Common trends in producers' expectations, the nonlinear linkage with Uruguayan GDP and its implications in economic growth forecasting

Preliminary version

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Abstract

This paper examines the common trends between producers' expectations and their interdependence with economic growth in Uruguay, for the last two decades (1998-2017).

We consider producers' expectation indicators derived from qualitative surveys collected by the "Cámara de Industrias del Uruguay" classified in four groups: exporters, low-trade industries, import-substitution industries and intra-sectoral trade industries. In base on Multivariate Structural Models estimations, we found that there is a common level between the expectation indicators of four manufacturing groups. The group who lead expectations of all manufacturing firms is the more exposed to international competition. So, the trend component of the exporters' expectations drives that of the other groups.

The research additionally shows that there is a nonlinear cointegration relationship between producers' expectations and Uruguayan GDP growth. Although it indicates that in the long-run there is bidirectional causality between both variables, in the short-run causality goes uniquely from expectations to GDP growth. Besides, this finding suggests that expectations could be an accurate leader indicator; the driver of the global expectation is the aggregate indicator of the more tradable manufacturers in Uruguay.

Key words: agents' expectations, common factors, Multivariate Structural Models, GDP forecasting, nonlinear cointegration.

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Introduction

Both theory and applied research have shown the importance of expectations concerning economic fundamentals and cyclical fluctuations. According to these studies, macroeconomic fluctuations are not only a product of the current economic situation but are also very frequently influenced (and stressed) by agents' expectations. Several and recent empirical studies have shown this fact (Karnizova, 2010; Leduc & Sill, 2010; Patel, 2011; Conrad & Loch, 2011).

Expectation indicators developed from opinion surveys among agents (entrepreneurs, consumers or experts), are nowadays widely used, essentially, because of their predictive power of the main macroeconomic variables (see among others, Svensson, 1997; Berk, 1999; Pesaran, Pierse & Lee, 1993; Rahiala & Teräsvirta, 1993; Smith & McAleer, 1995; Kauppi, Lassila & Teräsvirta, 1996; Öller, 1990; Hanssens & Vanden Abeele, 1987; Alfarano & Milakovic, 2010; Clavería, 2010; Clavería et al. 2006; 2007; 2015; 2016; 2017). In their extensive review of this empirical literature, Pesaran & Weale (2006) show that different approaches have been used to address many of these issues.

Authors such as Beaudry & Portier (2006) have found that in the US economy, share prices are predictors of total factor productivity growth and financial booms are accompanied by a broad economic expansion. Karnizova (2010) proposed a model to explain fluctuations caused by expectations, incorporating what she calls the intrinsic desire for wealth accumulation. Eusepi & Preston, 2008 developed a theory of fluctuations driven by expectations based on learning, with agents possessing incomplete information. Using a neoclassical model, Floden (2007) has shown that excessive optimism about future productivity can lead to immediate economic expansions (on the assumption of variable capacity utilization). Li & Mehkari (2009) presented a model incorporating endogenous product creation, and Patel (2011) has studied the effect of investors' expectations on their investment decisions, finding that they are particularly important in contexts of poor-quality or limited information on assets.

Meanwhile, authors such as Eusepi & Preston (2008), have shown the potential of disaggregated analysis for research into the genesis of cyclical fluctuations, focusing on the role of information disparities between agents linked by the production chain. Others (Long & Plosser, 1983; Blanchard, 1987; Durlauf, 1991; Caballero & Lyons, 1990) have emphasized various mechanisms whereby sectoral interactions in the formation of expectations —such as the build-up of small menu costs, disjointed decision-making and coordination failures— influence macroeconomic dynamics. Beaudry & Portier (2007) argue that although expectations are often singled out as a factor that contributes to explain fluctuations, interactions can only be observed from a disaggregated sectoral analysis, i.e., a more detailed representation of the economy than macroeconomic models can provide. This influence arises because of production complementarities between the various sectors of the economy.

In the same line, Lee & Shields (2000) proposed (following Lee & Pesaran, 1994; Lee, 1994; and Lee, Pesaran & Pierse, 1992), an intersectoral VAR model for industrial production in the United Kingdom which uses direct measurements of expectations (gathered by the Confederation of British Industry). The authors found that these data provided invaluable information on the role of expectations and could be used to identify the sources of persistent effects from shocks and the mechanisms whereby these effects were transmitted across sectors and over time.

Although there is vast international empirical literature, little research has been done on this subject in Uruguay. Because it is a small, open country, its economy has traditionally been subject to external shocks, particularly from its neighbours Argentina and Brazil. Those shocks have brought about strong cyclical fluctuations and episodes of crisis.

The present paper analyses the importance of agents' expectations (industrialists' expectations) in predicting GDP growth, based on previous studies for Uruguay (Lanzilotta, 2006; 2015).

This paper takes a predominantly empirical and exploratory approach. It examines the influence of Uruguayan industrialists' expectations on economic performance, breaking down the sector into four groupings differentiated by their trade participation and production specialization. To examine the relationship between the expectations of these four industry groups we seek to identify common underlying trends between them. To this aim, following several studies (such as Carvalho & Harvey, 2005, and Carvalho et al., 2007) we estimate a multivariate structural time series model (Engle & Kozicki, 1993; Vahid & Engle, 1993) and identify the driver within this expectation. Finally, by applying the procedure proposed by Breitung (2001) and Holmes & Hutton we test the existence of a long-run relationship between producers' expectations the Uruguayan GDP growth.

The findings show that there is a common trend between industrialists' expectations. This common trend is identified with the one guiding the evolution of expectations in the export-oriented grouping, and expectations in the other groups depend on it. Additionally, this trend has a nonlinear cointegrated relationship with the Uruguayan GDP growth, which confirms the important role of the expectations of industrialists most exposed to international competition in the forecasting of economic growth. Therefore, the study revealed the influence of producers' expectations on overall economic activity, showing that the information they provided could be useful for predicting and anticipating cyclical fluctuations in Uruguay and are a valuable input for predicting the overall activity growth.

The empirical analysis makes use of the expectation measurements collected by the Chamber of Industry of Uruguay (CIU)[1] and industrial production indicators from the Monthly Survey of Manufacturing Industry conducted by the National Institute of Statistics (INE). Monthly data from January 1998 to July 2011 are considered.

The remainder of the document is organized as follow. The next section describes the data and the methodological framework. Section three shows the empirical results, and in the last section, we conclude and discuss the policy implications.

Data and methodological framework

The information on producers' expectations comes from the monthly industrial surveys conducted by the CIU since 1997. This survey asks entrepreneurs of the manufacturing sector, about their expectations on the national economy (among other dimensions) for the next 6 months. They are asked to state whether they expect the situation to improve, worsen or remain

[1] http://www.ciu.com.uy/innovaportal/v/15128/9/innova.front/expectativas-empresariales-industriales.html

the same.[2] Results of the expectation survey is public available 45 days after the reference month of the survey.

In their review of the literature on the use of expectations data, Pesaran & Weale (2006) stress two crucial aspects: the way that responses are gathered and the way that they are converted into aggregate quantitative data. Remond-Tiedrez (2005), also has an interesting discussion of this issue. This paper has attempted to deal with both aspects.

As Pesaran & Weale state, a key feature to be considered is the method of aggregation of expectation responses. In the monthly CIU survey, respondents from each company are asked the following question: "In view of the current situation, how do you expect the national economy, your sector and your company to perform in the next six months?" In this paper, the balance statistic method is used to aggregate the responses. This procedure is employed by Eurostat and is routinely used in applied studies on the subject (Kangasniemi, et al., 2010, and Kangasniemi & Takala, 2012). This methodology involves the construction of aggregate indicators of expectations by subtracting the number of negative responses from the number of positive responses, then dividing by the total number of responses. Each response is accorded equal weight in the indicator regardless of the size of the company or the branch of activity in which it operates.

To resume the expectation responses, we construct balance indicators for four groups of manufacturing firms. The classification in four groups follows Laens & Osimani (2000), who propose classify manufacturing industries according to the patterns of trade and production specialization of the firms, considering the import and export flows and domestic production.[3] They classified 73 sectors (disaggregated at the four-digit level of ISIC revision 2) into four groups: exporter industries, low-trade industries, import-substitution industries and intra-sectoral trade industries. This classification criterion ensures that growth determinants act in a reasonably homogeneous way within each group. As Lorenzo et al. (2003) state, breaking industry down into homogeneous groups enhances the diagnosis since sectoral specificities are manifested in clearly differentiated patterns of behaviour.

In addition to the indicators of expectations discussed above, this paper also considers Real Gross Domestic Product (GDP) of the Uruguayan economy. The data analysed in this study concern the period from January 1998 to December 2017, with quarterly frequency and is represented in Figure 1.

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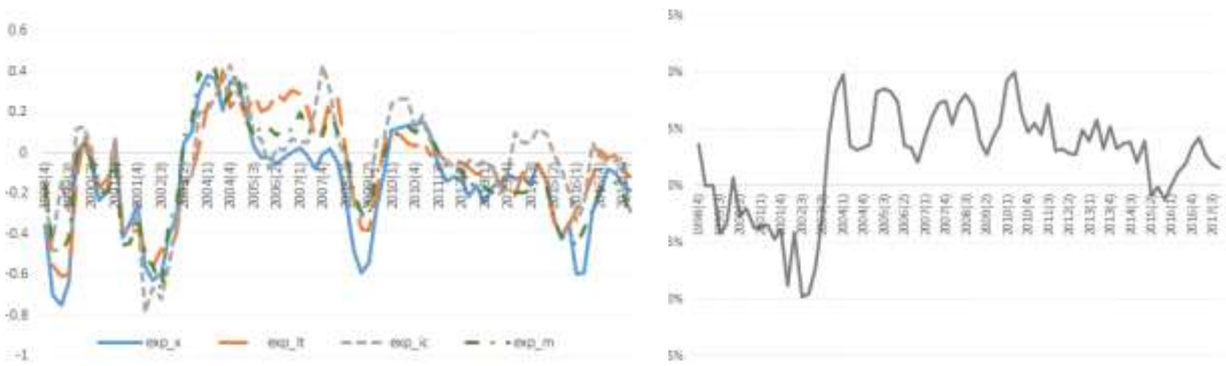
[2]The good fit between the CIU and official data of manufacturing sales provides reassurance that there are no serious sampling errors. Nonetheless, problems of framing or strategic bias could in principle be an issue.

[3] Sectors with an openness ratio (exports plus imports as a share of overall output) of under 5% are categorized as a *low-trade* group. Sectors with an openness ratio of over 5% are then analysed for intra-industry trade using the relevant Grubel-Lloyd indices. Industries with a Grubel-Lloyd index value of over 0.50 are classified as an intra-industry trade group. Those with Grubel-Lloyd scores of less than 0.50 are then separated according to whether their sectoral trade balance is positive or negative, sectors with a positive trade balance being classed as exporters and those with a negative balance as import-substitution industries.

Figure 1. Expectation indicators (left panel) and Uruguayan GDP growth (right panel). 1998.Q1-2017.Q4



Source: based on CIU and BCU. Note: exp_x= exporter industries' expectations, exp_lt=low-trade sector' expectations, exp_ic=intra sectorial commerce industries' expectations, exp_m=import substitution industry' expectations.

The methodological framework for the empirical analysis is based on the estimation of structural time series models (Koopman et al., 2009) and cointegration analysis. The basis for identifying common trends between time series is the application of multivariate structural models. The methodological framework for identifying common trends and (more generally) common factors was developed by Engle & Kozicki (1993) and Vahid & Engle (1993) and applied in several studies, such as Carvalho & Harvey (2005) and Carvalho, et al. (2007). The tests for identifying common trends in a multivariate structural model were developed by Nyblom & Harvey (2001).

In addition, in order to analise the role of expectations have a relevant role in GDP forecasting we analysed the existence of a cointegration relationship between the underlying trend of industrial expectations and the Uruguayan GDP growth ($\Delta_4 \ln GDP$) by applying a set of 'free models' (following Breitung, 2001, and Ye Lim et al., 2011). This procedure allows testing the existence of cointegration and also the linearity of the underlying relationship between the cointegrated variables.

Specifically, Breitung (2001) proposed a rank transformation for the series involved and checks whether the ranked series move together over time towards a linear or nonlinear long-term cointegrating equilibrium. The procedure starts checking the cointegration by using the rank test. If cointegration is accepted, the technique follows with examining linearity in the cointegration relationship, by using a *score statistic* $(\mathrm{T} \cdot \mathrm{R}^2)$. A more detailed description of these tests is included in Annex.

Results

The graphical analysis of the expectation indicators (Figure 1, left panel) of the four industry groups evidences that they have a similar evolution, and suggest the existence of a common trend between them. In order to identify the common factor between them we estimate a multivariate structural model (Engle & Kozicki, 1993; Vahid & Engle, 1993). In accordance with the characteristics of the four series, we initially formulate an unrestricted specification of a local level model with drift:

$$\exp\_i_t = \alpha_i + \mu_{it} + \epsilon_{it},\ \epsilon_{it} \sim \text{NIID}\left(0, \sigma^2_{i\epsilon}\right), \quad t = 1, \ldots .. T, i = x, lt, ic, m$$

$$\mu_{it} = \mu_{it-1} + \eta_{it}, \qquad \eta_{it} \sim \text{NIID}\left(0, \sigma^2_{i\eta}\right), \tag{1}$$

where μ_t is the underlying level, and ϵ_t and η_t are white noise disturbance, both normally distributed and independent of each other. Additionally the model present an autorregresive component in order to correct for autocorrelation of the process and qualitative variables were also included for outliers' correction. The results are presented in Table 1.

Table 1. Unrestricted multivariate structural model (UnModel). Vector of endogenous variables: [*exp_x, exp_lt, exp_ic, exp_m*]. Quarterly data, 1998QI – 2017Q.IV

Model estimated: Y = Level + Irregular + Cycle + AR(1) (strong convergence)	*exp_x*	*exp_lt*	*exp_ic*	*exp_m*
I. Standard deviations of the component residues:				
Irregular	0.0183213	0.0168855	0.03906136	0.0315031
Level	0.1435112	0.1253643	0.11070953	0.1072958
Cycle	-	-	-	-
AR(1)	0.0442764	0.04725177	0.09790924	1.02441375
AR coefficient	0.61585	0.86513	0.56430	0.12878
II. Model diagnostic statistics:				
Normality (Bowman-Shenton)	5.8586	7.4957	2.5458	7.6502
T	72	73	70	73
Rd^2	0.27656	0.21453	0.27642	0.34623

Source: own processing.

[a] A full list of outputs is available from the author on request.

Note: exp_*x*: expectations of export industries; exp_*m*: expectations of import-substitution industries; exp_*ic*: expectations of intra-sectoral trade industries; *iec_lt*: expectations of low-trade industries. AR(1): autoregressive process (order = 1).

The model's variance-covariance matrix shows a high correlation between the levels of the expectation series (Table 2) which suggests the existence of common trends.

Table 2. Variance-covariance matrix of the residuals of the unrestricted multivariate model

	exp_x	*exp_lt*	*exp_ic*	*exp_m*
exp_x	0.0206	0.9724	0.9053	0.9823
exp_lt	0.0175	0.01572	0.9495	0.9951
exp_ic	0.01438	0.01318	0.01226	0.9631
exp_m	0.01513	0.01339	0.01144	0.01151

Source: prepared by the author.

Note: exp_*x*: expectations of export industries; exp_*m*: expectations of import-substitution industries; exp_*ic*: expectations of intra-sectoral trade industries; *iec_lt*: expectations of low-trade industries. Grey shading denotes significant values.

The analysis of variance/correlation matrix suggest that the matrix rank is 1 (2 at a lower significance level). This justified the restriction of common levels between the series which is consistent with the preliminary graphical analysis.

In accordance with the eigenvalues of the matrix of variances, the expectations series for intra-sectoral trade, low-trade and import-substitution industries were specified as dependent. The results are presented in Table 3 and Figure 2.

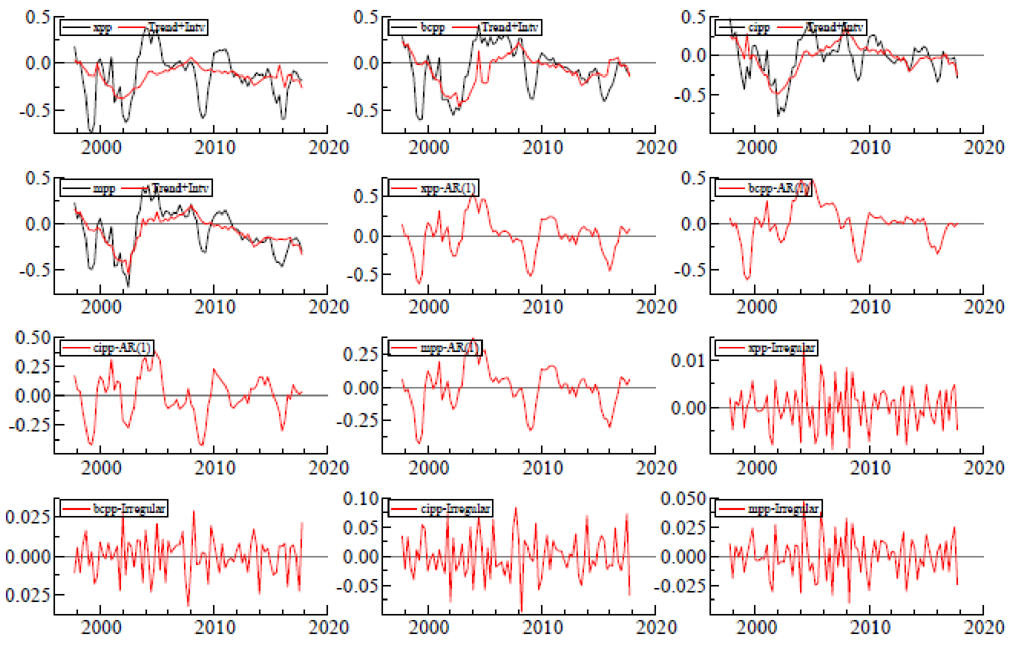
Table 3. Restricted multivariate structural model with common trends. Vector of endogenous variables: [*exp_x, exp_lt, exp_ic, exp_m*]. Quarterly data, 1998.I – 2017.IV

Model estimated: Y = Level + Irregular + Cycle + AR(1) (strong convergence) *exp_lt, exp_ic, exp_m: dependent*	*exp_x*	*exp_lt*	*exp_ic*	*exp_m*
I. Standard deviations of the component residues:				
Irregular	0.0075090	0.0180425	0.0511940	0.0249947
Level	0.0399903	-	-	-
Cycle	-	-	-	-
AR(1)	0.1406744	0.1179466	0.1192950	0.09542264
II. Model diagnostic statistics:				
Normality (Bowman-Shenton)	3.6559	6.4634	1.5909	5.4138
T	72	73	70	73
Rd^2	0.33485	0.26135	0.2985	0.42233

Source: own processing.

a A full list of outputs is available from the author on request.
Note: exp_*x*: expectations of export industries; exp_*m*: expectations of import-substitution industries; exp_*ic*: expectations of intra-sectoral trade industries; *iec_lt*: expectations of low-trade industries. AR(1): autoregressive process (order = 1).

Figure 2. Components of the multivariate structural model with common trends, 1998Q1 -2017Q4
(Index values)



Source: own processing.

The model estimated (ignoring cyclical and autoregressive components) can be written as:

$$\exp\_x_t = \mu^*_{t,} + \epsilon_{\exp\_xt},$$

$$\exp\_lt_t = 1.384\mu^*_{t,} + 0.03994 + \epsilon_{\exp\_ltt}\ ,$$

$$\exp\_ic_t = 1.865\mu^*_{t,} + 0.2439 + \epsilon_{\exp\_ict},$$

$$\exp\_m_t = 1.215\mu^*_{t,} - 0.1556 + \epsilon_{\exp\_mt},$$

where $\mu_t^*$is a univariate random walk with drift. Therefore the level components have the following relationship:

$$\mu_{\exp\_lt_t} = 1.384\,\mu_{\exp\_x_{t,}} + 0.03994,$$

$$\mu_{\exp\_ic_t} = 1.865\mu_{\exp\_x_{t,}} + 0.2439,$$

$$\mu_{\exp\_m_t} = 1.215\mu_{\exp\_x_{t,}} - 0.1556,$$

where the common trend is the one estimated for export industries: $\mu_{\exp\_x_t}$

As we stated, previous international (Kangasniemi et al. (2010); Kangasniemi & Takala, 2012) and local research (Lanzilotta, 2015) allows as hypothesizing that expectations have a relevant role in GDP forecasting. To prove this, we analysed the existence of a cointegration relationship between the underlying trend of industrial expectations and the Uruguayan GDP growth ($\Delta_4 \ln GDP$) by applying a set of 'free models' (following Breitung, 2001, and Ye Lim et al., 2011). As is was explained before, Breitung propose testing the existence of cointegration without imposing any parametric model. When cointegration is accepting, this author proposed testing the linearity of the underlying relationship between the cointegrated variables.

Results of cointegration and non-linearity test are shown in Table 4.

Table 4. . Results of nonparametric cointegration test and linearity test

	Test Statistics	
	$\Xi_T^*[1]$	$T \cdot R^2$
$[\mu_{\exp\_x_t}, \Delta_4 \ln GDP]$	0.0175**	7.4689***
Significance Level	**Critical values**	
10%	0.025	2.706
5%	0.020	3.841
1%	0.014	6.635

Notes: The hypothesis of no cointegration is rejected if the rank statistic, Ξ_T^* [2], is below the respective critical value and the hypothesis of linearity is rejected if the score statistic, T·R^2, exceeds the χ^2 critical values. *, ** and *** denote significance at 10%, 5%, according with the grades of freedom of each estimation.

According to the results, we can reject non-cointegration hypothesis and linearity. Therefore, results suggest that exists a long-run relationship between Uruguayan GDP growth and expectations (the underlying trend of industrial expectations), which is nonlinear.

Finally, we examine causality between the variables applying the nonparametric procedure proposed in Holmes & Hutton (1990). This test is more robust than conventional parametric tests usually applied (see Annex 3 for a more detailed explanation of this test). Results are shown in Table 5.

Table 5. . Results of nonparametric causality test

H-H causality test, H0 nc	**Uruguay**	
	Probability	**NC**
d(exp)-->d2(lGDP)	**0.000**	**A**
d2(lGDP)-->d(exp)	**0.143**	**R**
exp-->d4lGDP	**0**	**A**
d4lGDP-->exp	**0**	**A**

Notes: F-statistic, NC: H0: noncausality

Results confirm the bidirectional causality between Uruguayan GDP growth and expectations (the underlying trend of industrial expectations) when the test is performed in levels (i.e. for the long run). However, in the short-run (that is when the H-H causality test is run in first differences of the variables) the evidence uniquely allows accepting causality from expectation to GDP growth.

Main conclusions

This paper provides evidence on some aspects of the formation of industrialists' expectations and sheds light on how these ultimately relates to GDP growth. Two main findings emerge from this research.

Firstly, the results indicate that Industrialists' expectations (grouped into four classes according to their specialization and international insertion) follow a single common trajectory, which is determined by expectations in the export group. This finding shows the importance of export industries in spreading macroeconomic expectation shocks.

The key role played by the most trade-oriented industries is associated with the importance of this group in the Uruguayan manufactured production. Export industries account for over 50% of industrial production (excluding the oil refinery) and have significantly backwards spillover effect (because production inputs are primarily national). Besides their representativeness, their exposure to international trade makes them more competitive and provides them with access to extensive and complete information on the relevant macroeconomic and international context. Learning hypothesis postulated by Eusepi & Preston (2008) to explain the transmission of expectations to economic fluctuations, may also explain the findings of this research. This learning is held to take place among agents who do not receive information directly.

Secondly, results also confirm what some international studies have postulated (among the most recent, Kangasniemi et al., 2010; Kangasniemi & Takala, 2012): that expectation indicators provide valuable information for anticipating and predicting the future of the economy. This work verifies this result for the Uruguayan economy and industrialists' expectations (findings that are in line with previous studies for Uruguay: Lanzilotta, 2006; 2015). Another interesting result of this research is the confirmation that the relationship between expectations and the growth of Uruguayan GDP is non-linear. However, this work did not make any progress in specifying the underlying non-linear model, a topic that may stimulate future research.

The identification of a common trend in industrialists' expectations about the future of the economy, guided by the expectations of the export grouping, reveals and reflects the production structure of what is an open economy whose dynamics are highly dependent on the long-term performance of the external sector.

Although this research is exploratory, its findings have potentially important implications for economic policy. The influence of the most trade-oriented industries on expectations and then on GDP growth is a signal for policymakers seeking to mould expectations and create a climate of optimism during recessions so that their duration is lessened. The question of which factors ultimately determine expectations in these key sectors is certainly one of the issues raised by this study and could be the subject of future research.

References

Alfarano, S. & M. Milakovic (2010), "Identification of interaction effects in survey expectations: a cautionary note", *berg Working Paper Series*, No. 75, Bamberg, Bamberg Economic Research Group.

Beaudry, P. & F. Portier (2007), "When can changes in expectations cause business cycle fluctuations in neo-classical settings?"*Journal of Economic Theory*, vol. 135, No. 1, Amsterdam, Elsevier.

Beaudry, P. & F. Portier (2006), "Stock prices, news, and economic fluctuations", *American Economic Review*, vol. 96, No. 4, Nashville, Tennessee, American Economic Association.

Berk, J.M. (1999), "Measuring inflation expectations: a survey data approach", *Applied Economics,* vol. 31, No. 11, Taylor & Francis.

Blanchard, O.J. (1987), "Aggregate and individual price adjustments", *Brookings Papers on Economic Activity*, No. 1, Washington, D.C., The Brookings Institution.

Breitung, J. (2001). Rank Test for Nonlinear Cointegration. Journal of Business & Economics Statistics 19(3): 331-340.

Breitung, J. (2002). Nonparametric tests for unit roots and cointegration. Journal of Econometrics 108: 343-363.

Caballero, R.J. & R.K. Lyons (1990), "Internal versus external economies in the European industry", *European Economic Review*, vol. 34, No. 4, Amsterdam, Elsevier.

Carvalho, V. & A. Harvey (2005), "Growth, cycles and convergence in US regional time series", *International Journal of Forecasting*, vol. 21, No. 4, Amsterdam, Elsevier.

Carvalho, V., A. Harvey & T. Trimbur (2007), "A note on common cycles, common trends and convergence", *Journal of Business & Economic Statistics*, vol. 25, Taylor & Francis.

Claveria, O. (2010). Qualitative survey data on expectations. Is there an alternative to the balance statistic? In A. T. Molnar (Ed.), Economic Forecasting (pp. 181–190). Hauppauge, NY: Nova Science Publishers.

Claveria, O., Monte, E. & S. Torra (2015). A new forecasting approach for the hospitality industry. International Journal of Contemporary Hospitality Management 27(7): 1520–1538.

Claveria, O., Monte, E. & S. Torra (2016). Quantification of survey expectations by means of symbolic regression via genetic programming to estimate economic growth in Central and Eastern European economies. Eastern European Economics 54(2): 177–189.

Claveria, O., Monte, E. & S. Torra. (2017). A new approach for the quantification of qualitative measures of economic expectations. Quality & Quantity. In Press.

Claveria, O., Pons, E. & R. Ramo (2007). Business and consumer expectations and macroeconomic forecasts. International Journal of Forecasting 23(1): 47–69.

Claveria, O., Pons, E. & J. Suriñach (2006). Quantification of expectations. Are they useful for forecasting inflation? Economic Issues 11(2): 19–38.

Conrad, Ch. & K. Loch (2011), "Anticipating long-run stock market volatility", Heidelberg, Heidelberg University.

Durlauf, S. (1991), "Path dependence in aggregate output", *NBER Working Paper*, No. 3718, Cambridge, Massachusetts, National Bureau of Economic Research.

Engle, R. & Sh. Kozicki (1993), "Testing for common features", *Journal of Business & Economic Statistics*, vol. 11, No. 4, Alexandria, American Statistical Association.

Eusepi, S. & B. Preston (2008), "Expectations, learning and business cycle fluctuations", *NBER Working Paper*, No. 14181, Cambridge, Massachusetts, National Bureau of Economic Research.

Floden, M. (2007), “Vintage capital and expectations driven business cycles”, *CEPR Discussion Paper*, No. 6113, London, Centre for Economic Policy Research.

Granger, C. W. J. (1995). Modelling Nonlinear Relationship Between Extended-memory Variables. Econometrica 63: 265-279.

Hanssens, D.M. & P.M. Vanden Abeele (1987), “A time-series study of the formation and predictive performance of EEC production survey expectations”, *Journal of Business and Economic Statistics*, vol. 5, No. 4, Taylor & Francis.

Kangasniemi, J., P. Kangassalo & K. Takala (2010), “What affects the views about the economic sentiment? Evidence from the consumer and manufacturing surveys in Finland”, paper presented at the 30th ciret Conference, New York.

Kangasniemi, J. & K. Takala (2012), “The role of expectation surprises in production decisions evidence from the Finnish manufacturing survey”, paper presented at the 31st CIRET Conference, Vienna.

Karnizova, L. (2010), “The spirit of capitalism and expectation-driven business cycles”, *Journal of Monetary Economics*, vol. 57, No. 6, Amsterdam, Elsevier.

Kauppi, E., J. Lassila & T. Teräsvirta (1996), “Short-term forecasting of industrial production with business survey data: experience from Finland’s great depression 1990-1993”, *International Journal of Forecasting*, vol. 12, No. 3, Amsterdam, Elsevier.

Koopman, S. J., Harvey, A. C., Doornik, J. A., & Shephard, N. (2009). *Structural Time Series Analyser, Modeller and Predictor: Stamp 8.2*, London, Timberlake Consultants Ltd.

Laens, S. & R. Osimani (2000), “Patrones de comercio y desempeño exportador, el caso de Uruguay en los noventa”, Montevideo, Centre for Economic Research.

Lanzilotta, B. (2006), “Aporte de los índices líderes de actividad económica al análisis de la coyuntura y la predicción macroeconómica en Uruguay”, Montevideo, University of the Republic.

Lanzilotta, B. (2015). Expectativas empresariales: consecuencias en el crecimiento en Uruguay. Cuadernos de Economía, 34(65), 423-442.

Leduc, S. & K. Sill (2010), “Expectations and economic fluctuations: an analysis using survey data”, *Working Paper Series*, No. 2010-09, San Francisco, Federal Reserve Bank of San Francisco.

Lee, K. (1994), “Formation of price and cost inflation expectations in British manufacturing industries: a multi-sectoral analysis”, *The Economic Journal*, vol. 104, No. 423, Wiley.

Lee, K. & M. Pesaran (1994), “An empirical analysis of business cycle fluctuations in the context of a multisectoral model-Full Report”, University of Leicester/University of Cambridge.

Lee, K., M. Pesaran & R. Pierse (1992), “Persistence of shocks and their sources in a multisectoral model of uk output growth”, *Economic Journal*, vol. 102, No. 411, Wiley.

Lee, K. & K. Shields (2000), “Expectations formation and business cycle fluctuations: an empirical analysis of actual and expected output in uk manufacturing, 1975-1996”, *Oxford Bulletin of Economics and Statistics*, vol. 62, No. 4, Wiley.

Li, N. & M. Mehkari (2009), “Expectation Driven Firm Dynamics and Business Cycles”, Columbus, Ohio, Ohio State University.

Long, J. & Ch. Plosser (1983), “Real business cycles”, *Journal of Political Economy*, vol. 91, No. 1, Chicago, University of Chicago Press.

Lorenzo, F., B. Lanzilotta & I. Sueiro (2003), “Métodos cuantitativos para el análisis y predicción de la actividad industrial uruguaya”, *Documentos de trabajo*, Montevideo, Centre for Economic Research.

Nyblom, J. & A. Harvey (2001), “Testing against smooth stochastic trends”, *Journal of Applied Econometrics*, vol. 16, No. 3, Wiley.

Öller, L. (1990), “Forecasting the business cycle using survey data”, *International Journal of Forecasting*, vol. 6, No. 4, Amsterdam, Elsevier, December.

Patel, S. (2011), “Economic Optimism, Information Uncertainty and Future Investment Decisions: Evidence from the Mutual Fund Industry”, McGill University.

Pesaran, M., R. Pierse & K. Lee (1993), “Persistence, cointegration and aggregation. A disaggregated analysis of output fluctuations in the U.S. economy”, *Journal of Econometrics*, vol. 56, No. 1-2, Amsterdam, Elsevier.

Pesaran, M.H. & M. Weale (2006), “Survey expectations”, *Handbook of Economic Forecasting*, vol. 1, G. Elliot, C. Granger & A. Timmermann (eds.), Amsterdam, North Holland.

Rahiala, M. & T. Teräsvirta (1993), “Business survey data in forecasting the output of Swedish and Finnish metal and engineering industries: a Kalman Filter approach”, *Journal of Forecasting*, vol. 12, No. 3-4, Wiley.

Remond-Tiedrez, I. (2005), “From opinions to facts: links between short-term business statistics and business and consumer opinion surveys”, *Statistics in Focus. Industry, Trade and Services*, No. 15/2005, Eurostat.

Smith, J. & M. McAleer (1995), “Alternative procedures for converting qualitative response data to quantitative expectations: an application to Australian manufacturing”, *Journal of Applied Econometrics*, vol. 10, No. 2, Wiley.

Stock, J.H. and Watson, M.W. (1993). A simple Estimator of Cointegrating Vector in Higher Order Integrated Systems. Econometrica 61: 783-820.

Svensson, L. (1997), “Inflation forecast targeting: implementing and monitoring inflation targets”, *European Economic Review*, vol. 41, No. 6, Amsterdam, Elsevier.

Vahid, F. & R. Engle (1993), “Common trends and common cycles”, *Journal of Applied Econometrics*, vol. 8, No. 4, Wiley.

Ye Lim, S.; Ghazali, M. and Mun Ho, C. (2011). Export and economic growth in Southeast Asia current Newly Industrialized Countries: Evidence from nonparametric approach. Economics Bulletin 31(3): 2683-2693.

Annex

1. Unrestricted multivariate structural model

```
Strong convergence relative to 1e-07
       - likelihood cvg 0
       - gradient cvg 7.20782e-05
       - parameter cvg 0
       - number of bad iterations 5
Estimation process completed.

UC(111) Estimation done by Maximum Likelihood (exact score)
       The database used is C:\Users\blanzilotta\Google
Drive\iecon\expectativas\2019\estimaciones\series para stamp 2019.xlsx
       The selection sample is: 1997(4) - 2017(4) (N = 4, T = 81)
       The dependent vector Y contains variables:
                 xpp         bcpp         cipp          mpp
       The model is: Y = Trend + Irregular + AR(1) + Interventions
       Component selection: 0=out, 1=in, 2=dependent, 3=fix
                   Level       Slope       AR(1)   Irregular
    xpp                1           1           1           1
    bcpp               1           1           1           1
    cipp               1           1           1           1
    mpp                1           1           1           1

Profile Log-Likelihood:                  770.0760
Akaike Information Criterion (AIC):     -17.7056
Bayesian Information Criterion (BIC):   -16.1388
Prediction error variance/correlation matrix:
            xpp        bcpp        cipp         mpp
xpp      0.02198     0.90177     0.79833     0.94292
bcpp     0.01762     0.01736     0.68227     0.91033
cipp     0.01805     0.01371     0.02325     0.76980
mpp      0.01613     0.01384     0.01354     0.01331

Summary statistics:
                       xpp        bcpp        cipp         mpp
 T                      72          73          70          73
 Normality          5.8586      7.4957      2.5458      7.6502
 H(22)             0.25997     0.21715      0.3931     0.20625
 DW                 1.8213      1.7861      1.8058      1.8632
 r(1)             0.068501     0.10622    0.045745    0.060072
 q                      11          11          11          11
 p                       4           4           4           4
 r(q)            -0.061326    -0.11908    0.039315   -0.066776
 Q(q,q-p)           14.987       9.671      14.384      9.3485
 Rd^2              0.27656     0.21453     0.27642     0.34623

Variances of disturbances in Eq xpp:
                     Value    (q-ratio)
Level            0.0205955  (    61.36)
Slope             0.000000  (   0.0000)
AR(1)           0.00196040  (    5.840)
Irregular      0.000335669  (    1.000)

Variances of disturbances in Eq bcpp:
                     Value    (q-ratio)
Level            0.0157162  (    46.82)
Slope             0.000000  (   0.0000)
AR(1)           0.00223273  (    6.652)
Irregular      0.000285120  (   0.8494)

Variances of disturbances in Eq cipp:
                     Value    (q-ratio)
Level            0.0122566  (    36.51)
Slope             0.000000  (   0.0000)
AR(1)           0.00958622  (    28.56)
Irregular       0.00152579  (    4.546)

Variances of disturbances in Eq mpp:
```

	Value	(q-ratio)
Level	0.0115124	(34.30)
Slope	0.000000	(0.0000)
AR(1)	0.000596031	(1.776)
Irregular	0.000992445	(2.957)

Level disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	0.02060	0.9724	0.9053	0.9823
bcpp	0.01750	0.01572	0.9495	0.9951
cipp	0.01438	0.01318	0.01226	0.9631
mpp	0.01513	0.01339	0.01144	0.01151

Slope disturbance scalar variance matrix:

	xpp	bcpp	cipp	mpp
xpp	0.0000	0.0000	0.0000	0.0000
bcpp	0.0000	0.0000	0.0000	0.0000
cipp	0.0000	0.0000	0.0000	0.0000
mpp	0.0000	0.0000	0.0000	0.0000

AR(1) disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	0.001960	0.4730	0.9990	0.7573
bcpp	0.0009897	0.002233	0.4906	0.9311
cipp	0.004331	0.002270	0.009586	0.7676
mpp	0.0008186	0.001074	0.001835	0.0005960

Irregular disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	0.0003357	0.2503	0.1209	0.9681
bcpp	7.742e-05	0.0002851	-0.9298	0.03544
cipp	8.653e-05	-0.0006133	0.001526	0.3304
mpp	0.0005588	1.885e-05	0.0004066	0.0009924

AR(1) other parameters:

	xpp	bcpp	cipp	mpp
AR coefficient	0.61585	0.86513	0.56430	0.12878

State vector analysis at period 2017(4):

Equation xpp

	Value	Prob
Level	-0.13290	[0.00304]
Slope	-0.00304	[0.85029]

Equation bcpp

	Value	Prob
Level	-0.25807	[0.03732]
Slope	-0.00649	[0.64752]

Equation cipp

	Value	Prob
Level	-0.14378	[0.05467]
Slope	-0.00577	[0.64442]

Equation mpp

	Value	Prob
Level	-0.38365	[0.00000]
Slope	-0.00723	[0.54920]

Equation xpp: regression effects in final state at time 2017(4):

	Coefficient	RMSE	t-value	Prob
Outlier 2015(4)	0.13487	0.03550	3.79948	[0.00029]
Outlier 2016(2)	-0.11191	0.03345	-3.34599	[0.00128]
Outlier 1999(4)	0.11321	0.03346	3.38347	[0.00113]

Equation bcpp: regression effects in final state at time 2017(4):

	Coefficient	RMSE	t-value	Prob
Outlier 2004(3)	0.28518	0.04164	6.84918	[0.00000]
Level break 2005(3)	0.20550	0.05236	3.92449	[0.00019]
Level break 2002(4)	-0.17811	0.05227	-3.40754	[0.00106]
Level break 2016(1)	0.14081	0.05448	2.58481	[0.01169]

```
Equation cipp: regression effects in final state at time 2017(4):
                Coefficient        RMSE     t-value     Prob
Outlier 1999(2)     0.33759     0.07522     4.48819 [0.00002]

Equation mpp: regression effects in final state at time 2017(4):
                    Coefficient        RMSE     t-value     Prob
Outlier 2002(3)        -0.17752     0.03061    -5.79853 [0.00000]
Outlier 2003(4)         0.11958     0.03025     3.95296 [0.00017]
Outlier 2005(1)         0.10959     0.03053     3.58973 [0.00059]
Level break 2003(2)     0.13565     0.03035     4.46903 [0.00003]

Variances of disturbances in Eq xpp:
                    Value    (q-ratio)
Level           0.0205955  (    61.36)
Slope            0.000000  (   0.0000)
AR(1)          0.00196040  (    5.840)
Irregular     0.000335669  (    1.000)

Variances of disturbances in Eq bcpp:
                    Value    (q-ratio)
Level           0.0157162  (    46.82)
Slope            0.000000  (   0.0000)
AR(1)          0.00223273  (    6.652)
Irregular     0.000285120  (   0.8494)

Variances of disturbances in Eq cipp:
                    Value    (q-ratio)
Level           0.0122566  (    36.51)
Slope            0.000000  (   0.0000)
AR(1)          0.00958622  (    28.56)
Irregular      0.00152579  (    4.546)

Variances of disturbances in Eq mpp:
                    Value    (q-ratio)
Level           0.0115124  (    34.30)
Slope            0.000000  (   0.0000)
AR(1)         0.000596031  (    1.776)
Irregular     0.000992445  (    2.957)

Standard deviations of disturbances in Eq xpp:
                    Value    (q-ratio)
Level            0.143511  (    7.833)
Slope            0.000000  (   0.0000)
AR(1)           0.0442764  (    2.417)
Irregular       0.0183213  (    1.000)

Standard deviations of disturbances in Eq bcpp:
                    Value    (q-ratio)
Level            0.125364  (    6.843)
Slope            0.000000  (   0.0000)
AR(1)           0.0472518  (    2.579)
Irregular       0.0168855  (   0.9216)

Standard deviations of disturbances in Eq cipp:
                    Value    (q-ratio)
Level            0.110710  (    6.043)
Slope            0.000000  (   0.0000)
AR(1)           0.0979092  (    5.344)
Irregular       0.0390613  (    2.132)

Standard deviations of disturbances in Eq mpp:
                    Value    (q-ratio)
Level            0.107296  (    5.856)
Slope            0.000000  (   0.0000)
AR(1)           0.0244137  (    1.333)
Irregular       0.0315031  (    1.719)

Level disturbance variance/correlation matrix:
              xpp        bcpp        cipp         mpp
xpp      0.02060      0.9724      0.9053      0.9823
```

```
bcpp     0.01750     0.01572      0.9495      0.9951
cipp     0.01438     0.01318     0.01226      0.9631
mpp      0.01513     0.01339     0.01144     0.01151

Slope disturbance scalar variance matrix:
             xpp        bcpp        cipp         mpp
xpp       0.0000      0.0000      0.0000      0.0000
bcpp      0.0000      0.0000      0.0000      0.0000
cipp      0.0000      0.0000      0.0000      0.0000
mpp       0.0000      0.0000      0.0000      0.0000

AR(1) disturbance variance/correlation matrix:
             xpp        bcpp        cipp         mpp
xpp     0.001960      0.4730      0.9990      0.7573
bcpp   0.0009897    0.002233      0.4906      0.9311
cipp    0.004331    0.002270    0.009586      0.7676
mpp    0.0008186    0.001074    0.001835   0.0005960

Irregular disturbance variance/correlation matrix:
             xpp        bcpp        cipp         mpp
xpp    0.0003357      0.2503      0.1209      0.9681
bcpp   7.742e-05   0.0002851     -0.9298     0.03544
cipp   8.653e-05  -0.0006133    0.001526      0.3304
mpp    0.0005588   1.885e-05   0.0004066   0.0009924

Analysis of variance matrices:
Level disturbance variance matrix is 4 x 4 with imposed rank 4 and actual rank 3
Variance/correlation matrix
             xpp        bcpp        cipp         mpp
xpp      0.02060      0.9724      0.9053      0.9823
bcpp     0.01750     0.01572      0.9495      0.9951
cipp     0.01438     0.01318     0.01226      0.9631
mpp      0.01513     0.01339     0.01144     0.01151
Eigenvectors and eigenvalues
                     xpp        bcpp        cipp         mpp
xpp              -0.5852     -0.6194     -0.4677      0.2349
bcpp             -0.5160    0.007489      0.7954      0.3180
cipp             -0.4405      0.7845     -0.3794      0.2158
mpp              -0.4442     0.02932     0.06848     -0.8928
eigenvalues      0.05833    0.001453   0.0002949  -4.802e-19
percentage         97.09       2.419      0.4908  -7.992e-16

Slope disturbance variance matrix is 4 x 4 with imposed rank 4 and actual rank 0
Variance/correlation matrix
             xpp        bcpp        cipp         mpp
xpp       0.0000      0.0000      0.0000      0.0000
bcpp      0.0000      0.0000      0.0000      0.0000
cipp      0.0000      0.0000      0.0000      0.0000
mpp       0.0000      0.0000      0.0000      0.0000
Eigenvectors and eigenvalues
                     xpp        bcpp        cipp         mpp
xpp               0.0000      0.0000       1.000      0.0000
bcpp              0.0000      0.0000      0.0000       1.000
cipp               1.000      0.0000      0.0000      0.0000
mpp               0.0000       1.000      0.0000      0.0000
eigenvalues       0.0000      0.0000      0.0000      0.0000
percentage        0.0000      0.0000      0.0000      0.0000

AR(1) disturbance variance matrix is 4 x 4 with imposed rank 4 and actual rank 4
Variance/correlation matrix
             xpp        bcpp        cipp         mpp
xpp     0.001960      0.4730      0.9990      0.7573
bcpp   0.0009897    0.002233      0.4906      0.9311
cipp    0.004331    0.002270    0.009586      0.7676
mpp    0.0008186    0.001074    0.001835   0.0005960
Cholesky decomposition LDL' with L and D
                xpp        bcpp        cipp         mpp
xpp           1.000      0.0000      0.0000      0.0000
bcpp         0.5048       1.000      0.0000      0.0000
cipp          2.209     0.04816       1.000      0.0000
mpp          0.4176      0.3813     -0.3345       1.000
```

```
diag(D)    0.001960    0.001733   1.609e-05   3.867e-07
Eigenvectors and eigenvalues
                    xpp        bcpp        cipp         mpp
xpp             -0.3913     -0.1377     -0.6191      0.6669
bcpp            -0.2469      0.9024      0.2372      0.2616
cipp            -0.8677     -0.2606      0.3503     -0.2376
mpp             -0.1819      0.3143     -0.6617     -0.6560
eigenvalues     0.01257    0.001801   5.437e-06   1.718e-07
percentage        87.44       12.53     0.03782    0.001195

Irregular disturbance variance matrix is 4 x 4 with imposed rank 4 and actual rank 4
Variance/correlation matrix
             xpp        bcpp        cipp         mpp
xpp    0.0003357      0.2503      0.1209      0.9681
bcpp   7.742e-05   0.0002851     -0.9298     0.03544
cipp   8.653e-05  -0.0006133    0.001526      0.3304
mpp    0.0005588   1.885e-05   0.0004066   0.0009924
Cholesky decomposition LDL' with L and D
                xpp        bcpp        cipp         mpp
xpp           1.000      0.0000      0.0000      0.0000
bcpp         0.2307       1.000      0.0000      0.0000
cipp         0.2578      -2.369       1.000      0.0000
mpp           1.665     -0.4117      0.5879       1.000
diag(D)   0.0003357   0.0002673   3.225e-06   1.584e-05
Eigenvectors and eigenvalues
                    xpp        bcpp        cipp         mpp
xpp             -0.1808      0.4807      0.8155     -0.2667
bcpp             0.2883      0.3224      0.1639      0.8866
cipp            -0.8303     -0.3772      0.1616      0.3772
mpp             -0.4414      0.7230     -0.5310    -0.02123
eigenvalues    0.001974    0.001160   4.581e-06   4.370e-07
percentage        62.88       36.96      0.1459     0.01392
```

2. Restricted multivariate structural model

```
Strong convergence relative to 1e-07
- likelihood cvg 0
- gradient cvg 3.4825e-05
- parameter cvg 0
- number of bad iterations 5
Estimation process completed.

UC(110) Estimation done by Maximum Likelihood (exact score)
The database used is C:\Users\blanzilotta\Google
Drive\iecon\expectativas\2019\estimaciones\series para stamp 2019.xlsx
The selection sample is: 1997(4) - 2017(4) (N = 4, T = 81)
The dependent vector Y contains variables:
       xpp         bcpp          cipp          mpp
The model is: Y = Trend + Irregular + AR(1) + Interventions
Component selection: 0=out, 1=in, 2=dependent, 3=fix
                    Level       Slope       AR(1)   Irregular
    xpp                 1           1           1           1
    bcpp                2           1           1           1
    cipp                2           1           1           1
    mpp                 2           1           1           1

Profile Log-Likelihood:                 770.6330
Akaike Information Criterion (AIC):     -17.8675
Bayesian Information Criterion (BIC):   -16.4781
Prediction error variance/correlation matrix:
             xpp        bcpp        cipp         mpp
xpp      0.02021     0.89729     0.79153     0.93804
bcpp     0.01630     0.01633     0.66752     0.89935
cipp     0.01689     0.01281     0.02254     0.76129
mpp      0.01446     0.01246     0.01239     0.01176

Summary statistics:
                      xpp        bcpp        cipp         mpp
 T                     72          73          70          73
 Normality         3.6559      6.4634      1.5909      5.4138
```

H(22)	0.24889	0.22633	0.36764	0.21811
DW	1.7475	1.6912	1.8866	1.8323
r(1)	0.10881	0.14932	0.016015	0.077727
q	11	11	11	11
p	4	4	4	4
r(q)	-0.05246	-0.10037	0.043408	-0.046749
Q(q,q-p)	15.774	6.8589	12.455	8.7873
Rd^2	0.33485	0.26135	0.2985	0.42233

Variances of disturbances in Eq xpp:

	Value	(q-ratio)
Level	0.00159203	(28.23)
Slope	0.000000	(0.0000)
AR(1)	0.0197893	(351.0)
Irregular	5.63852e-05	(1.000)

Variances of disturbances in Eq bcpp:

	Value	(q-ratio)
Slope	0.000000	(0.0000)
AR(1)	0.0139114	(246.7)
Irregular	0.000325532	(5.773)

Variances of disturbances in Eq cipp:

	Value	(q-ratio)
Slope	0.000000	(0.0000)
AR(1)	0.0142313	(252.4)
Irregular	0.00262083	(46.48)

Variances of disturbances in Eq mpp:

	Value	(q-ratio)
Slope	0.000000	(0.0000)
AR(1)	0.00910548	(161.5)
Irregular	0.000624735	(11.08)

Level disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	0.001592	1.000	1.000	1.000
bcpp	0.002203	0.003048	1.000	1.000
cipp	0.002969	0.004108	0.005538	1.000
mpp	0.001934	0.002676	0.003607	0.002350

Level disturbance factor variance for xpp: 0.00159203

Level disturbance factor loading matrix:

	xpp
bcpp	1.384
cipp	1.865
mpp	1.215

	xpp	bcpp	cipp	mpp
Constant	0.0000	0.03994	0.2439	-0.1556

Slope disturbance scalar variance matrix:

	xpp	bcpp	cipp	mpp
xpp	0.0000	0.0000	0.0000	0.0000
bcpp	0.0000	0.0000	0.0000	0.0000
cipp	0.0000	0.0000	0.0000	0.0000
mpp	0.0000	0.0000	0.0000	0.0000

AR(1) disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	0.01979	0.9114	0.8796	0.9762
bcpp	0.01512	0.01391	0.7597	0.9406
cipp	0.01476	0.01069	0.01423	0.7650
mpp	0.01310	0.01059	0.008709	0.009105

Irregular disturbance variance/correlation matrix:

	xpp	bcpp	cipp	mpp
xpp	5.639e-05	0.08938	0.1148	0.9238
bcpp	1.211e-05	0.0003255	-0.9761	-0.1226
cipp	4.414e-05	-0.0009016	0.002621	0.3351
mpp	0.0001734	-5.531e-05	0.0004288	0.0006247

```
AR(1) other parameters:
                       xpp        bcpp        cipp         mpp
AR coefficient     0.80226     0.85589     0.75111     0.78937

State vector analysis at period 2017(4):
Equation xpp
             Value     Prob
Level     -0.26504 [0.06225]
Slope     -0.00379 [0.47879]

Equation bcpp
             Value     Prob
Level     -0.32680 [0.07558]
Slope     -0.00702 [0.32178]

Equation cipp
             Value     Prob
Level     -0.25042 [0.02340]
Slope     -0.00651 [0.45208]

Equation mpp
             Value     Prob
Level     -0.47756 [0.00001]
Slope     -0.00789 [0.17560]

Equation xpp: regression effects in final state at time 2017(4):
                Coefficient        RMSE     t-value     Prob
Outlier 2015(4)     0.12698     0.03494     3.63437 [0.00050]
Outlier 2016(2)    -0.11686     0.03361    -3.47664 [0.00084]
Outlier 1999(4)     0.10348     0.03355     3.08382 [0.00285]

Equation bcpp: regression effects in final state at time 2017(4):
                    Coefficient        RMSE     t-value     Prob
Outlier 2004(3)         0.29154     0.04214     6.91790 [0.00000]
Level break 2005(3)     0.20038     0.05122     3.91189 [0.00020]
Level break 2002(4)    -0.18140     0.05143    -3.52684 [0.00072]
Level break 2016(1)     0.16518     0.05231     3.15782 [0.00229]

Equation cipp: regression effects in final state at time 2017(4):
                Coefficient        RMSE     t-value     Prob
Outlier 1999(2)     0.32352     0.07602     4.25578 [0.00006]

Equation mpp: regression effects in final state at time 2017(4):
                    Coefficient        RMSE     t-value     Prob
Outlier 2002(3)        -0.17993     0.03099    -5.80682 [0.00000]
Outlier 2003(4)         0.12436     0.03056     4.06890 [0.00012]
Outlier 2005(1)         0.11416     0.03068     3.72066 [0.00038]
Level break 2003(2)     0.14005     0.03191     4.38930 [0.00004]
```

3. Rank test for cointegration and Rank test for (neglected) nonlinearity

Rank test for cointegration

Breitung (2001) introduces a nonparametric test procedure to test the hypothesis of a cointegration relationship and to identify whether this link is nonlinear. Breitung procedure proposed a rank transformation for the series involved and checks whether the ranked series move together over time towards a linear or nonlinear long-term cointegrating equilibrium. The procedure starts checking the cointegration by using the rank test. If cointegration is accepted, the technique follows with examining linearity in the cointegration relationship, by using a scoring test.

Let $f(x_t)$~ I(1) and $g(y_t)$~ I(1) nonlinear increasing functions of x_t and y_t, and μ_t~I(0). Let suppose that a nonlinear cointegration relationship between x_t and y_t is given by

$$\mu_t = g(y_t) - f(x_t) \qquad (1)$$

The rank statistic is constructed by replacing $f(x_t)$ and $g(y_t)$ by the ranked series

$$R_T[f(x_t)] = R_T(x_t) \quad (2)$$

and

$$R_T[g(y_t)] = R_T(y_t) \quad (3)$$

Given that the sequence of ranks is invariant under monotonic transformations of the variables, if x_t or y_t are random walk process then $R_T[f(x_t)]$ and $R_T[g(y_t)]$ behaves like the ranked random walks as $R_T(x_t)$ and $R_T(y_t)$.

The rank test procedure is based on two "distance measures" between the sequences of $R_T(x_t)$ and $R_T(y_t)$. The cointegration test is based on the difference between the sequences on the ranks can be detected by the bivariate statistics K_T^*: and ξ_T^*:,

$$K_T^* = T^{-1} \max_t |d_t| / \hat{\sigma}_{\Delta d} \quad (4)$$

$$\xi_T^* = T^{-3} \sum_{t=1}^{T} d_t^2 / \hat{\sigma}_{\Delta d}^2, \quad (5)$$

where

$$d_t = R_T(y_t) - R_T(x_t), \quad (6)$$

for $R_T(y_t)$ = Rank [of y_t among $y_1, \ldots, y_T$] and $R_T(x_t)$ = Rank [of x_t among $x_1, \ldots, x_T$]. The $\max_t |d_t|$ is the maximum value of $|d_t|$ over t=1,2, ..., T and

$$\hat{\sigma}_{\Delta d}^2 = T^{-2} \sum_{t=2}^{T} (d_t - d_{t-1})^2 \quad (7)$$

adjusts for possible correlation between the series of interest.

Rank test for (neglected) nonlinearity

If cointegration is not neglected in the first step, then we test the linearity of the cointegration relationship. For a convenient representation of the alternative and null hypothesis Breitung (2002) follows Granger (1995) and represents the nonlinear relationship as:

$$y_t = \gamma_0 + \gamma_1 x_t + f^*(x_t) + u_t, \quad (8)$$

where $\gamma_0 + \gamma_1 x_t$ is the linear part of the relationship. Only when $f^*(x_t) = 0$ there is a linear relationship between the variables. In this test the multiple of the rank transformation is used instead of using $f^*(x_t)$.

Under the assumption that x_t is exogenous and u_t is a white noise with $u_t \sim N(0, \sigma^2)$ a *score test* is obtained as the T^*R^2 statistic of the MCO:

$$\tilde{u}_t = c_0 + c_1 x_t + c_2 R_t(x_t) + e_t. \quad (9)$$

Breitung (2001) generalizes the score test for the ECM representation and applies it to contrast the null hypothesis of linear cointegration against the alternative hypothesis of nonlinear cointegration. To compute the score statistic, the following two multiple regressions are run, consecutively:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} y_{t-i} + \alpha_2 x_t + \sum_{i=-p}^{p} \alpha_{3i} \Delta x_{t-i} + u_t \quad (10)$$

$$\tilde{u}_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \beta_2 x_t + \sum_{i=-p}^{p} \beta_{3i} \Delta x_{t-i} + \cdots + \theta_1 R_T(x_t) + .. + \tilde{v}_t, \quad (11)$$

where $\beta_0 + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \beta_2 x_t + \sum_{i=-p}^{p} \beta_{3i} \Delta x_{t-i}$ is the linear part of the relationship and it involves the ranked series $R_T(x_{jt})$.

Under the null hypothesis, it is assumed that the coefficients for the ranked series are equal to zero, $\theta_1 = 0$. The appropriate value of p is selected based on Akaike Information Criterion, such that serial correlation $\tilde{u}_t$ and possible endogeneity are adjusted based on Stock and Watson (1993). The *score statistic* $T \cdot R^2$, is distributed asymptotically as a χ^2 distribution, where T is the number of observations and R^2 is the coefficient of determination of the second equation. The null hypothesis may be rejected in favour of nonlinear relationship if the score statistic value exceeds the χ^2 critical values with one degree of freedom (when two variables are involved).

Causality Rank Test

Conventional Granger causality test uses Vector Autoregression (VAR) or Vector Error Correction Model (VECM). However, results from the conventional parametric tests are limited by the augmenting hypothesis of the specific functional forms of the variables and the assumptions of homoscedasticity and normality of the error terms. As pointed by Ye Lim et al. (2011), violation of these conditions can cause spurious causality conclusions. For these casas, Holmes & Hutton (1990) proposed a multiple rank F-test, more robust than the standard Granger causality test. In case that the conditions of Granger estimations are satisfied, the multiple rank F-test results are alike the Granger results.

Holmes & Hutton (1990) analysed the small sample properties of the multiple rank F-test, showing that with non-normal error distributions the test has significant power advantages both in small and in large sample. This is valid for both weak and strong relationships between the variables.

The Holmes & Hutton (1990) multiple rank F-test is based on rank ordering of each variable. In this test, the causal relationship between y_t and x_t involves a test of a subset of *q* coefficients in the Autoregressive Distributed Lag (ARDL) model. The multiple rank F-test in ARDL (p,q) model can be written as:

$$R(y_t) = a_0 + \sum_{i=1}^{p} a_{1i} R(y_{t-i}) + \sum_{i=1}^{q} a_{2i} R(x_{t-i}) + e_t \qquad (14)$$

$$R(x_t) = b_0 + \sum_{i=1}^{p} b_{1i} R(x_{t-i}) + \sum_{i=1}^{q} b_{2i} R(y_{t-i}) + \varepsilon_t, \qquad (15)$$

where $R(\cdot)$ represents a rank order transformation and, each lagged values of the series in each model are treated as separate variables when calculating their ranks, for example, $R(Y_t)$ and $R(Y_{t-1})$. The residuals, e_t and ε_t are assumed to be serially uncorrelated, and *p* and *q* may differ in each equation. When choosing *p* and *q*, two things have to be considered: the significance of the estimated coefficients and the serial correlation of resulting residuals.

From (14) rejection of the null hypothesis $(a_{2i} = 0)$ implies causality from X to Y; whereas in (15), rejection of the null hypothesis $(a_{2i} = 0)$ implies the reverse causality from Y to X. The null hypothesis is rejected if the F-test statistic is significant with respective q´s value and N-K (K=p+q+1) degrees of freedom.