Persistence of Economic Uncertainty: A Comprehensive Analysis

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Abstract

One of the most heavily researched and cited issues in applied economics is the relationship of uncertainty indices with the financial and macroeconomic variables. While the statistical features of financial and macroeconomic variables have been thoroughly examined, virtually nothing has been done to examine uncertainty indices under the statistical perspective. In this paper, we focus on two primary characteristics of uncertainty indices: persistence and chaotic behavior. In order to evaluate the persistence and the chaotic behavior we analyze 72 popular uncertainty indices constructed by forecasting models, text mining from news articles and data mining from monetary variables to measure the Hurst and Lyapunov exponents in rolling windows. The examination in rolling windows provides a dynamic evaluation of the specific characteristics revealing significant variations of persistence and chaotic dynamics with time. More specifically, we find that almost all uncertainty indices are persistent, while the chaotic dynamics are detected only sporadically and for certain indices during recessions of economic turbulence. Thus, we suggest that the examination of persistence and chaos should be a prerequisite step before using uncertainty indices in economic policy models.

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1. Introduction

In the wake of the "Great Recession", a large international literature has emerged that analyzed the (negative) impact of uncertainty on macroeconomic variables and financial markets (see Chuliá et al., (2017) and Gupta et al., (forthcoming a, b) for detailed literature reviews). In parallel, numerous studies have also analyzed the spillover of uncertainty across economies (see Gabauer et al., (forthcoming) and references cited therein for the discussion of the associated literature), to suggest that international uncertainty linkages are likely to prolong the impact of an uncertainty shock in the domestic economy.

Despite the importance of the effect of uncertainty on financial markets and the macro economy, little attention has been given to the statistical characteristics of the various uncertainty indices in the literature and more specifically on the persistence¹ and the chaotic characteristics of the series. Starting from the former, a more persistent uncertainty series would take longer to revert to its long-run equilibrium after the imposition of a shock. Thus, the more persistent the uncertainty variable the more prolonged would be the negative impact of an uncertainty shock on the economy and the financial market. This in turn, would imply that the strength of the corrective actions required by the government to nullify the impact of this uncertainty shock would be contingent on the persistence property of the measure of uncertainty used in the empirical models. In addition, if the persistence of the uncertainty variable is so high that its deviation from its long-run equilibrium is permanent, then this variable becomes difficult to forecast. With uncertainty being a leading indicator, it implies that macroeconomic variables and financial markets become difficult to predict using information from the uncertainty variable.

From the perspective of chaos, a series that exhibits chaotic behavior is dependent upon initial conditions. In other words, similar shocks to different situations create different

¹ To the best of our knowledge, Caporale et al., (2017) , is the only paper that deals with persistence property of some sort of measure of uncertainty. In particular, the authors analyse Chicago Board Options Exchange (CBOE)'s Volatility Index, known as VIX, which in turn, is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options. The findings indicated that its properties change over time: in normal periods it exhibits anti-persistence, while during crisis periods the level of persistence increases.

future paths. Thus, the behavior of the series is difficult to predict and probably given the complexity of all chaotic systems, any detected causal linkage between economic variables and uncertainty series should be attributed to chance and not to a concrete causal relationship.

Given that uncertainty indices are theoretically assumed to be stationary, we depart from the typical unit root methodology and apply the Hurst exponent in an extended dataset of 72 uncertainty indices in a time-varying (rolling window) framework to analyze how the persistence of uncertainty evolves over time. Understandably, if persistence of uncertainty is indeed time-varying, then it also points to the fact that econometric analysis involving the impact of uncertainty on the economy, should also be conducted in a timevarying manner rather than in a static fashion to obtain accurate inferences and predictions. The typical examination of persistence in the literature includes unit root tests, while some authors treat persistence as a fractionally integrated process or use signal processing methodologies such as the Fourier transformation to test for the existence of stochastic trends in the data. Nevertheless, all these applications are sensitive to the presence of structural breaks and usually call for some initial ad hoc assumptions, such as the determination of model parameters exogenously (Enders and Lee, 2012). The existence of structural breaks on relatively long-spans of economic data, such as volatile uncertainty indices, is highly likely. In contrast, the methodology we follow in this study, namely the Hurst exponent, is not affected by the existence of structural breaks and is based entirely on a data driven procedure making it ideal for our case.

Moreover, in this paper we depart from the typical examination of the persistence of a series, and also evaluate the existence of chaotic behavior for the uncertainty series. In the context of a chaotic time series, a shock apart from a permanent change in the series also creates a diverging path measured by the Lyapunov exponent, another nonparametric and nonlinear methodology. To the best of our knowledge this is the first attempt to examine the statistical properties of uncertainties based on the persistence and chaos in order to obtain a complete picture of the statistical characteristics of uncertainty, and hence, its impact on the broader economy. Another innovation introduced in our study is the use of rolling windows in order to unveil dynamic changes of the statistical features of the series with time. Most empirical literature applies some form of unit root test on

the entire sample, and infers upon the results of the test on the mean-reverting behavior of the series. Nevertheless, this one-time-examination smooths out important changes in the evolution of the series, especially an uncertainty index that is likely to drive changes in the economy. Note that, if the persistence property of uncertainty indices do vary over time, so will its impact, and hence, to capture the true impact of uncertainty on macroeconomic and financial variables, one would need to carry out analyses based on time-varying rather than constant parameters-based models to obtain accurate inferences. The rest of the paper is organized as follows: Section 2 outlines the methodologies used, while Section 3 presents the data and results. Finally, Section 4 concludes.

2. Methodology

2.1 Hurst Exponent

The Hurst exponent belongs to the broader category of nonparametric analysis methods and was first proposed by Hurst (1951) as a method for analyzing long-range dependence in the hydrology series. The exponent H (Hurst exponent) takes values on the range $[0, 1]$ 1]. Values close to zero indicate an anti-persistent series—the series under examination is mean-reverting. Values close to 1 indicate that the series is persistent— the series never returns to equilibrium after an exogenous shock. An $H = 0.5$ indicates a Random Walk (RW). Hurst exponent analysis has been applied extensively in financial time series (e.g. equities, exchange rates, commodities, derivatives etc.²), but only sporadically in macroeconomic variables and never before in measuring the persistence of economic uncertainty indices.

The Detrended Fluctuation Analysis (DFA) in estimating the exponent *H* was proposed by Peng et al. (1994) for identifying long-dependence in DNA nucleoids series as an alternative to the R/S method used up to that period. The initial series *X* of length *N* is divided into *q* equally sized parts of length $n = N/q$. Each of the new segments $m=1,2,3,\ldots,q$ is integrated by the cumulative sums:

$$
Y_{i,m}^{(n)} = \sum_{j=1}^{i} x_{j,m}^{(n)}, \qquad i = 1,2,3,\dots,q.
$$
 (1)

² Due to space restrictions the interested reader is referenced to Mulligan and Koppl (2011) and the papers cited therein.

We then estimate the OLS line for the points in each segment $Y_{m,i}^{(n)} = a_m^{(n)} i + b_m^{(n)}$ and calculate the standard deviation residuals:

$$
F_m^{(n)} = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(Y_{m,i}^{(n)} - a_{m,j}^{(n)} - b_m^{(n)} \right)^2}.
$$
 (2)

The average SD is calculated for all segments of length *n*:

$$
F(n) = \frac{1}{q} \sum_{m=1}^{q} F_m^{(n)}.
$$
 (3)

The F_n values are calculated for every partition and plotted against the partition segment size *n* in a log–log scale. The slope of the linear fit expresses the Hurst exponent *H*.

2.2 Lyapunov Exponent

The use of the Lyapunov exponent in detecting deterministic chaos in economic time series has been applied extensively to financial market series, e.g. exchange rates (Serletis and Gogas, 1997), stocks (BenSaida and Litimi, 2013 and Hsieh, 1991), etc. The basic idea behind the detection of chaos lies with the dependence of chaotic systems to initial conditions. More specifically, if we consider two points of the same series X_0 and $X_0 + \Delta X_0$ and generate a path for each one of them, these two points evolve in two different time paths. The difference in the trajectories of the two paths depends on the initial position X_0 and the elapsed time, getting the form $\Delta x(X_0, t)$. If the system is stable this difference decreases asymptotically with time. In contrast, in a chaotic system the difference diverges exponentially. The Lyapunov exponent *λ* measures this difference $\Delta x(X_0,t)$ between the two paths. In order to identify a system as chaotic, the corresponding Lyapunov exponent should be strictly positive and near unity. In this paper, we follow the procedure described in BenSaida and Litimi (2013) in order to estimate the maximum Lyapunov exponent. In mathematical notation:

$$
x_t = f(x_{t-L} + x_{t-2L} + \dots + x_{t-mL}) + \varepsilon_t.
$$
 (4)

Where L is the time delay, f is an unknown chaotic map, m is the embedding dimension of the system and ϵ_{r} represents the added noise. BenSaida and Litimi (2013) adopt the

Jacobian-based approach to compute λ since the direct approach is inefficient in the presence of noise. Briefly, the exponent is given by:

$$
\hat{\lambda} = \frac{1}{2M} ln v_i \tag{5}
$$

where *M* is an arbitrary selected number of observations often approximating the $\frac{2}{3}$ of the total span and v_i is the largest eigenvalue of the matrix $(T_M U_o)(T_M U_o)'$, with

$$
U_0 = (1 \ 0 \ 0 \ ... 0)'
$$
 (6)

$$
T_M = \prod_{t=1}^{M-1} J_{M-t} \tag{7}
$$

$$
J_{t} = \begin{bmatrix} \frac{\partial f}{\partial x_{t-L}} & \frac{\partial f}{\partial x_{2t-L}} & \dots & \frac{\partial f}{\partial x_{t-mL+L}} & \frac{\partial f}{\partial x_{t-mL}} \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \ddots & \vdots & \vdots \\ \vdots & \vdots & \dots & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} .
$$
 (8)

In the case of scalar time series, the chaotic map *f* generating the series is usually unknown; as a result the Jacobean matrix in (8) cannot be estimated. Thus, we need to approximate the chaotic map with a data adapting function that can produce an exact approximation of the series. The authors choose to estimate the chaotic map based on a neural network with one hidden layer of neurons and one output layer. In mathematical notation the chaotic map *f* is approximated by the equation:

$$
x_t \approx a_0 + \sum_{j=1}^q a_j \tanh(\beta_{0,j} + \sum_{i=1}^m \beta_{i,j} x_{t-iL}) + \varepsilon_t \tag{9}
$$

where *q* declares the hidden layers of the neural network with a tangent activation function. The order of *(L,m,q)* defines the complexity of the system and is selected according to the triplet that provides the maximum value of the exponent *λ*.

A common problem in the identification of the maximum Lyapunov Exponent is the determination of noise in the system and misspecifications in the selection of the *(L,m,q)* values. As BenSaida and Litimi (2013) argue, when the noise frequency added to the system is sufficiently larger with respect to the output of the chaotic system, the chaotic map tends to be absorbed by noise and thus the system imitates a stochastic process, leading to small or negative values of the calculated exponent *λ*. The authors overcome these misspecification issues by proposing an auxiliary statistical test to the procedure of the evaluation of the maximum Lyapunov exponent, based on its asymptotic values. Assuming the existence of chaos as the null hypothesis of the test they attempt to reject it in favor of the non-existence of chaos in a one-sided statistical test.³ In this way, a system is identified as chaotic when both assumptions are met: a) we find a positive Lyapunov exponent close to unity and b) we are unable to reject the null hypothesis on the existence of chaos.

3. Empirical results

We compile a dataset of uncertainty indices from various sources.⁴ More specifically, we compile the economic policy uncertainty indices of Baker et al. (2016) for 22 countries, a global uncertainty and a U.S. monetary policy uncertainty index again by Baker et al. (2016). While there exists alternative measures of uncertainty derived from estimation of factor models (Jurado et al., 2015) or disagreement of professional forecasters (Rossi and Sekhposyan, 2015, 2017), and of course the options-based financial market uncertainties (i.e., the various VIXs), one attractive choice is the news-based indices of Baker et al., (2016). The approach is model-free and also it is a broader measure of uncertainty (not just financial markets as in the case of VIX) and is for a large number of countries around the world. Nevertheless, for comparison reasons with the existing literature we also examine the macroeconomic uncertainty indices for the U.S. of Jurado et al. (2015). The specific index is quantified as the error in forecasting U.S. GDP in various horizons, based on a forecasting model with stochastic trend and volatility. Nevertheless, its broad acceptance has made it the typical benchmarks in the field.⁵ We also look at two uncertainty indices based on the Fed announcement and two indices based on FOMC announcements provided by Husted et al. (2016), 36 uncertainty indices based on the expected interest rate forecasts of professional forecasters reported in Istrefi and Mouabbi (2017), and the monetary policy uncertainty index of Arbatli et al. (2017) for Japan that use the same news-based technique of Baker et al. (2016) to construct their index.

³ For more information on the derivation of the test, the interested reader is referred to BenSaida and Litimi (2013).

⁴ Details for each index are reported in the Appendix.

⁵ We examined the Hurst exponents of the Rossi and Sehkposyan (2015) uncertainty indices for the U.S. and the Rossi and Sehkposyan (2017) uncertainty indices for the Eurozone. Due to the limited number of the available observations our results are mixed exhibiting both anti-persistent and persistent behavior based on the window length. We report these results in the Appendix.

3.1 Hurst exponents

We begin our analysis examining both the entire time span and rolling windows of 40%, 50% and 60% of the total length with a sliding window of one. With this smooth transition in time we uncover time patterns that may exist during distinct time periods, but are typically hidden during the examination of the entire sample. In Table 1, we report the Hurst exponents for the entire sample and the rolling window estimates for the news-based uncertainty indices of Baker et al. (2016) and Arbatli et al. (2017).

[Table 1]

As we observe, both in the entire sample and in rolling windows estimation, most economies exhibit persistent behaviour with many values reaching to unity. Thus, an economic shock poses permanent changes to the uncertainty indices. In the smaller (40%) rolling window, Australia, Germany, Korea, Russia, South Africa and Hong Kong span from anti-persistent to persistent values from below 0.5 to unity, with the mean value being clearly above 0.5. Given that medium length window (50%) only Russia and South Africa keep this behaviour and only Russia in the largest (60%) window; we attribute this unstable behaviour in the smallest window to the length of the window and the smaller samples that affect the estimation of the Hurst exponent. Thus, we focus on the indices of Russia and South Africa. In figure 1, we depict the time evolution of the Hurst exponent for the three rolling windows.

[Figure 1]

The uncertainty indices for both countries are mostly above the 0.5 threshold for all three rolling windows, with the exception of the smaller rolling window for Russia (figure 1, left graph) that exhibits some periods that move towards a Random Walk (RW) behaviour. These periods are mainly detected in the 2006-2009 period of the global financial crisis and the 2011 EU sovereign crisis. Both periods are characterized by economic and financial turbulence and uncertainty. We would expect to observe a structural (persistent) change in the uncertainty index, but instead we observe a tendency towards a RW. Thus, we should examine for the existence of chaotic behaviour to justify this finding. A chaotic series is hard to forecast and given its dependence on the initial conditions may exhibit unexpected behaviour. We keep further analysis for the next section where we measure the Lyapunov exponent. The examination of the Hurst exponent for South Africa (figure 1, right graph) reveals that during periods of economic turbulence and increased uncertainty (2005 government sanction, 2007 global financial crisis, etc.) the exponent moves towards the 0.5 threshold exhibiting a less persistent and more chaotic behaviour. Thus, our rolling window examination unveils that during periods of recession of high economic anxiety the uncertainty index exhibits a stochastic behaviour suggesting that its path is hard to foresee, increasing the uncertainty even more. This finding is hidden in the entire sample examination. In Table 2, we report the Hurst exponents for the indices constructed by interest rate projections and Fed and FOMC announcements.

[Table 2]

The examination of the Hurst exponents on the entire sample reveals that all indices are persistent, since they all exceed the 0.5 threshold. The rolling windows estimations again reveal a similar pattern with the news-based uncertainty indices. While on the smaller window a number of indices vary from anti-persistent to persistent series, on the larger window only the spread of the 3-month with the 12-month interest rates for France provides an exponent that spans from 0.39 to 1.00. In figure 2, we depict the evolution of the value of the exponent in time.

[Figure 2]

As we observe from figure 2, the uncertainty index constructed by the interest rates spreads rise as the economy moves away from the 2007 financial crisis, suggesting once again that during periods of high economic uncertainty the index moves towards a RW while in more tranquil periods the uncertainty index exhibits high persistence. An interesting finding is that this index is based on monetary (interest rate) data while the EPU indices of figure 1 are based on newspaper articles. Nevertheless, these two indices exhibit similar behaviours suggesting that newspaper articles could be a source of information for the monetary policy authority and vice versa, i.e., interest rate fluctuation could be reflected in the newspaper headlines. Given that the determination of a causal relationship between the two is not in the scope of this paper, we leave this finding for

future research. In Table 3, we report the Hurst exponents from the examination of the model-based approaches of Jurado et al. (2015).

[Table 3]

As with the other uncertainty indices, the macroeconomic uncertainty indices of Jurado et al. (2015) are highly persistent with the Hurst exponents taking values close to one. An interesting finding is that the index is highly persistent even in all rolling windows, mostly due to the fact that the model focuses on forecasting GDP and thus omits information from other sources of economic uncertainty included in the other uncertainty indices.

3.2 Lyapunov exponents

Given our empirical finding from the examination of the Hurst exponents that uncertainty indices tend to move towards the 0.5 threshold during crisis periods, we proceed in examining the chaotic behaviour of all indices using the Lyapunov exponent. A positive Lyapunov exponent indicates the existence of chaotic dynamics in the data generating process. We separate again our findings into news-based indices and monetary policy ones. In Table 4, we report the Lyapunov exponents for the news-based indices. Given that we are interested in both the sign and the statistical significance of our results, we follow a different approach from the Hurst exponent results. More specifically, we report the percentage of instances that the exponent is positive in all examined windows, instead of its minimum, average and maximum value. In those instances that the exponent is positive, we also test the statistical significance of the exponent in order to infer whether we can reject the null hypothesis about the existence of chaos.

[Table 4 here]

As we observe from Table 4, we detect chaos only episodically and for a limited number of countries. More specifically, the examination on the entire sample reveals that we do not detect positive values for any country, while the statistical test fails to reject the null hypothesis for the existence of chaos only for Brazil, Singapore and the United Kingdom. Nevertheless, the λ exponent is negative and close to zero. The detection of chaos calls for both a positive exponent and a failure to reject the null hypothesis. The rolling windows examination reveals that in the smallest (40%) window a number of countries exhibit a positive Lyapunov exponent and the statistical test fails to reject the null hypothesis in all those instances. Thus, we detect chaos only episodically in rolling windows but the percentage of detections is very low and in largest windows this percentages become even smaller. We should note here that chaos is deterministic and not a stochastic process and thus it it differentiates itself from the RW findings of the previous section. Despite being a deterministic function, the difficulty in forecasting a chaotic series stems from its complexity and the dependence to the initial conditions that evades the forecasting models. The only countries in which we detect chaos consistently are Singapore and South Africa, while for France, Germany and Mexico this finding is detected only for the small window.

Considering our findings in the entire sample and the rolling windows examination, we depict in figure 3 the time evolution of the Lyapunov exponents for the Global uncertainty, the United Kingdom, the South Africa and the Singapore uncertainty index. The uncertainty index of Brazil has a very low detection rate of chaos in the rolling windows examination, so we skip it.

[Figure 3 here]

The Lyapunov exponent for Singapore (figure 2, subplot a) is positive for the smallest window before 2010 exhibiting a chaotic behaviour in the aftermath of the 2008 global financial crisis and the worst recession in the history of Singapore. Moreover, we observe another significant spike around the end of 2015 a period of international turbulence in the region with territorial claims of China over the South China Sea. The positive values in the other windows are rare and very small. The U.K. index (figure 2, subplot b) exhibits positive peaks for the small and the middle window in the period 2010-2011, a period of elevated general economic uncertainty in the European economy. The different timing of the peaks between windows could be attributed to the length of the windows, as the smaller window detects changes in the value of the exponent faster than the larger window. The situation in the case of South Africa (figure 2, subplot c) is more complicated since we observe many positive and large peaks suggesting a chaotic behaviour of the uncertainty index for South Africa.

The examination of the global uncertainty index (figure 2, subplot d) also exhibits some interesting results. The global financial crisis creates a positive peak with a delay of one year around the summer of 2009 for the smaller more volatile window reporting a nonchaotic, predictable increase of the uncertainty index. In contrast, all windows exhibit positive peaks in the period 2011-2013, the period of the European sovereign crisis. This fact coincides with the view of Bauer and Becker (2014) that despite the lessons from the 2008 financial crisis the emergence of the European crises found the European regulatory authorities ill-prepared and necessitated major changes such as the creation of the European Stability Mechanism, a fund dedicated to funding indebted countries to avoid a new sovereign debt crisis. Moreover, our findings also reveal that the uncertainty index followed a chaotic trajectory, making it very hard to forecast its future path and thus increasing the overall uncertainty of the global economy.

In Table 5, we report the Lyapunov exponents for the monetary uncertainty indices. As we observe from Table 5, in two instances we detect chaos in the entire sample (France 3-month interest rate at the 12-month horizon and Italy 3-month interest rate at the 3 month horizon) while in all other cases where we cannot reject the null hypothesis of the existence of chaos the exponent is negative. In the aforementioned instances, we cannot reject the null hypothesis and the exponent although close to zero is positive. Thus, we detect a low level of deterministic chaos. Nevertheless, the rolling windows examination provides a different image. In 11 out the 36 forecasts in the small window the exponent is positive and statistically significant above 50% of all windows, while this high ratio is observed in three out of a total of 36 instances in the medium window. In the large window, we observe positive and statistically significant exponents in all countries and horizons for a number of windows but none exceeds the 50% threshold and in only four instances it exceeds the 30% threshold. Apparently, most positive exponents are observed in the forecasts of the 3-month interest rate and less in the 10-year rate. This finding could be attributed to the overall uncertainty in the short term amid a debt crisis in the Eurozone and the short-term turbulence that makes difficult to forecast the decisions of the central monetary authority (reflected in the short-term rate). The debt crisis has not altered significantly in the long-run expectations for the economy. The examination of the Fed and FOMC announcements rejects the existence of chaos in the entire sample while in the rolling windows the detection of chaos is rare.

[Table 5 here]

In figure 4, we depict the Lyapunov exponents of the rolling windows for the 3-month interest rate in a 12-month forecasting horizon for France and the 3-month interest rate in a 3-month horizon for Italy, where we detect positive and statistically significant Lyapunov exponents for the entire sample and high ratios of positive values in the rolling windows.

[Figure 4 here]

Both uncertainty indices exhibit multiple positive peaks that do not last for large time periods. The overall assessment is that both indices have an upward trend after 2010 that is more prominent in the middle and large window. This finding could be attributed to the overall political and economic turbulence due to the sovereign debt crisis in the Eurozone and the frustrating macroeconomic conditions in the south periphery of the Eurozone that creates uncertainty and makes it hard to forecast the future evolution in the short term. In Table 6, we report the respective Lyapunov exponents for the uncertainty indices of Jurado et al. (2015).

[Table 6]

As we observe, while in the entire sample and the rolling windows examination for the 1 and 3-months ahead GDP forecasts we do not detect chaos, the situation is different for the 12-months ahead forecasts. In the majority of the examined windows we detect chaotic behavior that poses under skepticism the usefulness of the specific index. To relieve possible chaotic dynamics stemming from inflation (Plakandaras et al., 2015), we focus on the index based on Real GDP prices and present the index values for the different windows in figure 5.

[Figure 5]

The smaller window exhibits significant positive peaks in the value of the Lyapunov exponent during the time period February to June 2004 and on July 2008 and March 2009. The sources of the chaotic dynamics during those periods should be attributed to different causes. The 2004 chaotic behavior of macroeconomic uncertainty is a tangible empirical finding on the difficulty of the policy authorities to measure accurately the macroeconomic uncertainty imposed to the economy by the housing bubble that reached its peak during that period. The other two periods capture the global anxiety from the 2008 financial crisis and the anxiety during the first period of 2009 as the consequences of the financial crisis were seen to the global economy.⁶ The values of the exponents on the larger windows are smaller, given that the chaotic dynamics are smoothed out.

4. Concluding Remarks

In this paper, we focus on the statistical characteristics of a plethora of uncertainty indices in terms of their persistence and chaotic behavior. In doing so, we compile a dataset of 72 uncertainty indices based on newspaper articles, economic activity forecasting models and interest rate forecasts and measure their Hurst and Lyapunov exponents in rolling windows. The aforementioned methodologies are capable of detecting persistent and chaotic dynamics in non-linear, non-stationary systems and have never been used before in this context. Our empirical findings show that all series exhibit a persistent behavior; the imposition of a shock to the economy that changes uncertainty will have a permanent effect on the uncertainty index departing from its long-run equilibrium. Moreover, during periods of recession or economic turbulence, many indices exhibit stochastic behavior, resembling a RW process. These findings are apparently due to our rolling window examination and have been overlooked in the past. The result, however, suggests that the impact of uncertainty is likely to be non-constant over time (with it being stronger especially during extreme periods – a finding also discussed in detail in Gupta et al., (forthcoming a, b)), and should be best studied using time-varying frameworks. The detection of chaos is achieved only episodically mostly on the monetary-based indices. Overall, our findings call for a closer examination of the persistence properties of uncertainty indices before using them in econometric models.

⁶ On the 19 January the Danish government applied for financial help creating panic in the markets for a second wave of financial crisis, the S&P and Dow Jones indices plunging to historical lows for the first and levels close to the 1929 crisis for the second, the announcement of a quantitative easing program from the Bank of England amplified the fears for an increase in inflation, etc.

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(continued)

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Figure 1: Hurst exponents for Russia (left) and South Africa (right) based on uncertainty indices extracted from news. The continuous (blue) line depicts the small (40%) rolling window results, the dotted (red) line depicts the mid (50%) window length and the dashed (green) line depicts the large (60%) window length.

Figure 2: Hurst exponents for the spread of the 3-month with the 12-month interest rates for France. The continuous (blue) line depicts the small (40%) rolling window results, the dotted (red) line depicts the mid (50%) window length and the dashed (green) line depicts the large (60%) window length.

Figure 3: Lyapunov exponents for the Singapore (subplot a), the U.K. (subplot b), the South Africa (subplot c) and the global (subplot d) uncertainty indices. The continuous (blue) line depicts the small (40%) rolling window results, the dotted (red) line depicts the mid (50%) window length and the dashed (green) line depicts the large (60%) window length.

Figure 4: Lyapunov exponents for the 3-month interest rate index at the 3-month horizon for France (upper subplot) and for the 3-month interest rate index at the 3-month horizon for Italy (bottom subplot). The continuous (blue) line depicts the small (40%) rolling window results, the dotted (red) line depicts the mid (50%) window length and the dashed (green) line depicts the large (60%) window length.

Figure 5: Lyapunov exponents for the 12-month ahead forecasts of the real uncertainty indices of Jurado et al. (2015). The continuous (blue) line depicts the small (40%) rolling window results, the dotted (red) line depicts the mid (50%) window length and the dashed (green) line depicts the large (60%) window length.

Appendix

 Note: many series exhibit anti-persistent or persistent behaviour in different windows, which should be attributed to the small (<100) number of observations that creates stability problems to the estimation of the exponents.