Abstract: This paper examines the relationship between consumer confidence and consumption expenditures in the US for the period 1970:1-2007:4. Consumer confidence surveys are widely reported in the business and economics media and play an important role in the direction of business decisions and equity market movements. Despite the widely cited importance and popularity of consumer confidence indices, empirical studies attempting to establish a causal relationship between consumer confidence indices and consumption expenditures are mixed. This paper employs disaggregated consumer expenditures on services, nondurable and durable goods. The consumption functions for the three categories were obtained from the well-established Fair (2009) Macro-econometric model of the US economy. The results of our regression estimation and cointegration analysis, for both the short and long-run, suggests that consumer confidence is a determining factor for expenditures on consumer durable goods only. This finding supports the work of Blanchard (1993) and Hall (1993).

JEL Classification: C2, E0, E2, E21

Keywords: Consumer sentiment, Cointegration, Macroeconomic models, Household consumption

1. Introduction

There has been a long standing interest in determining whether consumer and investor confidence influences the real economy. The monthly release of consumer confidence surveys, particularly in the US, is arguably one of the most watched indicators of predictive future economic activity. It is regularly postulated in the financial press and academic circles that consumer confidence surveys have predictive information on household consumption expenditures over and above the standard economic variables used to forecast household consumption expenditures. However, despite the popularity and often-cited importance of consumer confidence surveys, the transmission mechanism in which consumer attitudes may influence the real economy is not clearly understood. Do consumer confidence surveys contain meaningful independent explanatory power over and above the explanatory power of standard macroeconomic models of consumption? Do the surveys capture important information regarding future household spending? The impact of consumer surveys cannot be understated. Therefore, developing robust models that assist to explain and forecast consumption expenditures so that policymakers are able to take appropriate action in the event of sharp swings in consumption expenditures is important.
The role of consumer expenditures in the US economy is significant. Approximately seventy percent of the GDP in the US is consumed, and with the globalization of the world economies, US consumption expenditures have stimulated enormous global economic growth. Therefore, US consumer expenditures may be viewed as deficit spending by US consumers, resulting in a stimulus for the economies of its trading partners. Furthermore, the rising cost of production and the falling US unemployment rate, prior to the financial meltdown of 2008, has allowed the economies of China, Taiwan, Korea, and other newly industrialized economies to experience higher economic growth rates.

A closer examination of the US current account deficit sheds important light on globalization and its relationship with US consumption. For instance, an examination of the basic macroeconomic relationship between the current account deficit and the deficits in the private and public sectors of the US economy, i.e. \( M-X= (I-S) + (G-T) \), shows that the meager private savings rate in the US until recently, has significantly contributed to the chronic US current account deficit. This rate of 0.7 percent of GDP is currently the lowest among advanced industrial nations.

It is commonly argued that consumer confidence surveys capture psychological motives that are reflected in present and future consumption expenditures. Therefore, the financial media and analysts regularly report the changes in consumer confidence/sentiment as a key determinant of volatility in equity prices. Moreover, analysts hypothesize a relationship between consumer confidence, consumer spending, and corporate capital expenditures. For instance, financial markets typically react negatively to reports of a fall in consumer confidence in the US because they expect a fall in future household consumption expenditures will impact adversely on future corporate profitability. However, the findings of many empirical studies seeking to establish a relationship between consumer confidence surveys and consumption expenditures are mixed.

Researchers have been examining the relationship between consumer sentiment and its impact on consumption expenditures for several decades. Adams and Green (1965) found that the information contained in the University of Michigan consumer sentiment index (UMSI) simply duplicates the macroeconomic announcements of variables like employment and financial conditions and as a result, contains no additional information. Therefore, it may be argued that consumer confidence is endogenously determined and simply reflects current macroeconomic conditions that are captured by standard macroeconomic variables. Conversely, others argue that psychological motives of present and future consumption decisions, which are in line with Keynes’ notion of “animal spirits”, are not captured in the range of economic variables used in standard economic models. Therefore, consumer confidence indices serve as an important input in present and future consumption decisions. For example, Garner (1991) and Throop (1992) conducted event studies and suggested that these indices could be helpful as a source of additional explanatory information during major economic or political events, as they tend to diverge from a path consistent with other macroeconomic variables.

Following this line of thought, Katona (1968) argued that consumer confidence levels not only reflect economic conditions but are also reliable measures of consumer mood. Katona made a clear distinction between a household’s ability and willingness to consume. He argued that a household’s willingness is important for discretionary or durable consumption because it captures subjective factors. Hardouvelis and Thomakos (2007) investigated the behavior of consumer confidence around national elections in the EU-15 countries for the period 1985:1-2007:3. They concluded that consumer confidence and political behavior are positively related. Moreover, their findings indicated that consumer confidence is a reliable predictor of the performance of the incumbent party and, also increased the probability of re-election of the incumbent.

Desroches and Marc-André (2002) found that consumer confidence indices such as the UMSI and the Consumer Confidence Index issued by the Conference Board (CBCI) contained relatively little information in forecasting US aggregate consumer spending once the relevant macroeconomic control variables are taken into account. However, they found, using a threshold
model, that strong variations in consumer confidence indices during periods of economic and political volatility contains important information that may influence future consumption decisions. Garner (1991) and Throop (1992) also found that consumer confidence indices were helpful in predicting consumption behavior during periods of major economic or political shocks by estimating a consumption function in which only large variations of confidence influenced consumption spending.

In recent years, consumer confidence levels and consequently the relationship between the consumer confidence level and consumer expenditures has become increasingly relevant in light of the geopolitical events, namely, large corporate accounting scandals, global financial crises, and wars with global impacts (see for example, Carroll, Fuhrer and Wilcox, (1994); Bram and Ludvigson (1998); Easaw and Heravi, (2004); Easaw, Garratt and Heravi (2005); Bryant and Macri (2005); Jansen and Nahuis (2003)).

Blanchard (1993) and Hall (1993) underlined the importance of consumer sentiment in forecasting household consumption. They argued that a fall in household consumption of durable goods was an important contributing factor to the world-wide recession in the early 1990s.

Carroll, Fuhrer and Wilcox (1994) offered perhaps the first empirical evidence of a positive relationship between consumer confidence levels and various categories of consumption expenditures for the US. A similar study by Easaw, Garratt, and Heravi (2005) provided similar evidence for the UK. Bryant and Macri (2005) found, using Australian data and a well-specified aggregate consumption function (TRYM Model), an independent and explanatory role for consumer confidence in explaining aggregate household consumption.

Golinelli and Giuseppe (2004) examined the predictive role of consumer confidence (or sentiment) indices as a leading and coincident indicator of economic activity in France, Germany, Italy, the UK, the USA, Japan, Canada and Australia over a period of about thirty years, spanning from the beginning of the 1970s to the first quarter of 2002. Their cointegrated vector autoregression (VAR) formulation of the relationship between the consumer confidence, consumption, and output concluded that consumer confidence indices have some predictive ability in forecasting the economic activity under certain assumptions and restrictions. In a recent and interesting study, Chua and Tsiaplias (2009) examine, using a Bayesian error correction approach, whether the disaggregation of consumer sentiment data into its sub-components improves the capacity to forecast GDP and consumption. Using Australian data, they find that disaggregated consumer sentiment data consistently increases the accuracy of GDP and consumption forecasts.

In this paper we investigate the relationship between consumer confidence and consumption expenditures for the US. Our paper differs from previous studies in three distinct ways. First, we disaggregate consumer expenditures into three categories, namely, services, nondurable goods and durable goods. Second, we employ a range of empirical consumption functions for these three categories from the Fair Macroeconometric model of the US. Finally, we employ a cointegration and error-correction approach to complement our regression findings. Our findings show that consumer confidence is only a determinant of consumer expenditures on durable goods. This finding supports the conclusions of both Blanchard (1993) and Hall (1993).

Section II of the paper discusses the theoretical and empirical framework of the paper. The paper data and their sources are discussed in Section III. Section IV offers a brief summary and conclusions.
2. Theoretical and Empirical Framework

Macroeconomic theory hypothesizes that aggregate consumption expenditures are functions of income, which are usually measured by GNP, wealth, and price levels. Variations of this general functional relationship have also been examined in the literature. For instance, Friedman’s permanent income hypothesis holds that the present value of future earnings may be a better representation of current consumer income. This theory may be of particular relevance in the present study because of the separation of consumption expenditures. For instance, while permanent income may be insignificant when considering consumption expenditures on services and nondurables, it may be important in the case of consumption on durable goods.

While deriving explicit consumption expenditure functions for various categories of goods is not within the empirical scope of this paper, our empirical tests are motivated by a theoretical framework. We assume that consumers make consumption decisions in order to maximize their utility as a function of vectors of durable goods, non-durable goods, and services. The endowment constraint at any given time, $t$, is assumed to be a combination of current time $t$ income, accumulated past savings for the planning horizon (net worth), and the permanent income represented by the present value of the future stream of income expected by consumers. To keep matters simple and notations traceable, we make the following assumptions:

1. The growth rate of consumer income for the entire planning horizon is a constant $g$.
2. The growth rate of consumption of non-durable and services is also equal to $g$.
3. The rate of return on savings is given by $r$.
4. Any portion of income that is not consumed is invested at the rate of $r$.
5. The discount rate for future stream on income is equal to $r$, the opportunity cost of investment.
6. Consumers purchase all goods by using current income, the stock of savings. Any credit purchases are equal to the present value of the permanent income stream.

Based on these assumptions, consider the consumption decision at time $t$ in the following graph.

At time $t$, the following constrained maximization of the utility function determines the consumption expenditures on categories C and D, i.e., non-durable goods and services, C, and durable goods as D.

Maximize $U = f(C, D)$

Subject to:

Resource endowment $= \sum_{n=0}^{t-1} (y - c)(1 + k)^n + y,(y(1 + g)^{m-t})/(1 + r)^{m-t}$.

Where $k = (1+g)(1+r)$.

The above resource endowment combines the permanent income hypothesis with consumer past plans to acquire durable goods by saving and investing for that purpose. Furthermore, the stock of consumer net worth at time $t$ may be viewed as a measure of wealth. The net worth at time $t$ may also be in the form of financial assets or durable goods acquired prior to time $t$. For instance, any individual may be in possession of investment portfolio, vehicles, and home appliances.
The constrained optimization problem above implies that consumer expenditure on three
categories of goods, i.e., services, non-durable goods, and durable goods are functions of current
income, total net worth, and the permanent income at time t. Furthermore, it implicitly includes the
consumer confidence through saving and investments. Aggregating the above resource endowment
for all households, results in national net worth, GDP, and the national permanent income,
respectively.

The empirical framework of this paper is based on the consumption equations of the Fair
(2009) Macroeconometric model of the US economy. We opt to use Fair model consumption
functions for several reasons. First, Fair model consumption functions are consistent with the
theoretical discussion above. For instance, the Fair model disaggregates consumption expenditures
into three equations, namely, services, non-durable goods, and durable goods. Second, they are
enhanced by appropriate variables for the three types of consumption expenditures. For instance,
the demographic characteristics of the population may be captured by including the age variable in
these equations to accommodate the life cycle theory of consumption (see Modigliani and
Brumberg (1990)). Third, the model is a well-established macrøeconometric model of the U.S.
economy.

For this paper we augment each equation to include the consumer sentiment index and in
some cases its lagged values as exogenous variables. In the following section we outline the
equations extracted from the Fair Model and its variable definitions. Fair (2009) has constucted
and estimated three stochastic consumption equations for consumer services, consumer nondurable
and consumer durable goods, which are outlined as follows:

1. Consumer Expenditures on Services

\[
\log(\frac{CS}{POP}) = f(cnst, AG1, AG2, AG3, \log(\frac{CS}{POP})_{-1}, \log(\frac{YD}{(POP \cdot PH)}), \log(\frac{AA}{POP})_{-1}, T)
\]

2. Consumer Expenditures on Nondurables

\[
\log(\frac{CN}{POP}) = f(cnst, AG1, AG2, AG3, \log(\frac{CN}{POP})_{-1}, \Delta \log(\frac{CN}{POP})_{-1}, \log(\frac{AA}{POP})_{-1}, \log(\frac{YD}{(POP \cdot PH)}), RMA)
\]

3. Consumer Expenditures on Durables

\[
\Delta \frac{CD}{POP} = f(cnst, AG1, AG2, AG3, DELD(KD/POP)_{-1} - (CD/POP)_{-1}, (KD/POP)_{-1}, \frac{YD}{(POP \cdot PH)}), RMA \cdot CDA, (\frac{AA}{POP})_{-1})
\]

Variables:

\(AA\) = Total net wealth, billions of dollars (B$).

\(AG1\) = exogenous, Percent of 16+ population 26-55 minus percent 16-25.

\(AG2\) = exogenous, Percent of 16+ population 56-65 minus percent 16-25.

\(AG3\) = exogenous, Percent of 16+ population 66+ minus percent 16-25.

\(YD\) = Household disposable income, B$.

\(RMA\) = After tax mortgage rate, percentage points.

\(KD\) = Stock of durable goods, B$.

\(PH\) = Price deflator for CS + CN + CD + IHH inclusive of indirect business taxes.

\(CD\) = Consumer expenditures for durable goods, B$.
\[ CN = \text{Consumer expenditures for nondurable goods, B$}. \]
\[ CS = \text{Consumer expenditures for services, B$}. \]
\[ CDA = \text{exogenous, peak to peak interpolation of CD/POP}. \]
\[ DELD = \text{exogenous, physical depreciation rate of the stock of durable goods, rate per quarter}. \]

Following the same methodology as Fair’s Macroeconomic Model, we disaggregate U.S. aggregate consumption into three distinct categories, namely, expenditures on durable goods, nondurable goods and services. We are of the view that disaggregating consumption in this manner will enable us to explore the predictive role of consumer sentiment and consumption expenditures more effectively. For instance, Van Raaij and Gianotten (1990) showed that consumer sentiment may be particularly important in decisions regarding the consumption expenditures on durable goods and credit demand. Moreover, augmenting the Fair Model consumption equations will be particularly useful for investigating the empirical relationship between consumer sentiment and consumer expenditures on various categories of goods and services for the U.S. economy.

Our \textit{a priori} expectation is that in the case of durable goods, consumer confidence may play a role in consumption decisions. For most nondurable goods, consumption may be inelastic with respect to consumer sentiments.

3. Data and Empirical Results

We investigate the role of consumer confidence in explaining household spending using the consumption equations derived from the Fair (2009) US Macroeconomic Model. We use quarterly data for the period 1970:1-2007:4. The estimated period excludes the recent US recession and its effects on consumption. The rationale for quarantining this period is that this recession, which was triggered by the global financial crisis, was an exceptional event due to the turmoil in the financial markets.

The data were obtained from the Federal Reserve Banks, Board of Governors of Federal Reserve System, The Census Bureau, and Bureau of Economic Analysis, among others. The consumer confidence is represented by the University of Michigan Consumer confidence Index (UMCSI), which is widely reported by the media. The UMCSI is a monthly series that is also averaged over quarters to produce the quarterly series. The UMCSI is derived from a telephone survey of five main questions that seeks to gauge how consumers view their financial situation in the present and in the future. Statistical tests are performed in order to understand both the short-run and long-run relationships and dynamics among the model variables. The short-run relationships are tested by estimating regression models based on the Fair (2009) Macroeconometric Model of the US economy. The long-run tests are based on Johansen and Juselius cointegration tests. We start with the regression results and then present the findings of the cointegration tests.

3.1 Short-run and regression results

As a first step, consumption equations of the Fair Model are augmented with the UMCSI series. We hypothesize that consumer confidence in any period may have an effect on consumption decisions for the next period. Therefore, we estimate regression equations that include lagged and contemporaneous values of the UMCSI. The Ordinary Least Squares (OLS) estimates of the equations employing the lagged UMCSI and the UMCSI are qualitatively identical. We present, in the interest of brevity, the estimated regression results that include only lagged values of UMCSI. The graphs of the consumption values for the three categories over the entire sample period
demonstrate a clear deterministic trend over time. To avoid spurious estimation results and, to account for the rising trend in consumption in the three categories, we also include a deterministic trend variable (T) in the original Fair Model equations.

Tables 1 through to 3 report the estimation results. Table 1 shows that the majority of explanatory variables are statistically insignificant in the equation of the service consumption. Furthermore, the high values of $R^2$ and the F test suggests serious multicollinearity problems. The lagged value of the UMCSI is also statistically insignificant. As the Fair Model is designed specifically for forecasting the behavior of the US economy and multicollinearity is a common problem in equations and models designed for forecasting, we therefore, do not attempt to alter or correct this equation for multicollinearity.

Table 2 reports the estimation results of OLS for equation (2), which is the equation for nondurable consumption goods. The estimation results show that three explanatory variables are statistically significant. Again, these results may indicate the presence of multicollinearity. The lagged UMCSI is again statistically insignificant. This is consistent with our a priori expectations. The consumption decisions for most services and nondurables may not be related to consumer confidence for several reasons. First, a large number of service expenditures and nondurable items tend to be necessities that possess low income and price elasticity. Second, these items tend to be low cost and therefore, may not be affected by consumers’ feelings or perceptions regarding the state of the economy. Third, a majority of these expenditures are recurring costs, independent of consumer confidence concerns.

Table 3 presents the OLS estimation results of the consumption equation for durable goods. However, before analyzing the parameter significance, we note that the low value of the D-W statistic suggests that the estimation results are spurious because of autocorrelation problems. Therefore, we re-estimate equation (3) by the maximum likelihood estimation method. The maximum likelihood estimates are presented in Table 4. The estimation results in Table 4 show that all of the explanatory variables, with the exception of one variable, are statistically significant. In particular, the lagged value of the UMCSI is statistically significant showing that the consumer confidence in any period is positively and significantly correlated with the expenditures on durables in the following period. This finding supports the conclusions of Van Raaij and Gianotten (1990), Blanchard (1993) and Hall (1993) regarding consumer spending on durable goods and consumer confidence. The estimation results indicate that the effect of permanent income, measured by the lagged consumption variable, on the consumption of durable goods in the US is statistically insignificant. Furthermore, it seems that the inclusion of the lagged dependent variable contributes to the multicollinearity problems and therefore presents some counterintuitive results. These statistical findings are not presented here in the interest of brevity.

### 3.2 Long-run equilibrium relationships and cointegration tests

Prior to embarking on tests of cointegration, variables were tested to determine if they were integrated of order zero, $I(0)$ or order one, $I(1)$. The Johansen and Juselius (1992) cointegration tests are designed to test variables that are $I(1)$.

Table 5 presents the Dickey-Fuller, augmented Dickey-Fuller (1979), Phillips-Perron (1988) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS, 1992) unit root tests. Table 5 shows that the variables tested are mainly $I(1)$, while their first differences are $I(0)$. In some instances, the four tests used reveal conflicting results. In these cases, we assume that the variables in question are integrated at an order close to one and thus are non-stationary.
We test for cointegration among the variables of equation (3) to determine whether long run equilibrium relationships exist among the variables. Cointegration refers to the existence of a long-run equilibrium relationship among non-stationary variables. The following is a summary of the material found in Johansen (1995) and Pesaran et al. (1996) regarding the cointegration among I(1) variables. If we have a vector of m I(1) variables \( y_t \), the unrestricted vector autoregressive equation in the levels of the variables is given as:

\[
y_t = a + \sum_{i=1}^{k} \Pi_i y_{t-i} + e_t \tag{4}
\]

Where \( \Pi_i \) is an \((m \times m)\) matrix of parameters which are the long-run multipliers.

The above system of equations may be reparametrized and expressed in vector error correction formant (VECM) as:

\[
\Delta y_t = a + \sum_{i=1}^{k} \Gamma_i \Delta y_{t-i} + \Gamma_k y_{t-k} + e_t \tag{5}
\]

Where \( \Gamma_i = -I + \sum_{i=1}^{k} \Pi_i \) \( \tag{6} \)

\( I \) is the identity matrix, and \( \Gamma_k \) are the coefficients matrices capturing short-run dynamic effects.

If \( y_t \) represents a vector of I(1) variables, the term \( \Gamma_k y_{t-k} \) is a linear combination of I(1) variables. The linear combinations of the levels of \( y_t \) which are highly correlated with the remaining I(0) terms in equation (2) are defined as co-integrating vectors.

If the parameters of the long-run multiplier matrix, \( \Pi \), are such that \( \Pi y_{t-i} \) is I(0) then the \( y \) variables are cointegrated and the rank of the matrix \( \Pi \) should be less than the number of variables, \( m \), in the vector \( y \). If this is the case then \( \Pi \) is rank deficient and can be decomposed as \( \Pi = a \beta^t \) where \( a \) and \( \beta^t \) are \( m \times r \) matrices, with full rank, \( r \). When \( \Pi \) is rank deficient, \( y_t \) is I(1), \( \Delta y_t \) is I(0), and \( \beta^t y_{t-k} \) is I(0) as well. The \( r \times 1 \) trend-stationary vector \( \beta^t y_{t-k} \) are defined as the co-integrating relationships, and represent the long-run equilibrium or steady state of the vector error correction model VECM. The matrix \( \beta \) contains the \( r \) co-integrating vectors, while the elements of the \( a \) matrix measure the speed of adjustment to the long-run equilibrium.

In our analysis, we will concentrate on the matrix \( \beta \). Specifically, we will test whether there are linear relationships among the variables of equation (3) in the Fair model. If so, we will test whether the UMCSI variable should be included in the long-run co-integrating space with consumer expenditures on the durable goods. To accomplish this, we impose restrictions on the parameters of matrix \( \beta \) and test their validity. Johansen (1995) suggests a likelihood ratio with a \( \chi^2 \) distribution for this purpose. In the following, we present the findings of the cointegration analysis.

### 3.2.1 Empirical findings of the Johansen-Juselius cointegration tests

The first step in Johansen-Juselius procedure of testing for cointegration involves the lag order determination in the co-integrating VAR. Consider the following vector autoregressive model of order \( p \):

\[
y_t = C_0 + \sum_{i=1}^{p} \Omega_i y_{t-i} + \mathbf{u}_t \tag{7}
\]

Where \( y_t \) is an \( m \times 1 \) vector of endogenous variables, and \( \mathbf{u}_t \) is an \( m \times 1 \) vector of normally distributed, homosecedastic, non-auto correlated residuals that satisfy certain stability and orthogonality conditions. To begin, we set \( p = 6 \) to ensure a long enough lag order for our quarterly data. By choosing a high enough value for \( p \) the lag order, we may avoid autocorrelation problems that often exist in time series analyses. We estimate the VAR model here by the maximum likelihood estimation method. The Akaike Information Criteria (AIC), Schwarz Bayesian Criteria (SBC), and the likelihood ratio test (LR) point to a VAR of order five, while the adjusted LR test is
significant only up to four lags. Given the overwhelming evidence in support of the lag order five, the remainder of the analysis is based on estimating VARs of order five.

With the VAR order determined, we re-estimate the above VAR of order five, and perform the Granger block causality test of whether UMCSI Granger causes the consumption expenditures on durable goods. The Granger block causality test can be explained as follows. The vector of endogenous variables $y_t$ may be decomposed into two $k*1$ and $l*1$ vectors of $y_{1t}$ and $y_{2t}$ such that $k+l=m$, where $y_t = (y'_{1t} + y'_{2t})'$. The VAR model above may be decomposed into two blocks as follows:

$$y_{1t} = c_{10} + \sum_{i=1}^{p} \Theta_{11,i} y_{1t-i} + \sum_{i=1}^{p} \Theta_{12,i} y_{2t-i} + u_{1t} \quad (8)$$

$$y_{2t} = c_{20} + \sum_{i=1}^{p} \Theta_{21,i} y_{1t-i} + \sum_{i=1}^{p} \Theta_{22,i} y_{2t-i} + u_{2t} \quad (9)$$

If the subset $y_{2t}$ does not Granger cause the subset $y_{1t}$, the following null hypothesis will not be rejected.

$H_0: \Theta_{12} = 0$, where $\Theta_{12} = (\Theta_{1,12} \Theta_{2,12} \ldots \Theta_{6,12})$.

It shows that the coefficients of the lagged UMCSI variable in all equations, including the equation of the consumption expenditures on durable goods which are statistically significant, as indicated by the value of the $\chi^2$ statistic, and the P-value 0.074. Therefore, the consumer confidence index does not Granger cause consumer expenditures on durable goods.

In order to test the hypothesis that there are linear relationships among the non-stationary model variables that are stationary, we employ the maximum eigenvalue and trace tests of the matrix $\Gamma_k$ in equation (5). The maximum eigenvalue statistic tests the following null and alternative hypotheses:

$H_r: \text{Rank}(\Gamma_k) = r$

$H_{r+1}: \text{Rank}(\Gamma_k) = r+1$

Where $r = 0, 1, 2, \ldots, m-1$. The appropriate log-likelihood ratio test is based on the statistic given by equation (10).

$$\lambda_{\text{max}}(r, r+1) = -N \ln(1 - \hat{\lambda}_{r+1}) \quad (10)$$

To test the same null hypothesis above against the alternative hypothesis of trend-stationarity, we form the following two hypotheses:

$H_r: \text{Rank}(\Gamma_k) = r$

$H_m: \text{Rank}(\Gamma_k) = m$.

The likelihood ratio test is completed by the following test statistic known as the trace test.

$$\lambda_{\text{trace}}(r) = -N \sum_{i=r+1}^{m} \ln(1 - \hat{\lambda}_i) \quad (11)$$

In equations (10) and (11), $N$ is the number of observations, and $\hat{\lambda}_i$ are the estimated eigenvalues of the matrix $\Gamma_k$. Johansen (1991), Osterwald-Lenum (1992), and Pesaran et al. (1996)
offer critical values for the test statistics (10) and (11). Our tests are based on the critical values tabulated by Pesaran et al. (1996).

Table 8 presents the findings of the cointegration tests. Panel A presents the test statistic given by equation (10). According to the λ_{max} test in Panel A, the null hypothesis of r ≤ 3 is rejected in favor of three cointegrating vectors. However, λ_{trace} suggests up to seven co-integrating vectors amongst the variables under consideration. The conclusion is that there are several long-run equilibrium relationships among the variables. In the following, we test the long run equilibrium relationship between the UMCSI and the expenditures on nondurable goods by imposing a restriction that the coefficient of UMCSI in the β is zero. Therefore, the UMCSI should not be included in the cointegrating space.

The cointegrating relationship is given by equation (12) as follows:

\[ c_t = \alpha + \beta_1 CD_{POP} + \beta_2 AG1 + \beta_3 AG2 + \beta_4 AG3 - \beta_5 KD_{CD} + \beta_6 YD_{POP} + \beta_7 RMACDA, \]

\[ \beta_8 UMCSI \]  

(12)

Where \( e_t \) is a white noise stationary residual term, thus, the right hand side of the equation, the linear combination of I(1) variables must also be stationary. As explained above, there are multiple cointegrating relationships among the variables in this study. We estimate one cointegrating vector by imposing two (over-identifying) restrictions. This allows us to test the relevance of the UMCSI in the cointegrating space for expenditures on durable goods in the long-run. The restriction on the cointegrating relationship take the form of \( R \beta = b \) where \( \beta \) is the co-integrating vector, \( R \) is a diagonal matrix of the coefficients of linear restrictions, and \( b \) is the vector of restrictions. In the present study, the over-identifying restrictions that are imposed on equation (12) are as follows:

\[ H_0: \beta_1 = 1 \beta_8 = 0 \]

\[ H_0: \beta_1 \neq 1 \beta_8 \neq 0 \]  

(13)

The estimation results are presented in Table 9 and the estimated long-run, co-integrating vector is given by equation (14).

\[ CD_{POP} = 0.015 + 0.064 AG1 + 0.035 AG2 + 0.106 AG3 - 0.077 KD_{CD} + 2.88 YD_{POP} + 0.074 RMACDA \]  

(14)

Table 9 also presents the results of the restriction that the coefficient of the consumer confidence variable in the co-integrating relationship is statistically insignificant and is rejected as shown by the value of the chi-squared statistic. Once again, we are of the view that this test supports the findings reported by regressions above.

3.2.2 Impulse response analysis

The impulse response analysis of the VECM given by equation (5) can be performed by taking into account the necessary restrictions to be imposed on the long-run multiplier matrix \( \Pi \). The orthogonalized impulse response function of a unit shock to the ith variable at time t in equation (5) on the jth variable at time t+K is given by

\[ \hat{I}_{ijK} = \varepsilon'_j (c(1) + c'_K) N \varepsilon_i \]  

(15)

Where N is a triangular matrix, \( \varepsilon \) is a vector of 0s and 1s, and \( c(1) \) and \( c'_K \) are coefficient matrices.

As Pesaran and Shin (1996) show, it is more informative to analyze the effects of shocks to a variable on the cointegrating relationship. This is called the system-wide shock. The persistence profile of the system-wide shocks on the co-integrating relationship \( \beta' y_t \) is given by
\[ p(\beta_j y, K) = \beta_j B_k \sum \beta_k / \beta_j \sum \beta \] (16)

Where \( j = 1, 2, \ldots r \), and \( K = 0, 1, 2, \ldots \).

The value of \( P \) in equation (16) is equal to one initially, but approaches zero as \( K \) moves toward infinity. Equation (16) also provides critical information on the speed of adjustment toward equilibrium when the effects of shocks on the cointegrating equation \( \beta_j y \), vanishes. To examine the effects of shocks to the equation of the consumer confidence on other variables of the model, we examine the generalized impulse responses. The generalized impulse response of one standard deviation shock to the equation of consumer confidence on consumer expenditures on durable goods is presented in Figure 5.

Impulse response analyses of system-wide shocks (not presented here for the purpose of brevity) as well as the shock effects of the expenditures on durable goods indicate that consumer confidence is an important variable in determining the consumption of durable goods. The shock effects on the durables sector last many quarters and do not completely dissipate. The implication of this observation is that the shocks to consumer confidence in the US may be an important determinant of the speed of the economic recovery. For instance, flagging consumer confidence could curtail expenditures on durable goods, which, in turn, through the acceleration principle, may discourage investments in capital goods by the business firms and the result may be a prolonged period of recovery from major recessions. The finding further justifies the role of the government in providing stimulus packages to cope with the effects of recessionary trends on consumer confidence, which may have a significant impact on economic growth.

How do the results of this paper compare to other studies that have adopted a similar methodological approach? Bryant and Macri (2005) is the only other study that we are aware of, in which a theoretically justified model of aggregate consumption is used as the baseline against which consumer sentiment is tested for additional independent explanatory power. The aggregate consumption equation used in their study was extracted from the Treasury Model of the Australian Economy (TRYM) and can be interpreted as being consistent with both the Life-Cycle Hypothesis (LCH) and the Permanent Income Hypothesis (PIH), which is also consistent with Fair’s macroeconomic model of the US. The final results of this current study are broadly consistent with Bryant and Macri (2005), which suggests that the variation in consumer sentiment is positively and significantly related to the variation in consumption expenditures.

While there are important similarities between the current study and others in the literature, there are some important differences.

First, previous researchers use aggregate consumption as their dependent variable, whereas the current study disaggregates consumption expenditures into services, nondurables and durables. The results of this study suggests that only the variation in expenditures on durable goods is explained by the variation in consumer sentiment – services and nondurables are not explained by the variation in consumer sentiment.

Second, previous studies mainly use regression analysis only, whereas this current study examines the short and long-term variation of both consumer sentiment and consumption by using both regression and cointegration analyses.

Third, this current study examines the dynamic properties of consumer sentiment on durable goods by examining impulse shocks. It is important to note that most other studies have typically adopted the Carroll, Fuhrer and Wilcox (1994) methodology, which examines whether lagged consumer confidence and an arbitrary range of control variables (for example, lagged income growth, short-term interest rates and the real stock price index) can forecast changes in current consumption (see for example, Bram and Ludvigson, 1998; Fan and Wong, 1998; Mehra
and Martin, 2003; Easaw and Heravi, 2004; Easaw, Garratt, Heravi, 2005, Kwan and Cotsonitis, 2006; among others). It is not surprising, given the ad hoc nature of their methodology and arbitrary choice of variables, that the results across many countries are mixed.

4. Summary and Concluding Comments

This paper has investigated the short and long-run relationship between consumer confidence and consumption expenditures on services, nondurable and durable goods for the US. The short-run was examined by using the “well-specified” consumption equations obtained from the well established Fair (2009) US Macroeconomic Model. The long-run relationship was tested using the standard Johansen and Juselius cointegration tests. The results of our investigation suggest that a significant relationship exists between consumer confidence and consumption expenditures on durable goods for both the short and long-run period. We found no evidence of a relationship between consumer confidence and consumption expenditures for services or nondurables for either the short or long-run period. Our work has attempted to pay particular attention to the specification of a set of credible control variables, namely the consumption equations obtained from the Fair (2009) US Macroeconomic model, against which the influence of consumer can be estimated. The results support the important work of Blanchard (1993) and Hall (1993) of an independent role of consumer confidence in explaining consumption expenditures on durables.

These findings also raise an important theoretical issue. First, the permanent income and life-cycle models, which are the predominant consumption models that seek to explain household consumption behavior, do not take into account consumer confidence as an independent explanatory variable. Therefore, if consumer confidence does contain meaningful information, which our results seem to suggest for durable goods, then it can be argued that more research is required in improving the theoretical underpinnings of the standard consumption models.

Acknowledgments: We are indebted to an anonymous reviewer for constructive comments. This paper benefited from the comments of attendees of the empirical economics/finance session at the ABEAI Annual Conference, November 2008. Remaining errors are ours.

References


Appendix

Figure 1: Generalized Responses of Consumer Durables Spending to One Standard Error Shock to the Equation of Consumer Confidence
Table 1. OLS estimation results of Fair Equation (1), consumer spending on services
\[
\log(\text{CS}/\text{POP}) = f(AG_1, AG_2, AG_3, \log(\text{CS}/\text{POP}) - 1, \log(YD/(POP*PH)), RMA, \log(\text{AA}/\text{POP}) - 1, T)
\]

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.241</td>
<td>0.319</td>
<td>-0.755</td>
<td>0.452</td>
</tr>
<tr>
<td>AG1</td>
<td>-0.013</td>
<td>0.298</td>
<td>-0.044</td>
<td>0.964</td>
</tr>
<tr>
<td>AG2</td>
<td>0.038</td>
<td>0.169</td>
<td>0.228</td>
<td>0.820</td>
</tr>
<tr>
<td>AG3</td>
<td>-0.128</td>
<td>0.452</td>
<td>-0.283</td>
<td>0.777</td>
</tr>
<tr>
<td>LCS_P(-1)</td>
<td>0.983</td>
<td>0.014</td>
<td>69.660</td>
<td>0.000</td>
</tr>
<tr>
<td>LYD_P*H(-1)</td>
<td>-0.026</td>
<td>0.031</td>
<td>-0.826</td>
<td>0.410</td>
</tr>
<tr>
<td>LAA_P(-1)</td>
<td>0.013</td>
<td>0.009</td>
<td>1.501</td>
<td>0.136</td>
</tr>
<tr>
<td>RMA</td>
<td>-7.56E-05</td>
<td>0.0005</td>
<td>-0.131</td>
<td>0.895</td>
</tr>
<tr>
<td>UMCSI(-1)</td>
<td>3.54E-05</td>
<td>4.91E-05</td>
<td>0.720</td>
<td>0.472</td>
</tr>
<tr>
<td>T</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.513</td>
<td>0.609</td>
</tr>
</tbody>
</table>

R²: 0.99  
F-statistic: 169935.6  
Durbin-Watson stat: 2.02

Notes: * indicates significance at 1 percent level. Variable names have been modified but match those of equation (1). \(\log(\text{CS}/\text{POP}) - 1 = \text{LCS}_P(-1)\), \(\log(YD/(\text{POP}*\text{PH})) = \text{LYD}_P*\text{H}(-1)\), \(\log(\text{AA}/\text{POP}) - 1 = \text{LAA}_P(-1)\)

Table 2. OLS estimation results of Fair Equation (2), consumer spending on nondurable goods
\[
\log(\text{CN}/\text{POP}) = f(AG_1, AG_2, AG_3, \log(\text{CN}/\text{POP}) - 1, \Delta\log(\text{CN}/\text{POP}) - 1, \\
\log(\text{AA}/\text{POP}) - 1, \log(YD/(\text{POP} \times \text{PH})), RMA)
\]

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-5.589</td>
<td>0.554</td>
<td>-10.080(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>AG1</td>
<td>-0.884</td>
<td>0.463</td>
<td>-1.909(^b)</td>
<td>0.059</td>
</tr>
<tr>
<td>AG2</td>
<td>0.257</td>
<td>0.290</td>
<td>0.885</td>
<td>0.377</td>
</tr>
<tr>
<td>AG3</td>
<td>1.105</td>
<td>0.738</td>
<td>1.497</td>
<td>0.137</td>
</tr>
<tr>
<td>LCN_P(-1)</td>
<td>0.929</td>
<td>0.028</td>
<td>33.652(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>DLCN_P(-1)</td>
<td>-0.000</td>
<td>0.092</td>
<td>-0.005</td>
<td>0.995</td>
</tr>
<tr>
<td>LAA_P(-1)</td>
<td>0.014</td>
<td>0.015</td>
<td>0.943</td>
<td>0.347</td>
</tr>
<tr>
<td>LYD_P*H</td>
<td>0.172</td>
<td>0.056</td>
<td>3.038(^a)</td>
<td>0.003</td>
</tr>
<tr>
<td>RMA</td>
<td>0.001</td>
<td>0.001</td>
<td>1.294</td>
<td>0.198</td>
</tr>
<tr>
<td>UMCSI(-1)</td>
<td>1.77E-05</td>
<td>9.31E-05</td>
<td>0.190</td>
<td>0.849</td>
</tr>
</tbody>
</table>

R²: 0.99  
F-statistic: 21760.81\(^a\)  
Durbin-Watson stat: 1.98\(^a\)

Notes: ** indicate significance at 1 and 5 percent levels. Variable names have been modified but match those of equation (2). \(\log(\text{CN}/\text{POP}) - 1 = \text{LCN}_P(-1)\), \(\Delta\log(\text{CN}/\text{POP}) - 1 = \text{LCN}_P(-1)\) 
\(\log(\text{AA}/\text{POP}) - 1 = \text{LAA}_P(-1)\), \(\log(YD/(\text{POP} \times \text{PH})) = \text{LYD}_P*\text{H})\)
Table 3. Maximum likelihood estimation results of Fair Equation (3), consumer spending on durable goods

\[ \Delta CD/POP = f(AG1, AG2, AG3, DELD(KD/POP) - 1 - (CD/POP) - 1, (KD/POP) - 1, Y D(POP * PH), RMA * CDA, (AA/POP) - 1) \]

Dependent Variable: CD\_POP

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.002</td>
<td>0.0004</td>
<td>-5.196(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>AG1</td>
<td>0.016</td>
<td>0.0028</td>
<td>5.617(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>AG2</td>
<td>0.005</td>
<td>0.0021</td>
<td>2.228(^a)</td>
<td>0.028</td>
</tr>
<tr>
<td>AG3</td>
<td>-0.032</td>
<td>0.0059</td>
<td>-5.336(^a)</td>
<td>0.000</td>
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<tr>
<td>KDP_CDP(-1)</td>
<td>-0.158</td>
<td>0.0255</td>
<td>-6.186(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>KD_POP(-1)</td>
<td>200.598</td>
<td>30.8771</td>
<td>6.497(^a)</td>
<td>0.000</td>
</tr>
<tr>
<td>YD_POP*PH</td>
<td>-6.84E-12</td>
<td>2.15E-12</td>
<td>-3.183(^a)</td>
<td>0.002</td>
</tr>
<tr>
<td>RMA*CDA</td>
<td>-2.05E-05</td>
<td>8.32E-06</td>
<td>-2.459(^a)</td>
<td>0.016</td>
</tr>
<tr>
<td>AA_POP(-1)</td>
<td>0.001</td>
<td>0.0009</td>
<td>1.161</td>
<td>0.248</td>
</tr>
<tr>
<td>UMC_SI(-1)</td>
<td>2.37E-06</td>
<td>6.46E-07</td>
<td>3.677(^a)</td>
<td>0.000</td>
</tr>
</tbody>
</table>

\(^2\) 0.99
Log likelihood 967.42
F-statistic 1467.058\(^a\)

Notes: \(^a\) indicates significance at 1 percent level.
Variable names have been modified but match those of equation (3). \(DELD(KD/POP) - 1 - (CD/POP) - 1 = KDP\_CDP\(-1\), (KD/POP) - 1 = KD\_POP(-1), YD(POP * PH) = YD\_POP*PH, (AA/POP) - 1 = AA\_POP(-1), \(\Delta CD/POP = DCD\_POP\)

Table 4. Unit Root Tests of variable stationarity

<table>
<thead>
<tr>
<th>Variable</th>
<th>DF</th>
<th>ADF</th>
<th>PP</th>
<th>KPSS (LM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ag1</td>
<td>-1.48</td>
<td>-1.47</td>
<td>-3.62(^a)</td>
<td>0.2600(^a)</td>
</tr>
<tr>
<td>(\Delta Ag1)</td>
<td>-5.08(^a)</td>
<td>-5.08(^a)</td>
<td>-13.11(^a)</td>
<td>0.0570(^a)</td>
</tr>
<tr>
<td>Ag2</td>
<td>-0.13</td>
<td>-2.93(^b)</td>
<td>-2.93(^b)</td>
<td>0.4500(^b)</td>
</tr>
<tr>
<td>(\Delta Ag2)</td>
<td>-2.74(^b)</td>
<td>-2.50</td>
<td>-12.01(^a)</td>
<td>0.8964</td>
</tr>
<tr>
<td>Ag3</td>
<td>-0.16</td>
<td>-1.82</td>
<td>-1.87</td>
<td>0.3700(^c)</td>
</tr>
<tr>
<td>(\Delta Ag3)</td>
<td>-1.99(^b)</td>
<td>-1.94</td>
<td>-13.33(^a)</td>
<td>0.3990(^c)</td>
</tr>
<tr>
<td>KDP_CDP</td>
<td>0.27</td>
<td>-0.90</td>
<td>-0.87</td>
<td>1.0570</td>
</tr>
<tr>
<td>(\Delta KDP_CDP)</td>
<td>-2.04(^b)</td>
<td>-2.78(^b)</td>
<td>-11.87(^a)</td>
<td>0.0500(^c)</td>
</tr>
<tr>
<td>KD_POP</td>
<td>-0.12</td>
<td>-0.49</td>
<td>-0.48</td>
<td>1.1800</td>
</tr>
<tr>
<td>(\Delta KD_POP)</td>
<td>-1.91(^c)</td>
<td>-2.14</td>
<td>-11.98(^a)</td>
<td>0.0600(^a)</td>
</tr>
<tr>
<td>YD/(POP*PH)</td>
<td>1.48</td>
<td>0.48</td>
<td>0.62</td>
<td>1.4100</td>
</tr>
<tr>
<td>(\Delta YD/(POP*PH))</td>
<td>-2.57(^b)</td>
<td>-3.45(^b)</td>
<td>-15.03(^b)</td>
<td>0.0800(^b)</td>
</tr>
<tr>
<td>RMA*CD</td>
<td>0.01</td>
<td>-1.83</td>
<td>-1.78</td>
<td>1.1700</td>
</tr>
<tr>
<td>(\Delta RMA*CD)</td>
<td>-3.42(^a)</td>
<td>-3.40(^b)</td>
<td>-12.48(^a)</td>
<td>0.1100(^b)</td>
</tr>
<tr>
<td>AA_POP</td>
<td>2.48</td>
<td>1.14</td>
<td>1.95</td>
<td>1.4000</td>
</tr>
<tr>
<td>(\Delta AA_POP)</td>
<td>-3.38(^a)</td>
<td>-4.14(^a)</td>
<td>-13.44(^a)</td>
<td>0.3900(^b)</td>
</tr>
<tr>
<td>UMC_SI</td>
<td>-1.88</td>
<td>-2.20</td>
<td>-2.59</td>
<td>0.5600(^c)</td>
</tr>
<tr>
<td>(\Delta UMC_SI)</td>
<td>-2.23(^b)</td>
<td>-2.43</td>
<td>-14.02(^a)</td>
<td>0.0600(^a)</td>
</tr>
</tbody>
</table>

Notes: \(^a, \(^b, \) and \(^c\) indicate significance at 1, 5, and 10 percent levels. \(DELD(KD/POP) - 1 - (CD/POP) = KDP\_CDP, (KD/POP) = KD\_POP(-1), YD(POP * PH) = YD\_POP*PH, (AA/POP) - 1 = AA\_POP(-1), \(\Delta CD/POP = DCD\_POP\)

~ 16 ~
Table 5. Likelihood Ratio Test of Block Granger Non-Causality in the Order of VAR = 5

List of variables included in the unrestricted VAR:
\( \Delta CD_{POP}, \Delta AG1, \Delta AG2, \Delta AG3, \Delta KD_{CD}, \Delta YD_{POP}, \Delta RMACDA, \Delta UMCSI \)

List of deterministic and/or exogenous variables:
\( C \)

Maximized value of log-likelihood = 5308.2

H0: Coefficients of the lagged values of DUMCSI = 0 in the block of equations explaining the variables:
\( \Delta CD_{POP}, \Delta AG1, \Delta AG2, \Delta AG3, \Delta KD_{CD}, \Delta YD_{POP}, \Delta RMACDA \)

\( \chi^2 (28)= 39.45 \)  
\( P \)-Value = 0.074

Notes: * indicates significance at the 10 percent level.  \( \Delta \) represents the first difference operator.

Table 6. Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on \( \lambda_{\text{max}} \) of the Stochastic Matrix

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Critical Values</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null</td>
<td>Alternative</td>
<td>( \lambda_{\text{max}} )</td>
<td></td>
</tr>
<tr>
<td>( r = 0 )</td>
<td>( r = 173.52^a )</td>
<td>52.06</td>
<td>49.04</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>( r = 2 )</td>
<td>55.80( b )</td>
<td>46.47</td>
</tr>
<tr>
<td>( r \leq 2 )</td>
<td>( r = 3 )</td>
<td>39.18( a )</td>
<td>40.53</td>
</tr>
<tr>
<td>( r \leq 3 )</td>
<td>( r = 4 )</td>
<td>30.55</td>
<td>34.40</td>
</tr>
<tr>
<td>( r \leq 4 )</td>
<td>( r = 5 )</td>
<td>27.70</td>
<td>28.27</td>
</tr>
<tr>
<td>( r \leq 5 )</td>
<td>( r = 6 )</td>
<td>14.44</td>
<td>22.04</td>
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<tr>
<td>( r \leq 6 )</td>
<td>( r = 7 )</td>
<td>10.88</td>
<td>15.87</td>
</tr>
<tr>
<td>( r \leq 7 )</td>
<td>( r = 8 )</td>
<td>7.53</td>
<td>9.16</td>
</tr>
</tbody>
</table>

Table 6 (Cont’d). Cointegration with restricted intercepts and no trends in the VAR

Cointegration LR Test Based on \( \lambda_{\text{trace}} \) of the Stochastic Matrix

<table>
<thead>
<tr>
<th>Panel B</th>
<th>Critical Values</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null</td>
<td>Alternative</td>
<td>( \lambda_{\text{max}} )</td>
<td></td>
</tr>
<tr>
<td>( r = 0 )</td>
<td>( r \geq 1 )</td>
<td>259.64( b )</td>
<td>166.12</td>
</tr>
<tr>
<td>( r \leq 1 )</td>
<td>( r \geq 2 )</td>
<td>186.11( b )</td>
<td>132.45</td>
</tr>
<tr>
<td>( r \leq 2 )</td>
<td>( r \geq 3 )</td>
<td>130.30( b )</td>
<td>102.56</td>
</tr>
<tr>
<td>( r \leq 3 )</td>
<td>( r \geq 4 )</td>
<td>90.11( b )</td>
<td>75.98</td>
</tr>
<tr>
<td>( r \leq 4 )</td>
<td>( r \geq 5 )</td>
<td>60.56( b )</td>
<td>53.48</td>
</tr>
<tr>
<td>( r \leq 5 )</td>
<td>( r \geq 6 )</td>
<td>32.86( a )</td>
<td>34.87</td>
</tr>
<tr>
<td>( r \leq 6 )</td>
<td>( r \geq 7 )</td>
<td>18.41( a )</td>
<td>20.18</td>
</tr>
<tr>
<td>( r \leq 7 )</td>
<td>( r = 8 )</td>
<td>7.53</td>
<td>9.16</td>
</tr>
</tbody>
</table>

Notes: Critical values are from Pesaran et al. (1996b).  
\( a, b \) indicate significance at 1 and 5 percent levels.  Order of VAR = 5

List of variables included in the cointegrating vector: CD_{POP}, AG1, AG2, AG3, KD_{CD}, YD_{POP}, RMACDA, UMCSI, Intercept.
List of eigenvalues in descending order: 0.49, 0.40, 0.30, 0.24, 0.22, 0.12, 0.09, 0.06
<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CD_POP</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.015$^a$</td>
<td>(0.002)</td>
</tr>
<tr>
<td>AG1</td>
<td>-0.064$^a$</td>
<td>(0.014)</td>
</tr>
<tr>
<td>AG2</td>
<td>-0.035$^a$</td>
<td>(0.011)</td>
</tr>
<tr>
<td>AG3</td>
<td>0.107$^a$</td>
<td>(0.024)</td>
</tr>
<tr>
<td>KD_CD</td>
<td>0.077</td>
<td>(0.049)</td>
</tr>
<tr>
<td>YD_POP</td>
<td>-2.887$^a$</td>
<td>(0.632)</td>
</tr>
<tr>
<td>RMACDA</td>
<td>-0.074$^a$</td>
<td>(0.025)</td>
</tr>
<tr>
<td>UMCSI</td>
<td>-0.000</td>
<td></td>
</tr>
</tbody>
</table>

LR Test of Restrictions $\chi^2(1) = 15.46^a$

Notes: Estimates of Restricted Cointegrating Relations (standard errors in Brackets).
Cointegration with restricted intercepts and no trends in the VAR.
$^a$ indicates significance at the 1 percent level.
Restrictions Imposed: The coefficient of CD_POP $a_1=1$, and the coefficient of UMCSI, $a_8=0$.
DF=Total number of restrictions (2) - number of just-identifying restrictions (1)
LL subject to exactly identifying restrictions = 5337.2
LL subject to over-identifying restrictions = 5329.5
Order of VAR = 5, chosen $r =1$.
List of variables included in the co-integrating vector:
CD_POP, AG1, AG2, AG3, KD_CD, YD_POP, RMACDA, UMCSI, Intercept