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Macroeconomic Uncertainty, Growth and Inflation in the Eurozone: A Causal Approach

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Abstract

In this paper, we evaluate the causal relationship between macroeconomic uncertainty indices, inflation and growth rate for 17 Eurozone countries on a county level examination. In performing a series of linear and non-linear causality tests we find little evidence of a causal relationship between uncertainty and macroeconomic variables. Thus, macroeconomic analysis based on uncertainty indices should be treated with caution.

JEL codes: C32, E23, E27, E31, E37

Keywords: Output growth, inflation, uncertainty, causality

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1. Introduction

In the aftermath of the global financial and the European debt sovereign crisis, a growing literature has resuscitated the interest on the effect of macroeconomic uncertainty on output growth and inflation. In the presence of uncertainty, policy authorities and investors are hesitant on the proper course of actions, hindering economic activity. While all previous research is focused on examining the correlation between uncertainty and economic activity, little has been done towards examining a causal relationship between the two.

In his Nobel lecture Friedman (1976) argues that high inflation uncertainty leads to higher future inflation, which is later empirically validated by Cukierman and Meltzer (1986). Later studies reach to contradicting results on a bi-directional relationship between inflation and uncertainty, mainly due to different definitions of uncertainty: in favor (Grier and Perry, 2000; Thornton, 2007; Neanidis and Savva, 2013) or against (Hartmann and Herwartz, 2012; Conrad and Karanasos, 2005). In contrast, the literature reports the existence of a causal relationship between uncertainty and output growth (among others Jurado et al., 2015).

Since uncertainty cannot be observed directly, a common approach is to measure the error in forecasting. Rossi and Sekhposyan (2015, 2017) state that uncertainty is associated with the likelihood of observing a certain value of the forecasting error. Taking the historical unconditional distribution of the errors, uncertainty is the quantile that the forecast error appears; if the 99th percentile is 3% and the actual forecast error is 3% then uncertainty is high. This index adheres closely to economic fluctuations, it is easy to produce in country level and it is highly correlated with the typical indices in the literature (VSTOXX and Baker *et al.*, 2016). In order to evaluate the connection between uncertainty and the economy, we perform a battery of linear and nonlinear causality tests between uncertainty, output growth and inflation of the Eurozone area.

2. Causality tests

Among a plethora of alternatives, in this paper we apply five causality tests in as follows:

A. The Granger (1969) causality test is the cornerstone in testing causal relationships in economics. The test examines whether a variable x and its lags can be used in forecasting a variable y and vice versa. Given a stationary bivariate VAR model with series x_t and y_t:

$$\Delta y_t = a_{11} + \sum_{i=1}^{k} \beta_{11i}\, \Delta y_{t-i} + \cdots + \sum_{j=1}^{k} \beta_{12j}\, \Delta x_{t-j} + \varepsilon_{12t} \tag{1}$$

$$\Delta x_t = a_{21} + \sum_{i=1}^{k} \beta_{21i}\, \Delta x_{t-i} + \cdots + \sum_{j=1}^{k} \beta_{22j}\, \Delta y_{t-j} + \varepsilon_{22t} \tag{2}$$

where is k the maximum number of lags, Δ the difference operator, α, β coefficients for estimation and ε the error term. The null hypothesis is that $H_0: \beta_{12j} = 0, \quad j = 1,2,3, \ldots, q$. If the null is rejected then past values of x have linear predictive power on current y.

B. Ashley and Tsang (2014) argue that the in-sample estimation of causality can be a poor approach to out-of-sample forecasting. Thus, they propose a cross sample validation (CSV) scheme; the sample is separated into equal segments and in a repetitive process one segment is considered each time as the "unknown" sample and the rest are used for calculating the *F*-statistic. The mean value of the errors over the entire sample should provide a better predictor on the existence of a causal relationship.

C. Under a different perspective, Hiemstra and Jones (1994) propose a non-linear causality test based on the concept of correlation integral. Given an *m*-dimensional time series x of length *T*, the correlation integral is:

$$C(T, e) = \sum_{i=1}^{T-1} \sum_{j=i+1}^{T} I\left(x_i, x_j, e\right) \times \frac{2}{T(T-1)} \tag{3}$$

Subject to $$I\left(x_i, x_j, e\right) = \begin{cases} 1 & \left|x_i, x_j\right| < e \\ 0 & otherwise \end{cases}$$

where $\left|x_i, x_j\right|$ is the Euclidean distance. In other words the correlation integral measures the fraction of data pairs that are within a maximum distance e. Examining the stationary trivariate process $\left\{x_t, y_{t-l_x}^{l_x}, y_{t-l_y}^{l_y}\right\}$, where l_x and l_y are lag orders. Then y does not Granger cause x if:

$$Pr\left(\|x_i, x_j\| < e \middle| \left\|x_{i-l_x}^{l_x} - x_{j-l_x}^{l_x}\right\| < e, \left\|y_{i-l_y}^{l_y} - y_{j-l_y}^{y}\right\| < e\right) =$$
$$Pr\left(\|x_i, x_j\| < e \middle| \left\|x_{i-l_x}^{l_x} - x_{j-l_x}^{l_x}\right\| < e\right) \quad (4)$$

where $Pr(\circ)$ denotes probability, *i,j* are values of the series x_t, y_t and $\|\circ\|$ the maximum norm. The Granger causality condition can be rewritten using the correlation integral as

$$H_0: \frac{C(m+l_x, l_y, e)}{C(l_x, l_y, e)} = \frac{C(m+l_x, e)}{C(l_x, e)} \quad (5)$$

for given values of l_x, l_y and $e > 0$.

D. Hill (2007) builds on the aforementioned trivariate system and proposes a rolling and a recursive parametric representation of causality chains for bivariate and trivariate VAR processes. With the proposed approach it is possible to test for causality in multi-steps ahead while a bivariate and a rolling window approach is also feasible.

E. We also examine the non-parametric quantile-based methodology proposed by Jeong *et al*. (2012). This approach is robust to extreme values in the data and captures general non-linear dynamic dependencies. Formally let $Z_t = (x_t, y_t)$. $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|y_{t-1}}(y_t, y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and y_{t-1}, respectively. If we denote $Q_\theta(Z_{t-1}) = Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(y_{t-1}) = Q_\theta(y_t|y_{t-1})$ the quantiles, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. Consequently, the causality in the θth quantile hypotheses to be tested can be specified as:

$$H_0\text{: } \Pr\left[F_{y_t|Z_{t-1}}\{Q_\theta(y_{t-1})|Z_{t-1}\} = \theta\right] = 1, \quad (6)$$

$$H_1\text{: } \Pr\left[F_{y_t|Z_{t-1}}\{Q_\theta(y_{t-1})|Z_{t-1}\} = \theta\right] < 1 \quad (7)$$

3. Empirical results

We compile a dataset of quarterly annualized output growth and monthly annualized inflation for 17 Eurozone countries. The quarterly and monthly uncertainty indices for output growth and inflation are from Rossi and Sekhposyan (2017). In the case of the trivariate Hill's test that builds on a trivariate VAR we also include the quarterly inflation and the monthly IPI for the causality tests on output and inflation, respectively. The descriptive statistics are reported in the Appendix. In Table 1 we report the results from

all causality tests on the null hypothesis that the output uncertainty index of Rossi and Sekhposyan (2017) does not granger cause output growth. In Table 2 we report the respective results for the inflation and the inflation index, respectively. Due to space restrictions the details for the parameters of each test are reported in the Appendix.

As we observe from Table 1, based on all tests, we cannot reject the null hypothesis that uncertainty does not granger-cause output growth. The results from Table 2 are similar. While the linear Granger causality test rejects the null hypothesis for certain countries, the rest of the tests do not corroborate to these results. Rejections of the null hypothesis are different between tests and are only episodically. Our empirical findings do not support the notion stated by Rossi and Sekposyan (2015), that the macroeconomic uncertainty is a measure of the degree that the economy is predictable, since we do not detect a causal relationship between their indices and the macroeconomic variables.

Table 1: Non Causality test results that output uncertainty index granger-causes output growth										
	Linear (Granger) Causality test		CSV test	Non-linear HJ test	Hill Bivariate	Hill Trivariate		Causality-in-quantiles test		
Country	Lags	F-stat	CSV75 p-values	t-stat	Rejection Percent (Recursive)	Rejection percent (Rolling)	Rejection percent (Recursive)	5% t-stat	Median t-stat	95% t-stat
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Austria	1	1.39	0.44	0.67	0.00	0.00	0.00	0.10	0.07	0.13
Belgium	1	1.28	0.59	0.96	0.00	1.92	0.00	0.04	0.02	0.00
Cyprus	4	5.94*	0.52	0.53	26.67	0.00	0.00	0.00	0.01	0.04
Estonia	2	1.62	0.45	-0.33	21.05	2.56	0.00	1.60	1.72	0.14
Finland	3	0.72	0.57	-0.77	9.38	5.56	0.00	1.76	1.67	0.37
France	2	1.36	0.59	-0.71	0.00	4.16	0.00	1.30	1.61	0.44
Germany	1	4.57*	0.59	-1.32	6.25	1.39	0.00	0.03	0.01	0.00
Greece	3	0.47	0.50	0.81	0.00	0.00	0.00	0.77	0.73	0.25
Ireland	3	4.71*	0.38	0.37	86.96	0.00	2.33	0.67	0.61	0.29
Italy	6	1.17	0.46	0.14	3.85	0.00	0.00	2.32*	2.41*	0.84
Latvia	2	6.25*	0.47	-0.43	5.26	0.00	0.00	3.48*	2.45*	0.71
Lithuania	1	1.33	0.57	-0.20	0.00	0.00	0.00	0.02	0.02	0.00
Portugal	2	0.51	0.39	1.32	0.00	0.00	0.00	0.19	0.60	0.07
Slovakia	1	0.09	0.52	0.95	0.00	0.00	0.00	2.09*	1.37	0.32
Slovenia	8	5.07*	0.45	-1.46	0.00	0.00	0.00	0.02	0.06	0.01
Spain	9	2.39	0.51	0.83	34.38	0.00	0.00	0.25	0.44	0.45
Netherlands	1	3.36*	0.50	-0.54	7.69	0.00	0.00	0.28	0.19	0.22

Note: * denotes rejection of the null hypothesis of non-causality at the 5% level of significance.

Table 2: Non Causality test results that inflation uncertainty index granger-causes inflation										
	Linear Causality test		CSV test	Non-linear HJ test	Hill Bivariate	Hill Trivariate		Quantile causality test		
Country	Lags	F-stat	CSV75 p-values	t-stat	Rejection percent	Rejection percent (Rolling)	Rejection percent (Recursive)	5% t-stat	Median t-stat	95% t-stat
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Austria	12	0.65	0.45	-0.18	0.00	0.36	0.00	0.12	0.12	0.04
Belgium	1	0.10	0.72	0.87	1.62	0.73	0.00	0.15	0.44	0.17
Cyprus	12	6.65*	0.05*	-0.28	4.70	0.00	0.00	0.21	0.50	0.48
Estonia	1	0.76	0.93	-0.93	0.00	1.71	0.00	2.03	3.07*	0.63
Finland	15	0.49	0.82	0.98	0.54	0.07	0.00	0.28	0.61	0.26
France	13	0.29	0.40	0.86	29.19	1.09	0.00	0.13	0.80	0.27
Germany	12	7.89*	0.74	-0.03	1.62	1.28	0.00	0.35	0.34	0.08
Greece	12	4.64*	0.53	0.69	58.33	0.07	0.00	0.30	0.64	0.30
Ireland	13	0.07	0.31	1.42	5.95	0.00	0.00	1.20	2.18*	0.71
Italy	12	0.01	0.21	1.77	9.73	0.07	0.00	0.05	0.10	0.02
Latvia	15	0.49	0.79	1.17	0.00	0.00	0.00	0.17	0.33	0.37
Lithuania	12	0.80	0.04*	0.02	1.62	0.00	0.00	0.01	0.02	0.02
Portugal	13	0.59	0.09	0.02	8.07	1.45	0.00	0.62	1.24	0.37
Slovakia	12	1.24	0.11	-0.05	4.03	0.00	0.00	0.01	0.01	0.00
Slovenia	15	2.36	0.10	1.24	21.08	0.05	0.04	0.02	0.02	0.01
Spain	14	1.91	0.36	-0.17	15.68	0.04	0.00	0.12	0.28	0.03
Netherlands	1	3.89*	0.45	1.64	0.00	0.07	0.00	0.66	0.76	0.24

Note: * denotes rejection of the null hypothesis of non-causality at the 5% level of significance

4. Concluding Remarks

In this paper we examine the causal relationship between the uncertainty indices of Rossi and Sekhposyan (2017) on inflation and growth rate with the actual macroeconomic variables, for 17 Eurozone countries on the country level. In doing so we apply a combination of linear and nonlinear causality tests used in the economic literature. Our empirical findings imply the lack of a causal relationship between uncertainty indices and specific macroeconomic variables. Rejections of the null hypothesis are only episodically between the various tests, with the nonlinear Hiemstra and Jones (1994) and the trivariate Hill (2007 tests to accept the null for all countries. Thus the literature on forecasting macroeconomic conditions based on the uncertainty indices should be treated with caution.

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Appendix

A. Descriptive statistics

We compile quarterly Gross Production Index (GDP) and monthly Consumer Price Index (CPI) for Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Portugal, Slovakia, Slovenia, Spain and the Netherlands from the OECD database. Additionally, we compile the Industrial Production Index for the aforementioned 17 Eurozone countries, in order to train the trivariate VAR models. Malta and Luxenburg where not examined due to data unavailability. We compute quarterly annualized growth rate based on the formula $Growth\,rate_t = 400 \times \left(ln(GDP_t/GDP_{t-1})\right)$ and monthly annualized inflation based on the formula $Inflation_t = 1200 \times \left(ln(CPI_t/CPI_{t-1})\right)$

When we test the quarterly non-causal relationship between the uncertainty index and the growth rate based on the Hill's trivariate test, we include the inflation value matching the end of the quarter. Under the same approach, we include the monthly IPI in the trivariate model that examines the causal relationship between inflation and uncertainty. In table A-1 we report the descriptive statistics for each series.

Table A-1: Descriptive statistics

	Growth rate						Inflation					
	Date	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera test (pvalue)	Date	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera test (pvalue)
Austria	1996Q1-2015Q1	1.76	2.77	-0.73	3.95	0.01	1990M01-2015M04	2.16	4.42	0.25	4.53	0.00
Belgium	1995Q1-2015Q1	1.77	2.22	-1.32	7.82	0.00	1990M01-2015M04	2.01	3.35	0.12	3.12	0.63
Cyprus	198Q1-2014Q4	4.35	7.63	-0.67	6.26	0.00	1998M05-2015M04	1.99	10.51	-0.57	3.04	0.00
Estonia	1998Q2-2015Q1	3.34	9.15	-1.74	8.51	0.00	1998M05-2015M04	3.53	5.36	0.69	4.56	0.00
Finland	1990Q1-2015Q1	1.50	5.18	-1.83	12.44	0.00	1990M01-2015M04	1.80	3.89	0.41	4.44	0.00
France	1990Q1-2015Q1	1.54	1.98	-1.08	6.64	0.00	1990M01-2015M04	1.64	3.25	-0.29	3.66	0.01
Germany	1990Q1-2015Q1	1.56	3.62	-1.44	11.16	0.00	1990M01-2015M04	1.89	3.97	0.65	5.56	0.00
Greece	1995Q2-2015Q1	0.83	6.09	-0.93	4.26	0.00	1993M06-2015M04	5.27	15.00	0.43	2.87	0.01
Ireland	1997Q2-2014Q4	4.13	8.57	0.18	3.21	0.77	1990M01-2015M04	2.20	5.16	-0.29	3.98	0.00
Italy	1990Q1-2015Q1	0.64	2.89	-0.99	6.59	0.00	1990M01-2015M04	2.73	2.49	0.16	3.91	0.00
Latvia	1998Q3-2015Q1	3.60	8.61	-1.01	4.83	0.00	1998M05-2015M04	3.84	7.28	0.51	4.14	0.00

Lithuania	1998Q3-2015Q1	3.79	8.95	-4.37	30.09	0.00	1998M05-2015M04	2.24	6.17	0.81	5.43	0.00
Netherlands	1990Q1-2015Q1	2.05	2.80	-1.72	10.01	0.00	1990M01-2015M04	2.16	5.33	0.17	2.50	0.10
Portugal	1995Q2-2015Q1	1.25	3.41	-0.62	3.32	0.07	1990M01-2015M04	3.51	6.11	0.70	5.61	0.00
Slovakia	1997Q2-2015Q1	3.64	7.48	-1.92	16.98	0.00	1995M02-2015M04	4.59	8.64	4.18	25.30	0.00
Slovenia	1998Q2-2014Q4	2.24	5.00	-1.58	7.89	0.00	1995M02-2015M04	4.41	6.97	-0.34	2.92	0.10
Spain	1995Q2-2015Q1	2.05	2.74	-1.11	3.46	0.00	1990M01-2015M04	3.00	5.73	-0.42	4.79	0.00

B. Test optimization details

The linear causality test of Granger (1969) are reported in columns (2) and (3) of Tables 1 and 2. The lag order of the regression models is selected according to the minimum SIC value. In column (4) we report the third-quartile cross-sample validation p-values (CSV75) for the CSV test, where Ashley and Tsang (2014) suggest that the test exhibits the highest rejection power. The t-statistics of the non-linear HJ test are reported in column (5), while in column (6) we report the rejection percent from a bivariate VAR model based on the recursive estimation of the Hill's test.

In the bivariate Hill causality test, starting from the 50% of the available observations we test recursively the null hypothesis using only the index and the output growth at the 5% level of significance for all horizons greater than $h=0$ and count the numbers that we reject the null hypothesis as the sample expands. The rejection percentage is reported in columns (7) and (8) for the trivariate Hill's test, where we add quarterly inflation in the model. Columns (7) and (8) refer to rolling and recursive estimation for all horizons greater than $h=0$, respectively. Finally, in columns (9), (10) and (11) we report the t-statistic from the 10%, the 50% and the 90% quantile of the quantiles causality test, evaluating typical (median) and the extreme (outlier) cases. The empirical implementation of causality in quantiles entails specifying three important choices: the bandwidth, the lag order, and the kernel type, respectively. In this study, a lag order of one is used on the basis of the minimum SIC. The bandwidth value is chosen by employing least squares cross-validation techniques. Finally, Gaussian-type kernels are employed.