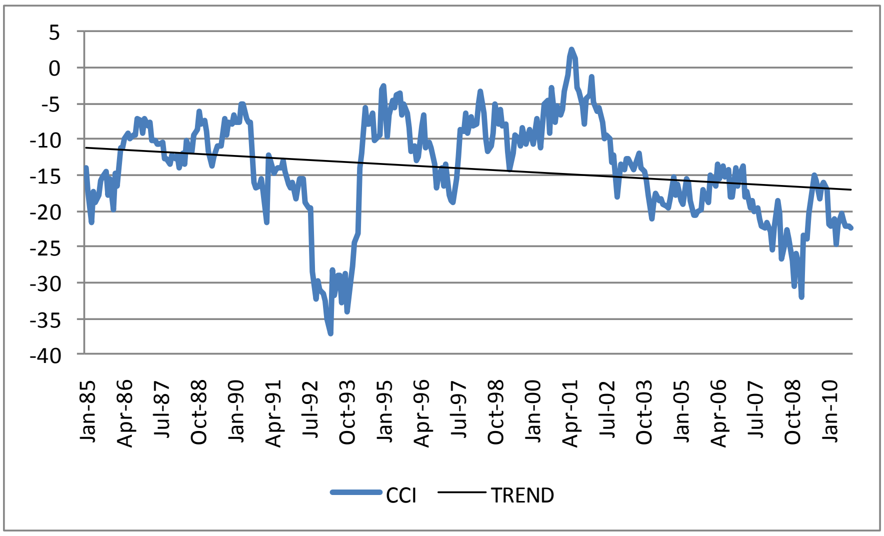
Appendix

Figure 1A: CCI historical pattern



$$CCI = -11.296 - 0.019TREND$$

Table 1A Unit Root Tests (sample 1985m1 – 2010m10)		
Variable	*ADF*	*KPSS*
CCI	-2.835	0.175**
ΔCCI	-21.656***	0.041
i	-1.569	1.981***
Δi	-10.188***	0.059
DINF	-2.348	1.227***
$\Delta DINF$	-18.174***	0.164
IP	-1.594	0.308***
ΔIP	-7.835***	0.317

Notes: *** Significance at 10%; **Significance at 5%. The $p_{\max}$ in ADF (Augmented Dickey-Fuller) test is selected according to the rule suggested by Schwert (1989): $p_{\max} = \text{int}\left(12(T/100)^{1/4}\right)$. The optimal number of lags is determined by using Schwartz Information Criterion (SIC), while in KPSS (Kwiatkowsky-Phillips-Schimdt-Shin) test the optimal number of lag is determined by Newey-West Bandwith using Bartlett kernel. The null hypothesis in ADF is that the variable is non-stationary and this is reversed in KPSS. The unit root tests on the variables *CCI* and *IP* for level are conducted including a constant plus a linear trend, whereas for other two variables only including a constant; this is because the presence of a trend is not consistent theoretically with long-run positive, but with non-accelerating interest rate and inflation.

Data Appendix

Data Source. Sample 1985m1 – 2010m10

Variable	Definition	Source
CCI	Consumer confidence index	European Commission

i	Short-term interest rate	OECD
IP	Industrial production index (edition January 2011)	OECD
$DINF$	Difference between inflation perceived (Questionnaire Q5 consumer survey of European Commission) and actual inflation (measured as $\ln\left[\frac{p_t}{p_{t-4}}\right]$ using CPI (OECD source)). Data are normalized before the subtraction.	European Commission and OECD