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Are Italian consumer confidence adjustments asymmetric? A macroeconomic and psychological motives approach

Antonio Paradiso [a,1], Saten Kumar [b,*], Patrizia Margani [c,2]

[a] Ca' Foscari University of Venice, Venice, Italy
[b] Auckland University of Technology, Auckland, New Zealand
[c] National Institute of Statistics (ISTAT), Rome, Italy

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ABSTRACT

This paper estimates the determinants of Italian consumer confidence indicator (*CCI*) using time series methods. We find there exists a long-run relationship between *CCI* and its determinants when an important political event 'operation clean hands', captured by a dummy, is considered. Using the asymmetric error correction model (Enders & Siklos, 2001), we find that consumers respond asymmetrically to different types of disequilibrium error under threshold autoregressive (TAR) adjustment specification. These findings are consistent with the psychological bias approach (Bovi, 2009).

1. Introduction

The consumer confidence indicator (*CCI*) released by the European Commission for the Euro Area is widely used by economists and practitioners to forecast private consumption. Monitoring the future paths of consumption spending is important because it contributes to the largest share of GDP. Numerous studies have attempted to explore the significance of *CCI* in predicting private consumption spending; however the findings are mixed and inconclusive. Most of the studies have focused on the US. For example Adams (1964), Kamakura and Gessner (1986), Kumar, Leone, and Gaskins (1995) and Allenby, Jen, and Leone (1996) find that consumers' confidence in the economy contributes significantly to the prediction of consumer expenditures. Alternatively, Carroll, Fuhrer, and Wilcox (1994) and Bram and Ludvigson (1998) present

* Corresponding author. Address: Department of Economics, Auckland University of Technology, Private Mail Bag 92006, Auckland 1142, New Zealand. Tel.: +64 9 6301563.

E-mail addresses: antonio.paradiso@unive.it (A. Paradiso), kumar_saten@yahoo.com (S. Kumar), pmargani@istat.it (P. Margani).

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evidence that *CCI* can improve the short-term forecast of consumption to a limited extent, while Croushore (2005) finds that *CCI* is completely ineffective in explaining future consumption patterns. In the case of Italy, existing evidence shows that *CCI* has a good forecasting performance. Dreger and Kholodilin (2011) investigate the role of *CCI* in predicting private consumption expenditure for various countries; for Italy, the gains in predicting capacity are about 20%. Malgarini and Margani (2007) show that the lagged values of *CCI* can improve the short-run behavior of Italian consumption expenditure.

This paper investigates the determinants of *CCI* for Italy over the period 1985m1–2010m10. The key variables used are *CCI*, short-term interest rate (*i*), industrial production index (*IP*) and the gap between perceived and measured inflation (*DINF*). The unit root tests indicate that *CCI* and *DINF* (*i* and *IP*) are stationary (non-stationary) in their levels and therefore we apply time series techniques that deal with the mixture of I(1) and I(0) variables to estimate the relationship between *CCI* and its determinants. The contribution of this paper is twofold. First, we find there exists a long-run relationship between *CCI*, *i*, *IP* and *DINF* when an important political event 'operation clean hands', captured by a dummy, is considered. We employ Pesaran, Shin, and Smith's (2001) autoregressive distributed lag model (ARDL) and the London School of Economics (LSE) Hendry's general to specific (GETS) (Hendry, 1995) time series techniques and we attain consistent results across the two methods. Second, using the asymmetric error correction model (Enders & Siklos, 2001), we find that consumers respond asymmetrically to different types of disequilibrium error under threshold autoregressive (TAR) adjustment specification. These findings are consistent with the psychological bias approach (Bovi, 2009). The above finding of threshold cointegration is quite surprising because *CCI* is a stationary dependent variable. Our intuition is that because some explanatory variables are non-stationary and hence cointegrated with each other, perhaps this may be the reason for existence of a threshold cointegration in the *CCI* model.

This paper is organized as follows. Section 2 provides a brief overview of the drivers of *CCI* and psychological sensitivity. Section 3 presents the data description and the unit root test results. Section 4 provides the methodological insights of symmetric and asymmetric models used in the empirical analysis. Section 5 details the empirical results. Section 6 concludes.

2. Consumer confidence drivers and psychological sensitivity

The *CCI* reflects public opinion about the state of the economy. This indicator is the arithmetic average of balances (over the next 12 months) of household finances, economic conditions, unemployment expectations and savings (see European Commission, 2007 for details). Katona (1975) argued that *CCI* is affected by economic and non-economic (psychological) factors. Since then several attempts have been made to investigate about the robust determinants of *CCI*. A first group of studies considered only the economic variables (for example, inflation, unemployment and interest rates) to explain the formation of consumers' confidence, for instance see Golinelli and Parigi (2004, 2005) and Vuchelen (2004). A second group of studies examined the *CCI* determinants using some international and/or socio-political factors, for example Vuchelen (1995), De Boef and Kellstedt (2004), Malgarini and Margani (2007) and Ramalho, Caleiro, and Dionfsio (2011). Among the above studies, Golinelli and Parigi (2004, 2005) and Malgarini and Margani (2007) used Italian data.

Golinelli and Parigi (2004) estimated a vector autoregressive (VAR) model for G7 countries over the period 1970Q1–2002Q1.[3] For Italy, they found a long-run relationship between *CCI*, inflation and the employment ratio. In another paper, Golinelli and Parigi (2005) found an unstable cointegrating relationship of *CCI* in Italy. Further, they asserted that including the inflation gap instead of inflation rate is crucial to attain a stable long-run relationship. Malgarini and Margani (2007) estimated the *CCI* model in first difference form over the period 1980Q1–2004Q4. They included explanatory variables such as GDP growth, interest rate, nominal exchange rate, debt-to-GDP-ratio and a series of dummy variables to capture the political electoral events and relevant international facts. Their findings suggested that consumer sentiment plays an important role in explaining consumption patterns of Italian households.

Empirical literature is silent on how consumers adjust their economic climate perception. In the context of psychology, permanent and widespread psychological biases affect both the subjective probability of future economic events and their retrospective interpretation (Bovi, 2009). Cognitive bias is defined as errors in the way the mind processes information causing the human brain to draw incorrect conclusions. These biases are common outcome of human thought in decision making (Tversky & Kahneman, 1974). Examples of cognitive biases in economic decision making are anchoring (Ariely, Loewenstein, & Prelec, 2003), availability heuristic (Sedlmeier, Hertwig, & Gigerenzer, 1998), conjuction fallacy (Charness, Karni, & Levin, 2010), false consensus effect (Engelmann & Strobel, 2000), confirmation bias (Jones, 2008), endowment effect and status quo bias (Ert & Erev, 2008), hyperbolic discounting (Benhabib, Bisin, & Schotter, 2010), optimism bias (Bracha & Brown, 2012), escalation of commitment and sunk cost fallacy (Camerer & Weber, 1999), money illusion (Fehr & Tyran, 2007), overconfidence (Moore & Healy, 2008), self-serving bias (Offerman, 2002), illusion of control (Charness & Gneezy, 2010) and Gambler's fallacy (Huber, Kirchler, & Stöckl, 2010). For a brief survey on cognitive biases in decision making process, see Hilbert (2012).

One of the most studied biases in the information processing literature is the anchoring and adjustment effect, see Epley and Gilovich (2004, 2006) and Mussweiler, Englich, and Strack (2004). Anchoring is a form of cognitive bias that affects

[3] Australia is also included in their sample.

judgments under uncertainty. Starting from an initial value agents seem to use this as an 'anchor', hence adjusting it to reach a more plausible value, even if the anchor is incorrect. The adjustment is frequently insufficient and so the final value is biased (Tversky & Kahneman, 1974).

From our perspective, anchoring occurs when agents form their confidence by adjusting from a starting point to yield a final point given by the long-run equilibrium. The starting point is the result of a partial computation of external news. The implication is that the confidence revisions are not smooth or continously adjusted. Rather, there may be a region of confidence in which there is a diminished incentive for adjustment by consumers. Confidence outside this region may instead bring swift adjustments. Accordingly, the econometric analysis needs to accommodate this potential non-linearity. A simply way to measure this bias empirically is to study the presence of asymmetry in the error correction process with respect to an equilibrium level. An optimistic consumer has a slow adjustment (i.e., confidence is anchored to higher levels) when disequilibrium is above the threshold (due to favorable news). Alternatively, a consumer has a quick recovery when disequilibrium is below the threshold (due to unfavorable news).

This paper investigates the presence of bias in the consumers' confidence. Application of the TAR specification shows that consumers tend to recover their confidence very quickly in the presence of unfavorable news. This implies that consumers' confidence is anchored on over-optimistic values which are consistent with other studies that agents are optimistically biased (Madsen, 1994; Tanner & Carlson, 2009).

3. Data description

We use monthly data for Italy. Following Golinelli and Parigi (2004, 2005), we transform the *CCI* as an index number (1995 = 100) and express it in the log-level form. Data on *CCI* is extracted from the European Commission survey database. It is based on the framework of the Joint Harmonised EU Programme of Business and Consumer Surveys for the period January 1985–October 2010. This indicator is defined as the arithmetic average of balances about four questions referring to the next twelve months, i.e. household financial situation, general economic conditions, unemployment and savings. Balances are calculated as the weighted difference between the percentages of respondents giving positive and negative replies; neutral answers are ignored (European Commission, 2007).[4] The other variables include *IP*, *DINF* and *i*. *IP* is expressed in log (multiplied with 100). *DINF* is calculated after normalizing the two measures of inflation (perceived and actual inflation). *i* is not transformed in any way, i.e. expressed in level. Details on data construction and sources are provided in Table A1 in Appendix A. A plot of the *CCI* is also plotted in Appendix A (Fig. A1).

The rationale for selecting the above variables (*CCI*, *IP* and *DINF*) is as follows. Praet and Vuchelen (1989) provided some useful discussion about the consumer confidence and interest rates. They argued that the confidence of individuals decreases as interest rate rises. In the same vein, higher interest rate raises the cost of capital, thereby increasing the liquidity constraints and the tightness in the credit markets. Industrial production is used as a proxy for GDP.[5] To this end, a rise in GDP or its growth rate increases consumers' confidence, that is, consumers expect higher employment and income and so they become optimist about the future prospects of the economy. Golinelli and Parigi (2005) argued that Italian households are concerned about the perceived inflation rates exceeding the expected official rates. In such situations, the confidence of consumers declines due to the decline in the purchasing power of income.

We construct a set of dummy variables to be used in our estimations. We construct a dummy (DUM_{92-94}) to capture some important political events in Italy.[6] The period 1992m9–1994m3 is characterized by some important facts in the Italian political scenario. In 1992 a pool of Italian magistrates began the investigations so called 'operation clean hands' against the Italian political corruption. The first clamorous event of this operation was the suicide of the Socialist Deputy Sergio Moroni in September 1992. Following this episode, a series of events took place until 1994. For example, Berlusconi entered the politics in March 1994 and this influenced agents' confidence. According to Malgarini and Margani (2007), political events may have a psychological impact on individuals.

The commitments' crisis in the Exchange Rate Mechanism (ERM) of the European Monetary System (EMS) effectively starts in September 1992 but it has a longer duration compared to our dummy (DUM_{92_94}). The Italian Lira was forced to

[4] For a comprehensive description, see Appendix A.

[5] Monthly data on GDP is not available.

[6] Our 'operation clean hands' dummy DUM_{92_94} is not ad-hoc dummy and covers a period of hostility (against political system), uncertainty and pessimism about the future diffused in the public opinion (Bull & Newell, 2005). With clean hands operation, Italian magistrates revealed the specifics of an institutionalized systems of bribes through which profits from state-owned enterprises had flowed to political officials. With the majority of Italy's ruling political class under investigation, uncertainty and pessimism spread throughout the country. Moroni's death, for confession in the suicide letter to the President of the Chamber of Deputies and his violent suicide act (rifle shot), has had an important impact on public opinion. In addition, the news and media played an important role in influencing public opinion during clean hands operation. Some of the previous episodes correlated to clean hands operation, comprised the politician Mario Chiesa's arrest in February 1992, had only a limited diffusion by media. In this phase of unoptimistic climate, Berlusconi's political entrance was perceived by Italian people as the 'new' and alternative respect to the old political class (Bull & Newell, 1995). His victory corresponds de facto to the end of Italy's First Republic and the end of transaction period perceived by electorate (Bull & Newell, 1995). It is not surprising that political events are more important in influencing the expectations and behavior of agents than some economic events, such as ERM crisis of 1992. Italy historically is characterized by weak and unstable political system. Italian governments in the post war period are characterized by political instability, scandal, and corruption. Studies that examined the Italian financial markets found that political events are particularly important compared to economic events (such as ERM crisis) in influencing the asset prices (Fratzscher & Stracca, 2009).

Table 1
Dummy variables entering in the short-run.

Events	Label	Specification
Political electoral events		
General elections held on June 1987	DUP87M6	1987m5 = 1, 1987m6 = 1, 1987m7 = 1; 0 elsewhere
General elections held on April 1992	DUP92M4	1992m3 = 1, 1992m4 = 1, 1992m5 = 1; 0 elsewhere
General elections held on March 1994	DUP94M3	1994m2 = 1, 1994m3 = 1, 1994m4 = 1; 0 elsewhere
General elections held on April 1996	DUP96M4	1996m3 = 1, 1996m4 = 1, 1996m5 = 1; 0 elsewhere
General elections held on May 2001	DUP01M5	2001m4 = 1, 2001m5 = 1, 2001m6 = 1; 0 elsewhere
General elections held on April 2006	DUP06M4	2006m3 = 1, 2006m4 = 1, 2006m5 = 1; 0 elsewhere
General elections held on April 2008	DUP08M4	2008m3 = 1, 2008m4 = 1, 2008m5 = 1; 0 elsewhere
Important domestic and international events		
Libyan missile attack against the Italian island of Lampedusa/Chernobyl nuclear disaster	DUI86M4	1986m4 = 1, 1986m5 = 1; 0 elsewhere
Nuclear power referendum	DUI87M11	1987m10 = 1, 1987m11 = 1, 1987m12 = 1; 0 elsewhere
Berlin wall fall	DUI89M11	1989m10 = 1, 1989m11 = 1, 1989m12 = 1; 0 elsewhere
Invasion of Kuwait (first Iraq war)	DUI90M8	1990m8 = 1, 1990m9 = 1,. . ., 1991m3 = 1; 0 elsewhere
End of communist regime in Russia	DUI91M12	1991m12 = 1, 1992m1 = 1; 0 elsewhere
Italy enters in the Eurozone	DUI99M1	1999m1 = 1, 1999m2 = 1; 0 elsewhere
Kosovo conflict	DUI99M3	1999m3 = 1, 1993m2 = 1,. . ., 1999m6 = 1; 0 elsewhere
Terrorist attack of 11 September	DUI01M9	2001m9 = 1, 2009m10 = 1; 0 elsewhere
The Euro begins circulation	DUI02M1	2002m1 = 1, 2002m2 = 1; 0 elsewhere
Second Iraq war	DUI03M3	2003m3 = 1, 2003m4 = 1; 0 elsewhere
Parliament approves law criminalizing illegal immigration and allowing citizens' patrols	DUI09M6	2009m6 = 1, 2009m7 = 1, 2009m8 = 1; 0 elsewhere

exit the ERM in September 1992 before rejoining it in November 1996. The length of this currency crisis is not compatible with our dummy used in the long-run relation (DUM_{92_94}: September 92–March 94).

Moreover, we construct dummies to capture the political electoral events and some other important domestic and international facts that occurred during the period under investigation (1985m1–2010m10). These events are considered to have only the short-run effects (see Malgarini & Margani, 2007; Ramalho et al., 2011). These dummies are presented in Table 1.

Political events are assumed to have an effect one month before and after considering that electoral campaigns (before election) and government formation and programme explanations (after election) may influence consumers' confidence. A similar argument is for nuclear referendum. The political campaigns by political forces for sustaining favorable or unfavorable position with respect to nuclear power and the subsequent effect of political discussions in the aftermath could affect consumers' confidence. For Berlin wall fall, we consider that the impact begins before the effective war fall (November 1989) because mass demonstrations against the government and the system in East Germany began at the end of September and continued until November 1989. With regard to the Euro circulation, we assume that the effect can be prolonged for one month later with respect to the effective data entrance (January 2002), since people took time to understand the lira/euro exchange rate and the importance of single money in the Europe. Lampedusa attack/Chernobyl disaster are the two important events that overlap with each other. It is assumed that nuclear disaster has effects for an additional month; some environmental disaster information was communicated in the aftermath.

Law about illegal immigration was discussed in the Parliament for three months (May–July 2009). Regarding the signs of the domestic and international effects, we expect that the war conflicts and nuclear disaster (DUI86M4, DUI90M8, DUI99M3, DUI01M9, DUI03M3) have negative impacts. The fall of oppressive political regimes (DUI89M11, DUI91M12) is expected to have a positive effect whereas the others (DUI87M11, DUI02M1, DUI09M6) are undefined a priori, i.e. the effect depends on the personal interpretation of the event. For the political electoral events, the sign also depends on the political views of the individuals.

In our estimation, DUM_{92_94} enters in the long-run relationship of *CCI*. When DUM_{92_94} is excluded from the long-run relationship, there occurs a large outlier in the mean reverting mechanism. Visual inspection of the long-run residuals shows that there are no structural changes (see Fig. A3 in Appendix A).[7] It is evident that there is only one large departure in the mean reverting process of residuals in correspondence of 1992:09–1994:03 (i.e., our 'clean hands' dummy). To this end, it is

[7] We attempt to estimate the long-run relationship substituting the DUM_{92_94} with a break dummy (DUMBREAK = 0 if t < September 2009 and 1 elsewhere). Results indicate that this break dummy is not statistically significant confirming that operation clean hands is only a temporary dummy.

sufficient to consider DUM_{92_94} to recover the mean reverting process over the sample period. The other dummies generally enter the short-run equations.[8] The international events received enormous media coverage. We choose these events (i.e., invasion of Kuwait, the Kosovo war, the terrorist attack of 11 September, the Euro circulation) following Malgarini and Margani (2007). Chernobyl disaster (which coincides with another important event, i.e. Lampedusa attack) was widely reported by Italian media and had a great impact on Italy influencing the anti-nuclear power movement inducing a popular referendum (Nuclear power referendum) that brought to the closure of all the existing nuclear stations (Koopmans & Duyvendak, 1995). The fall of Berlin wall and the end of communist regime had a huge and immediate impact on Italian political scenario (Bull & Newell, 1993) and consequently influenced agents' electorate. The second Iraq war and the decision of Italian government to take part was widely unpopular. The problem of immigrants and foreigners coming from the ex-Eastern-European-Bloc and from the African and Asian countries has exacerbated in Italy (see Triandafyllidou, 1999). Anxiety about the possible negative consequences of immigration on unemployment, on the one hand, and fear that the distinctiveness of Italian cultural identity might be blurred because of the influence of a large numbers of foreigners, on the other hand, led to significant negative opinions by population with regards to immigrants, with peaks of negative events against immigrants (see Calavita, 1994). For these reasons the introduction of a more rigid law against immigration was perceived positively by the Italian population.

4. Methods and specifications

4.1. Unit root tests

The integrated order of the time series is investigated by using the generalized least squares (GLS) based unit root test proposed by Carrion-i-Silvestre, Kim, and Perron (2009) (henceforth CKP). This test assumes multiple structural breaks under both the null and the alternative hypotheses. CKP considered the feasible point optimal statistic of Elliott, Rothenberg, and Stock (1996) and the class of *M*-tests introduced in Stock (1999) and analyzed in Ng and Perron (2001). The feasible point optimal statistic is given by:

$$P_T^{gls}(\lambda^0) = \{S(\bar{\alpha}, \lambda^0) - \bar{\alpha}S(1, \lambda^0)\}/s^2(\lambda^0) \tag{1}$$

where λ is the estimate of the break fraction, $\bar{\alpha} = 1 + \bar{c}/T$ ($\bar{c}$ is the noncentrality parameter) and $s^2(\lambda^0)$ is an estimate of the spectral density at frequency zero of υ_t. The M-class of tests is defined by:

$$MZ_\alpha^{GLS}(\lambda^0) = (T^{-1}\tilde{y}_T^2 - s(\lambda^0)^2)\left(2T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{-1} \tag{2}$$

$$MSB^{GLS}(\lambda^0) = \left(s(\lambda^0)^{-2}T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{1/2} \tag{3}$$

$$MZ_t^{GLS}(\lambda^0) = (T^{-1}\tilde{y}_T^2 - s(\lambda^0)^2)\left(4s(\lambda^0)^2T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{-1/2} \tag{4}$$

with $\tilde{y}_t = y_t - \hat{\psi}'z_t(\lambda^0)$, where $\hat{\psi}$ minimizes the objective function (see Eq. (4) in Carrion-i-Silvestre et al., 2009, p. 1759). For definition of $s(\lambda^0)^2$, see Eq. (6) in Carrion-i-Silvestre et al. (2009, p. 1759). Another statistic is a modified feasible point optimal test defined by:

$$MP_T^{GLS}(\lambda^0) = \left[c^{-2}T^2\sum_{t=1}^{T}\tilde{y}_{t-1}^2 + (1-\bar{c})T^{-1}\tilde{y}_t^2\right] \Big/ s(\lambda^0)^2 \tag{5}$$

Perron (1989) showed that the ability to reject a unit root decreases when the stationary alternative is true and an existing structural break is ignored. Since the work of Perron (1989), a number of structural break-based unit root tests have been developed in the time series literature, for example, Zivot and Andrews (1992), Lee and Strazicich (2003) and Lumsdaine and Papell (1997), among others. The CKP test is attractive compared to other structural break-based unit root tests because it allows for multiple breaks in the level and/or slope of the trend function under both the null and alternative hypotheses. This test also presents several tests (class of M-tests) which makes it easier to check for robustness of the results. Gauss 12.0 is used to perform the CKP test.

[8] The other two dummies (DUI89M11 (fall of the Berlin wall), DUI02M1 (Euro circulation)) enter only the short-run equations. We find that DUI02M1 is only a temporary dummy. DUI89M11 has no impact in the long-run and therefore it does not enter the ECM specification. DUM_{92_94} is the only dummy that is included in the long-run specification. Since all other dummies enter only the short-run equation, there is no problem of overlap because they capture only the short-run effects. Indeed, the short-run and long-run effects differ significantly. The partial overlap of dummies is common in econometric analysis. In addition, the partial overlap of political dummy events to important international events is not new, for example, Clarke and Stewart (1994) overlap many political events of US economy to important international events such as Vietnam conflicts and Gulf War in their ECM formulation. However, overlap in our case is quite minimal because DUP94M3 is not included in the estimations.

4.1.1. Symmetric specification

The long-run relationship of the symmetric version is specified as follows:

$$CCI_t = \alpha + \beta i_t + \varsigma DINF_t + \omega IP_t + \kappa DUM_{92-94} + \tau TREND + \varepsilon_t \varepsilon_t \approx N(o, \sigma^2) \tag{6a}$$

The unrestricted error correction version of Eq. (6a) is estimated using Pesaran et al.'s (2001) ARDL technique. Given the fact that *CCI* is a stationary dependent variable and some of the explanatory variables may be non-stationary, the ARDL bounds testing technique can be used. In this case, non-stationary time series techniques may not produce robust results. Ideally, a multivariate time series technique would have been feasible, however, to the best of our knowledge there is no such technique developed yet that could be suitably used on stationary dependent variable and non-stationary regressors. With prior information about the expected direction of the long-run relationship among the variables (see for example, Malgarini & Margani, 2007), *CCI* is treated as the dependent variable. For cointegration it is imperative that ΔCCI is modeled using the conditional unrestricted error correction model (ECM):

$$\begin{aligned}\Delta CCI_t = {} & \alpha + \theta CCI_{t-1} + \beta i_{t-1} + \varsigma DINF_{t-1} + \omega IP_{t-1} + \kappa DUM_{92-94} + \tau TREND + \sum_{k=1}^{p} \vartheta_k \Delta CCI_{t-k} + \sum_{l=0}^{q} \varphi_l \Delta i_{t-l} \\ & + \sum_{m=0}^{r} \delta_m \Delta DINF_{t-m} + \sum_{i=0}^{s} \psi_i \Delta IP_{t-i} + \sum_{j=1}^{N1} DUP_{j,t} + \sum_{h=1}^{N2} DUI_{h,t} \mu_t \end{aligned} \tag{6b}$$

where θ, β, ς and ω are long-run multipliers. Lagged values of ΔCCI and current and lagged values of Δi, $\Delta DINF$ and ΔIP model the short-run dynamic structure. *DUP* and *DUI* are dummies for political and domestic/international events, respectively.

Applying the *ARDL* technique comprises two simple steps, see Pesaran and Pesaran (1997, p. 304). The first step entails testing for the existence of a long-run relationship between the variables. The *F* tests are used to test for the existence of long-run relationships. When a long-run relationship is observed, the *F* test dictates which variable should be normalized. The asymptotic distributions of the *F*-statistics are non-standard under the null hypothesis of no cointegration relationship between the variables. The asymptotic critical values are provided in Pesaran and Pesaran (1997). If the computed *F* values fall outside the inclusive band, a conclusive decision could be drawn without knowing the order of integration of the variables. More precisely, the empirical analyses show that if the computed *F*-statistics are greater than the upper bound critical value, the null hypothesis of no cointegration is rejected and there exists a long-run relationship between the variables. If the computed *F*-statistics are less than the lower bound critical value, the null of no long-run relationship is not rejected. In the second step of *ARDL* technique, an additional two-step procedure is required to estimate the model. In the first stage the lag order in the *ARDL* model by either the Akaike Information Criteria (*AIC*) or the Schwarz Bayesian Criteria (*SBC*) is determined. In the second stage, the cointegrating vector is estimated with the *OLS*, i.e., the long-run coefficients. Furthermore, the final step entails estimating a short-run dynamic *ARDL* model.

For the purpose of robustness, we also apply the GETS technique. This procedure estimates the long-run and short-run counterparts simultaneously as follows[9]:

$$\begin{aligned}\Delta CCI_t = {} & \lambda(CCI_{t-1} - \varphi_0 - \varphi_1 i_{t-1} - \varphi_2 DINF_{t-1} - \varphi_3 IP_{t-1} - \varphi_4 DUM_{92-94} - \varphi_5 TREND) + \sum_{i=1}^{n1} \varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2} \theta_j \Delta IP_{t-j} \\ & + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m} + \sum_{k=1}^{n4} \mu_k \Delta CCI_{t-k} + \sum_{k=1}^{N1} DUP_{k,t} + \sum_{l=1}^{N2} DUI_{l,t} \end{aligned} \tag{7}$$

where λ is the speed of adjustment. It is assumed that *DUP* and *DUI* have only short-run effects, therefore they are not included in Eq. (6a) but included in Eq. (7). In this formulation it is expected that residuals of the long-run relation are stationary. Further, λ is expected to be less than zero and statistically significant. This parameter captures the negative feedback mechanism.

The long-run relationship is attained by imposing that all changes in the variables are zero and therefore Eq. (7) becomes:

$$CCI^* = \varphi_0 + \varphi_1 i^* + \varphi_2 DINF^* + \varphi_3 IP^* + \varphi_4 DUM_{92-94} + \varphi_5 TREND \tag{8}$$

4.1.2. Asymmetric specification

Conventional cointegration tests with linear adjustment are inappropriate if the dynamic adjustment of consumer confidence exhibits non-linear behavior. According to Enders and Granger (1998), the standard tests for cointegration have low power in the presence of mis-specified dynamics. In our case, linear specification would be inappropriate if the consumer confidence reacts more extensively to unfavorable changes than to comparable gains. Put simply, the standard tests for cointegration must be customized to account for the asymmetric behavior. According to Enders and Granger (1998) and Enders and Siklos (2001), a feasible way to introduce asymmetric adjustment is to allow the deviation from the long-run equilibrium behave as a threshold autoregressive (TAR) model. The simple version TAR model is:

[9] See Rao (2007) for details.

Table 2
Long-run equations 1985m1–2010m10.

$$\Delta CCI_t = \alpha + \theta CCI_{t-1} + \beta i_{t-1} + \varsigma DINF_{t-1} + \omega IP_{t-1} + \tau TREND + \sum_{i=1}^{p} \vartheta_i \Delta CCI_{t-i} + \sum_{j=0}^{q} \varphi_j \Delta i_{t-j} + \sum_{k=0}^{r} \delta_k \Delta DINF_{t-k} + \sum_{l=0}^{s} \psi_l \Delta IP_{t-l} + \mu_t \quad \text{ARDL}$$

$$\Delta CCI_t = \lambda(CCI_{t-1} - \phi_0 - \phi_1 i_{t-1} - \phi_2 DINF_{t-1} - \phi_4 TREND) + \sum_{i=1}^{n1} \varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2} \theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m} + \sum_{k=1}^{n4} \mu_k \Delta CCI_{t-k} \quad \text{GETS}$$

	ARDL	GETS
Intercept	0.162***	3.471***
	(0.050)	(0.968)
TREND	−0.002***	−0.001***
	(0.000)	(0.000)
DINF	−0.034***	−0.035**
	(0.007)	(0.018)
i	−0.013	−0.027***
	(0.008)	(0.007)
IP	0.008	0.003
	(0.006)	(0.002)
EG test	–	−3.900
ARDL test	1.258	–
	(4.378)	

Notes: Standard errors in parenthesis. EG is the Engle–Granger test for cointegration. ARDL is the bounds cointegration test and the computed F statistic is reported. The 95% critical value is reported in the parenthesis.
** Significance at 5%.
*** Significance at 1%.

$$\Delta\varepsilon_t = I_t\rho_1(\varepsilon_{t-1} - th) + (1 - I_t)\rho_2(\varepsilon_{t-1} - th) + \upsilon_t \tag{9}$$

$$I_t = \begin{cases} 1 & \text{if } \varepsilon_{t-1} \geqslant th \\ 0 & \text{if } \varepsilon_{t-1} < th \end{cases} \tag{10}$$

where ε is the residual of the long-run relationship, I is the Heaviside indicator and th is the value of the threshold. Enders and Siklos (2001) showed that the residual ε can be estimated employing the OLS method.[10]

Since the exact nature of non-linearity is not known, it is therefore possible to allow the adjustment to depend on the change in ε_{t-1} ($\Delta\varepsilon_{t-1}$). In this case, the Heaviside indicator in Eq. (10) becomes:

$$I_t = \begin{cases} 1 & \text{if } \Delta\varepsilon_{t-1} \geqslant th \\ 0 & \text{if } \Delta\varepsilon_{t-1} < th \end{cases} \tag{11}$$

This model is called momentum-threshold autoregressive (M-TAR) model. It allows a variable to display differing amounts of autoregressive decay depending on whether it is increasing or decreasing (see Enders & Granger, 1998). The F-statistics for the null hypothesis $\rho_1 = \rho_2 = 0$ using the TAR specification of Eq. (10) and M-TAR specification of (11) are called Φ_ε and Φ_ε^*, respectively. The Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) are used to select the appropriate threshold model.

Asymmetric adjustments are present when the magnitudes of ρ_1 and ρ_2 are different. If the null hypothesis $\rho_1 = \rho_2 = 0$ is rejected, it is possible to test for symmetric adjustment using a standard F-test. If the errors in Eq. (9) are serially correlated, it is possible to use a TAR or M-TAR specification with lagged values of $\Delta\varepsilon_t$ for the residuals. To this end, Eq. (9) is replaced by the following equation:

$$\Delta\varepsilon_t = I_t\rho_1(\varepsilon_{t-1} - th) + (1 - I_t)\rho_2(\varepsilon_{t-1} - th) + \alpha_1\Delta\varepsilon_{t-1} + \upsilon_t \tag{12}$$

The critical values to test the null hypothesis of cointegration are tabulated by Enders and Siklos (2001) and successively re-tabulated by Wane, Gilbert, and Dibooglu (2004) for more specific cases (that is, more than two variable case). The threshold value th is estimated using the Chan (1993) method (see Enders & Siklos, 2001). The $\{\varepsilon_t\}$ ($\{\Delta\varepsilon_t\}$ in the case of M-TAR) sequence is arranged in ascending order. The largest and smallest 15% of $\{\Delta\varepsilon_t\}$ are discarded and the remaining 70% are considered as threshold in Eqs. (10) and (11). A threshold estimate is appropriate when it yields the lowest residual sum of squares.

[10] For mantaining coherence with their method, we follow their approach and use OLS to estimate the cointegrating relationship. OLS estimates are consistent with the estimates from other methods, see Tables 2 and 5.

Table 3
Long-run equations 1985m1–2010m10.

$$\Delta CCI_t = \alpha + \theta CCI_{t-1} + \beta i_{t-1} + \varsigma DINF_{t-1} + \omega IP_{t-1} + \kappa DUM_{92-94} + \tau TREND + \sum_{k=1}^{p}\vartheta_k \Delta CCI_{t-k} + \sum_{l=0}^{q}\varphi_l \Delta i_{t-l} + \sum_{m=0}^{r}\delta_m \Delta DINF_{t-m} + \sum_{i=0}^{s}\psi_i \Delta IP_{t-i} + \sum_{j=1}^{N1} DUP_{j,t} + \sum_{h=1}^{N2} DUI_{h,t}\mu_t \qquad \text{ARDL}$$

$$\Delta CCI_t = \lambda(CCI_{t-1} - \phi_0 - \phi_1 i_{t-1} - \phi_2 DINF_{t-1} - \phi_3 DUM_{92-94} - \phi_4 TREND) + \sum_{i=1}^{n1}\varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2}\theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3}\vartheta_m \Delta DINF_{t-m} + \sum_{k=1}^{n4}\mu_k \Delta CCI_{t-k} + \sum_{k=1}^{N1} DUP_{k,t} + \sum_{l=1}^{N2} DUI_{l,t} \qquad \text{GETS}$$

	ARDL	GETS
Intercept	8.744***	3.161***
	(0.965)	(0.549)
TREND	−0.002***	−0.001***
	(0.000)	(0.000)
DINF	−0.027***	−0.022**
	(0.007)	(0.010)
i	−0.023***	−0.019***
	(0.005)	(0.004)
IP	0.002***	0.004***
	(0.000)	(0.001)
DUM_{92-94}	−0.195***	−0.171***
	(0.035)	(0.033)
EG test		−5.233
ARDL test	7.550	
	(4.378)	

Notes: Standard errors in parentheses. EG is the Engle–Granger test for cointegration. ARDL is the bounds cointegration test and the computed F statistic is reported. The 95% critical value is reported in the parenthesis.
** Significance at 5%.
*** Significance at 1%.

If the hypothesis of stationarity is accepted and the diagnostic checks on the residuals are satisfactory, the ECM specification is built as follows:

$$\Delta CCI_t = b_0 + \lambda_1 I_t(\varepsilon_{t-1} - th) + \lambda_2(1 - I_t)(\varepsilon_{t-1} - th) + \sum_{i=1}^{n1}\varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2}\theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3}\vartheta_m \Delta DINF_{t-m} + \sum_{h=1}^{n4}\mu_h \Delta CCI_{t-h} + \sum_{k=1}^{N1} DUP_{k,t} + \sum_{l=1}^{N2} DUI_{l,t} \qquad (13)$$

To examine robustness, Eq. (13) can be subjected to diagnostic (absence of serial correlation, heteroscedasticity and non-normality in the residuals) and stability (break) tests. For the latter, the Quandt–Andrews structural break point test is used.

5. Empirical results

5.1. Unit root tests

The integrated properties of the series are tested using the CKP test ($P_T^{gls}(\lambda^0)$, $MZ_\alpha^{GLS}(\lambda^0)$, $MSB^{GLS}(\lambda^0)$, $MZ_t^{GLS}(\lambda^0)$ and $MP_T^{GLS}(\lambda^0)$). Table A2 in Appendix A presents the unit root test results for *CCI*, *i*, *IP* and *DINF*. We test for a maximum of 3 structural breaks when deterministic time trend is included in the test regressions. The test results point to trend stationary processes in *CCI* and *DINF*. The test statistics are less negative than the critical values implying that the unit root null can be rejected at the 5% level. For *i* and *IP*, majority of the tests show that they are non-stationary. The only exceptions are $MZ_\alpha^{GLS}(\lambda^0)$ and $MP_T^{GLS}(\lambda^0)$ tests for *i* and $MP_T^{GLS}(\lambda^0)$ test for *IP*, pointing the trend stationarity in the series. The endogenous break dates yield by each test is plausible; most breaks correspond to the dummies we constructed (see Table 1 for details). As the *CCI* series cannot move freely between minus and plus infinity, the indicator is bounded and should be stationary as

Table 4
Symmetric short-run equations 1985m1–2010m10.

$$\Delta CCI_t = b_0 + \lambda ECM_{t-1} + \sum_{l=1}^{n1} \varpi_l \Delta i_{t-l} + \sum_{i=1}^{n2} \theta_i \Delta IP_{t-i} + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m} + \sum_{k=1}^{n4} \mu_k \Delta CCI_{t-k} + \sum_{j=1}^{N1} DUP_{j,t} + \sum_{h=1}^{N2} DUI_{h,t} \qquad \text{ARDL}$$

$$\Delta CCI_t = \lambda(CCI_{t-1} - \phi_0 - \phi_1 i_{t-1} - \phi_2 DINF_{t-1} - \phi_3 DUM_{92-94} - \phi_4 TREND) + \sum_{i=1}^{n1} \varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2} \theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3} \vartheta_m \Delta DINF_{t-m} + \sum_{k=1}^{n4} \mu_k \Delta CCI_{t-k} + \sum_{k=1}^{N1} DUP_{k,t} + \sum_{l=1}^{N2} DUI_{l,t} \qquad \text{GETS}$$

	ARDL	GETS
ECM_{t-1}	−0.235***	−0.249***
	(0.061)	(0.041)
DUP94M3	0.076***	0.072***
	(0.014)	(0.019)
DUP01M5	0.028***	0.052***
	(0.009)	(0.017)
DUI02M1	0.032**	0.039*
	(0.012)	(0.021)
DUI09M6	0.042***	0.062***
	(0.010)	(0.018)
$\overline{R}^2$	0.25	0.22
JB test	2.021	4.004
	[0.24]	[0.13]
BG(1) test	0.072	0.771
	[0.53]	[0.38]
BG(6) test	0.730	1.143
	[0.22]	[0.34]
BG(13) test	3.632	0.954
	[0.19]	[0.50]
BGP test	0.088	1.358
	[0.79]	[0.14]

Notes: Standard errors are below the coefficients in the paratheses and *p*-values are in square brackets. JB = Jarque Bera test for normality; BG(*p*) = Bresuch–Godfrey test for serial correlation of order *p*; BGP = Breush–Pagan–Godfrey heteroskedasticity test. In ECM equations lag length (starting from a maximum of 12 lags, since we are working with monthly data) are selected according to a 'testing down' process; all variables with coefficients that are not statistically significant are eliminated, leading to a simpler specific congruent model that ecompasses rival models (Hendry, 1995, p. 365).
* Significance at 10%.
** Significance at 5%.
*** Significance at 1%.

predicted by CKP test. The same holds for the *DINF* series. The *CCI* and *DINF* series show a fluctuating pattern (see Figs. A1 and A2 in Appendix A). The first differences of all series are stationary.[11]

5.2. Long-run relationship of CCI

Since the CKP unit root tests confirmed that *CCI* and *DINF* (*i* and *IP*) are trend stationary (non-stationary) in levels, we can estimate the long-run relationship of *CCI* using Pesaran et al.'s (2001) ARDL and Hendry's (1995) GETS methods. Both the methods can be used regardless of whether the variables are I(1) or I(0) or mixed (Rao, 2007). Initially, we consider only the macro-variables in estimating Eqs. (6b) and (7), i.e. excluding the dummies. Table 2 presents estimates of these versions.[12]

The ARDL technique is applied to test for the existence of a long-run relationship between the variables (excluding the dummy variable). This determines whether a long-run relationship exists between *CCI*, *i*, *IP* and *DINF*. The optimal lag order is selected following the minimum values of both *AIC* and *SBC* criterion. Both indicated a lag length of 2 periods. The existence of a long-run relationship between the variables is tested using the *F* test. We found that the computed *F* statistic (1.258) is less than the upper bound of the 95% critical value (4.378) resulting in the acceptance of the null hypothesis of no long-run relationship. This implies that the single-equation formulations do not exhibit a long-run relationship of

[11] These results are not reported to conserve space.
[12] Eviews 7.0 is used to estimate the ARDL and GETS equations.

Table 5
Asymmetric cointegration test statistics for *CCI*.

Estimates of long-run model (OLS method)		
$CCI_t = \beta_0 + \beta_1 DINF_t + \beta_2 i_t + \beta_3 IP_t + \beta_4 TREND + \beta_5 DUM_{92-94} + \varepsilon_t$		
Intercept	2.319***	
	(0.187)	
DINF	−0.025***	
	(0.004)	
i	−0.011***	
	(0.001)	
IP	0.005***	
	(0.000)	
TREND	−0.001***	
	(0.000)	
DUM_{92-94}	−0.186***	
	(0.011)	
Asymmetric Dickey–Fuller equation	TAR	M-TAR
$\Delta\varepsilon_t = I_t\rho_1(\varepsilon_{t-1}) + (1 - I_t)\rho_2(\varepsilon_{t-1}) + \alpha_1\Delta\varepsilon_{t-1} + \upsilon_t$		
ρ_1	−0.123***	−0.097*
	(0.047)	(0.059)
ρ_2	−0.352***	−0.273***
	(0.063)	(0.049)
α_1	−0.166***	−0.189***
	(0.055)	(0.056)
th	−0.0427	0.0080
BG(1) LM test	0.012	2.430
	[0.91]	[0.12]
BG(6) LM test	0.165	0.937
	[0.99]	[0.47]
BG(13) LM test	0.704	1.250
	[0.76]	[0.24]
$\rho_1 = \rho_2 = 0$ (Φ_ε or Φ_ε^*)	17.937***	16.105***
$\rho_1 = \rho_2$ (*F-test*)	8.991***	5.616***
BIC	−4.191	−4.188

Notes: Standard errors are below the coefficients in the parenthesis and *p*-values are in square brackets. *th* is the threshold level endogenously determined according to Chan's (1993) method. BG(*p*) = Bresuch–Godfrey test for serial correlation of order *p*. $\rho_1 = \rho_2 = 0$ is the *F*-statistic for the null hypothesis of no threshold cointegration; 5% critical values for Φ_ε (TAR) and Φ_ε^* (M-TAR) is 12.241 and 13.481, respectively. The critical values for Φ_ε and Φ_ε^* are simulated according with Wane et al. (2004) approach. $\rho_1 = \rho_2$ is the *F*-statistic that the two coefficients are equal.
** Significance at 5%.
* Significance at 10%.
*** Significance at 1%.

consumer confidence. A similar result is obtained if we perform a residual-based cointegration test applied to the long-run relation in the GETS formulation. MacKinnon (1991) reports computed critical values of ADF test statistics for cointegration for all sample sizes. Further, the coefficient of *IP* (*i* and *IP*) in GETS (ARDL) technique is (are) statistically insignificant at the conventional levels. For these reasons, we argue that macro-variables do not produce a statistically significant cointegrating relationship of consumer confidence. To this end, we extend the *CCI* model to include a dummy variable (DUM_{92-94}) to capture the impacts of exceptional political events of 1992–1994 ('operation clean hands'). The ARDL technique indicated there exists a stable long-run relationship of *CCI* when DUM_{92-94} is incorporated in the model. The computed *F* statistic (7.550) is higher than the upper bound of the 95% critical value (4.378). Residual-based cointegration test applied in the long-run specification of GETS version confirms the presence of a cointegrating relation; ADF cointegration test shows a value −5.233. Table 3 displays these results of *CCI* augmented with DUM_{92-94}.

The estimates in Table 3 are fairly consistent across the two estimation methods. The use of a deterministic trend in the long-run equation seems to capture the possible influence of non-economic exogenous factors on consumer confidence, such as trust in the country's political institutions. Trend is a temporary phenomenon and not in the true data generating process; however, we retain it to improve the fit of the model. The use of trend in *CCI* model is consistent with De Boef and Kellstedt (2004) and Pharr, Putnam, and Dalton (2001).[13]

[13] Also see Paradiso and Rao (2011).

Table 6
Estimates of asymmetric error correction for *CCI*.

ECM formulation:

$$\Delta CCI_t = b_0 + \lambda_1 I_t(\varepsilon_{t-1}) + \lambda_2(1 - I_t)(\varepsilon_{t-1}) + \sum_{i=1}^{n1}\varpi_i \Delta i_{t-i} + \sum_{j=1}^{n2}\theta_j \Delta IP_{t-j} + \sum_{m=1}^{n3}\vartheta_m \Delta DINF_{t-m} + \sum_{h=1}^{n4}\mu_h \Delta CCI_{t-h} + \sum_{k=1}^{N1} DUP_{k,t} + \sum_{l=1}^{N2} DUI_{l,t}$$

	TAR	M-TAR
λ_1	-0.147^{***}	-0.199^{***}
	(0.051)	(0.064)
λ_2	-0.400^{***}	-0.257^{***}
	(0.071)	(0.051)
DUP94M3	0.072^{***}	0.073^{***}
	(0.017)	(0.017)
DUP01M5	0.044^{***}	0.049^{***}
	(0.017)	(0.018)
DUI02M1	0.038^{*}	0.039^{*}
	(0.020)	(0.021)
DUI09M6	0.059^{***}	0.060^{***}
	(0.017)	(0.018)
$\overline{R}_2$	0.253	0.233
JB test	3.555	4.253
	[0.17]	[0.12]
BG(1) test	0.326	0.120
	[0.57]	[0.73]
BG(6) test	0.517	0.545
	[0.79]	[0.77]
BG(13) test	0.392	0.523
	[0.97]	[0.91]
BGP test	1.119	1.174
	[0.33]	[0.28]
$\lambda_1 = \lambda_2$ *(F-test)*	8.008	0.522
	[0.01]	[0.47]

Notes: Standard errors are below the coefficients in the parenthesis and *p*-values are in square brackets. JB = Jarque Bera test for normality; BG(*p*) = Bresuch–Godfrey test for serial correlation of order *p*; BGP = Breush–Pagan–Godfrey heteroskedasticity test. In ECM equations lag length (starting from a maximum of 12 lags, since we are working with monthly data) are selected according to a “testing down” process; all variables with coefficients that are not statistically significant are eliminated, leading to a simpler specific congruent model that encompasses rival models (Hendry, 1995, p. 365). $\lambda_1 = \lambda_2$ is the *F*-statistic that the two coefficients are equal.
** Significance at 5%.
* Significance at 10%.
*** Significance at 1%.

5.3. Short-run relationship of CCI

Estimates of the short-run dynamic equations with the lagged ECM are presented in Table 4. These have been estimated using the ARDL and GETS techniques.[14] Results show that the adjustment coefficients (λ) have the correct negative sign and are statistically significant in all cases. λ is very similar in both techniques. The standard diagnostic tests on residuals show absence of serial correlation (Breuch–Godfrey test) and heteroscedasticity (Breush–Pagan–Godfrey test). The residuals have a normal distribution (Jarque Bera test) in both cases. Both techniques seem to yield consistent estimates of the symmetric short-run error correction models.

5.4. Threshold cointegration tests

In what follows we apply the threshold cointegration tests to ascertain the links between *CCI* and its determinants. We recognize that the stationary variables (*CCI* and *DINF*) are embedded into the model with non-stationary variables (*i* and *IP*). In such case, a stability test is mandatory to verify robustness of the results. Therefore, in the final stage we employ the Quandt–Andrews stability tests to confirm our findings. Table 5 presents the cointegration test results assuming threshold and momentum adjustments.[15] The Breusch-Godfrey autocorrelation test performed at different lags (1, 6 and 13) indicates

[14] Since *CCI* is an I(0) series, differencing *CCI* results in over-differencing and this may have other implications. For brevity, we do not detail these implications.
[15] RATS 7.10 is used for testing threshold cointegration and estimating the adjustment equations.

Table 7
Quandt–Andrews structural break tests (asymmetric model), 1985m1–2010m10.

Statistics	TAR specification			M-TAR specification		
	Value	Break	Prob.	Value	Break	Prob.
Max LR *F*-stat	1.561	2006M10	1.00	1.723	2006M10	1.00
Max Wald *F*-stat	23.422	2006M10	0.56	25.853	2006M10	0.39
Exp LR *F*-stat	0.433	–	1.00	0.420	–	1.00
Exp Wald *F*-stat	8.709	–	0.56	10.019	–	0.35
Ave LR *F*-stat	0.835	–	1.00	0.783	–	1.00
Ave Wald *F*-stat	12.530	–	0.74	11.746	–	0.82

Note: Probabilities calculated using Hansen's (1997) method. Eviews 7.2 was used to perform this test.

that the threshold models (TAR and M-TAR) are correctly specified. The estimated Φ_ε and Φ^*_ε statistics are 17.937 and 16.105, well above the critical values at 5% level.[16] We reject the null hypothesis of unit root in favor of cointegration with asymmetric adjustment between *CCI*, *IP*, *DINF* and *i*. Despite the presence of cointegration in both TAR and M-TAR models, the BIC criterion favors the TAR specification. The F-statistics for the null hypothesis of symmetric adjustment ($\rho_1 = \rho_2$) reject symmetric adjustment for TAR and M-TAR at the 1% level. According to Enders and Siklos (2001), the M-TAR model is expected to have more power than the TAR model, even if the true adjustment is driven by a TAR process. Although the BIC criterion favors TAR specification, in what follows we focus on both specifications to examine if there exists different ECM formulations.

The estimates of ρ_1 and ρ_2 imply substantially faster convergence for negative (below threshold) deviations from long-run equilibrium than the positive (above threshold) deviations. However, the asymmetry is not defined in terms of positive versus negative deviations from the long-run equilibrium but instead it is the rate of change of deviations from long-run equilibrium that are below or above a certain threshold. Table 6 presents the estimates of the error correction model. All diagnostic tests (absence of serial correlation, heteroscedasticty and non-normality in the residuals) appear to be satisfactory. Upstream and downstream adjustments appear in the 'right' direction in both TAR and M-TAR models. In TAR model, consumer confidence adjusts by about 15 (40) percent of an above (below) threshold deviation from the long-run equilibrium. This implies that an optimistic view is restored in more than 6 months, whereas a pessimistic view is restored in less than 3 months. In contrast, the speed of adjustments (λ_1 and λ_2) in the M-TAR model is quite consistent. To this end, the M-TAR model predicts that consumer confidence adjusts by about 20 (26) percent of an above (below) threshold deviation from the long-run equilibrium, thus implying that an optimistic (pessimistic) view is restored in about (less than) 5 (4) months. Based on the findings of the TAR model, we argue that consumer confidence reacts somewhat more extensively to unfavorable than to favorable changes. However, this is not the case in the M-TAR model because the speed of adjustments is quite similar. The F-statistic indicates that λ_1 and λ_2 are symmetric in the M-TAR model.

CCI is a trend stationary dependent variable, therefore it may not be required for the equilibrium adjustments. From this perspective, the above results are quite surprising. However, our intuition is that because *i* and *IP* are non-stationary series and hence cointegrated with each other, perhaps this may be the reason for existence of threshold cointegration in the *CCI* model.

Moreover, we performed the stability tests for our estimated equations in Table 6. In doing so, we used the Quandt–Andrews structural break tests. Table 7 displays the results. The Quandt–Andrews structural break tests show that our estimates of TAR and M-TAR models are stable over the period 1985m1–2010m10. The stability of *CCI* relationship is also supported by Golinelli and Parigi (2004). They argued that including the inflation perceived as an explanatory variable in the long-run relationship of *CCI* eliminates the possible presence of a structural break. In our case, stability is also confirmed by the CUSUM and CUSUMSQ tests. The plots of CUSUM and CUSUM squares tests remain largely inside the 5% critical bounds with the exception of 1994–1996 and 2002–2004 periods in CUSUM test.[17] Moreover, when the dummies (especially DUM_{92_94} and DUI02M1) are substituted with a break dummy variable, their coefficients are not statistically significant. Overall, these tests suggest that the long-run relationship of *CCI* is stable.

6. Conclusion

In this paper we estimated the consumer confidence indicator (*CCI*) for Italy over the period 1985–2010. The unit root tests indicate that *CCI* and *DINF* (*i* and *IP*) are stationary (non-stationary) in their levels and therefore we apply time series techniques that deals with the mixture of I(1) and I(0) variables. To this end, we use Pesaran et al.'s (2001) autogressive

[16] Enders and Siklos (2001) did not tabulate the critical values for cointegrating vectors with more than two variables. Therefore, following Wane et al. (2004) we simulate the asymptotic critical values (the number of replications is 10,000).

[17] The CUSUM and CUSUMSQ test results are not reported to conserve space.

distributed lag model (ARDL) and Hendry's (1995) general to specific (GETS) techniques to estimate the relationship between *CCI* and its determinants. A long-run relationship between *CCI* and its determinants is found when an important political event (the "operation clean hands") is considered.

Our results show that consumers respond asymmetrically to different types of disequilibrium error under threshold autoregressive adjustment specification (TAR), suggesting the presence of a particular type of non-linear behavior of confidence. In particular, we find that an optimistic (pessimistic) view is restored in more (less) than 6 (3) months. To this end, consumers' confidence is restored quickly during unfavorable changes. However, this is not the case in the M-TAR model because the speed of adjustments is quite consistent. The results of M-TAR model implies that an optimistic view is restored in about 5 months, whereas a pessimistic view is restored in less than 4 months. This paper provides a psychological interpretation of a plausible presence of bias in the consumers' confidence (Bovi, 2009). Overall, the presence of threshold cointegration is quite surprising because *CCI* is a stationary dependent variable. Our intuition is that because short-term interest rate (i) and industrial production (*IP*) are non-stationary series and hence cointegrated with each other, perhaps this may be the reason for existence of threshold cointegration in the *CCI* model.

An important line of future research in this area is the use of similar time series methods to extend the analysis to other countries, allowing for an international comparison. In particular, it would be interesting to verify whether these conclusions about the asymmetry in the consumption behavior are also confirmed at the level of the other economies. Various subgroups of agents could be used as alternatives, as they might provide different information about perceptions, on the assumption that agents might have heterogeneous and partial information when formulating their predictions, using different information sets or having different capabilities for processing information. Finally, the relationship between *CCI* and macroeconomic variables could be bi-directional. Investigating the relation moving from *CCI* to macroeconomic variables is outside the scope of this paper, however, we hope to investigate this in the future.

Appendix A

The EU harmonised consumer confidence indicator (European Commission, 2007) is based on answers to the following four questions of consumer survey of the European Commission (see Table A1):

Financial situation of households over next 12 months (Question 2).
General economic situation over next 12 months (Question 4).
Unemployment over next 12 months (Question 7).
Saving over next 12 months (Question 11).

On the basis of the distribution of the various answering options for each question, aggregate balances are calculated for each question. Balances are the difference between positive and negative answering options, measured as the percentage points of total answer. There are six answering options: very positive, positive, neutral, negative, very negative and don't know. The balances (B) are calculated on the basis of weighted averages according to the formula:

$$\mathrm{B} = \mathrm{PP} + 0.5\mathrm{P} - 0.5\mathrm{M} - \mathrm{MM}$$

where PP = the percentage of respondents with the most positive answer, P = positive, M = negative and MM = most negative. Neither the neutral answering option nor the uncertain answer is taken into account. The balances are bounded between -100 (all respondents choose the most negative option) and +100 (all respondents choose the most positive option). The consumer indicator (CI) is then calculated by averaging the balances of the four questions above. The CI is expressed as follows:

$$\mathrm{CI} = (\mathrm{Q2} + \mathrm{Q4} - \mathrm{Q7} + \mathrm{Q11})/4$$

At the end the CI is transformed as an index number (*CCI*) (1995 = 100) and expressed in log-level (Golinelli & Parigi, 2004, 2005). A plot of the *CCI* is presented in Appendix A (Figs. A1–A3 and Table A2).

Table A1
Data definitions and source.

Variable	Definition	Source
CCI	Consumer confidence index (1995 = 100) expressed in log-level	European Commission
i	Short-term interest rate	OECD
IP	Log of industrial production index (edition January 2011) multiplied for 100	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. For more details on *DINF*, see Golinelli and Parigi (2005)	European Commission and OECD

Note: CCI, *IP*, inflation perceived and actual inflation are seasonally adjusted.

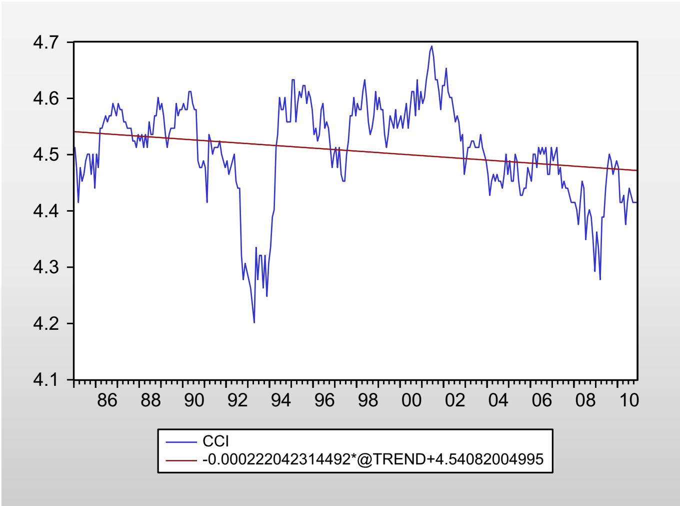

Fig. A1. CCI historical pattern.

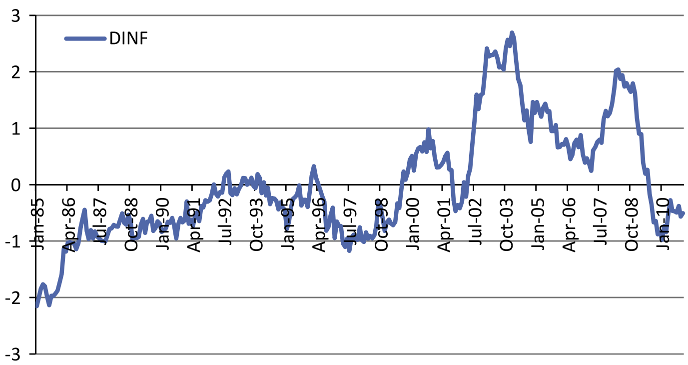

Fig. A2. DINF historical pattern.

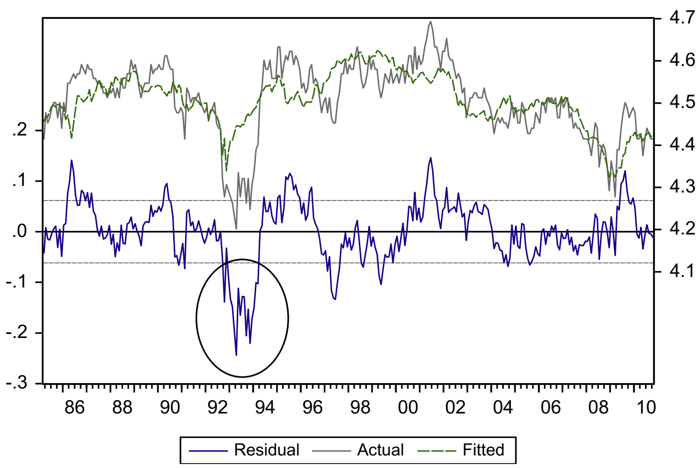

Fig. A3. Long-run residuals of CCI.

Table A2
Carrion-i-Silvestre et al. (2009) unit root test results, 1985m1–2010m10.

Test		Test statistic (critical value)	Break dates
$P_T^{gls}(\lambda^0)$	*CCI*	−19.239 (−15.935)	1992M6; 1996M3; 2001M9
	i	−7.263 (−20.260)	1987M5; 1993M7; 1992M10
	IP	−3.008 (−4.707)	1994M1; 1999M9; 1999M10
	DINF	−11.264 (−6.025)	1987M10; 2003M4; 2008M3
$MZ_\alpha^{GLS}(\lambda^0)$	*CCI*	−15.701 (−9.473)	1990M4; 1993M1; 1994M10
	i	−29.376 (−22.031)	1986M5; 1987M10; 1994M3
	IP	−10.730 (−17.219)	1991M2; 1992M5; 1993M9
	DINF	−28.300 (−21.344)	1996M3; 2001M4; 2006M3
$MSB^{GLS}(\lambda^0)$	*CCI*	−32.272 (−25.114)	1990M8; 1992M12; 1999M6
	i	−7.355 (−21.280)	2001M1; 2002M2; 2003M4
	IP	−11.201 (−18.009)	1990M5; 1993M7; 1994M1
	DINF	−12.642 (−7.925)	1986M8; 1992M9; 1994M10
$MZ_t^{GLS}(\lambda^0)$	*CCI*	−10.120 (−5.456)	1987M10; 1990M9; 1993M7
	i	−8.251 (−21.299)	1993M2; 1994M5; 2002M2
	IP	−5.117 (−6.253)	1996M4; 1999M7; 2001M8
	DINF	−19.027 (−15.433)	1992M10; 1993M4; 1999M5
$MP_T^{GLS}(\lambda^0)$	*CCI*	−4.203 (−3.250)	1994M5; 2001M9; 2006M4
	i	−11.270 (−6.102)	1986M11; 1992M3; 1993M10
	IP	−27.038 (−19.225)	1999M6; 2001M4; 2006M4
	DINF	−12.980 (−8.141)	1991M12; 1992M10; 1994M1

Note: The 5% critical values are given in parentheses.

References

Adams, F. G. (1964). Consumer attitudes, buying plans, and purchases of durable goods: A principal components, time series approach. *The Review of Economics and Statistics, 46*, 347–355.
Allenby, G. M., Jen, L., & Leone, R. P. (1996). Economic trends and being trendy: The influence of consumer confidence on retail fashion sales. *Journal of Business and Economic Statistics, 14*(1), 103–111.
Ariely, D., Loewenstein, G., & Prelec, D. (2003). "Coherent arbitrariness": Stable demand curves without stable preferences. *Quarterly Journal of Economics, 118*, 73–106.
Benhabib, J., Bisin, A., & Schotter, A. (2010). Present-bias, quasi-hyperbolic discounting, and fixed costs. *Games and Economic Behavior, 69*, 205–223.
Bovi, M. (2009). Economic versus psychological forecasting. Evidence from consumer confidence surveys. *Journal of Economic Psychology, 30*, 563–574.
Bracha, A., & Brown, D. J. (2012). Affective decision making: A theory of optimism bias. *Games and Economic Behavior, 75*, 67–80.
Bram, J., & Ludvigson, S. (1998). Does consumer confidence forecast household expenditure? A sentiment index horse race, Federal Reserve Bank of New York. *Economic Policy Review, 4*, 59–78.
Bull, M. J., & Newell, J. L. (1993). Italian politics and the 1992 elections: From 'stable instability' to instability and change. *Parliamentary Affairs, 46*, 203–227.
Bull, M. J., & Newell, J. L. (1995). Italy changes course? The 1994 elections and the victory of the right. *Parliamentary Affairs, 48*, 72–99.
Bull, M. J., & Newell, J. L. (2005). *Italian politics*. Malden, MA, USA: Polity Press.
Calavita, K. (1994). Italy and the new immigration. In W. A. Cornelius, P. Martin, & J. F. Hollifield (Eds.), *Controlling immigration: A global perspective*. Stanford, CA: Stanford University Press.
Camerer, C. F., & Weber, R. A. (1999). The econometrics and behavioral economics of escalation of commitment: A re-examination of staw and Hoang's NBA data. *Journal of Economic Behavior & Organization, 39*, 59–82.
Carrion-i-Silvestre, J. L., Kim, D., & Perron, P. (2009). GLS-based unit root tests with multiple structural breaks under both the null and the alternative hypotheses. *Econometric Theory, 25*, 1754–1792.
Carroll, C. D., Fuhrer, J. C., & Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? If so, why? *American Economic Review, 84*, 1397–1408.
Chan, K. S. (1993). Consistency and limiting distribution of the least square estimator of a threshold autoregressive model. *The Annals of Statistics, 21*, 520–533.
Charness, G., & Gneezy, U. (2010). Portfolio choice and risk attitudes: An experiment. *Economic Inquiry, 48*, 133–146.
Charness, G., Karni, E., & Levin, D. (2010). On the conjunction fallacy in probability judgment: New experimental evidence regarding Linda. *Games and Economic Behavior, 68*, 551–556.
Clarke, H. D., & Stewart, M. C. (1994). Prospections, retrospections, and rationality: The "Bankers" model of Presidential approval reconsidered. *American Journal of Political Science, 38*, 1104–1123.
Croushore, D. (2005). Do consumer-confidence indexes help forecast consumer spending in real time? *The North American Journal of Economics and Finance, 16*, 435–450.
De Boef, S., & Kellstedt, P. M. (2004). The political (and economic) origins of consumer confidence. *American Journal of Political Science, 48*, 633–649.
Dreger, C., & Kholodilin, K. (2011). Forecasting private consumption by consumer surveys. *Journal of Forecasting* (in press). doi: 10.1002/for.1245.
Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.
Enders, W., & Granger, C. W. J. (1998). Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business and Economic Statistics, 16*, 304–311.
Enders, W., & Siklos, P. L. (2001). Cointegration and threshold adjustment. *Journal of Business and Economic Statistics, 19*, 166–176.
Engelmann, D., & Strobel, M. (2000). The false consensus effect disappears if representative information and monetary incentives are given. *Experimental Economics, 3*, 241–260.
Epley, N., & Gilovich, T. (2004). Are adjustment insufficient. *Personality and Social Psychology Bulletin, 30*, 447–460.
Epley, N., & Gilovich, T. (2006). The anchoring and adjustment heuristic: Why adjustment are insufficient. *Psychological Science, 17*, 311–318.
Ert, E., & Erev, I. (2008). The rejection of attractive gambles, loss aversion, and the lemon avoidance heuristic. *Journal of Economic Psychology, 29*, 715–723.
European Commission (2007). The joint harmonised EU programme of business and consumer surveys, User guide.
Fehr, E., & Tyran, J.-R. (2007). Money illusion and coordination failure. *Games and Economic Behavior, 58*, 246–268.

Fratzscher, M., & Stracca, L. (2009). Does it pay to have the euro? Italy's troubled politics and financial markets under the lira and the euro. *International Finance, 12*, 1–31.
Golinelli, R., & Parigi, G. (2004). Consumer sentiment and economic activity: A cross country comparison. *Journal of Business Cycle Measurement and Analysis, 1*, 147–170.
Golinelli, R., & Parigi, G. (2005). Le famiglie italiane e l'introduzione dell'euro: Storia di uno shock annunciato. *Politica Economica, anno XVI*, 201–226.
Hansen, B. E. (1997). Approximate asymptotic p values for structural change tests. *Journal of Business and Economic Statistics, 15*, 60–67.
Hendry, D. F. (1995). *Dynamic econometrics*. Oxford: Oxford University Press.
Hilbert, M. (2012). Toward a synthesis of cognitive biases: How noisy information processing can bias human decision making. *Psychological Bulletin, 138*, 211–237.
Huber, J., Kirchler, M., & Stöckl, T. (2010). The hot hand belief and the Gambler's Fallacy in investment decisions under risk. *Theory and Decision, 68*, 445–462.
Jones, M. K. (2008). Positive confirmation in rational and irrational learning. *Journal of Socio-Economics, 37*, 1029–1046.
Kamakura, W. A., & Gessner, G. (1986). Consumer sentiment and buying intentions revisited: A comparison of predictive usefulness. *Journal of Economic Psychology, 7*, 197–220.
Katona, G. (1975). *Psychological economics*. New York: Elsevier Scientific Publishing Company.
Koopmans, R., & Duyvendak, J. W. (1995). The political construction of the nuclear energy issue and its impact on the mobilization of anti-nuclear movements in Western Europe. *Social Problems, 42*, 201–218.
Kumar, V., Leone, R. P., & Gaskins, J. N. (1995). Aggregate and disaggregate sector forecasting using consumer confidence measures. *International Journal of Forecasting, 11*(3), 361–377.
Lee, J., & Strazicich, M. C. (2003). Minimum Lagrange multiplier unit root test with two structural breaks. *Review of Economics and Statistics, 85*, 1082–1089.
Lumsdaine, R. L., & Papell, D. H. (1997). Multiple trend breaks and the unit-root hypothesis. *The Review of Economics and Statistics, 79*, 212–218.
MacKinnon, J. G. (1991). Critical values for co-integration tests. In R. F. Engle & C. W. J. Granger (Eds.), *Long-run economic relationships* (pp. 267–276). Oxford University Press.
Madsen, J. B. (1994). Tests of rationality versus an ''over optimist'' bias. *Journal of Economic Psychology, 15*, 587–599.
Malgarini, M., & Margani, P. (2007). Psychology, consumer sentiment and household expenditures. *Applied Economics, 39*, 1719–1729.
Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115*, 502–517.
Mussweiler, T., Englich, B., & Strack, F. (2004). Anchoring effect. In R. F. Pohl (Ed.), *Cognitive illusions: An handbook on fallacies and biases in thinking judgment, and memory* (pp. 183–200). London, UK: Psychology Press.
Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica, 69*, 1519–1554.
Offerman, T. (2002). Hurting hurts more than helping helps. *European Economic Review, 46*, 1423–1437.
Paradiso, A., & Rao, B. B. (2011). How to offset the negative trend growth rate in the Italian economy? *Applied Economics Letters, 15*, 1479–1483.
Perron, P. (1989). The great crash, the oil price shock and the unit root hypothesis. *Econometrica, 57*, 1361–1401.
Pesaran, M. H., & Pesaran, B. (1997). *Microfit 4.0*. England: Oxford University Press.
Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*, 289–326.
Pharr, S. J., Putnam, R. D., & Dalton, R. J. (2001). A quarter-century of declining confidence. *Journal of Democracy, 11*, 5–25.
Praet, P., & Vuchelen, J. (1989). The contribution of consumer confidence indexes in forecasting the effects of oil prices on private consumption. *International Journal of Forecasting, 5*, 393–397.
Ramalho, E. A., Caleiro, A., & Dionfsio, A. (2011). Explaining consumer confidence in Portugal. *Journal of Economic Psychology, 32*, 25–32.
Rao, B. B. (2007). Time-series econometrics of growth-models: A guide for applied economists. *Applied Economics, 42*, 73–86.
Sedlmeier, P., Hertwig, R., & Gigerenzer, G. (1998). Are judgments of the positional frequencies of letters systematically biased due to availability? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 24*, 754–770.
Stock, J. H. (1999). A class of tests for integration and cointegration. In *Cointegration, causality, and forecasting: A festschrift for Clive W.J. Granger* (pp. 135–167). Oxford University Press.
Tanner, R. J., & Carlson, K. A. (2009). Unrealistically optimistic consumers: A selective hypothesis testing account for optimism in prediction of future behavior. *Journal of Consumer Research, 35*, 810–822.
Triandafyllidou, A. (1999). Nation and immigration: a study of the Italian press discourse. *Social identities, 5*, 1999.
Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*, 1124–1131.
Vuchelen, J. (1995). Political events and consumer confidence in Belgium. *Journal of Economic Psychology, 16*, 563–579.
Vuchelen, J. (2004). Consumer sentiment and macroeconomic forecasts. *Journal of Economic Psychology, 25*, 493–506.
Wane, A., Gilbert, S., & Dibooglu, S. (2004). Critical values of the empirical F-Distribution for threshold autoregressive and momentum threshold autoregressive models. Calendar Year 2004 Discussion Papers (Paper 23) for the Department of Economics, Southern Illinois University at Carbondale.
Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the Great Crash, the oil-price shock, and the unit root hypothesis. *Journal of Business and Economic Statistics, 10*, 251–270.